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Welfare implications of intertemporal marketing margin manipulation
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Abstract

Purpose

In Indonesia rubber is the most valuable export crop produced by small scale agriculture and plays a key role for inclusive economic development. This potential is likely to be not fully exploited. The observed concentration in the crumb rubber processing industry raises concerns about the distribution of export earnings along the value chain. Asymmetric price transmission is observed.

Design/methodology/approach

This study investigates the price transmission between international prices and the factories' purchasing prices on a daily basis. An Auto-Regressive Asymmetric Error Correction Model is estimated to find evidence for asymmetric price transmission. In a subsequent step the rents that are redistributed from factories to farmers are calculated. The study then provides estimations of the size of this redistribution under different scenarios.

Findings

The results suggest that factories do indeed transmit prices asymmetrically, which has substantial welfare implications: around three million U.S. Dollars are annually redistributed from farmers to factories. If the price transmission was only half as asymmetric as it is observed, the majority of this redistribution was re-diverted.

Originality

This study combines 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. Especially the calculation of different scenarios of alternative price transmissions is a novelty. The dataset of prices on such a disaggregated level and high frequency as required by this approach is also unique.

Plain language summary

Indonesian rubber factories capture rents by transmitting positive price shocks slower to their suppliers than negative ones. This leads to a loss of income for small scale rubber farmers.

Keywords: Asymmetric Price Transmission; Error Correction Model; Intertemporal Marketing Margin Manipulation; Rubber; Indonesia.

Welfare Implications of Intertemporal Marketing Margin Manipulation

1. Introduction

The agricultural sector is of great importance in Indonesia. In 2011 it contributed 15% to the GDP and employed 36% of the workforce.^[1] More than 15 million people generate their main income from rubber cultivation, the most valuable export crop. With an annual output of three million metric tons, Indonesia is the second largest producer of natural rubber in the world, accounting for 27% of global production^[2] (Fathoni, 2009).

It is likely that the importance of rubber will increase in Indonesia for two reasons. First, economic growth in emerging economies; and secondly the rising price of crude oil, which will make synthetic rubber more expensive thus increasing the demand for its substitute, natural rubber on the margin.

The Jambi province (Sumatra) depends crucially on its agricultural sector and also represents a typical rubber production area. 52% of the workforce is employed in the agricultural sector and 0.6 million ha (of 1.4 million ha) are dedicated to rubber production, of which 99.6% are cultivated by smallholders (Regional Account and Statistical Analysis Division, 2012). Although Jambi is on average not an exceptionally poor province, the rural population is still disadvantaged compared to populations in other parts of Indonesia. The average income is 17.5 million Indonesian Rupiah (1 600 USD)^[3] per year (Arifin, 2005; Regional Account and Statistical Analysis Division, 2012), far below the national average of 26.8 million Rupiah (2 450 USD) per year.^[4] Other development indicators show a similar picture; life expectancy at birth is 71 years in Jambi, compared to 76 years in Jakarta (Regional Account and Statistical Analysis Division, 2012).

As rubber is predominantly cultivated by smallholders, it does have the potential for economic and social development in rural areas. In total, 252 000 Jambinese households (out of 619 000) depend on rubber cultivation (Regional Account and Statistical Analysis Division, 2012).

Therefore, malfunctions in this market can have a tremendous effect on the livelihoods of small scale farmers and their families. 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 charac-

30 terized by strong oligopsonistic market power. On the processing side we observe a
31 strong concentration of demand for farmer produce, as there are only nine crumb rubber
32 factories in Jambi, vis-à-vis 252 000 farmers. These factories, far from being in tight
33 competition, are collaborating rather closely and are organized in the association of
34 the rubber processing sector, Gapkindo. A report prepared for USAID (Peramune and
35 Budiman, 2007) found that Gapkindo is an efficiently organized and powerful lobbying-
36 institution representing the interests of rubber processors. There are strong indications
37 that some individual firms exploit their network in a way reminiscent of a cartel or
38 oligopsony (ibid.). The link between the evidence for asymmetric price transmission and
39 the occurrence of market power is based on Meyer and von Cramon-Taubadel (2004).

40 In order to shed light on the price formation process in the rubber value chain, we employ
41 a price transmission approach. As Ahmadi-Esfahani (2009) shows, market power has the
42 potential to affect price transmission. We study the vertical transmission between the
43 output and input prices of the five crumb rubber factories in Jambi City from 1 January
44 2009 to 31 December 2012 via an Asymmetric Error Correction Model (AECM), as
45 done so by von Cramon-Taubadel (1998). Previous research has shown that parametric
46 estimations of price transmission are sensitive to asymmetries in the error correction
47 process (Meyer and von Cramon-Taubadel, 2004). So in order to specify the error
48 correction model correctly without having to rely on a priori assumptions, we employ
49 the non-parametric technique of penalized splines before estimating a set of candidate
50 parametric models to test which one represents the data best, as suggested by Serra
51 et al. (2006). In addition to demonstrating the existence and extent of market power,
52 we also quantify a part of the resulting redistribution of welfare from the suppliers to
53 the factories. These welfare implications are shown to be substantial. Subsequently we
54 calculate the potential for redistributing forgone profits from factories to farmers under
55 different scenarios of altered error correction processes.

56 To the best of our knowledge, this is the first paper combining the approaches of non-
57 parametric and parametric estimation techniques of estimating asymmetric price trans-
58 mission processes with a welfare perspective to quantify the distributional consequences
59 of this intertemporal marketing margin manipulation. The calculation of different sce-
60 narios of alternative price transmissions and dataset of daily prices on such a disaggre-
61 gated and local level required by this approach are also unique.

62 The paper is organized as follows: section two provides background on the rubber market

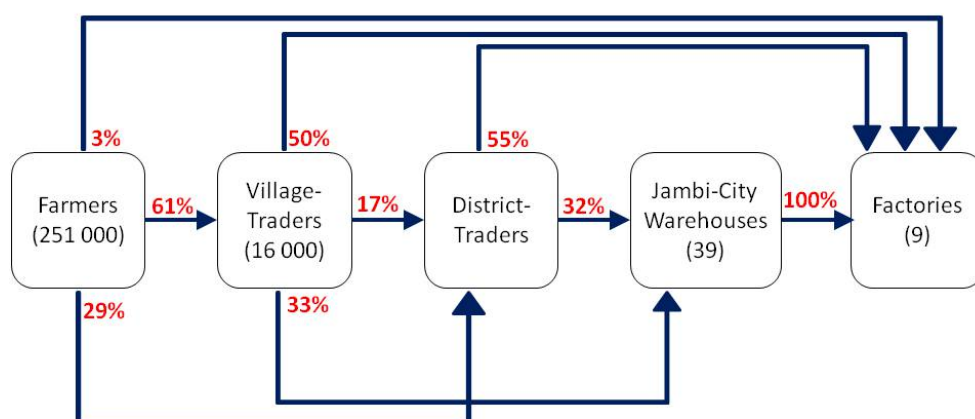
63 in the Jambi province and introduces the typical marketing chain for natural rubber
 64 originating from smallholder production in this area. In section three the rationale
 65 behind asymmetric price transmission is discussed. Section four is dedicated to model
 66 development, and section five presents the statistical results. Section six derives the
 67 resulting welfare implications before the concluding section seven.

68 2. Background

69 2.1 Rubber marketing in the Jambi Province

70 The structure of the Jambinese rubber sector is displayed in Figure 1.^[5] Most farmers sell
 71 to a village trader who then has the choice between three different kinds of stakeholders:
 72 a factory, a warehouse or another trader, for example at the district level. This choice is
 73 influenced by various factors, including the remoteness of the trader, his or her capital,
 74 access to credit and information, etc. (Sujarwo et al., 2014).

Figure 1: Marketing channels for rubber.



Source: author's calculations, based on own survey data (2012) and Euler et al. (2012).
 The percentages indicate which marketing channel is employed and for how often.

75 There are approximately 16 000 traders in the Jambi province and nine factories, five of
76 which are located in Jambi City (Regional Account and Statistical Analysis Division,
77 2012 and own survey data, 2012).

78 *2.2 Market concentration at the processing stage*

79 It appears that oligopsonistic market power occurs at several stages in this value chain.
80 On the village-level the traders' market power seems to be based on the farmers' credit
81 constraints as well as asymmetric information between traders and farmers (Kopp and
82 Brümmer, 2015).

83 In this paper, however, we are focusing on the market power at the next stage: the fac-
84 tory gates. The incriminating indicators are strong. During our traders survey in 2012
85 some respondents claimed that they were victims to the market power of downstream
86 stakeholders (other traders, warehouses, and factories). It seems possible that the cri-
87 tique they express is justified to some extent. Each of the five factories located in Jambi
88 City report the price that they are paying each day for their main input - slabs of raw
89 rubber - to one central agent (their association). They also have the option to attain
90 information on their competitors' prices from this agent. This enables each factory to
91 control its competitors' pricing.

92 Another piece of evidence for the power of the factories is the standard procedure that
93 follows when an external investor wants to construct a new crumb rubber factory. Before
94 getting the required permission by the government, officials will first consult with the
95 rubber processors' association on whether to give the permission or not (Jambi Provincial
96 Government Office for Trade and Industry, personal communication, 2012).

97 Anwar (2004, cited in Arifin, 2005) argues that the margin of Jambinese rubber facto-
98 ries is much higher than those in other provinces. While Anwar argues this to be the
99 result of close geographic proximity to one of the most important export market ports
100 (Singapore), it is much more likely that this observed increased margin stems from the
101 oligopsony power of the rubber factories (Arifin, 2005).

102 This market power has a tremendous effect on the distribution of welfare, both for the
103 rubber farmers and Jambinese society in general. Welfare loss experienced by the farmers
104 to the factories is due to lower pricing: the factories cause a transfer of income from the
105 farmers to themselves by paying prices below the competitive level. The welfare loss to
106 society in general stems from the farmers' total production below the competitive level

107 because of the reduced raw rubber prices. In the long run it is reasonable to argue that
108 the farmers could increase their rubber output, for example by shifting their production
109 from palm oil to rubber. After 20-25 years an oilpalm plantation has to be replanted
110 and the investments required for replanting oilpalm or rubber are similar.

111 However, as the supply function of rubber farmers is unknown, it is not possible to derive
112 how much the supplied quantity, and thus total welfare loss, would be in the case of a
113 general improvement of the price level. Therefore, we will concentrate on the farmers'
114 welfare loss based on a below competitive market price in times of price hikes. We show
115 *that* this oligopsonistic market power is exercised and *how large* the welfare loss to the
116 farmers is, which results from intertemporal marketing margin manipulation.

117 3. Methodology

118 While the literature of the New Empirical Industrial Organization provides a direct
119 approach to finding indications of market power (Bresnahan, 1982), these approaches
120 require detailed information on the firms' demand and supply structures, data we do
121 not have access to. One alternative way of finding empirical evidence for the existence
122 of market power is by testing for a non-constant transmission of price changes (Kinnu-
123 can and Forker, 1987; McCorrison et al., 2001; Meyer and von Cramon-Taubadel, 2004).
124 Weldegebriel (2004) derive from a theoretical model that the adjustment coefficient alone
125 cannot be used as an indicator for market power. However, their argumentation refers
126 to the absolute level of the adjustment coefficient while our study focuses on differences
127 between adjustments to positive and negative changes of the leading price. The asym-
128 metry that we are discussing here implies that positive changes of an agent's selling
129 price are passed on to the provider at a lower speed than negative price changes. This
130 means that when the agent's margin increases – that is in times of international price
131 hikes – the buying price is corrected slower than when the margin decreases, enabling
132 the processors to enjoy excess profits.

133 If asymmetries in the short-term dynamics occur (not only in the adjustment parameter)
134 it would also be interesting to analyse these dynamics via impulse response functions.
135 As we will see however, there are no asymmetries in the short-run dynamics, so the
136 generation of impulse response functions would not increase the quality of information.

137 The assumption behind the asymmetric price transmission between the international
138 rubber price and the Jambinese price for raw rubber is that the factories are price

139 takers at the international market. While Indonesia as a whole can be assumed to
 140 have an influence on international rubber prices, this is unlikely to be true for the five
 141 Jambinese factories under consideration. Mundlak and Larson (1992) finds that world
 142 market prices are the main reason for variations in domestic prices, also in the presence
 143 of policy intervention. In the domestic market, however, it can be assumed that they are
 144 price setters. (Both these assumptions are tested below). One can therefore understand
 145 the shocks that arise in the first one as exogenous and the ones arising in the latter as
 146 reactions to that shock.

147 3.1 Non-stationarity and co-integration

148 Given that we are working with prices, a non-stationarity nature of the data is expected
 149 which is tested via the Augmented Dickey-Fuller (ADF) test with both variables of
 150 interest ($\ln p^{Sell}$ and $\ln p^{Buy}$). As will be shown, they are indeed non-stationary, which
 151 we address by taking the first differences. We will then test whether the two series are
 152 co-integrated which is done by employing both the Johansen test (Johansen, 1998) and
 153 the Engle-Granger Two-Step method (Engle and Granger, 1987). For both tests we need
 154 to find the optimal lag-length. As we are using daily data, it is likely that the price of one
 155 day depends also on past shocks. To select the optimal number of lags we consider the
 156 Akaike's Information Criterion (AIC), Schwarz's Bayesian information criterion (SBIC),
 157 and the Hannan and Quinn information criterion (HQIC).

158 3.2 Error correction model

159 We assume a multiplicative mark-up model. The rationale for using a multiplicative
 160 instead of additive model is that the margin is assumed to be a percentage markup.
 161 This has been concluded from qualitative interviews with representatives at the rubber
 162 factories. We tested both approaches, and the results confirmed that taking the loga-
 163 rithm represents the data better. p_t^{Buy} refers to the buying price at time t and p_t^{Sell} to
 164 the selling price. The long-run ('co-integrating') relationship in its logarithmic form is
 165 given by

$$\ln p_t^{Buy} = \beta_0 + \beta_1 \ln p_t^{Sell} + \varepsilon \quad (1)$$

166 which we estimate with the Johansen method. The reason for doing so (despite our
 167 general approach of the Engle-Granger two-step method) is that the Johansen approach
 168 delivers better results when estimating the co-integrating relationship (Gonzalo, 1994).

169 From the residuals of this relation we can generate the error correction term (ect) which
 170 is defined as follows:

$$ect_t = \ln p_t^{Buy} - \hat{\beta}_0 - \hat{\beta}_1 \ln p_t^{Sell} \quad (2)$$

171 In the case of a positive price shock on the international level (i. e. a positive deviation
 172 from the long-run equilibrium in which the factories' margin increases) the ect will be
 173 < 0 and if the price is shocked negatively, the ect is > 0 . The error correcting process
 174 (symmetric case) is expressed as

$$\Delta \ln p_t^{Buy} = \xi_0 + \alpha ect_{t-1} + \sum_{\omega=1}^M \left(\gamma_{\omega} \Delta \ln p_{t-\omega}^{Buy} + \lambda_{\omega} \Delta \ln p_{t-\omega}^{Sell} \right) + \varepsilon \quad (3)$$

175 M is the number of lags, ξ_0 a constant, and γ_{ω} and λ_{ω} the coefficients of short-run
 176 dynamics. ε represents an error term.

177 For the thoughts laid out in the theoretical section above, the model is extended to a
 178 threshold error correction process, which is the generalization of a simple asymmetric
 179 adjustment. The existence of any threshold is tested for with a SupLM test as suggested
 180 by Hansen and Seo (2002). Based on model (3) the ect is split up into N regimes by
 181 $N - 1$ thresholds, which are located at Ψ_{λ} for $\lambda \in [1, \dots, N - 1]$ and $ect_t^{\zeta} := ect_t$ if
 182 $\Psi_{\zeta-1} < ect_t \leq \Psi_{\zeta}$ for $\zeta \in [1, \dots, N]$:

$$\Delta \ln p_t^{Buy} = \xi_0 + \sum_{\zeta=1}^N \alpha_{\zeta} ect_{t-1}^{\zeta} + \sum_{\omega=1}^M \left(\gamma_{\omega} \Delta \ln p_{t-\omega}^{Buy} + \lambda_{\omega} \Delta \ln p_{t-\omega}^{Sell} \right) + \varepsilon \quad (4)$$

183 An 'asymmetric' process, which is the simplest form of a threshold error correction, is
 184 characterized by the parameters $N = 2$ and $\Psi_1 = 0$, i.e. the error correction term is
 185 split into two variables, one for negative and one for positive price changes.^[6]

186 3.3 Non-parametric estimation

187 Most authors in the literature on threshold error correction models use a parametric
 188 estimation technique (Hansen and Seo, 2002, Lloyd et al., 2006, and Ihle et al., 2012).
 189 The drawback of this procedure is that one has to make certain a priori assumptions
 190 for specifying the model, such as the number of thresholds. In order to overcome this

191 limitation, we employ a non-parametric approximation. While using non-parametric es-
192 timation techniques to detect unknown relationships is a widely used technique in the
193 statistical and financial literature (Krivobokova et al., 2010; Escribano, 2004), in the
194 agricultural economics literature this has not been often employed. One exception is the
195 work by Serra et al. (2006) who use a local polynomial fitting approach in order to under-
196 stand the error correction process without the need for restrictive a priori assumptions.
197 Contrary to that, we work with penalized splines (Eilers and Marx, 1996). Regression
198 splines consist of the sum of a number of polynomial functions. The spline is fitted to
199 match the data by giving each of these functions an individual shape. Penalizing the
200 splines refers to the method of including a penalty-term, which smoothes the spline by
201 penalizing excessive zigzagging (i.e. big differences between neighboring values) of the
202 spline (Wood, 2003).

203 3.4 Candidate models for parametric estimation

204 In order to get to know the exact slope-coefficients necessary for calculating the distri-
205 butional effects, we continue with a parametric regression approach. Several approaches
206 are employed to model the error correction process before the model that represents the
207 data best is chosen via a testing procedure described below.

208 To start with, we estimate a simple linear error correction model (M1) which corresponds
209 to the model described in equation 3. The second model (M2) is an asymmetric error
210 correction model which corresponds to equation 4 with the specifications $N=2$ and $\Psi_1=0$.
211 For the third model (M3) we assume a one-threshold model with no restriction on the
212 location of the threshold. The rationale behind model three (M3) is that the price gets
213 corrected quickly during price drops (regime 3) and moderate hikes (regime 2) when the
214 factories generate a normal margin. In times of large price increases (regime 1) however,
215 the prices get corrected at a much slower rate; the factories generate a greater margin.
216 M3 corresponds to equation 4 with $N=2$ and an unknown value of Ψ_1 .^[7]

217 The exact location of this threshold can be found via a grid search approach. We test
218 each possible value of the *ect* as the threshold value Ψ_1 , estimate the model and save
219 the log-likelihood value. We then select the model with the highest log-likelihood.

220 3.5 Threshold determination and model choice

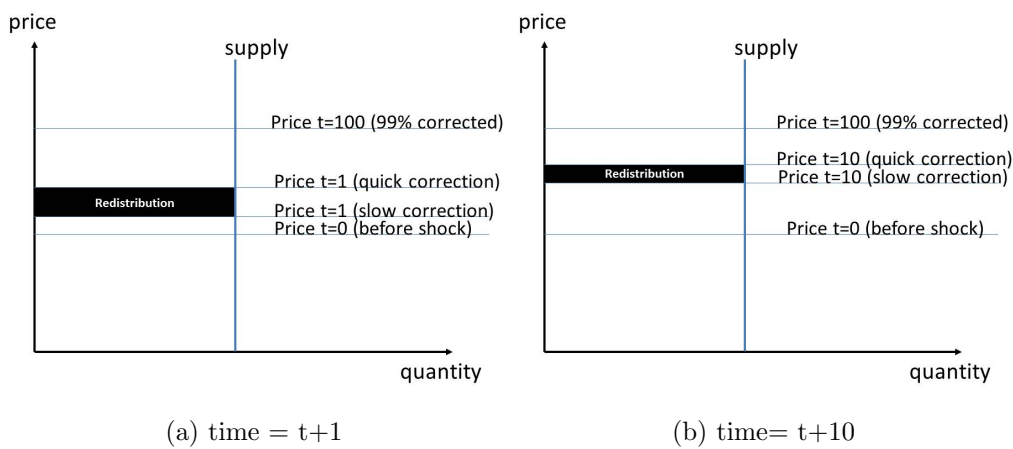
221 We find the threshold of model M3 via the grid-search following the method laid out
222 above. No assumptions are made about the location of the threshold until then.

223 After estimating the different models described (M1-M3), we test which of them repre-
 224 sents the data best. As we compare models with different specifications concerning the
 225 number of regimes (one and two), we rely on information criterion again. We employ the
 226 AIC which is in this case superior to other information criteria as laid out by Burnham
 227 and Anderson (2002).

228 3.6 Distributional effects

229 The quantification of the distributional effects stemming from asymmetric price trans-
 230 mission is based on the forgone income of smallholders due to slower price transmission
 231 in times of tremendous price hikes, compared to a baseline scenario of the fastest ad-
 232 justment possible which is assumed to be the adjustment that occurs in times of price
 233 decreases (see Figure 2). As discussed above, we do not focus on the total welfare effect
 234 because the price elasticities of the supply and demand are unknown. The part of the
 235 welfare effect which stems from the intertemporal marketing margin manipulation is
 236 calculated as the difference between the price that is theoretically possible in times of
 237 price hikes and the price that is actually paid, multiplied by the quantity.

Figure 2: Welfare effect during adjustment process after shock at $t=0$



Source: author's draft.

238 In order to quantify the effect that the intertemporal marketing margin manipulation
 239 had on all Jambinese farmers, we calculate the differences between two hypothetical
 240 scenarios of local price development after 14 periods (the time after which a farmer sells
 241 his/her produce is around two weeks) following each shock to the global price during

242 2009-2012. The two scenarios differ in the assumed adjustment parameter, following the
 243 results from the asymmetric error correction model.

244 We start with the following equation

$$\ln p_t^{Buy} = \ln p_{t-1}^{Buy} + \Delta \ln p_t^{Buy} + \varepsilon \quad (5)$$

245 in which we substitute $\Delta \ln p_t^{Buy}$ from a simplified version (without lagged prices)^[8] of
 246 equation 3 and then ect_t from equation 2 in order to calculate the adjusted price after
 247 one period:^[9]

$$\ln p_t^{Buy} = \ln p_{t-1}^{Buy} + \hat{\alpha} \left(\ln p_{t-1}^{Buy} - \hat{\beta}_0 - \hat{\beta}_1 \ln p_{t-1}^{Sell} \right) + \varepsilon \quad (6)$$

248 Iterating this procedure 14 times generates the price after 14 periods after the shock in
 249 period 1. In the computation the error term is set to zero. The difference p^{diff} between
 250 the two scenarios is given as

$$p^{diff} = \exp \left(\ln p_{t+14}^{Buy(\alpha^+)} \right) - \exp \left(\ln p_{t+14}^{Buy(\alpha^-)} \right) \quad (7)$$

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

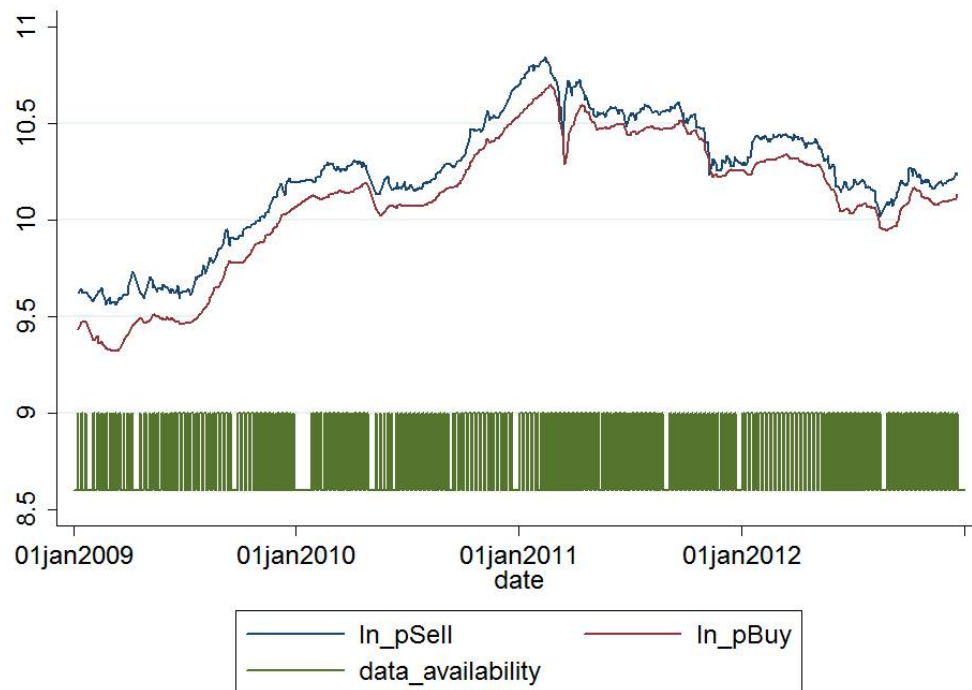
$$RED = \sum_{t=1}^T \left(p_t^{diff} q_{t+14} \right) \quad (8)$$

253 4. Data

254 The daily buying prices of the five factories in Jambi City were provided by Gapkindo.
 255 There is one price for each factory available for each day between 1 January 2009 and 31
 256 December 2012, except for Thursdays, public holidays and one holiday week in August
 257 or September. Out of these five series, an unweighted average for the Jambi-buying price
 258 was generated. The selling prices were drawn from PT. Kharisma (2013), a marketing
 259 company located in Jakarta. These prices represent the average results of the auctioning
 260 of Standard Indonesian Rubber (SIR20) on each day rubber was sold (maximum four
 261 days per week, except for two weeks of holidays in December). In combination, this

262 gives us 701 days for which we have both selling and buying prices. The price series are
 263 graphed in Figure 3.

Figure 3: Time series of buying and selling prices.



Source: author's production. Values are the logarithm of the prices in Indonesian Rupiah. 1.00 USD = 10.93 Indonesian Rupiah (December, 2013). 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.

264 5. Results

265 5.1 Non-stationarity and co-integrating relationship

266 The initial suspicion is confirmed. The series are indeed both non-stationary (the H0 of
 267 non-stationarity cannot be rejected at a confidence level of 10%). To avoid the problem
 268 of spurious regressions, we take the first differences. As the results of the ADF test
 269 show (H0 can be rejected at a 1% confidence level), this solves the problem. The SBIC
 270 suggests a lag-length of the order two, the HQIC three lags, and the AIC opts for four
 271 lags. Following Ivanov and Kilian (2005), who suggests we trust the AIC in situations of

272 large sample sizes (>250) and data of relatively high frequency ($>$ weekly), we use four
273 lags. The second reason for choosing the lag order suggested by the AIC is the danger of
274 biasing the results by under-parametrizing the model; over-parametrizing does not cause
275 too much damage (Gonzalo, 1994). So the lag length was specified as four periods in
276 each case, including a constant and without trend. Test results are available on request.

277 From the test for a simple (i. e. non-threshold) ARVECM with the Johansen method we
278 can confirm our assumption that the factories are clearly price-takers on the international
279 market and price setters on the domestic market. The selling price does not react signif-
280 icantly to the buying price ($\alpha = -.0152704$, p -value= 0.511), while the reaction of the
281 buying price is strong and highly significant ($\alpha = -.0593225$, p -value = 0.001)^[10]. Us-
282 ing the Engle-Granger two-step approach results in a very similar adjustment parameter
283 of $-.0582281$ for the buying price and is also highly significant (p -value=0.001). Hence,
284 the use of the Engle-Granger two-step approach seems appropriate. The co-integrating
285 relationship is presented in Table 1. We continue the analysis using the residuals of the
286 co-integrating relationship generated with the Johansen method ($p^{Buy} = 0.45(p^{Sell})^{1.07}$),
287 following the results of Gonzalo (1994) who finds that the Johansen method delivers the
288 best results when estimating long-run relationships. An F-Test confirms that the con-
289 stant is significantly (1% level) different from the value one. Testing the residuals with
290 the ADF test yields a test statistic of -6.980 , with which we can reject the H_0 of non-
291 stationarity at the 1% level. The results of Hansen and Seo's (2002) SupLM test indicate
292 the presence of a threshold, as the H_0 of an error correction process without a threshold
293 can be rejected at a 10% level (robust SupLM), and respectively a 1% level (standard
294 SupLM) of significance.

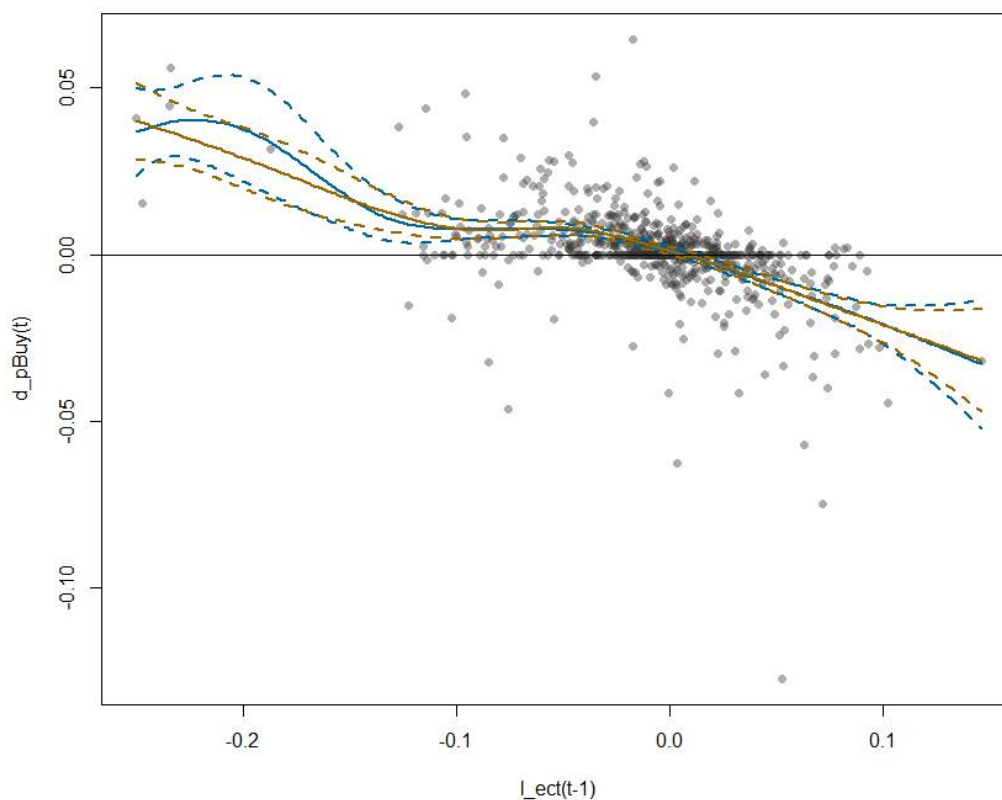
Table 1: Estimates of long-run relation.

295 5.2 Penalized splines

296 Figure 4 shows the penalized spline (blue line). The dotted lines represent the 5%
297 confidence intervals.^[11] In order to deal with the small numbers of observations at both
298 ends of the population, we add a thin plate penalized spline for comparison (bronze line)
299 (Wood, 2003). The thin plate regression splines penalize by compiling the spline of the
300 group of functions which are the most relevant. These are chosen via an Eigenvalue
301 decomposition.

302 The splines exhibit narrow confidence intervals in the area of many observations and

Figure 4: Penalized splines.



Source: author's production.

303 show one threshold in the region $[-0.05; 0]$, thus indicating at least two regimes. The two
304 regimes can be characterized as follows: the slope is steeper for positive values of ect_{t-1} ,
305 which means that the shock gets corrected more rapidly in cases of negative price-shocks
306 than in the case of positive price-shocks. While in the area $[-0.1; 0.1]$ the splines are
307 robust to changes in their specification,^[12] the confidence intervals widen substantially at
308 the rather extreme values in $]-\infty; -0.1[\cup]0.1; \infty[$, which is caused by the small number
309 of observations in those areas.

310 5.3 Model choice

311 Table 2 presents the AIC values of the models M1-M3. Following this criterion, M3
312 represents the data best. Executing an F-Test indicates that the two slope-coefficients
313 of Model 3 are different from each other with a significance of 6.58%. The following
314 discussion is therefore based on the two-regime model with one threshold at -0.038 (M3).

Table 2: Results of Akaike Information Critereon.

315 5.4 Parametric regressions

316 The estimation results are presented in Table 3. The specification of M3 stems from
317 a one-dimensional Gridsearch. Its results are shown in Figure 5. The display of the
318 likelihood values shows two peaks which indicate possible locations for the threshold,
319 one at the *ect* value of -0.038 (splitting up the *ect* into one regime of 135 observations
320 and one of 571 observations) and one at the value of 0.052 (662 and 44 observations per
321 regime). Considering that the likelihood values are nearly identical (2226.714 with the
322 threshold at the 135th observation vs. 2226.863 at the 662nd observation) but the latter
323 value produces one regime of only 44 observations, we chose the first possibility.^[13]

Table 3: Results of all models discussed.

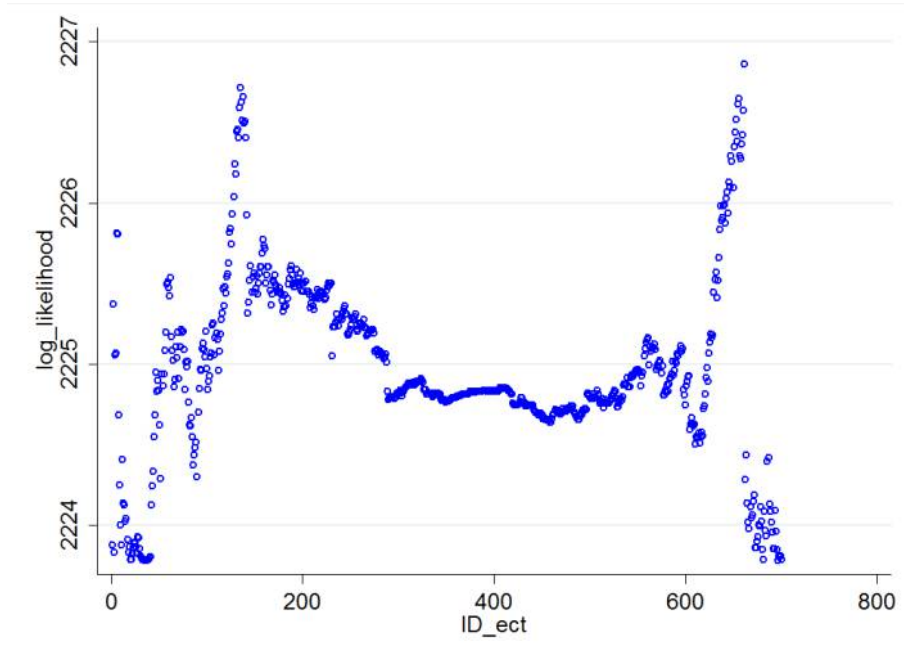
324 6. Discussion

325 6.1 Interpretation of coefficients

326 Table 3 displays the results of the three models of the parametric estimation. On average
327 (column M1), 5.83% of a price shock is corrected per day. If the buying price deviates
328 from the long-run equilibrium price by 100% for example (i. e. it is half of what it should
329 actually be in the long-run), 5.83% of that shock is, on average, corrected the following
330 day. This is equivalent to an average half-life of a price shock of 11.4 days. Reasons for
331 these deviations include a shock to the international price, or past shocks which have
332 not been fully corrected.

333 When accounting for the asymmetric price adjustment, the picture looks different. Dur-
334 ing the last four years, after 135 out of 390 price hikes (positive shocks to the price,
335 i. e. *ect* < 0), which is roughly 1/3 of these cases, the price was corrected significantly
336 slower than during price declines. More specifically, these 135 cases occurred at times

Figure 5: Results of one-dimensional grid search.

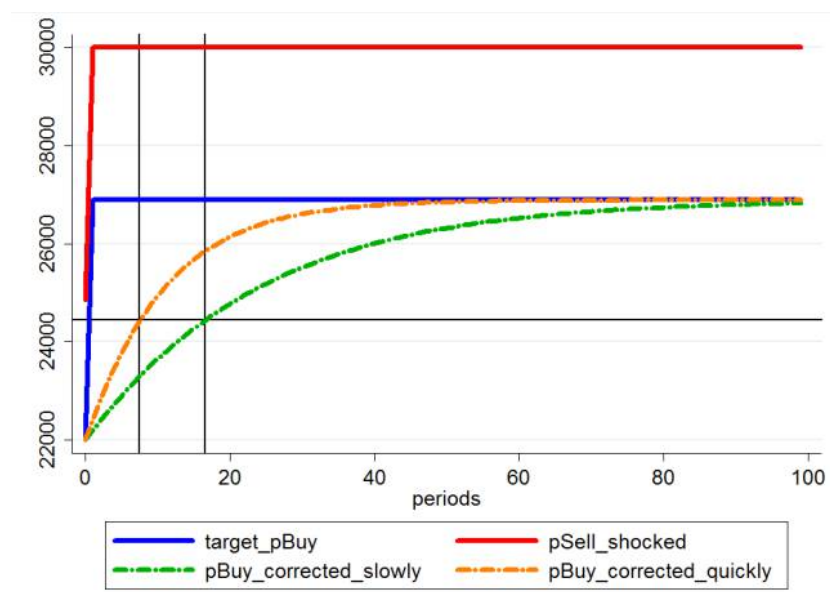


Source: author's production.

337 of extreme price hikes, i. e. $ect < -0.038$. It takes 16.5 days to correct half of a strong
 338 positive price change and only 7.5 days in the case of a negative or small positive shock
 339 (see Figure 6. The simulations are based on equations 6 and 7, see below). The sign
 340 of the threshold value is counterintuitive (negative *ects* refer to positive price changes)
 341 because the *ect* is defined as the long-run equilibrium price minus the actual price in
 342 that period. This means that when the international price sinks, the factories' buying
 343 prices decrease twice as fast as when the international price rises strongly. The time
 344 needed to correct 99% of a shock is 49 days in the case of a negative shock and 107
 345 days in the case of a strong positive shock. The lagged values of p_t^{Sell} are positive and
 346 significant while the lags of p_t^{Buy} are insignificant which supports the results from the
 347 Johansen test above that p_t^{Sell} is the leading price.

348 There are two explanations as to why the price shocks are not transmitted in an instant
 349 (9.4% per period is a very quick error correction, considering that we are working with
 350 daily data). Firstly, technical reasons in the factories, such as communication between
 351 the selling and buying departments. The second reason is more of a methodological issue.

Figure 6: Correction of shocks over time.



Source: author's calculations. In Indonesian Rupiah; 1.00 USD = 10.93 Indonesian Rupiah.

352 For the analysis, the average prices of five crumb rubber factories was generated. There
 353 are always small differences between the five prices. These small differences impact the
 354 average in a way that leads to an apparent short delay in the transmission time that is
 355 the average between the firms.

356 6.2 Market power or not?

357 As asymmetries in price adjustments can result from different kinds of processes other
 358 than market power (von Cramon-Taubadel, 1998), this kind of analysis cannot provide
 359 a definite 'proof' of market power. Meyer and von Cramon-Taubadel (2004) show that
 360 asymmetric price transmission (APT) is not necessarily caused by market power. In their
 361 literature review, they present an overview of reasons for asymmetric price transmission
 362 other than market power, arguing that evidence for asymmetric price transmission is not
 363 equivalent to a proof of market power. For the case of our study however, the alternative
 364 explanations that can lead to APT discussed in the literature can be ruled out. This
 365 leads us to the conclusion that the APT observed in the rubber processing sector in
 366 Jambi is indeed most likely caused by market power, based on cartel-like behaviour or

367 an oligopsonistic market structure.

368 a) ‘*Menu costs*’ or the costs associated with changing the price: the prices the factories
369 pay to their suppliers change every day. There is no reason to believe that the costs
370 of changing the price depend on the direction of the price change.

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

374 c) Perishability generates an incentive to sell the product quickly: processed crumb
375 rubber is not perishable.

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

380 e) Policy interventions, price support, etc. can also lead to asymmetric price trans-
381 mission, but this has not occurred in Jambi (or on a national level in Indonesia)
382 during the timeframe under consideration. Neither were new factories built or a new
383 national/provincial government elected. Other input prices have also stayed con-
384 stant (energy has been subsidized at a constant level, and the minimum wage did not
385 change during the time of analysis). Hassouneh et al. (2010) suggest searching for a
386 regime-switch which was not found in the data.

387 f) Processing time: though a delayed reaction (caused by processing time) in combi-
388 nation with high inflation can show misleading signs of APT, this does not apply
389 here for two reasons: 1.) While it is true that inflation is high in Indonesia (4.3% in
390 2012),^[14] we work with daily data. During the typical reaction times price hikes due
391 to inflation are close to zero. 2.) Besides that, we are observing a potentially mono-
392 oligopsonistic setting, implying that the shock that hits the leading (selling) price
393 occurs after the processing. If factories who set their buying price (and take their
394 selling price) would want to set the buying price according to what they receive for
395 that specific load of rubber after processing, they would have to anticipate the price
396 after the processing already at the time of purchasing. This is impossible.

397 g) Non-cooperative game: there are cases where it looks like price-fixing has happened,
398 while in fact there was no outspoken agreement. It occurred in situations in which

399 firms could threaten to punish another firm which deviated from the cartel-solution
400 (Perloff et al., 2007). However, only rarely could it be argued that these companies
401 would have had an agreement that was not the subject of debate, especially given
402 the fact that in all other respects they are such close companions. Besides, even if
403 there were indeed no explicit agreement on pricing, the oligopsony-hypothesis would
404 still hold.

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

410 *6.3 Distributional consequences*

411 In order to account for the distributional consequences of the intertemporal marketing
412 margin manipulation we calculate the difference between the observed distribution of
413 rents to hypothetical distributions in two alternative scenarios (equations 6 to 8).

414 The first scenario assumes perfect symmetry by setting α^- equal to α^+ . This means
415 that the asymmetry is fully eradicated. In the second scenario half of the asymmetry
416 remains. This is operationalised by setting α^- to the arithmetic mean between the two
417 estimated coefficients (6.9%).

418 The 252 000 Jambinese rubber producing smallholders produce 281 000 tons of rubber
419 per year on average (Regional Account and Statistical Analysis Division, 2012) and we
420 assume them to sell, on average, the same amount every day at which they sell.

421 The results for scenario 1 yield an estimated forgone revenue of 32.4 billion IDR (3.0
422 million USD) for the Jambinese rubber farmers in times of rising prices in every year.
423 This is only the amount that was redistributed from farmers in Jambi to the factories,
424 due to the asymmetric price transmission of the factories. The total welfare loss due
425 to the below free-market prices can be assumed to be substantial, too. For a single
426 farmer, this amount represents 2.25% of his or her annual revenue. Considering that
427 around 32% of the revenue turns into income (calculation based on Euler et al., 2012),
428 the calculation of the forgone income is based on the following: profit π is equal to rs
429 with r being the revenue, and s the profit share of the revenue (32%). $\pi = r - c$ with
430 c representing the costs. The possible increased revenue (if the price transmission was

431 symmetrical) r' is equal to $r(1 + x)$ with x being the percentage share of the possible
432 increase of the revenue (2.25%). Then $\pi' = r' - c$. The potential increase of income can
433 be calculated as

$$(\pi' - \pi) / \pi = (r(1 + x) - c - (r + c)) / (rs) \quad (9)$$

434 According to this analysis, increasing the revenue by 2.25% would have led to an in-
435 creased income of 7.03%. So effectively each farmer could have generated 6.97% more
436 income when the prices were increasing by more than the threshold value.

437 In the second scenario we find an estimated forgone income of only 13.5 billion IDR (1.2
438 million USD) for the farmers due to the factories' price rigging. Due to the logarithmic
439 nature of the price transmission effect, this is significantly less than half of the amount
440 calculated in scenario 1, although only half of the asymmetry is balanced out.

441 7. Conclusions

442 Indications that the five rubber processing businesses in Jambi City, Sumatra, possess
443 market power and use it to rig the prices they pay to their suppliers are strong. In this
444 paper we found evidence for an asymmetric transmission of prices, which has led to a
445 great redistribution of revenue from the farmers to the processors during the four years
446 of observation. Compared to a non-monopsonistic market situation, the rubber farmers
447 have missed out on an income of 7%. The net welfare loss generated in the process could
448 not be quantified in this analysis but can be assumed to be substantial. It is likely that
449 these kinds of processes occur all over Indonesia.

450 The group has achieved its advantage by correcting price changes on the international
451 market (where its members act as price takers) asymmetrically. If the international price
452 drops, the buying price decreases much quicker than in times of great price hikes. All
453 alternative explanations for asymmetric price transmission - other than market power -
454 could be ruled out for the rubber processing sector in Jambi. Risk managing strategies
455 would lead to a generally lower price level but not to a different reaction, depending on
456 the direction of price changes.

457 One policy recommendation that could be drawn from our results is to involve all stake-
458 holders (including farmer representatives) in consultations before deciding to grant per-
459 mits for the construction of new crumb rubber factories. If more factories were competing

460 for the input of raw rubber, the general price level would be expected to increase. The
461 calculation of an alternative scenario shows that if the asymmetric price transmission
462 was halved, the farmers' loss of income would be reduced significantly.

463 Another issue that has been touched upon only briefly is the behaviour *between* Jam-
464 binese rubber processors. It would be interesting to know if there is a rather random
465 section of stakeholders who apply price changes first, or one clear Stackelberg leader
466 determining the price. With this sort of game-theoretical approach one would be able
467 to get a clearer picture of the roles of different stakeholders within the group, and the
468 functioning of it as a whole. This calls for research at a more disaggregated level.

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553 Notes

554 [1]WorldBank World Development Indicators. Accessed March 2015, available at [http://databank.](http://databank.worldbank.org)
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557 [2]FAO FAOSTAT. Accessed March 2015, available at <http://faostat3.fao.org/home/E>.

558 [3]Exchange rate (December 2013) from Oanda Corporation.

559 [4]WorldBank: WorldBank World Development Indicators. Accessed March 2015, available at <http://databank.worldbank.org>.

561 [5]Farmers' marketing channels do not add up to 100, because they sell a minor share on auction
562 markets (6%) where the buyer is unknown, as well as to farmers' associations (1%). The missing 13%
563 of the district traders stem from the fact that they can also sell to another trader, which was omitted
564 from this graph.

565 [6]I was checked whether the non-linearities in the error correction do not only occur in dependence of
566 the direction of the price change, but also in the form of structural breaks between regimes such as high-
567 or low- price phases as done so by Rajcaniova and Pokrivcak (2013). It was also checked for asymmetries
568 in the short term adjustments. Since none of these have altered the results they were omitted from the
569 tables to save space. They are available upon request.

570 [7]It was also experimented with a smooth-transition type of model as employed by Hassouneh et al.
571 (2012). The results did not show statistical significance, but can be made available on demand.

572 [8]We can make this simplification of equation 3 since the short-run dynamics are not asymmetric.

573 [9]The adjustment of p^{Sell} to p^{Buy} is close to zero, since p^{Sell} was shown above to be clearly the leading
574 price, and not reacting to p^{Buy})

575 [10]The full results of the ARVECM can be made available upon request.

576 [11]These calculations were carried out with the software R 3.0.1 and version 1.7-22 of R package MGCV.

577 [12]Available on request.

578 [13]For model tests see below. The results of the estimation that assumes the other threshold can be
579 made available on demand. We also executed a two-dimensional grid-search and estimated a three-
580 threshold model, whose results can also be made available on demand.

581 [14]Inflation in 2009: 4.8%, 2010: 5.1%, 2011: 5.4%. All from World Bank Database, 2015, dataset
582 'Inflation, consumer prices (annual %).

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Table 1: Estimates of long-run relation.

<i>ln_pBuy</i>	OLS	Johansen
<i>ln_pSell</i>	1.067*** (0.0071)	1.067*** (0.0186)
<i>Constant</i>	-0.811*** (0.0723)	-0.800
Observations	701	701
R-squared	0.982	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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.

Table 2: Results of Akaike Information Critereon.

Model	$\ln(L)$	k	AIC	Rank
M1	2223.7814	10	-4427.5628	3
M2	2224.8331	11	-4427.6662	2
M3	2226.7141	11	-4431.4282	1

Table 3: Results of all models discussed.

	(M1)	(M2)	(M3)
<i>d.ln_pBuy</i>	Regular OLS	One Threshold (at zero)	One Threshold (at -0.0383844)
<i>L.ect</i>	-0.0583*** (-4.234)		
<i>L.ect_pos</i>		-0.0875*** (-2.954)	-0.0935*** (-4.284)
<i>L.ect_neg</i>		-0.0473*** (-2.601)	-0.0438** (-2.561)
<i>LD.ln_pSell</i>	0.156*** (5.676)	0.149*** (5.055)	0.145*** (4.882)
<i>L2D.ln_pSell</i>	0.139*** (4.535)	0.136*** (4.385)	0.134*** (4.289)
<i>L3D.ln_pSell</i>	0.109*** (4.078)	0.110*** (4.115)	0.110*** (4.124)
<i>L4D.ln_pSell</i>	0.0364 (1.136)	0.0360 (1.121)	0.0357 (1.113)
<i>LD.ln_pBuy</i>	0.0544 (1.081)	0.0541 (1.070)	0.0543 (1.069)
<i>L2D.ln_pBuy</i>	-0.0192 (-0.371)	-0.0211 (-0.411)	-0.0222 (-0.433)
<i>L3D.ln_pBuy</i>	0.0365 (0.893)	0.0330 (0.817)	0.0308 (0.772)
<i>L4D.ln_pBuy</i>	0.130** (2.057)	0.125** (1.971)	0.124** (1.969)
<i>Constant</i>	4.98e-05 (0.125)	0.000646 (1.112)	0.000529 (1.260)
Observations	701	701	701
R-squared	0.387	0.389	0.392

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1