Have Indonesian Rubber Processors Formed a Cartel?

Analysis of Intertemporal Marketing Margin Manipulation

Thomas Kopp, Zulkifli Alamsyah, Raja Sharah Fatricia and Bernhard Brümmer

EFForTS discussion paper series Nr. 3

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Georg-August-Universität Göttingen
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Abstract

In Indonesia the agricultural sector plays a key role for broad based economic development in rural areas. Rubber is one of the most important crops, and Indonesia is the second largest producer in the world. However, a high level of concentration in the processing industry limits the spread of the incoming wealth. In Jambi province on Sumatra, the strong market power of the crumb rubber factories is based on cartelization. This has tremendously negative welfare effects on the rural population, effects which are also likely to be relevant for many other provinces throughout Indonesia. For the society in general and policy makers specifically, it is essential to know about the extent of the whole issue. Thus we study the price transmission at these factories and assess their true market power. We make use of the non-parametric estimation technique of penalized splines in order to understand the error correcting process without having to make a priori assumptions about it. We then estimate an Auto-Regressive Asymmetric Threshold Error Correction Model to quantify both the extent of the threshold effect as well as the rents that are redistributed from the farmers to the factories. The analysis is based on daily price information from a period of four years (2009-2012). To the best of our knowledge, this is the first paper to quantify the additional distributional consequences of intertemporal marketing margin manipulation based on cartelistic market power.

Keywords: Intertemporal marketing margin manipulation, rubber cartel, Indonesia, asymmetric price transmission, threshold co-integration

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1. Introduction

For Indonesia the agricultural sector is of great importance. In 2011 it contributed 15 % to the GDP and employed 36% of the workforce (World Bank Database). The most valuable export crop is natural rubber. With an annual output of 3.01 million metric tons, Indonesia is the second largest producer of natural rubber in the world, accounting for 27% of global production (FAOSTAT). More than 15 million people generate their main income from rubber cultivation (Fathoni 2009).

In the future, it is likely that the importance of rubber for Indonesia will increase for two reasons. Firstly, the total demand for any kind of rubber will increase, due to economic growth in the emerging economies; and secondly the ever-rising price of crude oil will make synthetic rubber more expensive and thus increases the demand for its substitute natural rubber.

Rubber is predominately produced on the islands of Sumatra and West Kalimantan. They contribute 72% to the total production of the country (Arifin 2005). The province of Jambi (Sumatra) is one example of a province that depends crucially on its agricultural sector. It also represents a typical rubber production area. 52 % of the workforce is employed in the agricultural sector and 653,000 ha (out of 1,354,000 ha) are dedicated to rubber production, of which 99.6% are cultivated by small-holders (Statistical Year Book of Estate Crops). Although Jambi is on average not an exceptionally poor province, the rural population is still disadvantaged compared to the populations in other parts of Indonesia. The average income is 17.5 million RP/year (Jambi in Figures 2011 and Arifin 2005), which is far below the national average of 26.8 million RP/year (World Bank Database). Other development indicators show a similar picture, for example the life expectancy at birth is 71 years in Jambi, compared to 76 years in Jakarta (Jambi in Figures 2011).

As rubber is mainly cultivated by smallholders, rubber does have the potential to be one key to economic and social development in rural areas, improving the socio economic situation of millions. In total, 250,000 Jambinese households (out of 619,000) depend on rubber cultivation (numbers for 2011, source: Statistical Year Book of Estate Crops). This means that roughly one million people in Jambi are affected.

It follows that malfunctions in this market can have a tremendous effect on the livelihoods of small scale farmers and their families if these imperfections are disadvantageous for this group. It should therefore be a primary policy target to ensure that these markets function properly.

However, this does not seem to be the case. The Jambinese rubber sector is characterized by strong monopsonistic market power. On the processing side we can observe a strong concentration of the demand for the produce of the farmers, as there are only nine rubber factories in Jambi, vis-à-vis 250,000 farmers. These factories do not appear to be in tight competition, but are rather collaborating closely. All of them are organized in the association of the rubber processing sector, GAPKINDO ("Gabungan Perusahaan Karet Indonesia", i.e. the "Rubber Association of Indonesia") whose target is to "develop and improve production, processing and marketing of Indonesian natural rubber" (Gapkindo, 2013). A report prepared for the development agency USAID found that GAPKINDO is a very efficiently organized and politically powerful lobbying-institution that represents the interests of rubber processors and brokers. Its main role is "the development of rubber processing industries" and to "network among members". There are strong indications that some individual firms exploit their network to behave in a way that resembles a classical cartel (Peramune and Budiman, 2007: 32).

In order to shed light on the price formation process in the rubber value chain, we are employing a price transmission approach. In particular we study the vertical transmission between the output- and input prices of the five crumb rubber factories in Jambi City from 01 January 2009 until 31 December 2012 via an Asymmetric Threshold Error Correction Model (ATECM). To specify the error correction model correctly and without having to rely on a priori assumptions, we employ the non-parametric technique of penalized splines before estimating a set of candidate parametric models and test which one represents the data best. Instead of stopping at this point and only proving the existence and extent of market power, we also quantify a part of the resulting redistribution of welfare from the suppliers to the factories. These welfare implications are shown to be tremendous.

To the best of our knowledge, this is the first paper combining the approaches of non-parametric and parametric estimation techniques of estimating asymmetric price transmission processes with a welfare perspective to quantify the distributional consequences of this intertemporal marketing margin manipulation. The dataset of daily prices on such a disaggregated and local level is also quite unique.

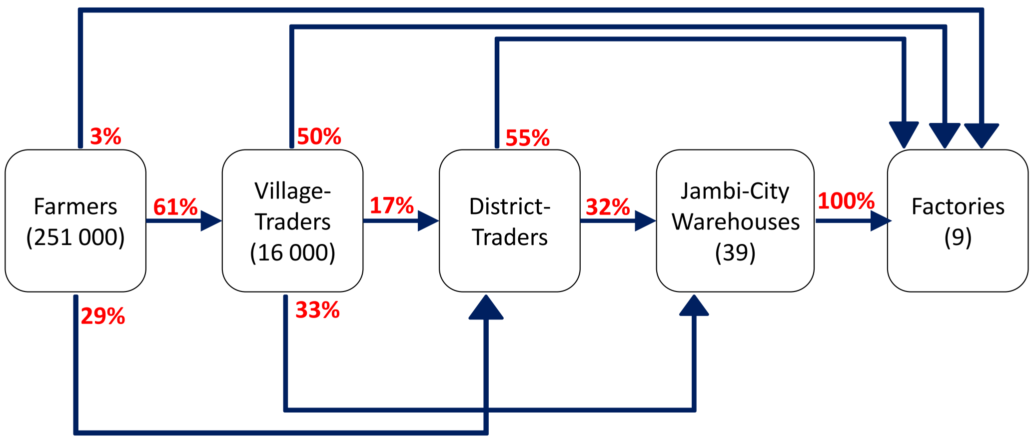
The paper is organized as follows: chapter two provides the background of the rubber market in Jambi province and introduces the typical marketing chain for natural rubber originating from smallholder production in this area. In chapter three the intuition behind asymmetric price transmission is discussed. Chapter four is dedicated to the model development, and chapter five presents the statistical results. The subsequent chapter derives the resulting welfare implications before chapter seven concludes.

2. Background

Rubber marketing in Jambi Province

Rubber had first been introduced in Indonesia by the Dutch colonialists. In Jambi, the colonial military expansion started in 1901 and was followed by the establishment of rubber plantations from 1906 onwards (Martini et al., 2010 and Locher-Scholten 1994).

The Jambinese rubber sector is displayed in Figure 1. Most farmers sell to a village trader who then has the choice between three different kinds of stakeholders to sell to: a factory, a warehouse or another trader, for example on the district level. This choice is influenced by various factors, including the remoteness of the trader, her capital, access to information, etc.[2] The percentages indicate which marketing channel is employed and for how often. The channel Farmer-Trader-Factory is selected in half of the cases and the channel Farmer-Trader-Warehouse in another third. The remaining 17% of the transactions are from Farmer to Trader



Source: own calculations, based on survey data from Euler et al., 2012 and Kopp et al., 2012

There are approximately 16,000 traders in Jambi province. On the processing side there are nine factories. Five of them are located in the capital Jambi City, two in Bungo district and one each in Batanghari and Sarolangun (Kopp et al., 2012 and Jambi in Figures 2011).

The factories market the rubber internationally in different qualities: Standard Indonesian Rubber 20 (SIR20), SIR10, SIR 3L and Ribbed Smoked Sheet (RSS). The dominant quality is the SIR20, accounting for 59 % of all rubber exports from Jambi province (source: interview with Jambi Provincial Government Office for Trade and Industry). SIR20 is internationally recognized as being equivalent to the standard of Technically Specified Rubber (TSR).

Most of the SIR20 rubber sales are facilitated by brokers located in Singapore. The rubber is shipped from Jambi either directly to the overseas buyers, or via Singapore. The reason is that the Jambinese Talangduko harbor is not a deep sea port, so bigger shipments are brought to Singapore by smaller vessels where they are moved to large freighters (Peramune and Budiman 2007, information from interviews with GAPKINDO representatives).

Market concentration and cartelization of factories

It appears likely that monopsonistic market power occurs at several stages of this value chain. On the village-level the traders' market power seems to be based on the farmers' credit constraint as well as asymmetric information vis-à-vis the farmers.

[2] Information stems from a representative survey with 335 traders from all over Jambi province, undertaken in 2012 by the author. It is referred to as Kopp et al. (2012) hereafter.

[3] Farmers' marketing channels do not add up to 100, because they sell a minor share on auction markets (6%) where the buyer is unknown, as well as to farmers' associations (1%). The missing 13% of the district traders stem from the fact that they can also sell to another trader, which was omitted from this graph.

In this paper however, we are focusing on the market power at the next stage: the gates of the factories. The incriminating indicators are strong. During the survey of Kopp et al. (2012) some respondents claimed that they were victims of market power of downstream stakeholders (other traders, warehouses and factories). One could argue that most traders/businesspeople would blame their buyers for playing unfair in order to lobby for an improvement of their own position. But in this case it seems possible that the critique they are expressing is justified to at least some extent. Each of the five factories that are located in Jambi province reports the base price[4] that it is paying each day for their main input to one central agent (their association) and also has the option to get the information on its 'competitors'' prices from this agent. This makes it possible for each factory management to control its competitors' pricing.

Another piece of evidence for the power of the factories is the standard procedure that follows if an external investor wants to construct a new crumb rubber factory. Before getting the required permission by the government, the officials responsible will first consult with the rubber processors' association on whether to give the permission or not (source: interview with Jambi Provincial Government Office for Trade and Industry).[5]

Anwar (2004, cited in Arifin 2004) argues that the margin of Jambinese rubber factories is much higher than those in other provinces. While Anwar argues this to be the result of the close geographic proximity of Jambi to one of the most important export market ports (Singapore), it is much more likely that this observed increased margin comes from the cartelization of the rubber factories.

Distributional effect

This market power has a tremendous effect on the distribution of welfare, both for the rubber farmers and the Jambinese society in general. Figure 2 illustrates that the welfare loss experienced by the farmers consists of the income that is redistributed from them to the factories (A) due to the lower price and the general welfare loss (B) due to lower production.[6]

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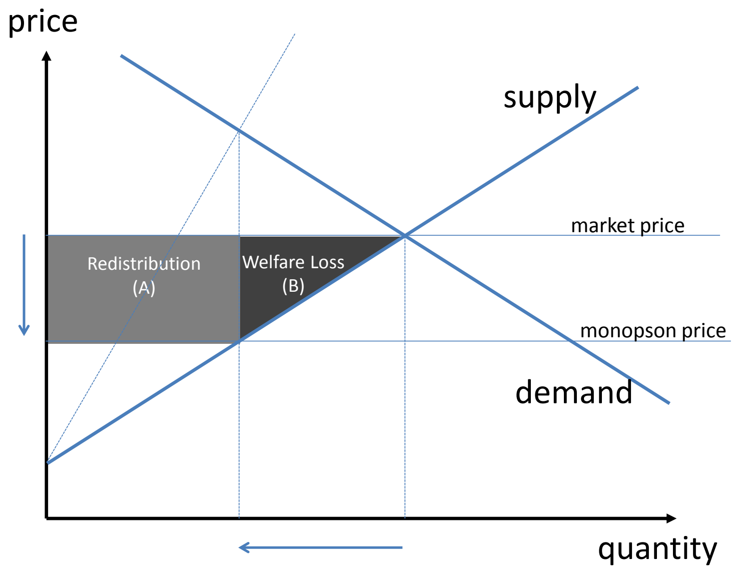
[4] This price is not the price that the sellers (farmers and village traders) receive, because it gets multiplied by a factor that indicates the purity of the rubber, i.e. the contamination with dirt, etc.

[5] That this is not only a mere story but indeed the common procedure is shown by the events in the village Muhajirin in Jambi province. In early 2013 a Thai firm wanted to establish a new rubber factory, but after the negative assessment of GAPKINDO that permission for the project was refused. This is based on information from one GAPKINDO official at the workshop "Kajian Pengembangan Komoditi PBK, SZG, dan PL", held at Dinas Perindustrian dan Perdagangan on 11.10.2013. The alleged reason for the decision was that the existing factories were already running below their capacity, so there would be no need for another factory.

[6] In the long run it is reasonable to argue that the farmers have the possibility to increase their rubber output, for example by shifting their production from palm oil to rubber. After 20-25 years a palm oil plantation has to be replanted and the investment required for replanting palm oil or establishing rubber are similar.

Figure 2: Welfare effect of monopsonistic market power



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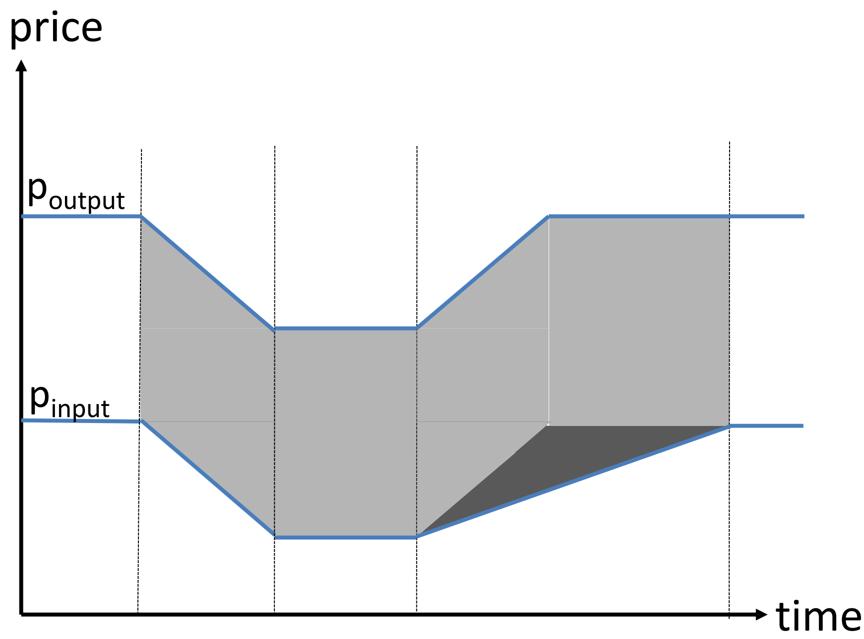
However, as the supply function of the rubber farmers is unknown, it is not possible to derive how much the supplied quantity and thus the total welfare loss (B) would be in the case of a price change. So in the remainder of this article we will concentrate on the farmers' welfare loss due to the redistribution based on lower than free-market price in times of price hikes. We are going to show that this monopsonistic market power is exercised, how it is exercised and how large the welfare loss to the farmers is.

3. Asymmetric price transmission

One way of empirically proving the existence of market power is by testing for a non-constant transmission of price changes (Kinnuncan & Forker 1987, Miller & Hayenga 2001, McCorriston 2002, Lloyd et al. 2003). In the process of the kind of asymmetry that we are addressing here, positive changes of the price at which agent one sells (i.e. when the agent's margin increases) are passed on to the next upstream agent where agent one buys from at a lower speed than negative price changes (i.e. when her margin decreases).

The assumption behind the asymmetric price transmission between the international rubber price and the Jambinese price for raw rubber is that the factories are price takers at the international market and price setters at the domestic market. One can therefore understand the shocks that arise in the first one as exogenous and the ones in the latter as reactions to that shock. In figure 3, the two lines represent the input- and output-prices. The margin of the factory is the light-grey shaded area. Negative shocks are transmitted faster than positive ones, which means that in the case of a negative shock the margin of the processor stays constant, while after a positive shock the margin increases (dark-grey shaded area).

Figure 3: Intuition of asymmetric price transmission



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As Meyer and von Cramon-Taubadel (2004) show, asymmetric price transmission (APT) is not necessarily caused by market power. In their literature review, they present an overview of reasons for asymmetric price transmission other than market power, arguing that the proof of asymmetric price transmission is not necessarily equal to a proof of market power. For the case of our study however, all these alternative explanations that can lead to APT can be ruled out, leaving only the conclusion that the APT is caused by market power, based on cartel behavior:

(a) "Menu costs" or the costs associated with changing the price: the prices that the factories are paying to their suppliers are changing every single day. There is no reason to believe that the costs of changing the price depend on the direction of the price change.

(b) Fixed costs forcing a firm to operate close to its production capacity: as the agricultural input, the slabs of coagulated rubber are extremely durable; the factories always have a stock available, big enough to keep the factory running for more than a week.

(c) Perishability generates an incentive to sell the produce quickly: processed crumb rubber is not perishable.

(d) A strong inflation in times of rising prices leads to data that exhibit asymmetry: while the inflation of the Indonesian Rupiah is greater than that of the US Dollar, it is not great enough to have any impact on a daily basis which is the horizon of our data.

(e) Policy interventions, price support, etc. can also lead to asymmetric price transmission, but have not occurred in Jambi (or on a national level in Indonesia) during the timeframe under consideration.[7]

(f) Processing time: Though a delayed reaction (caused by processing time) in combination with high inflation can show misleading signs of APT[8], this does not apply here because of

[7] Neither were new factories built or a new national/provincial government elected.
[8] See appendix C: APT caused by delayed reaction to shock and high inflation.

two reasons: 1.) Yes, inflation is high in Indonesia (4.3% in 2012[9]). However, we are working with daily data. During the typical reaction times the price hike due to inflation is close to zero. 2.) Secondly, we are observing a potentially monopsonistic setting, implying that the shock that hits the leading (selling) price occurs after the processing. If factories who set their buying price (and take their selling price) would want to set the buying price according to what they receive for that specific load of rubber after processing, they would have to anticipate the time after the processing already at the time of purchasing. This would be impossible.
(g) Non-cooperative game: there are cases where it looks like price-fixing has happened, while in fact there is no outspoken agreement. It occurs in situations in which firms possess a credible threat of punishing another firm which deviates from the cartel-solution (Perloff et al., 2007). However, only very rarely could it be argued that these companies would have an agreement that is not the subject of debate, especially given the fact that in all other respects they are such close companions.

4. Statistical procedure

Non-stationarity and co-integration

Given that we are working with prices, a non-stationarity nature of the data is expected which will be tested via the Augmented Dickey-Fuller (ADF) test with both variables of interest (ln_p^{Sell} and ln_p^{Buy}). As will be shown, they are indeed non-stationary, which we address by taking the first differences. We will then test whether the two series are co-integrated which is done by employing both the Johansen test (Johansen, 1995) and the Engle-Granger Two-Step Method (Engle and Granger, 1987). For both tests we need to find the optimal lag-length. As we are using daily data, it is likely that the price of one day depends also on past shocks. To select the optimal number of lags we consider the Akaike's Information Criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and Hannan and Quinn information criterion (HQIC).

Basic model

Assume a multiplicative mark-up model.[10] p_t^B refers to the buying price at time *t* and p_t^S to the selling price:

$$p_{\mathrm{t}}^{\mathrm{Buy}} = \beta_0 * (p_{\mathrm{t}}^{\mathrm{Sell}})^{\beta_1} + \varepsilon \tag{1}$$

Thus the long run ("co-integrating") relationship in its logarithmic form is

$$\ln p_{\mathrm{t}}^{\mathrm{Buy}} = \beta_0 + \beta_1 \ln p_{\mathrm{t}}^{\mathrm{Sell}} + \varepsilon \tag{2}$$

[9] Inflation in 2009: 4.8%, 2010: 5.1%, 2011: 5.4%. All were drawn from World Bank development indicators, dataset "Inflation, consumer prices (annual %)", accessed on 25.09.2013.
[10] The intuition behind using a multiplicative instead of an additive model is that the margin is likely to be a percentage markup and the processing costs are likely to be fixed. Besides that, due to the strong inflation in the long-run, the model would end up to be multiplicative even in the presence of a fixed (non-percentage) mark-up.

which we estimate with the Johansen method. The reason for doing so (despite our general approach of the Engle-Granger two-step method) is that it delivers better results when estimating the co-integrating relationship (Gonzalo, 1994). From the residuals of this relation we can generate the error correction term (*ect*) which is defined as follows:

$$ect_t := \ln p_{\mathrm{t}}^{\mathrm{Buy}} - \hat{\beta}_0 - \hat{\beta}_1 \ln p_{\mathrm{t}}^{\mathrm{Sell}} \tag{3}$$

In the case of a positive price shock on the international level (i.e. a positive deviation from the long-run equilibrium in which the factories' margin increases) the *ect* will be < 0 and if the price is shocked negatively, the *ect* is > 0. The error correcting process (symmetric case) is expressed as

$$\Delta \ln p_{\mathrm{t}}^{\mathrm{Buy}} = \xi_0 + \alpha\, ect_{t-1} + \sum_{\flat=1}^{M} \left(\gamma_\flat \Delta \ln p_{\mathrm{t}-\flat}^{\mathrm{Buy}} + \lambda_\flat \Delta \ln p_{\mathrm{t}-\flat}^{\mathrm{Sell}}\right) + \varepsilon \tag{4}$$

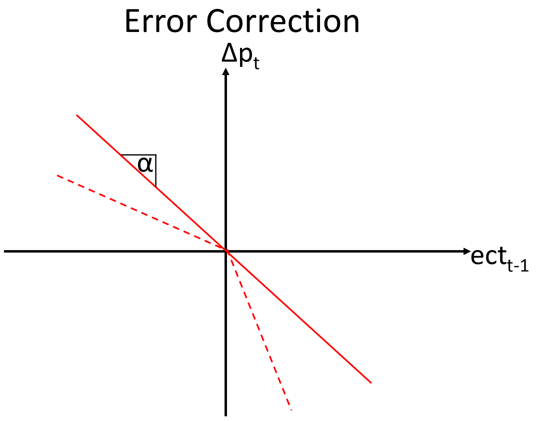
with M being the number of lags. Figure 4 (continuous line) illustrates the error correcting process by graphing the *ect* from the previous period against the change of the buying price in the current period. In the 2nd quadrant we see the correction of positive price shocks while the correction of negative shocks is represented in the 4th quadrant.

For the thoughts laid out in the theoretical section above, the model is extended to a threshold error correction process, which is the generalization of a simple asymmetric adjustment. The existence of any threshold is tested for with a SupLM test as suggested by Hansen and Seo (2002). Based on model (4) the *ect* gets split up into N regimes by N-1 thresholds, which are located at ψ_λ with $\lambda \epsilon [1;N-1]$ and $ect_{\mathrm{t}}^{\varsigma} := ect_{\mathrm{t}} \;\; if\; \psi_{\varsigma-1} < ect_{\mathrm{t}} \leq \psi_{\varsigma} \quad \forall\; \varsigma \epsilon [1;N]$:

$$\Delta \ln p_{\mathrm{t}}^{\mathrm{Buy}} = \xi_0 + \sum_{\varsigma=1}^{\mathrm{N}} \alpha_\varsigma ect_{\mathrm{t}-1}^{\varsigma} + \sum_{\flat=1}^{M} \left(\gamma_\flat \Delta \ln p_{\mathrm{t}-\flat}^{\mathrm{Buy}} + \lambda_\flat \Delta \ln p_{\mathrm{t}-\flat}^{\mathrm{Sell}}\right) + \varepsilon \tag{5}$$

For an "asymmetric" process, which is the simplest form of a threshold error correction (N=2 and ψ_1=0), the error correction is displayed in figure 4 (dotted line).

Figure 4: Symmetric, non-threshold error correction (continuous line) and asymmetric error correction (dotted line)



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Non-parametric estimation

Most authors in the literature on threshold error correction models use a parametric estimation technique. The drawback of this procedure is that one has to make certain a priori assumptions for specifying the model, like for example the number of thresholds. In order to overcome this limitation we employ a non-parametric approximation. While using non-parametric estimation techniques to detect unknown relationships is a widely used technique in the statistical literature (Krivobokova et al., 2010), in the agricultural economics literature this has only recently been suggested by Serra et al. (2006) who use a local polynomial fitting approach. Contrary to that, we are working with penalized splines (Eilers & Marx, 1996). Regression splines consist of the sum of a number of polynomial functions. The spline is fitted to match the data by giving each of these functions an individual shape. Penalizing splines refers to the method of including a penalty-term, which smoothes the spline by penalizing extensive zigzagging (i.e. big differences between neighboring values) of the spline (Wood 2003).

Candidate models for the parametric estimation

In order to get to know the exact slope-coefficients which are necessary to calculate the distributional effects, we will continue with a parametric regression approach. Several approaches are employed to model the error correction process before the model that represents the data best will be chosen via a testing procedure described below.

To start with, we estimate a simple linear error correction model (M1) which corresponds to the model described in equation (4). The second model (M2) is an asymmetric error correction model which corresponds to equation (5) with the specifications N=2 and $\psi_1=0$.

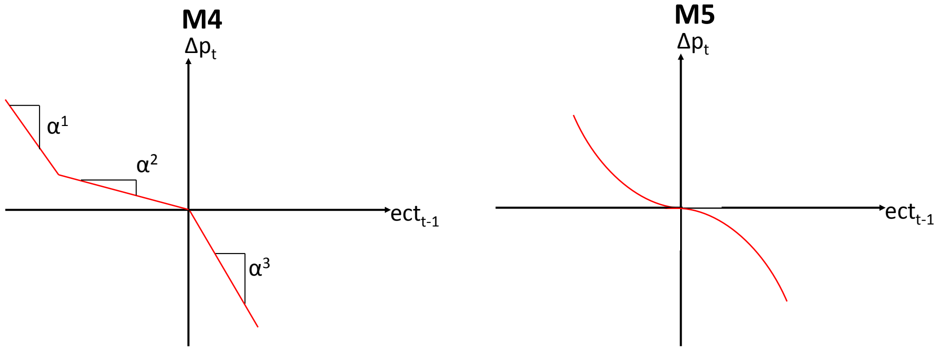
For the third model (M3) we assume a one-threshold model with no restriction on the location of the threshold. The intuition of model three (M3) is that the price gets corrected quickly during price drops (regime 3) and moderate hikes (regime 2) when the factories generate a normal margin. In times of large price increases (regime 1) however, the prices get corrected much slower. The factories generate a greater margin. M3 corresponds to equation (5) with N=2 and an unknown value of ψ_1.

The exact location of this threshold can be found via a grid search approach. We test each possible value of the *ect* as the threshold value ψ_1, estimate the model and save the log-likelihood value. We then select the model with the highest log-likelihood.

As we will see, the non-parametric analysis indicates a second threshold (figure 5, M4). This is economically difficult to justify. One possible explanation would be that there is in fact a non-linear error correction for negative values of the *ect* (figure 5, M5).

The rationale behind this kind of threshold behavior is that there is some kind of “normal” error correction which is the fastest correction possible and exclusively limited by technical constraints, like time of information processing, etc. This “normal” error correction takes place during times of price decreases, meaning that the factories minimize potential profit losses. In times of price increases, however, the reaction slows down, with a distinction between the sizes of price-increases. In M4, regime 2 represents times of “moderate” price hikes and regime 1 of “extreme” price increases. In regime 1, the companies do not dare to take the extra profit, based on their assumption that during times of extreme price hikes the suspicion is the highest that there might be some distortion taking place. As we cannot draw a clear distinction between “moderate” and “extreme” price increases, the true model might be the smooth-transition one (M5), while the two-threshold/three-regime model (M4) is a simplified version of the aforementioned, actually converging to it with an increasing number of thresholds.

Figure 5: Threshold error correction- and smooth transition models



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M4 can be represented by equation (5) with N=3 and unknown values of ψ_1 and ψ_2. To follow this indication from the non-parametric estimation, we looked for a second threshold via a two-dimensional grid-search.

M5 is a smooth-transition error correction model which includes the square of the *ect*[11] and is represented in equation (6) with N=2 and an ψ_1=0:

$$\Delta \ln p_{t}^{Buy} = \xi_0 + \sum_{\varsigma=1}^{N} \alpha_\varsigma ect_{t-1}^{\varsigma} + \sum_{\rho=1}^{N} \delta_\rho sq\_ect_{t-1}^{\rho} + \sum_{b=1}^{M}\left(\gamma_b \Delta \ln p_{t-b}^{Buy} + \lambda_b \Delta \ln p_{t-b}^{Sell}\right) + \varepsilon$$
(6)

Threshold determination and model choice

We find the threshold(s) of models M3, M4 and M6 via the grid-search following the method laid out above. At the same time, no assumptions are made about the location of the threshold(s).

After estimating the different models described (M1-M6), we will test which of them represents the data best. As we compare models with different specifications concerning the number of regimes (one, two and three) and different behavior (linear, quadratic), we rely on an information criterion again. We employ the AIC which is superior to other information criteria as suggested by Burnham & Anderson (2002).

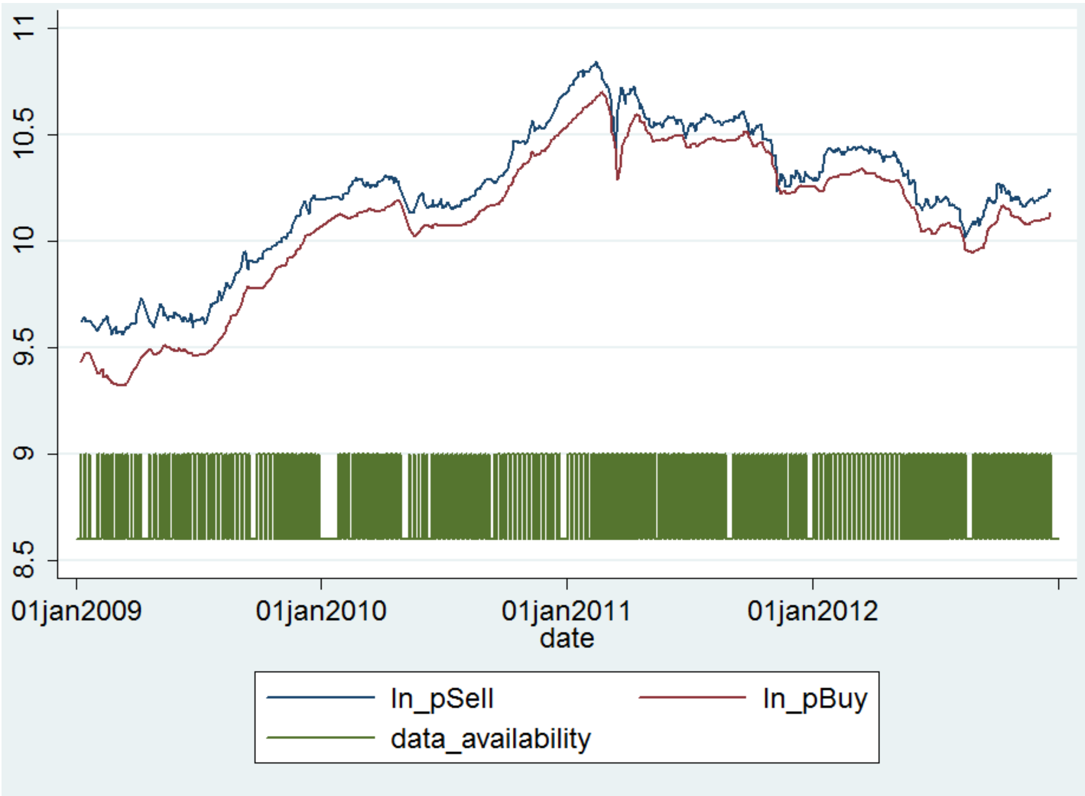
[11]Again we are differentiating between positive and negative shocks: *L.sq_ect_pos* = $(ect\_neg_{t-1})^2$ and *L.sq_ect_neg* = – $(ect\_neg_{t-1})^2$.

5. Empirical results

Data

The daily buying prices from the five factories in Jambi City were provided by GAPKINDO. There is one price for each factory available for each day from 1 January 2009 until 31 December 2012, except for Sundays and public holidays. Out of these five series, an unweighted average for the Jambi-buying price was generated. The selling prices were drawn from PT Kharisma (2013), a marketing company located in Jakarta. These prices represent the average results of the auctioning of SIR20 rubber on each day when rubber was sold (four or five days per week, except for two weeks of Christmas holidays and two weeks during Ramadan). In combination, this gives us 706 days for which we have both selling and buying prices. The price series is graphed in figure 6.[12]

Figure 6: Time series of buying and selling prices, in ln(Rupiah)



Source: own calculations

(Non)-stationarity and cointegrating relationship

The initial suspicion could be confirmed. The series are indeed both non-stationary (the H0 of non-stationarity cannot be rejected at a confidence level of 10%).[13] To avoid the problem of

[12] The green bar indicates the existence of data, so the holes in the green bar represent days without data. In the graph, the last point before a gap was connected with the first one after it. The values are the logarithm of the prices in Indonesian Rupiah.

[13] The lag length was specified as 4 in each case, following the Akaike's Information Criterion (see below), including a constant and without trend. Test results are available in appendix A.

spurious regressions, we take the first differences. As the results of the ADF test show (H0 can be rejected at a 1% confidence level), which solves the problem.[14]

The SBIC suggests a lag-length of the order two, the HQIC three lags, and the AIC opts for four lags. Following Ivanov and Kilian (2005), who suggest to trust the AIC in situations of large sample sizes (>250) and data of relatively high frequency (>weekly), we use four lags. The second reason to chose the lag order suggested by AIC is the danger of biasing the results by under-parametrizing the model, while over-parametrizing does not cause too much damage (Gonzalo, 1994).

From the test for a simple (i.e. non-threshold) AR-VECM (results: see appendix B) with the Johansen method we can confirm our assumption that the factories are clearly price-takers on the international market and price setters on the domestic market. The selling price does not react significantly to the buying price (α= -.0152704, p-value= 0.511. Appendix B, column 1), while the reaction of the buying price is strong and highly significant (α= -.0593225, p-value= 0.001. Appendix B, column 2). Using the Engle-Granger two-step approach results in a very similar adjustment parameter of -.0582281 for the buying price, also highly significant (p-value=0.001. Appendix B, column 3). Hence, the use of the Engle-Granger two-step approach seems appropriate. We continue the analysis using the residuals of the co-integrating relationship generated with the Johansen method (p^{Buy}=0.45 * $(p^{Sell})^{1.07}$) following the results of Gonzalo (1994) who finds that the Johansen method delivers the best results when estimating long-run relationships.[15] Testing the residuals with the ADF test yields a test statistic of -6.980, with which we can reject the H0 of non-stationarity at the 1% level. Figures 7a and 7b provide descriptive information on the *ect*.[16] The results of Hansen and Seo's (2002) SupLM test indicate the presence of a threshold, as the H0 of an error correction process without a threshold can be rejected at a 10% level (robust SupLM), and respectively at a 1% (standard SupLM) level of significance (results: see appendix F).

Table 1: Estimates of long-run relation

dep. Var: ln_pBuy	OLS	Johansen
ln_pSell	1.067***	1.067***
	(0.0071)	(0.0186)
Constant	-0.811***	-0.800
	(0.0723)	
Observations	706	702
R-squared	0.982	

Robust standard errors in parentheses[17]
*** p<0.01, ** p<0.05, * p<0.1

[14] Same specifications as above.
[15] An F-Test confirmed that the constant is significantly (1%-level) different from the value one.
[16] The extreme values at the left end of the distribution in Figures 7a and 7b are not outliers, but all plausible values for the ect. They all occurred during one tremendous price hike from 17.-24. March 2011.
[17] Since the VEC is not linear, it does not report t-statistics. The Johansen results have four observations less, because they include lags, while the first step of the Engle-Granger method does not require the inclusion of lags.

Figure 7a: Histogram of *ect* values

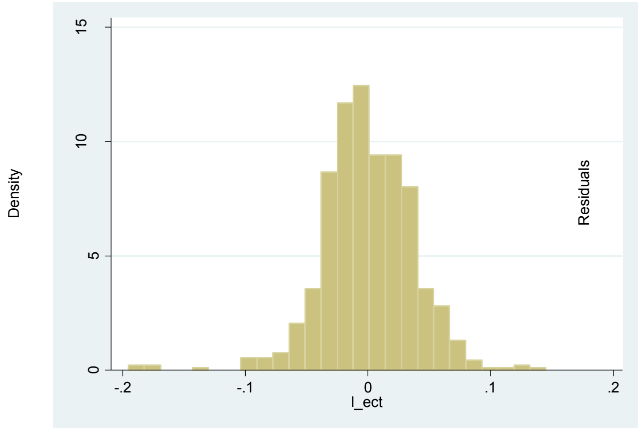
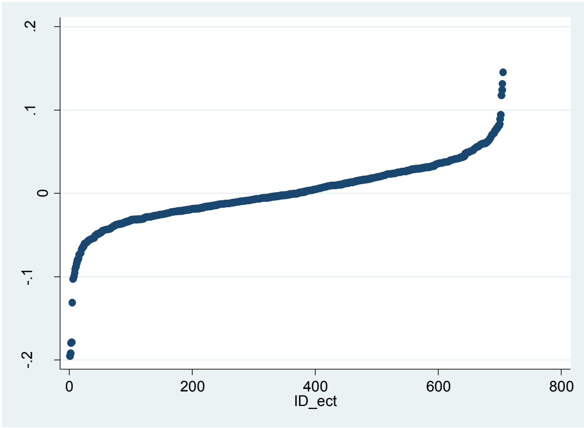


Figure 7b: *Ect* values sorted by their sizes

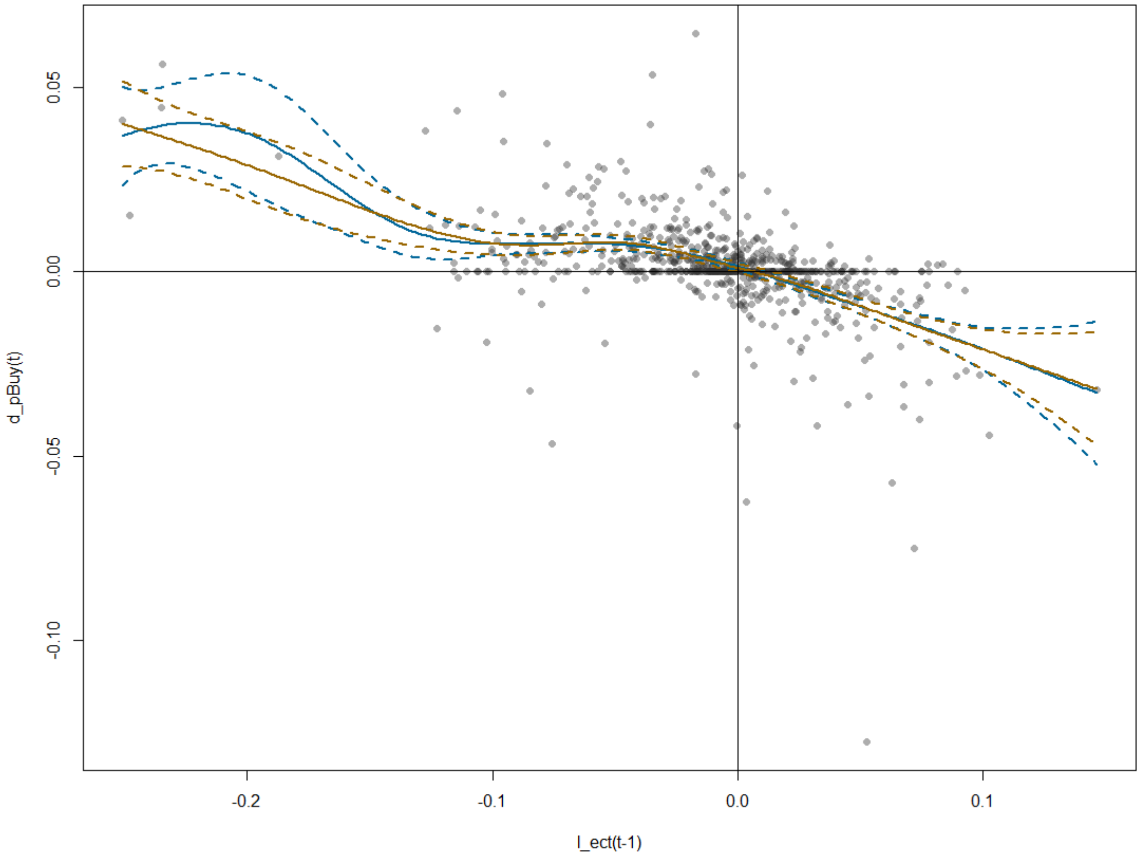


Source: own calculations

Penalized splines

In order to deal with the small numbers of observations at both ends of the population, we add a thin plate penalized spline for comparison (bronze line) (Wood 2003).[18] The dotted lines represent the 5%-confidence intervals.[19]

Figure 8: Penalized splines



Source: own calculations

[18] The thin plate regression splines penalize by compiling the spline of the group of functions which are the most relevant. These are chosen via an eigen-value decomposition.

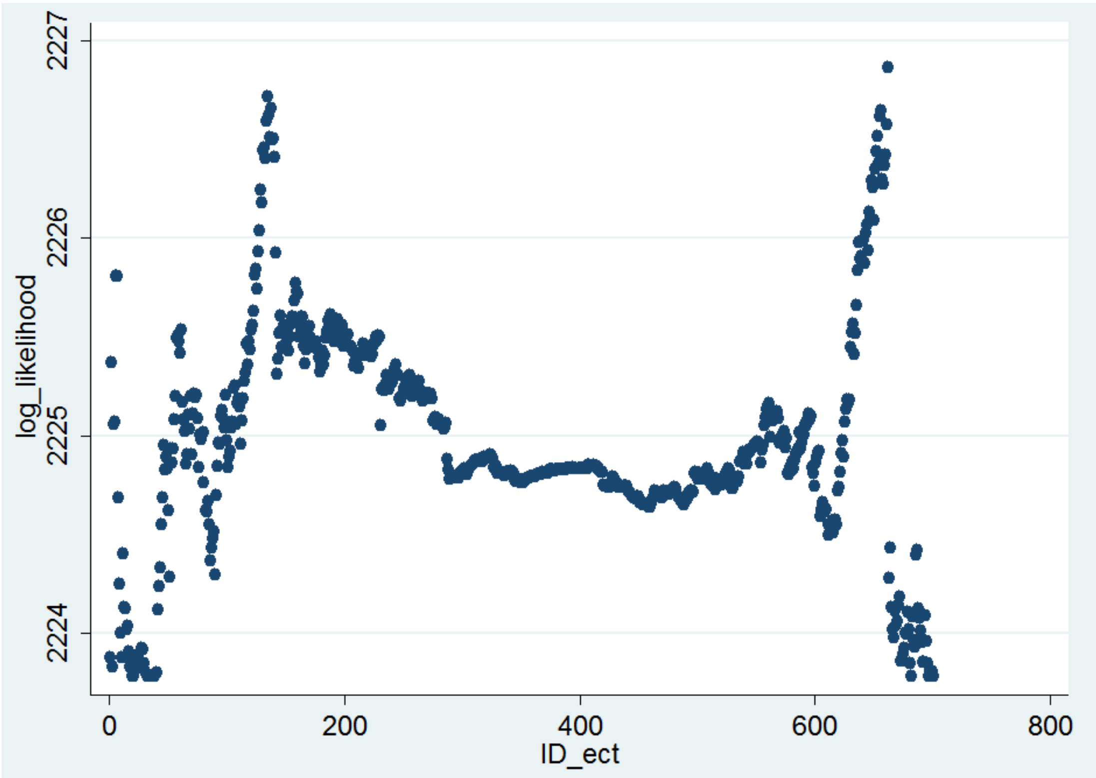
[19] These calculations were carried out with the software R 3.0.1 and version 1.7-22 of R package MGCV.

The splines exhibit narrow confidence intervals in the area of many observations and show one threshold in the region [-0.05; 0][20], thus indicating at least two regimes. The two regimes can be characterized as follows: the slope is steeper for positive values of ect_{t-1}, which means that the shock gets corrected more rapidly in cases of negative price-shocks than in the other cases. While the splines are robust to changes in specification[21] of the area [-0.1; 0], the confidence intervals widen substantially at the rather extreme values (<-0.1 and >0.1), which is caused by the small number of observations in these areas. A possible second threshold [-0.15; -0.1] lies in this region.

Parametric regressions

The specification of M3 stems from a one-dimensional Gridsearch. Its results are shown in figure 9. The display of the likelihood values shows two peaks which indicate possible locations for the threshold, one at the *ect* value of -0.0383844 (splitting up the *ect* into one regime of 135 observations and one of 571 observations) and one at the value of 0.052372 (662 and 44 observations per regime). Considering that the likelihood values are nearly identical (2,226.714 with the threshold at the 135th observation vs. 2,226.863 at the 662nd observation) but the latter value produces one regime of only 44 observations we chose the first possibility.[22] (Note that a combination of two thresholds will be considered below in M4.)

Figure 9: Results of one dimensional grid search



Source: own calculations

[20] The red bars indicate the approximate location of the threshold, based on the visual inspection of the splines.
[21] Available on request.
[22] For model tests see below. The results of the estimation that assumes the other threshold can be found in appendix E.

The two-dimensional grid search indeed seems to support the two threshold values that were indicated by the one-dimensional search. Thus M4 is specified with one threshold at -0.0383844 and one at 0.052372. The results of the grid search are displayed in Appendix D.

Table 2: Results of all models discussed

dep. var: d_ln_pBuy	(M1) Regular OLS	(M2) One Threshold (at zero)	(M3) One Threshold (at -0.0383844)	(M4) Two Thresholds	(M5) Smooth Transition
L.ect	-0.0583***				
	(-4.234)				
L.ect_pos		-0.0875***	-0.0935***		-0.134**
		(-2.954)	(-4.284)		(-2.570)
L.ect_neg		-0.0473***	-0.0438**		-0.00522
		(-2.601)	(-2.561)		(-0.156)
L.ect_1				-0.0440**	
				(-2.568)	
L.ect_2				-0.0756***	
				(-3.604)	
L.ect_3				-0.113***	
				(-3.073)	
L.sq_ect_neg					-0.288
					(-1.161)
L.sq_ect_pos					0.488
					(0.893)
LD.ln_pSell	0.156***	0.149***	0.145***	0.142***	0.148***
	(5.676)	(5.055)	(4.882)	(4.729)	(5.180)
L2D.ln_pSell	0.139***	0.136***	0.134***	0.132***	0.131***
	(4.535)	(4.385)	(4.289)	(4.331)	(4.400)
L3D.ln_pSell	0.109***	0.110***	0.110***	0.110***	0.104***
	(4.078)	(4.115)	(4.124)	(4.128)	(3.942)
L4D.ln_pSell	0.0364	0.0360	0.0357	0.0353	0.0306
	(1.136)	(1.121)	(1.113)	(1.096)	(0.945)
LD.ln_pBuy	0.0544	0.0541	0.0543	0.0547	0.0558
	(1.081)	(1.070)	(1.069)	(1.071)	(1.141)
L2D.ln_pBuy	-0.0192	-0.0211	-0.0222	-0.0215	-0.0128
	(-0.371)	(-0.411)	(-0.433)	(-0.422)	(-0.248)
L3D.ln_pBuy	0.0365	0.0330	0.0308	0.0302	0.0396
	(0.893)	(0.817)	(0.772)	(0.754)	(0.961)
L4D.ln_pBuy	0.130**	0.125**	0.124**	0.122*	0.137**
	(2.057)	(1.971)	(1.969)	(1.935)	(2.123)
Constant	4.98e-05	0.000646	0.000529	0.000583	0.00132**
	(0.125)	(1.112)	(1.260)	(1.431)	(2.109)
Observations	701	701	701	701	701
R-squared	0.387	0.389	0.392	0.393	0.392

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model Choice

Table 3 presents the AIC values of the models M1-M5. Following this criterion, M3 represents the data best. Executing an F-Test proves that the two slope coefficients of Model 3 are different from each other with a significance of 6.58%. The following discussion is therefore based on the two regimes model with one threshold at -0.0383844 (M3).

Table 3: Akaike Information Critereon

Model	ln(L)	k	AIC	Rank
M1	2223.7814	10	- 4427.5628	4
M2	2224.8331	11	- 4427.6662	3
M3	2226.7141	11	- 4431.4282	**1**
M4	2227.421	12	- 4430.8420	2
M5	2226.4759	13	- 4426.9518	5

Discussion of econometric results

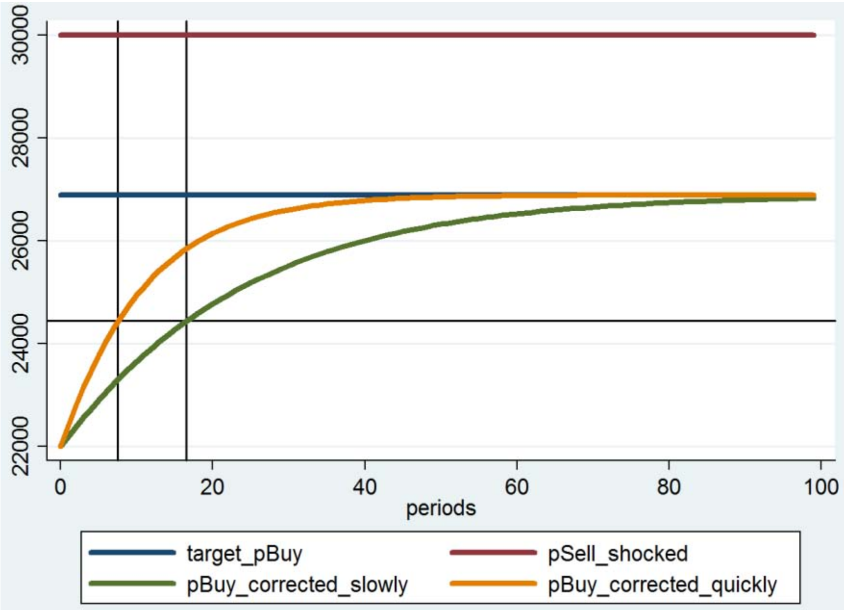
On average (M1), 5.83% of a price shock is corrected per day. If the buying price deviates from the long-run equilibrium price by 100% for example (i.e. it is half of what it should actually be), 5.83% of that shock is, on average, corrected on the following day. This is equivalent to an average half-life of a price shock of 11.4 days. Reasons for these deviations include a shock to the international price, or past shocks which have not been fully corrected.

When accounting for the asymmetric price adjustment, the picture looks different. During the last four years, after 135 out of 390 price hikes (positive shocks to the price, i.e. $ect<0$), which is roughly 1/3 of these cases (34.62%), the price was corrected significantly slower than during price declines. More specifically, these 135 cases were at times of extreme price hikes, i.e. $ect < -0.0383844$. It takes 16.5 days to correct half of a strong positive price change[23] and only 7.5 days in the case of a negative or small positive shock (see figure 11, in Indonesian Rupiah).[24] This means, more plainly, that when the international price sinks, the factories' buying prices decrease twice as fast as when the international price rises strongly. The time needed to correct 99% of a shock is 49 days in the case of a negative shock and 107 days in the case of a strong positive shock.

[23] The sign of the threshold is counterintuitive (negative *ects* referring to positive price changes) because the *ect* in the analysis was defined as the long run equilibrium price minus the actual price in that period.

[24] The simulations are based on equations (8) and (9), see below.

Figure 10: Correction of shocks over time



Source: own calculations

There are two reasons explaining why the price shocks are not transmitted in an instant (9.4% per period is a very quick error correction, considering that we are working with daily data). Firstly, technical reasons in the factories are an issue, e.g. the communication between the selling and buying departments, etc. The second reason is more of a methodological issue. For the analysis, the average of the prices of five Jambinese factories was generated. As changing their prices identically would be too much of an obvious indication of collusion, there are always small differences between the five prices. These small differences impact the average in a way that leads to an apparent short delay in the transmission time that is the average between the firms.[25]

An explanation why cartels adjust (increase) their buying prices at all – i.e. why they do not always pay a low price to the farmers – is that even cartels face restrictions concerning their price setting. There is always one margin that cannot be exceeded without risking government interference. This is the margin that is realized in times of constant or falling prices but secretly increased when the prices rise.

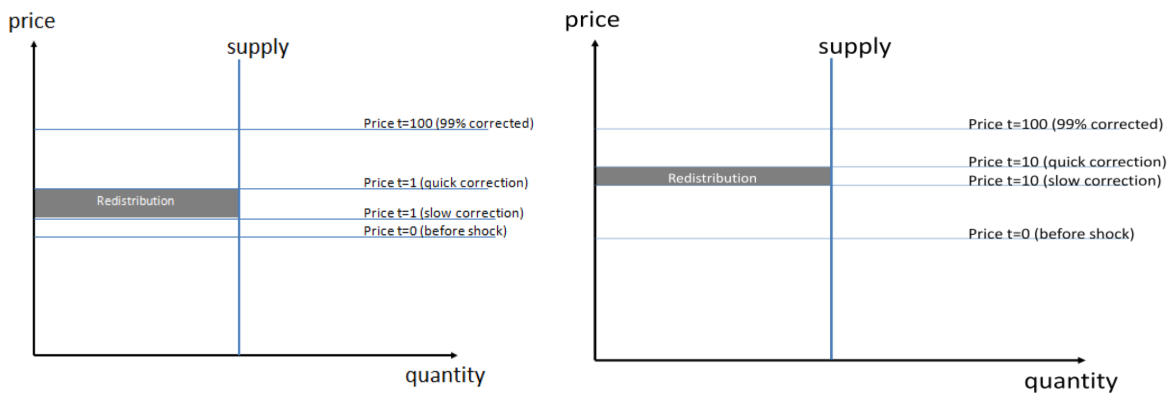
6. Redistribution effect

The distribution effect of the asymmetric price transmission is based on the forgone profit for smallholders due to slower price transmission in times of tremendous price hikes, compared to a baseline scenario of the fastest adjustment possible which is assumed to be the adjustment that occurs in times of price decreases. As discussed above, we do not focus on the total

[25] For an outlook on further research opportunities from here on see below.

welfare effect because the price elasticities of the supply and demand are unknown. The part of the welfare effect which stems from the intertemporal marketing margin manipulation is calculated as the difference between the price that is theoretically possible in times of price hikes and the price that is actually paid, multiplied by the quantity.[26]

Figure 11: Welfare effect at time t+1 (Graph 1) and t+10 (Graph 2), during adjustment process after shock at t=0



Source: own draft

In order to quantify the effect that the intertemporal marketing margin manipulation had on all Jambinese farmers, we calculate the differences between two hypothetical scenarios of the local price development after 14 periods (the time after which a farmer sells his/her produce is around two weeks) following each shock to the global price during 2009-2012. The two scenarios differ in the assumed adjustment parameter, following the results from the asymmetric error correction model.

We start with the following equation

$$\ln p_{\mathrm{t}}^{\mathrm{Buy}} = \ln p_{\mathrm{t-1}}^{\mathrm{Buy}} + \Delta \ln p_{\mathrm{t}}^{\mathrm{Buy}} + \varepsilon_t \qquad (7)$$

in which we substitute $\ln \mathrm{p}_{\mathrm{t}}^{\mathrm{Buy}}$ from a simplified version (without lagged prices)[27] of equation (4) and then ect_{t} from equation (3) in order to calculate the adjusted price after one period[28]:

$$\ln p_{\mathrm{t}}^{\mathrm{Buy}} = \ln p_{\mathrm{t-1}}^{\mathrm{Buy}} + \hat{\alpha}\left(\ln p_{\mathrm{t-1}}^{\mathrm{Buy}} - \hat{\beta}_0 - \hat{\beta}_1 \ln p_{\mathrm{t-1}}^{\mathrm{Sell}}\right) + \varepsilon_t \qquad (8)$$

[26] The generation of impulse response functions would not increase the quality of information, as the short run dynamics were not proven to be asymmetric.

[27] We can make this simplification of equation (4) since the short run dynamics were not proven to be asymmetric.

[28] The adjustment of p^{Sell} to p^{Buy} does not need to be accounted for, as p^{Sell} was proven above to be clearly the leading price, not reacting to p^{Buy} at all.

Iterating this procedure 14 times generates the price after 14 periods after the shock in period 1.[29] The difference between the two scenarios is given as

$$p_{t+13}^{diff} = \ln p_{\mathrm{t+14}}^{\mathrm{Buy}\,(\alpha+)} - \ln p_{\mathrm{t+14}}^{\mathrm{Buy}\,(\alpha-)} \qquad (9)$$

The total redistribution (*RED*) based on intertemporal marketing margin manipulation is then the sum of all price differences, multiplied by the quantity sold at time t+14:

$$RED = \sum_{t=1}^{T} \{ p_{t+14}^{diff} * q_t \} \qquad (10)$$

The 250,000 Jambinese rubber producing smallholders produce 281,000 tons of rubber per year on average (Jambi in Figures 2011) and we assume them to sell, on average, the same amount every day at which they sell. Entering all numbers into the formulas above yields a forgone revenue of 31.7 billion IDR (2.9 billion US$)[30] for the Jambinese rubber farmers in times of rising prices in every year.[31] For a single farmer, this amount represents 2.25% of his/her annual revenue. Considering that around 32% of the revenue turns into profit (calculation based on Euler et al. 2012), increasing the revenue by 2.25% would have lead to an increased profit of 6.75%. So effectively each farmer could have generated 6.75% more profit when the prices were increasing.[32]

7. Conclusions

The five rubber processing businesses in Jambi City, Sumatra have formed a cartel to rig the prices which they are paying to their suppliers. This has led to a tremendous redistribution of revenue from the farmers to the processors during the last four years. Compared to a non-monopsonistic market situation, the farmers have missed out on revenue of 2.25%. The net welfare loss that has been generated in the process could not be quantified in this analysis (due to missing information on the price elasticities on the supply and demand sides), but can be assumed to be substantial. It is likely that these kinds of processes occur all over Indonesia.

The cartel has achieved its advantage by correcting price changes on the international market (where its members act as price takers) asymmetrically. If the international price drops, the buying price decreases much quicker than in times of great price hikes.

As some authors suggest, there are many potential factors that can result in asymmetric price transmission apart from market power. All these reasons could be ruled out for this case. The

[29] In the computation we omit the error term, assuming it to be zero.
[30] Exchange rate from Oanda (2013)
[31] This is only the amount that is redistributed from farmers all over Jambi to the factories, due to the asymmetric price transmission of the factories' cartel. The total welfare loss due to the lower-than-market prices can be assumed to be substantial, too.
[32] Only periods were accounted for in which the deviation from the long-run equilibrium was below the threshold.

asymmetry proven in this study can therefore be explained by nothing other than market power.

One topic that has not been addressed in this analysis is the exact organization of the value chain between the farmers and the factories. A farmer selling directly to a factory is rather the exception than the rule. The vast majority of all rubber produce that enters a factory has passed through the hands of a variety of other stakeholders: middlemen on the village level, larger district level traders or warehouses which can act either as large scale traders, too, or as buying agents for the factories. The market power that is exercised by the factories is subject not only to the farmers, but to all the stakeholders along this value chain. It is also important to consider that it is likely that market imperfections also occur upstream from the factories, and other agents also have an over-proportional ability to shape the prices in their favor.

Another issue that was touched upon only briefly is the behavior within the Jambinese rubber cartel. It would be interesting to know if there is a rather random selection of the stakeholder who applies price changes first, or one clear Stackelberg leader determining the price with others who are following. With this sort of game-theoretical approach one would be able to get an even more detailed picture of the roles of the different stakeholders within the cartel, and the functioning of it as a whole. This calls for research at a more disaggregated level.

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Appendix A: Tests for stationarity

dfuller ln_pBuy, lags(0)

Dickey-Fuller test for unit root Number of obs = 705

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.611	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0908

. dfuller ln_pSell, lags(0)

Dickey-Fuller test for unit root Number of obs = 705

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.076	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2541

. dfuller d.ln_pBuy, lags(0)

Dickey-Fuller test for unit root Number of obs = 704

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-18.210	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

. dfuller d.ln_pSell, lags(0)

Dickey-Fuller test for unit root Number of obs = 704

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-24.306	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

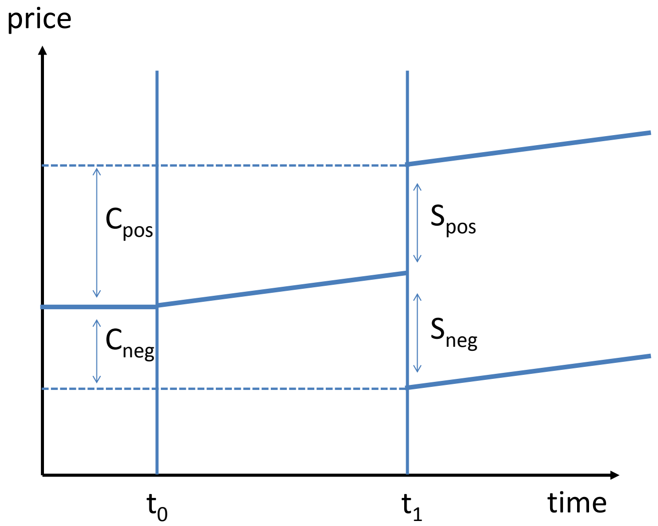
Appendix B: Error Correction Process (simple / symmetric adjustment)

	Johansen D_ln_pSell	Johansen D_ln_pBuy	Engle-Granger Two-Step D_ln_pBuy
L.ect	-0.0153	-0.0593***	-0.0583***
	(0.511)	(8.47e-08)	(2.62e-05)
LD.ln_pBuy	-0.119	0.0548	0.0544
	(0.120)	(0.134)	(0.280)
L2D.ln_pBuy	0.0987	-0.0192	-0.0192
	(0.190)	(0.594)	(0.711)
L3D.ln_pBuy	-0.0879	0.0365	0.0365
	(0.223)	(0.289)	(0.372)
L4D.ln_pBuy	0.000486	0.130***	0.130**
	(0.994)	(5.45e-05)	(0.0400)
LD.ln_pSell	0.112**	0.155***	0.157***
	(0.0151)	(0)	(2.00e-08)
L2D.ln_pSell	-0.0818*	0.138***	0.139***
	(0.0776)	(3.69e-10)	(6.77e-06)
L3D.ln_pSell	0.0467	0.109***	0.109***
	(0.311)	(7.39e-07)	(5.06e-05)
L4D.ln_pSell	-0.0294	0.0360*	0.0364
	(0.507)	(0.0883)	(0.256)
Constant	0.000806	-0.000207	0.000500
	(0.340)	(0.606)	(0.247)
Observations	701	701	701

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C: APT caused by delayed reaction to shock and high inflation

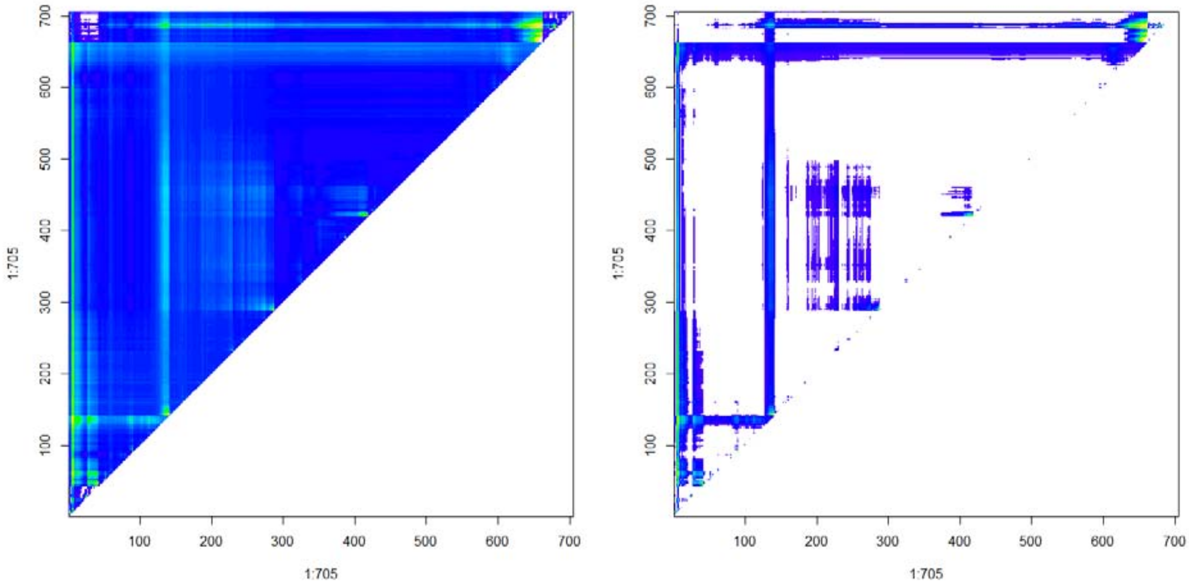
- Model:
  - Permanent price hike due to high inflation
  - Buying price is shocked randomly at $t=t_0$
  - Selling price reacts perfectly symmetrically, but delayed due to processing time T: at $t=t_1$
- Intuition of asymmetry:
  - Change of selling price ($p=pt_1-pt_0$) consists of two components: inflation and shock of buying price
  - At time t_1, the first component of the price change p has already been applied automatically, because the inflation is a permanent process. This means, however, that the "jump" at t_1 when the correction of the shock kicks in will be smaller than expected if the shock is positive and larger than expected if the shock is negative



- C_{pos} and C_{neg} represent the full price change between t_1 and t_1
- S_{pos} and S_{neg} stand for the shock-component of the price change and are equal
- As we can see, the full price change is asymmetric ($C_{pos} \neq C_{neg}$), but this is due to the inflation while the shocks are transmitted symmetrically ($S_{pos} = S_{neg}$)

Appendix D: Results of two dimensional gridsearch

The following graphs show the relative size of log-likelihood values that are estimated via the two-dimensional Gridsearch (M4, the lighter the color, the higher the value). The second graph only shows the gridpoints with the highest values of the log-likelihood.



The highest values are situated along two lines, representing all estimations with the lower threshold at possibility #135 (value: -0.038) and all estimations with the upper threshold at possibility #660 (value: 0.052). The other high values are too close to the boarder of the area of observations as to leave enough observations for the estimation. We thus select the point where both lines cross (Threshold 1 at -0.038 and Threshold 2 at 0.052) as the locations of the two thresholds for M4.

Appendix E: Results of M3 with alternative threshold value[33]

VARIABLES	(M3b) One Threshold (at 0.052372)
L.ect_neg	-0.0501***
	(-3.442)
L.ect_pos	-0.111***
	(-3.035)
LD.ln_pSell	0.146***
	(5.041)
L2D.ln_pSell	0.134***
	(4.499)
L3D.ln_pSell	0.110***
	(4.128)
L4D.ln_pSell	0.0352
	(1.094)
LD.ln_pBuy	0.0547
	(1.072)
L2D.ln_pBuy	-0.0200
	(-0.393)
L3D.ln_pBuy	0.0323
	(0.800)
L4D.ln_pBuy	0.124**
	(1.966)
Constant	0.000418
	(1.205)
Observations	701
R-squared	0.392

[33] The welfare implications can be made available on request.

Appendix F: Results of tests for structural stability

Test Statistics and Estimated Asymptotic P-Values

Robust LM Statistics

SupLM	18.00196	0.058
ExpLM	6.02526	0.05
AveLM	8.969252	0.035

Standard LM Statistics

SupLMs	41.01233	0
ExpLMs	16.59242	0
AveLMs	18.62208	0