Palm Oil and Rubber Price and Trader's Behavior at International towards Local Level

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--- *and this Corona virus pandemic situation shall never be forgotten* ---

Table of Contents

Acknowledgements i
Table of Contents ii
List of Tables iv
List of Figures v
List of Appendices vi
1. General Introduction 1
2. Does the Biodiesel EU Antidumping Duty Affect the Indonesian CPO Price? 5
    2.1. Introduction 6
    2.2. Background: dumping and retaliation 10
        2.2.1 Dumping 10
        2.2.2 Retaliation 13
    2.3. Model Specification 16
    2.4. Data 21
    2.5. Result and Discussion 24
    2.6. Conclusion 29
3. Fight or Flight: Factors Affecting Local Traders to Remain in or Exit the Market 30
    3.1. Introduction 31
    3.2. Role of Local Traders in Jambi 33
        3.2.1 The Importance of Traders 33
        3.2.2 Rubber and Oil Palm Fresh Fruit Bunch (OPFFB) Trading Activities in Jambi 34
    3.4. Model Specification 36
        3.4.1 Determinants in Exiting the Market 36
        3.4.2 Binary Logistic Regression and Marginal Effect 38
        3.4.3 Goodness of Fit and Logit Postestimation 39
        3.4.4 Statistical Test 40
    3.5. Data 40
    3.6. Result and Discussion 42
        3.6.1 Remainers versus Leavers 42
        3.6.2 New versus Existing Traders 47
    3.7. Conclusion 49
4. The Perils of a Loan: Interdependency between Rubber Quality and Farmer’s Debt in Buying Choices by Local Rubber Traders in Jambi Province, Indonesia 50
    4.1. Introduction 51
    4.2. Overview: *Basi* versus Price Reduction 53
    4.3. Background: Random Utility Model (RUM) 56
    4.4. Model Specification 59
    4.5. Data 63
        4.5.1 Data Source 63
        4.5.2 Choice Experimental Design 63

4.5.3 Descriptive Statistics of Socio-Demographic Characteristic Data ... 65
4.6. Result and Discussion ... 67
4.7. Conclusion ... 73

5. General Conclusion ... 74

Bibliography ... 76

Appendices ... 84
7.1. Appendices of Chapter 2 ... 84
7.2. Appendices of Chapter 3 ... 95
7.3. Appendices of Chapter 4 ... 109

Curriculum Vitae ... 125

Declaration ... 126

List of Tables

Table 2. 1 The definitive EU AD rate for Indonesian biodiesel producers. 14
Table 2. 2 Summary Statistics of Price Variables (USD/kg) 23
Table 2. 3. Log-likelihood Values of Restricted and Unrestricted Models 26

Table 3. 1 Number of All Active Traders in the Survey Area 35
Table 3. 2 Transition Matrix of Traders in Period 1 (2012-2015) 35
Table 3. 3 Transition Matrix of Traders in Period 2 (2015-2018) 35
Table 3. 4 Average Income of Traders Existing both in 2012 and 2015 (million IDR) 36
Table 3. 5 Average Income of Traders Existing both in 2015 and 2018 (million IDR) 36
Table 3. 6 Definition of Variables 37
Table 3. 7 Number of All Active Traders in the Survey Area 41
Table 3. 8 Result of Logit and Marginal Effect Estimation 44
Table 3. 9 New and Existing Traders' Characteristics in 2018 48

Table 4. 1 Definition of Variables 60
Table 4. 2 Attributes, Levels and Descriptions 64
Table 4. 3 An example of a Choice Set (simplification) 64
Table 4. 4 Village and Larger Traders' Characteristics 65
Table 4. 5 Credit Providers and Traders not Providing Credit Characteristics 66
Table 4. 6 Estimation Statistics of All Model Estimations 68
Table 4. 7 Log-likelihood Ratio Test 69
Table 4. 8 Parameter Estimates from the ML_2 Model Estimation 70
Table 4. 9 Rubber Traders' Willingness to Charge Price Reduction for Rubber Attributes 71

List of Figures

Figure 2. 1 Net CO2 Life Cycle Emissions of Petroleum Diesel and Biodiesel Blends 6
Figure 2. 2 Biodiesel and Renewable Diesel (HVO) in the European Union 7
Figure 2. 3 AD Initiations between 1995-2018. 10
Figure 2. 4 Dumping Illustration 11
Figure 2. 5 Value of Export Tariff (USD/ton) of Indonesian CPO and Biodiesel 12
Figure 2. 6 Indonesian Biodiesel Dumping Illustration 13
Figure 2. 7 Home Equilibrium without Trade, with Trade and with AD in Trade 15
Figure 2. 8 The AD duty Illustration Effect in Indonesia 16
Figure 2. 9 Share of Indonesian CPO Export Value based on Importing Countries 21
Figure 2. 10 Share of Indonesian CPO Export Value based on Ports' Location 22
Figure 2. 11 Area and Production of Oil Palm Plantation in the Jambi Province 22
Figure 2. 12 Time Series Plot of Price Variables 23
Figure 2. 13 Value of Export Tariff and Levy (USD/ton) of Indonesian CPO 24
Figure 2. 14 Time Series Plot with Structural Break 25
Figure 2. 15 Export Value of Biodiesel from Indonesia to the EU (USD thousand) 27
Figure 2. 16 Visualization of VECM estimation between PID and PW 28
Figure 2. 17 Visualization of VECM estimation between PID and PW 29

Figure 3. 1 Price Volatility of Palm Oil and Rubber Price (2008-2019) 32
Figure 3. 2 Map of Jambi 41
Figure 3. 3 Illustration of the Increase of Probability per Unit Variable 45
Figure 3. 4 Illustration of the Increase of Probability per Unit Interacted Variable 47
Figure 3. 5 Frequency of Existing and New Traders by Traded Product 48

Figure 4. 1 Number of Farmers by Ownership 51
Figure 4. 2 Probability Design in Unrelated Response Randomized Response Technique 55
Figure 4. 3 Illustration of rubber trader individual preferences 57

List of Appendices

Appendix 2. 1 Unit Root Tests 84
Appendix 2. 2 Johansen Cointegration Test between Indonesian and World CPO Prices . 84
Appendix 2. 3 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices 84
Appendix 2. 4 Gregory-Hansen Cointegration Test between Indonesian and World CPO Prices 85
Appendix 2. 5 Gregory-Hansen Cointegration Test between Jambi FFB and Indonesian CPO Prices 85
Appendix 2. 6 Johansen Cointegration Test between Indonesian and World CPO Prices before the Breakpoint 86
Appendix 2. 7 Johansen Cointegration Test between Indonesian and World CPO Prices after the Breakpoint 86
Appendix 2. 8 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices before the Breakpoint 86
Appendix 2. 9 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices after the Breakpoint 86
Appendix 2. 10. VECM Estimation between Indonesian and World CPO Prices 87
Appendix 2. 11 VECM Estimation between Indonesian and World CPO Prices allowing Structural Break 88
Appendix 2. 12 VECM Estimation between Indonesian and World CPO Prices before the Breakpoint 89
Appendix 2. 13 VECM Estimation between Indonesian and World CPO Prices after the Breakpoint 90
Appendix 2. 14 VECM Estimation between Jambi FFB and Indonesian CPO prices 91
Appendix 2. 15 VECM Estimation between Jambi FFB and Indonesian CPO allowing Structural Break 92
Appendix 2. 16 VECM Estimation between Jambi FFB and Indonesian CPO before the Breakpoint 93
Appendix 2. 17 VECM Estimation between Jambi FFB and Indonesian CPO after the Breakpoint 94

Appendix 3. 1 Name of Regencies, Districts and Villages of Survey Location 95

Appendix 3. 2 Stata Output of Variable Descriptive Statistics Year 2012 96
Appendix 3. 3 Stata Output of Variable Descriptive Statistics Year 2015 96
Appendix 3. 4 Stata Output of Variable Descriptive Statistics Year 2018 97
Appendix 3. 5 Stata Output of Logit Estimation Year 2012 98
Appendix 3. 6 Stata Output of Marginal Effect Estimation Year 2012 99
Appendix 3. 7 Stata Output of Logit Estimation Year 2015 100
Appendix 3. 8 Stata Output of Marginal Effect Estimation Year 2015 101
Appendix 3. 9 Stata Output of Specification Error Year 2012 102
Appendix 3. 10 Stata Output of Specification Error Year 2015 102
Appendix 3. 11 Stata Output of Collinearity Diagnostics Year 2012 103
Appendix 3. 12 Stata Output of Collinearity Diagnostics Year 2015 104
Appendix 3. 13 Stata Output of Wilcoxon Rank-sum (Mann-Whitney Test of Farming Revenue by Traders' Status 105
Appendix 3. 14 Stata Output of Trading Revenue Summary Statistics by Remain Year 2015 106
Appendix 3. 15 Stata Output of Trading Revenue Summary Statistics Year 2012 and 2015 106
Appendix 3. 16 Wilcoxon rank-sum (Mann-Whitney) non-parametric test 107
Appendix 3. 17 Pearson Chi2 test 108

Appendix 4. 1 A Choice Set 109
Appendix 4. 2 Descriptive Statistics of Respondents (n=210) 110
Appendix 4. 3 Stata Output of Shapiro-Wilk Normality Test 111
Appendix 4. 4 Stata Output of Wilcoxon Rank-sum (Mann-Whitney) Test by Traders' Status (left) and Credit Provision Status (right) 112
Appendix 4. 5 Stata Output of Spearman's Rank Correlation Coefficients 113
Appendix 4. 6 Results across Different Model Estimations 114
Appendix 4. 7 Stata Output of CL_1 Model Estimation 115
Appendix 4. 8 Stata Output of CL_2 Model Estimation 116
Appendix 4. 9 Stata Output of ML_1 Model Estimation 117
Appendix 4. 10 Stata Output of ML_2 Model Estimation 118
Appendix 4. 11 Stata Output of ML_3 Model Estimation 119
Appendix 4. 12 The Cholesky Factorization of the Covariance Matrix 120
Appendix 4. 13 Stata Output of the ML_3 Random Coefficients Covariance Matrix 120

Appendix 4. 14 Summary of Rubber Traders' WTC Price Reduction for All Attributes across Different Model Estimations 121
Appendix 4. 15 WTC Stata Output of CL_1 Model Estimation 122
Appendix 4. 16 WTC Stata Output of CL_2 Model Estimation 122
Appendix 4. 17 WTC Stata Output of ML_1 Model Estimation 122
Appendix 4. 18 WTC Stata Output of ML_2 Model Estimation 123
Appendix 4. 19 WTC Stata Output of ML_3 Model Estimation 123
Appendix 4. 20 Stata Output of Wilcoxon Rank-sum (Mann-Whitney) Test of Rubber Quantity Purchased Variable by Transmigrant Status 124

Chapter 1

General Introduction

Trade dynamics are inseparable from the influence of policies, prices, and the role of traders themselves. Trade policies differ between exporting and importing countries (Reed, 2001), with many trade policies supporting domestic markets while simultaneously threatening the foreign markets with whom they are engaged in trade. The impact of the importing countries' policies can be detrimental to the domestic trade sector of the exporting countries and vice versa; one common example is import tariffs created by the importing country to protect its domestic industries which subsequently limit the import quantities produced by exporting countries (Reed, 2001). This impact can usually be observed through changes in domestic price trends due to the emergence of a policy, so research aiming to predict the effects of these policies and subsequent price trends on domestic markets can help governments to be better prepared in facing challenges which will inevitably emerge.

Furthermore, changes in price trends can affect the decisions of traders to remain in or exit a market, and ultimately change the structure of the market itself. Due to increased market competition, higher numbers of traders typically result in more favourable the market conditions, while lower numbers of traders typically mean a higher potential for disproportionate market power (Mas-Colell, Whinston, & Green, 1995). In the agricultural sector of developing countries, traders are able to bridge the gap between factories and farmers due to farmers' lack of capital, information and knowledge (Kopp, Alamsyah, Fatricia, & Brümmer, 2014; Zúñiga-Arias, 2007). Understanding traders' behavior is relevant for policy makers in suitably anticipating market structure changes and can help protect farmers by maintaining their market power.

Additionally, as we show in chapter 3, another factor affecting traders' behavior to remain in or exit a market is credit provision. In the agricultural sector, it is a common practice to provide credit for suppliers or farmers, since they still depend on loans, not only for farming activities but also for their daily needs. Carranza and Niles (2019) found that food, agricultural and livestock inputs, and medical expenses are the main loan-dependent expenses among smallholder farmer households. Money lenders certainly carry the risk of losing their money to suppliers who default on their debt, especially when price trends are declining. This may affect traders' decision in determining a price. Observing the effects of individual loan quantities on price determination then becomes very compelling.

To achieve these objectives, we study the case of oil palm and rubber traders in Jambi province, Indonesia. Indonesia represents a largely agricultural country, with an agricultural sector that accounted for nearly 13% of total Gross Domestic Product in 2018 (Statistics Indonesia, 2019). Among its agricultural outputs, Indonesia's oil palm and rubber trade provide a large contribution to the country's foreign exchange (Directorate General of Estate Crops, 2017a, 2017b). Plantation land area in Jambi province, located on Sumatra island, has rapidly expanded, bringing with it many indirect land use change issues (Directorate General of Estate Crops, 2015, 2016a, 2016b, 2017a, 2017b). However, all stakeholders related are benefiting from the sector due to higher income (Bou Dib, Krishna, Alamsyah, & Qaim, 2018). Moreover, the Indonesian palm oil and rubber industries have resulted in many new domestic employment opportunities. Labor usage within the Palm Oil and Rubber industries increased by about 36 % and 7 %, respectively, from 2013 to 2018 (Directorate General of Estate Crops, 2015, 2016a, 2016b, 2017a, 2017b). The contrasting trajectories of these two valuable industries makes studies related to palm oil and rubber of particular interest to policy makers and national governments.

The research objectives of this study are therefore to:

a. Observe the effects of an importing country’s trade policy on price in a targeted exporting country
b. Analyse factors affecting local traders’ decisions to remain in or exit the market
c. Investigate the influence of farmer’s debt on local traders’ buying choices and price determination

We pursue these research objectives through three separate papers, summarized below:

Paper 1

The European Union’s Biodiesel Antidumping Duty (AD) is one of the most hotly debated international biodiesel trade policies in existence today. In 2013, the EU imposed a biodiesel AD on exporting countries known to engage in biodiesel dumping, and Indonesia was one of the main countries affected The EU accused Indonesian biodiesel producers of charging artificially lower prices than the world market in the purchasing of raw materials (CPO), which was said to affect the performance of EU biodiesel producers. To the best of our knowledge, this is the first study specifically focusing on the price effects of the EU ADs in countries targeted by the duties. The study aims to observe the effects of the AD on Indonesian exports and local CPO prices by applying a Vector Error Correction Model (VECM) approach to time series data. Result shows that the implementation of the AD has a negative effect on the price of Indonesian CPO and oil palm FFB in Jambi province.

Paper 2

Traders play a significant and often underestimated role in agricultural trading activities. Having more traders in the market is favorable for competition, as farmers have more choices as to whom they may sell their products and can choose their most preferred trader. Understanding this role is crucial in understanding the trader's behavior in the market. Some may remain, and some may exit the market, which can then in turn alter the market structure. Therefore, this study focuses on traders' decisions to remain in or exit the market, and the factors influencing this decision. To analyse the probability they remain in the market, we employ a binary logistic regression method to key variables obtained from a 3-round data collection process in Jambi. We find clear evidence that human capital (education and experience), trading structure (traded product, credit provision, land area, operational vehicle ownership, and trader status), structural environment (number of competitors), and socioeconomic (trading revenue) factors all affect the decision of traders to remain in or exit the market.

Paper 3

In the Jambi rubber trade, it is a common practice to reduce the price of rubber to compensate for a contaminated product. However, a farmer's dependence on loans offered by traders may also have an influence on this price reduction. This study aims to observe to what extent, if any, price reduction, rubber quality, and farmers' debt influence rubber traders' preferences in buying rubber, and to estimate how much of a price reduction traders will charge to obtain higher quality rubber or lower farmer's debt. Using data from 210 rubber traders in Jambi Province, Indonesia, we apply a Discrete Choice Experiment and a willingness-to-pay measurement approach to observe this phenomenon. To the best of our knowledge, there is no study implementing this method to capture agricultural traders' or middlemen's behavior in sourcing product and using price reduction as a replacement for willingness to pay; therefore, the methods applied in this study are novel. Result shows that price reduction, rubber quality, and farmer's debt influence traders' preferences in buying rubber, whereas higher price reduction, higher rubber quality, and lower farmer's debt will increase a trader's utility.

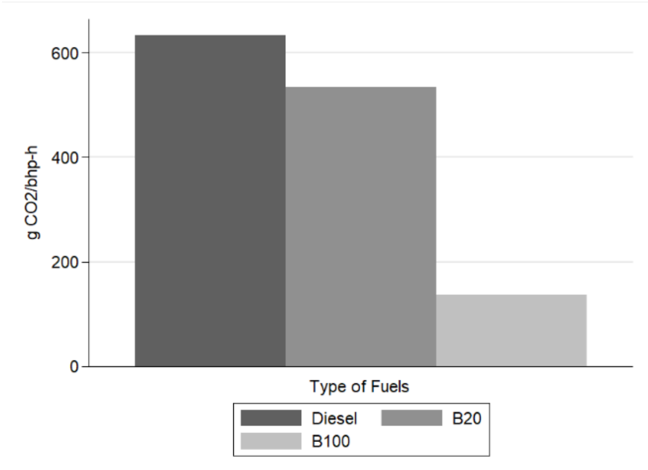
Chapter 2

Does the Biodiesel EU Antidumping Duty Affect the Indonesian CPO Price?

Rakhma Melati Sujarwo , Bernhard Brümmer , Thomas Kopp

2.1. Introduction

In 2003, the European Union (EU) issued a directive advising member states to increase the use of biofuels and other renewable fuels in the transport sector (European Commission, 2003) in an effort to reduce CO_2 emission in transportation. Biodiesel[1] is the most widely used type of biofuel in the EU, with a share of 80.7 % of the market in 2017 (Tiseo, 2019). A study performed by (Sheehan, Camobreco, Duffield, Graboski, & Shapori, 1998) reported that blending higher amounts of biodiesel into petroleum diesel leads to a lower amount of net CO_2 life cycle emissions overall[2] (Figure 2. 1).

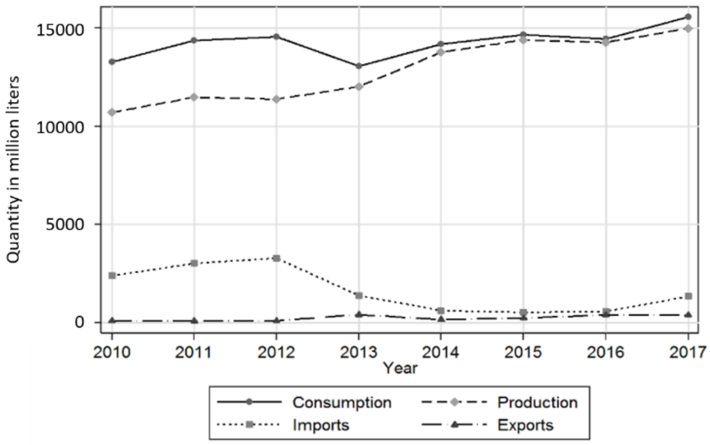


Source: Own production based on data from (Sheehan et al., 1998).

Figure 2. 1 Net CO2 Life Cycle Emissions[3] of Petroleum Diesel and Biodiesel Blends[4]

The directives aim for new renewable energies to account for at least 32% of total energy needs in the EU by 2030 (European Commission, 2018). The directives have been further expanded a number of times. One of these changes, issued in 2009, requires that renewable fuel be applied not only to motor vehicles, but also to machinery (Bourguignon, 2015). The directives have caused both an increase in the consumption of biofuels and an expansion of the domestic biodiesel industry; however, this growth in domestic consumption has not entirely translated into production increases, and as of 2011 production quantity was still 21.5% lower than consumption (Flach, Lieberz, Lappin, & Bolla, 2018) (Figure 2. 2). The remaining domestic demand was met through imports.

[1] Biodiesel is a renewable diesel fuel substitute made from natural oil or fat mixed chemically with alcohol (Sheehan et al., 1998).
[2] Net CO_2 was calculated by setting biomass CO2 emissions from the tailpipe to zero (Sheehan et al., 1998).
[3] The value is expressed in grams per brake horsepower-hour (g/bhp-h) which is the standards for heavy duty engines (Sheehan et al., 1998).
[4] B20 and B100 are biodiesel blends that are respectively 20 and 100 percent biodiesel mixed with petroleum diesel.



Source: Own production based on Flach et al. (2018) and Flach, Lieberz, Rondon, Williams, & Wilson (2016).

Figure 2. 2 Biodiesel and Renewable Diesel (HVO[5]) in the European Union

Opening international trade channels for biodiesel commodities put the European producers under competitive pressure from foreign imports. Indonesia is one of the world's leading biodiesel exporters, contributing to around 30% of total biodiesel imported by the EU in 2012 (Flach et al., 2018; UFOP, 2017). Biodiesel prices charged by Indonesia are very competitive, since it has a competitive advantage in sourcing Crude Palm Oil (CPO), one of the main raw materials used in producing biodiesel

To confront such a challenge, the EU may enforce certain trade barriers to protect domestic producers. According to Reed (2001), there are four reasons a country or region may have such barriers. First, the government may seek to gain more income by charging tariffs to exporters, which are easier to implement and more discrete than raising income taxes outright. Second, the government may attempt to protect certain products, such as staple foods, to achieve self-sufficiency, and price distortions through trade barriers can be a viable option to this end. Third, the government may attempt to politically protect domestic producers from international rivalry in order to obtain higher subsequent bargaining power in the international market. Lastly, very large importing countries may take advantage of their high market power by restricting imports of certain products to reduce the world price; thereby increasing their welfare.

One of the most debated international biodiesel trade policies created by the EU is the Biodiesel EU Antidumping Duty (AD) created in late 2013 (European Commission, 2013a). The EU imposed a biodiesel AD on exporting countries known to engage in biodiesel dumping, with Indonesia being one of the main targets of the policy. The country

[5] Hydrogenated Vegetable Oil

was accused of having set export prices below the competitive market price, which negatively affected domestic producers' performance.

This presumption was based on a 2012 study conducted by the EU, which found that Indonesian biodiesel producers were charged far below the world market price in the purchasing of raw materials from Indonesian CPO producers (European Commission, 2012). The price difference was developed by imposing high-value export tariffs on Indonesian CPO inputs, while maintaining very low export tariffs for the output product of Indonesian biodiesel. The margins generated on dumping were revealed to be between 8.8% and 23.3% (European Commission, 2013b).

In response, Indonesia made an appeal against the policy at the World Trade Organization's (WTO) Dispute Settlement Body (DSB) in 2015, as its discussions with the EU had failed to reach a resolution (World Trade Organization, 2018). The court ruled in favor of Indonesia, arguing that the EU failed in their assessment of the situation through inaccurate estimation of production costs, improper formulation of an export price, and insufficient evidence for the existence of a price undercutting scheme. The policy was terminated by the end of 2018, and as of today there are no more ADs imposed by the EU on Indonesian biodiesel (European Union External Action, 2018).

The implementation of trade duties can have important and long-lasting economic effects on stakeholders in target countries. Measuring the effects of the biodiesel AD on the Indonesian CPO industry can provide an important analysis into the economic impacts of trade duties and allow for a quantitative assessment of the effects of ADs on agricultural markets, particularly in developing economies. To the best of our knowledge, there are few studies focusing on the effects of AD's, especially those imposed by the EU, on target countries (Cheong, 2007; Cuyvers & Dumont, 2005; Jabbour, Tao, Vanino, & Zhang, 2009). Most studies focus on the effects of AD's in home countries (Asche, 2001; Avşar, 2013; Konings & Vandenbussche, 2013; Pierce, 2011), with a primary focus on trade destruction and diversion as a result of duty implementation.

The preceding studies (Cheong, 2007; Cuyvers & Dumont, 2005; Jabbour et al., 2009) applied Ordinary Least Square (OLS) or Propensity Score Matching (PSM) to identify the EU AD's effects on target countries' export growth by measuring export value and volume. Other studies (Brambilla, Porto, & Tarozzi, 2012; Chandra & Long, 2013; Lu, Tao,

& Zhang, 2013) concentrated on the effects of United States AD's on income and labor productivity in target countries by applying Cross-section and Panel Regression Models.

Even though biodiesel usage may lead to decreased CO_2 emissions, the expansion of palm oil production land for the biodiesel industry may have detrimental environmental effects, such as biodiversity loss and indirect land use change (Croezen, Bergsma, Otten, & van Valkengoed, 2010; Matsuda & Takeuchi, 2018). Indirect land use change involves the conversion of land from its initial purpose, such as protected forest, grassland, pasture, or agricultural land, into arable land used for biofuel feedstock cultivation, which results in an increase in emissions (Croezen et al., 2010). This indirect increase in emissions is one of the reasons why biodiesel made from palm oil is currently considered unsustainable by the EU[6]. (European Commission, 2019).

On the positive side, the Indonesian palm oil industry has provided many employment opportunities in the national economy. There was a massive increase in labor usage in the palm oil production sector of about 78% from 2012-2014 (Directorate General of Estate Crops, 2016a). Furthermore, the industry has boosted the Indonesian national income. The value of Indonesian biodiesel exports reached around 1.1 billion USD in 2014, a 17% increase from 2012 (UN Comtrade, 2019).

This contrast between potential environmental benefits and ecological harm make any study of the palm oil industry both interesting and complex. This study differs from previous literatures in its aim to observe the effects of the EU AD on Indonesian exports and local CPO prices by employing time series data to a Vector Error Correction Model (VECM). By comparing Johansen and Gregory-Hansen tests in our model specification, we can prove whether there is a structural break representing the AD duty implementation which captures the effect of the policy implementation on both Indonesian CPO prices and local prices

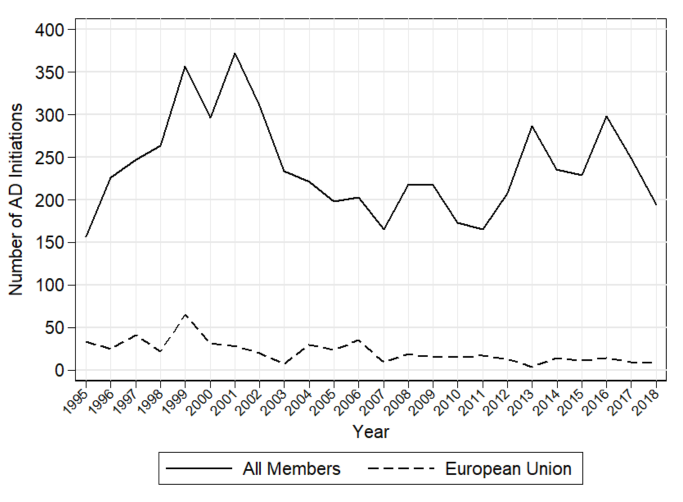
The study is structured as follows: the subsequent section provides an overview of the alleged dumping occurring in Indonesia and subsequent EU response to the situation. The model specification section describes the methodology implemented and is followed by a description of the data used in the study. We discuss the results before summarizing our study in the conclusion section.

[6] The EU stated that 45% of the oil palm area expansion caused forest devastation; in contrast, that the case for only 8% and less for other biodiesel sources (European Commission, 2019).

2.2. Background: dumping and retaliation

2.2.1 Dumping

The implementation agreement of Article VI of the 1994 General Agreement on Tariffs and Trade expressed an opposition to the practice of dumping (World Trade Organization, 1994). However, many countries still engage in the practice with various products (Figure 2. 3). From an international trade perspective, dumping is associated with a form of price discrimination wherein exporting countries charge a lower price on the world market than they do domestically, or evaluate a product at a value lower than the product's average cost (Feenstra & Taylor, 2014).

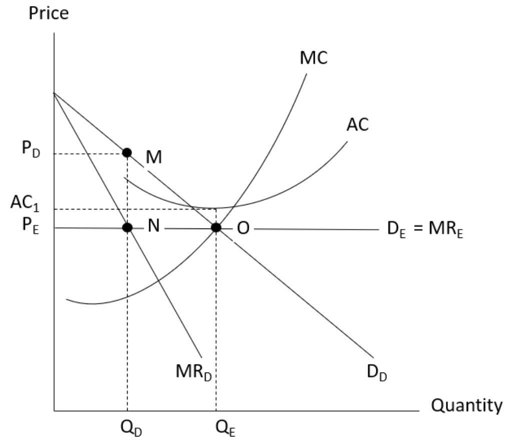


Source: Own production based on data from World Trade Organization (2019).

Figure 2. 3 AD Initiations between 1995-2018.

However, Lindsey and Ikenson (2003) argue that a country can be accused of dumping even when charging equal prices on both the world market and the domestic market; or even a higher world price than domestic price. According to the authors, reasons for this include the effect of fluctuation, the asymmetric treatment of indirect selling expenses, and the exclusion of below-cost sales which are able to influence the value of dumping margins.

To illustrate the general dumping situation, we assume a condition called Foreign Discriminating Monopoly (Feenstra & Taylor, 2014) as shown in Figure 2. 4. The firm is assumed to be in perfect competition on the world market and exercises monopolistic market power on the domestic market. It sets Marginal Cost (MC) equal to Marginal Revenue (MR) to maximize profits. Also, it discriminates between prices set on the local market and those of export markets. To maximize profit, it produces Q_E, where its local MC meets export market MR_E at point O. However, it sells only at Q_D to its local market, where MR_D meets MR_E at point N. The difference between Q_E and Q_D is the quantity to be exported.



Source: Own production based on data from Feenstra and Taylor (2014).

Figure 2. 4 Dumping Illustration

Additionally, it charges a price P_D on the domestic market, while P_E is charged on the export market. In this case, P_E is lower than $P_{D,}$ even lower than the local Average Cost (AC). This price discrimination is called dumping. In such a condition, nevertheless, the firm still profits. Feenstra and Taylor (2014) mentioned that, even though the export price value is lower than that of average cost (AC), the firm, or the foreign monopoly producer, still benefits from this condition if the export price value is higher than the MC[7].

However, the alleged dumping scheme exercised by Indonesia is a more complex case. The EU claimed that CPO, the raw material for Indonesian biodiesel, is sold at artificially cheaper prices domestically than internationally (European Commission, 2013b). This reduces Indonesian biodiesel manufacturers costs below the costs of outside CPO manufacturers, which rely on CPO from Indonesia as an input. The EU further claims that this was caused by a large difference between the value of export tariffs between CPO and biodiesel, where dumping margin arises (European Commission, 2013b). This situation, where there is a difference in the value of export tariffs between input and output products is known as an export tariff escalation (Nogués, 2011).

The objective of imposing an export tariff escalation is to protect the processing industries in the exporting countries (Nogués, 2011). Consequently, the tariff escalation is visible when the raw material export tariff is higher than that of processed product (Corzine,

[7] Every unit exported raises profit by the discrepancy between price and MC

2008; Nogués, 2011). Thus, it will encourage the domestic processing industries to grow and increase their competitiveness.

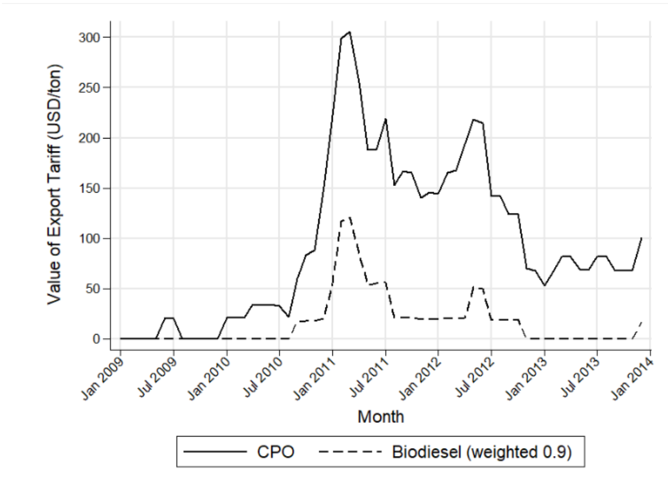
$$TW = T - t \tag{1}$$

TW = Normal tariff wedge

T = Tariff in ad valorem equivalent of the output commodity

t = Tariff in ad valorem equivalent of the input commodity

There is a measurement of tariff escalation, called tariff wedge (TW)[8] (Elamin & Khaira, 2003), which is defined as the discrepancy between output and input commodity tariff values (eq. 1). It is more often applied to calculate import than export tariff wedge. Thus, the interpretation of TW should be reversed, where export tariff escalation appears when TW<0. Meanwhile, export tariff de-escalation occurs when tariff wedge is higher than zero. Another condition called export tariff parity happens when TW=0.



Source: Own calculation based on data from Minister of Trade of the Republic of Indonesia (2019) and Ministry of Finance of the Republic of Indonesia (2019).

Figure 2. 5 Value of Export Tariff (USD/ton) of Indonesian CPO and Biodiesel[9]

Figure 2. 5 depicts the deviation of export tariff values[10] of Indonesian CPO and biodiesel. Since the export tariff value of Indonesian CPO is mostly higher than that of

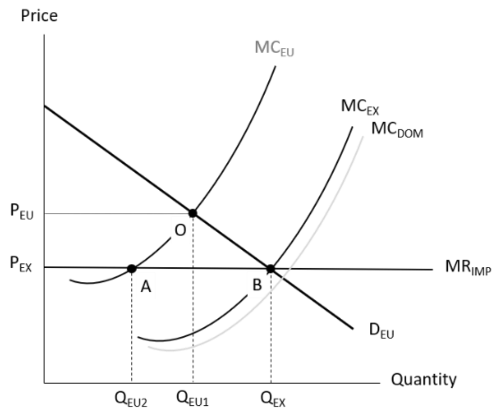
[8] Another measurement, called Effective Rate of Protection, is applied to avoid issue caused by the presence of multiple input and/or output. However, in this case TW is sufficient since CPO is the main raw material in biodiesel production, while other additional materials are negligible.

[9] By processing 1 ton of CPO, 0.9 ton of biodiesel is produced (Andarani, Nugraha, & Wieddya, 2017)

[10] The CPO export tariff value was calculated by multiplying its export tariff with its Export Standard Price (ESP), where similar process was conducted for biodiesel. The ESP for both CPO and biodiesel were defined based on the CPO Free on Board (FOB) average price. Both CPO and biodiesel export tariffs refer to the CPO reference price which were based on Cost, Insurance, and Freight (CIF) Rotterdam CPO average price and Malaysian and/or Jakarta exchange CPO average price. The export tariff classification regulations were determined by the Ministry of Finance of the Republic of Indonesia. Each is valid until the Ministry decides

Indonesian biodiesel, it can be concluded that the tariff wedge is mostly lower than 0 in the period of 2009-2013. This condition indicates that the export tariff escalation exists. In addition to that, the figure only presents the condition before the EU AD duty imposition, which was started at the end of 2013.

The export tariff imposition will create higher MC for the CPO producers overseas. Since the domestic CPO price is below the world CPO price due to the export tariff, the MC in exporting biodiesel by Indonesia (MC_{EX}) becomes lower than that incurred by the EU (MC_{EU}) (Figure 2. 6), which is also due to biodiesel low export tariff[11]. This difference moves the equilibrium along the demand curve (D_{EU}); from point O to B. In response to this new price (P_{EX}), the quantity produced by the EU is reduced from Q_{EU1} to Q_{EU2}, where the EU also starts to import Q_{EX}-Q_{EU2}. This artificially low MC_{EX} means this situation was previously counted as dumping, which was also supported by the dumping margin calculation by the EU. It is consistent with the previous statement by Lindsey and Ikenson, (2003) that even though the world price is higher than the domestic price, a country can still be accused of dumping.



Source: Own illustration.

Figure 2. 6 Indonesian Biodiesel Dumping Illustration

2.2.2 Retaliation

To tackle dumping, the EU imposed an AD. The case was initiated in August 2012. It was a follow up from the complaint the European Biodiesel Board's (EBB) filed one month before. The EU biodiesel producer who filed the case represents more than 60% of the total EU biodiesel production (European Commission, 2013a). The evidence provided

that the new regulation is required to be authorized. On the other hand, the CPO reference price and ESP were determined by the Ministry of Trade of the Republic of Indonesia on a monthly basis (Minister of Trade of the Republic of Indonesia, 2019; Ministry of Finance of the Republic of Indonesia, 2019).

[11] The low biodiesel export tariff creates the gap between export market MC_{EX} and local MC_{DOM}.

was deemed by the EU to be sufficient to initiate a proper investigation into a potential a dumping scenario. Then, the EU began an investigation into Indonesian exporting producers as well as EU producers, and both parties were required to provide data to be processed as part of the investigation.

Further, dumping and injury margins were examined, and both were compared to determine the AD rates (Table 2. 1), which were imposed at the end of 2013 (European Commission, 2013a). These rates were adjusted to the level of the purity of the biodiesel imported. Additionally, according to Feenstra and Taylor (2014) there are three ways to determine the AD rate: by (1) comparing the import price to the exporter's local price, (2) comparing this to that of a similar product in another country, and (3) comparing that to the exporter's AC.

Table 2. 1 The definitive EU AD rate for Indonesian biodiesel producers.

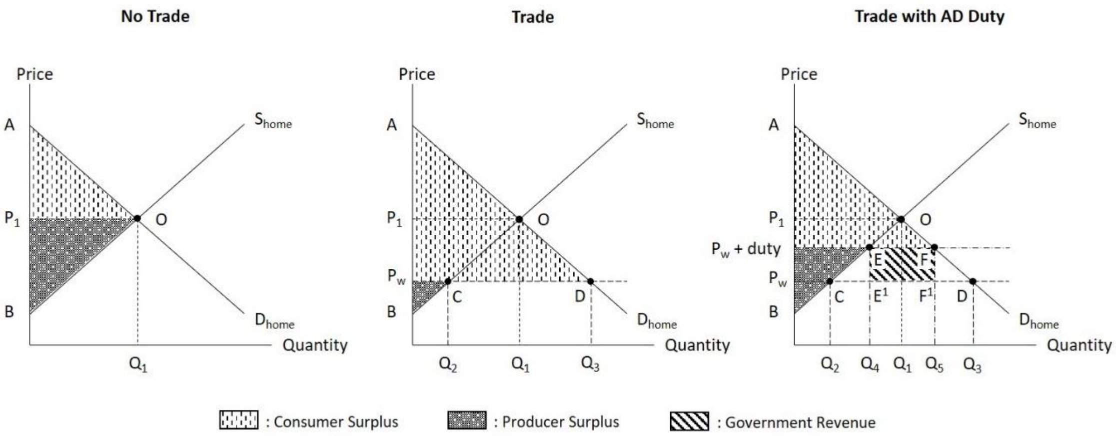
Company	Dumping Margin	Injury Margin	AD rate
PT Ciliandra Perkasa, Jakarta	8.8%	19.7%	8.8% (EUR 76.94)
PT Musim Mas, Medan	18.3%	16.9%	16.9% (EUR 151.32)
PT Pelita Agung Agrindustri, Medan	16.8%	20.5%	16.8% (EUR 145.14)
PT Wilmar Bioenergi Indonesia, Medan; PT Wilmar Nabati Indonesia, Medan	23.3%	20.0%	20.0% (EUR 174.91)
Other cooperating commpanies	20.1%	18.9%	18.9% (EUR 166.95)
All other companies	23.3%	20.5%	20.5% (EUR 178.85)

Source: (European Commission, 2013a).

In the same period, the EU imposed the biodiesel AD not only on Indonesia but also on Argentina, where the value of dumping and injury margins, as well as AD rates, are higher for Argentina than they are for Indonesia. The AD rates for Argentina were between 22.0-25.7% (European Commission, 2013a). Additionally, the United States (US) has also imposed the AD on both Argentina and Indonesia since April 2018, when the International Trade Commission (ITC), an independent US federal trade regulations agency, affirmed that the industry in the US was negatively affected as a result of dumping (Smith, 2018). The estimated weighted-average dumping margins are much higher than those implemented by the EU.

In the EU, the AD causes an increase in import prices as illustrated in Figure 2. 7, where the price increases from P_w to P_w + duty. When trade is introduced, the Home Consumer Surplus (CS) expands excessively, while Home producers are worse off. However, there is an increase in the Home total surplus, where area AOB (No Trade) shifts into area ABCD (Free Trade). Under this condition, the import quantity becomes Q_3-Q_2, while home producers produce only Q2. If producers charge a price higher than Pw, the consumers will import the product.

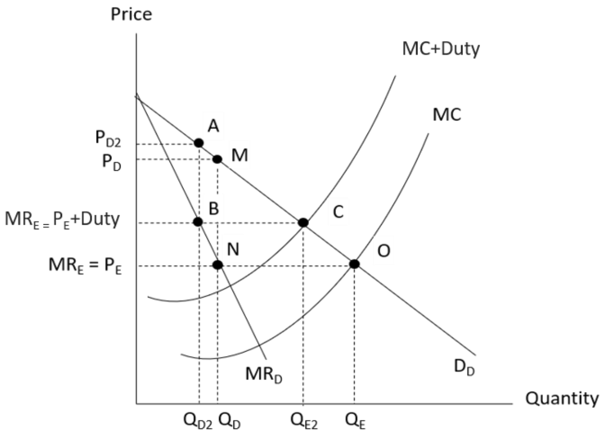
In a case where the government imposes an AD (Free Trade with AD), the price will increase to Pw + duty. Consequently, the import quantity will fall to Q_5-Q_4. The Home CS decreases, while there is surplus transfer from consumer to producer. Apart from that, the government will gain revenue from the duty not exceeding the area of EE_1FF_1. In this case, area CEE1+DFF1 is Dead Weight Loss, and is no longer part of the total surplus. Even though the total surplus decreases by issuing an AD, the government still considers that imposing this policy is beneficial for the reasons mentioned in the previous chapter (Reed, 2001). In this situation, the EU seeks to protect its domestic biodiesel producers from dumping.



Source: Own production based on Reed (2001) and Feenstra and Taylor (2014).

Figure 2. 7 Home Equilibrium without Trade, with Trade and with AD in Trade

On the other hand, the possible effect that occurs in Indonesia is illustrated in Figure 2. 8, which is derived from the Foreign Discriminating Monopoly curve. When the export price increases to P_E + duty, the domestic price increases. Moreover, the quantity produced will be limited to Q_{E2} where Q_{D2} is sold domestically and Q_{E2}-Q_{D2} is exported. Both the quantity sold domestically and exported may be less than before, and are shown by Q_D and Q_E-Q_D, respectively. However, the effect of the biodiesel AD duty on the Indonesian CPO industry will be discussed further in the results section.



Source: Own illustration.

Figure 2. 8 The AD duty Illustration Effect in Indonesia

2.3. Model Specification

We aim to observe the effects of the EU biodiesel AD on Indonesian export prices and local prices by applying a VECM to time series data. To do so, we test for the existence of a structural break (SB) in the long-run relationship between two price time series. We analyze two relationships - the relationship between world CPO price and Indonesian CPO price, as well as the relationship between Indonesian CPO price and the local price of Fresh Fruit Bunches (FFB) of oil palm in Jambi Province. The existence of a structural break (SB) would indicate changes in long- or short-run relationship between prices caused by the duty imposition if a significant SB occurs around the duty imposition date.

The first step is to ensure that all price variables are stationary on the first difference (I(1)) to avoid the problem of a spurious regression. Thus, we employed Augmented Dicky Fuller (ADF), Phillips-Perron (PP), and Zivot-Andrews (ZA) unit root tests to examine the stationarity. ADF and PP test model are shown by equation 2 and 3 (Asteriou & Hall, 2016). Dickey-Fuller extended their test procedure by suggesting an augmented version of the test which includes lagged terms of the dependent variable to eliminate autocorrelation (Waheed, Alam, & Ghauri, 2007). the unit root presents itself, i.e. the variable is non-stationary, when the null hypothesis cannot be rejected. Therefore, to obtain the I(1) variable, we expect to reject it on the first difference. Another stationarity test is ZA test (eq. 4) (Zivot & Andrews, 1992), which allows for the univariate existence of a SB. The purpose of the ZA test is to ensure the stationarity robustness and test the initial SB indication in each variable.

$$\Delta y_t = a_o + \beta y_{t-1} + \gamma t + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + e_t \tag{2}$$

$$\Delta y_t = a_o + \beta y_{t-1} + e_t \tag{3}$$

$$\Delta y_t = a_o + \beta y_{t-1} + \gamma\, t + \zeta DU_t + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + e_t \tag{4}$$

$DU = 1$ if $t > break\ date$ and 0 if otherwise

Next, we must test the cointegration of the two-pair time series to confirm that they hold a long-run relationship. They are cointegrated if both are integrated in the same order, in this case on I(1), and if there is a linear combination of both series on the level I(0) where in this case the e_t in equation 5 or 6 is stationary. Initially, we conducted Johansen cointegration test to observe the cointegration. In a later step, we performed a Gregory-Hansen (GH) cointegration test to analyze the cointegration allowing for a SB. These results will be compared to identify whether the SB genuinely exists or not, in the form of VECM.

Before we proceed to the cointegration tests, we need to determine the optimum lag order necessary to reduce bias by using model selection criterions in the form of Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC) (Mills & Prasad, 1992). We consider all criterions for robustness motivation. The difference between these criteria lie in how the number of estimated parameters and observations are penalized (Mills & Prasad, 1992).

The Johansen cointegration test determines the rank of a time series relationship or the number of cointegrating vectors in a bivariate relationship study with only one possible cointegrating vector (eq. 5). The Johansen test is a maximum likelihood method based on specific correlations (Johansen, 1988). Trace and maximum eigenvalue statistics are also approaches to be observed (Asteriou & Hall, 2016; Johansen, 1988).

$$y_{1t} = a_1 + \beta y_{2t} + e_t \tag{5}$$

Meanwhile, the GH cointegration test is based on ADF and Phillips (Z_α and Z_t) test statistic to examine the presence of cointegration allowing SB (Gregory & Hansen, 1996). There are three different possibilities of SB in the cointegration vector (equation 6); these are (1) a level shift (eq. 6a), (2) a level shift and trend (eq. 6b), and (3) a regime shift (eq.

6c). We determine the best of these a la Gregory and Hansen (1996). The best model is determined by model selection criteria and test statistics and is presented in the results section. However, in this study, we do not consider cointegration with SB in level and trend (eq. 6b) since there is no indication of trend present in the series and there is a common price volatility. Also, the breakpoint is suggested during this test. Nevertheless, we currently have 2 possibilities left of equation 6 (eq. 6a and 6b), since equation 6b is neglected.

$$y_{1t} = a_1 + a_2 DU_t + \beta y_{2t} + e_t \quad (6a)$$

$$y_{1t} = a_1 + a_2 DU_t + a_3 T + \beta y_{2t} + e_t \quad (6b)$$

$$y_{1t} = a_1 + a_2 DU_t + a_3 (DU_t . y_{2t}) + \beta y_{2t} + e_t \quad (6c)$$

$DU = 1$ if $t > breakpoint\ and\ 0\ if\ otherwise$

When the relationships are properly cointegrated, we proceed to estimate and interpret the long-run relationship by using VECM with log-likelihood function. Equations above (eq. 5, 6a, and 6c) capture the two long-run relationships between the two-pair time series which are distinctly presented below (eq. 7, 8a, 8b and 9, 10a, 10b). All price variables, namely world CPO price (P_W), Indonesian CPO price (P_{ID}), and Jambi FFB price (P_{JB}), are in the natural logarithm form. However, we consider extra variables, namely export tariff values in USD/ton (ET) and tax levy (TL) in dummy form, in the relationship between P_{ID} and P_{JB}, since those extra variables are part of P_{ID}. The coefficient α_1, α_2, α_3, β, ξ, and ρ are the parameters to be estimated.

$$lnP_{ID} = \alpha_{1_1} + \beta_1 . lnP_W + ect \quad (7)$$

$$lnP_{ID} = \alpha_{1_2} + \alpha_{2_1} SB + \beta_2 . lnP_W + ect \quad (8a)$$

$$lnP_{ID} = \alpha_{1_3} + \alpha_{2_2} SB + \alpha_{3_1} SB . lnP_W + \beta_3 . lnP_W + ect \quad (8c)$$

and

$$lnP_{JB} = \alpha_{1_4} + \beta_4 . lnP_{ID} + \xi_1 . ET + \rho_1 . TL + ect \quad (9)$$

$$lnP_{JB} = \alpha_{1_5} + \alpha_{2_3} SB + \beta_5 . lnP_{ID} + \xi_2 . ET + \rho_2 . TL + ect \quad (10a)$$

$$lnP_{JB} = \alpha_{1_6} + \alpha_{2_4} SB + \alpha_{3_2} SB . lnP_{ID} + \beta_6 . lnP_{ID} + \xi_3 . ET + \rho_3 . TL + ect \quad (10c)$$

In addition to that, VECM can segregate the long-run equilibrium, represented by the error correction term (ect), from the short-run dynamics. Thus, any shock that occurs in a certain period lets both prices adjust to return to the equilibrium (Patterson, 2000). The short-run equations are presented below. Equation 11a and 11b represent the short-run equilibrium of the relationship between P_{ID} and P_W, while equation 12a and 12b represent the relationship between P_{JB} and P_{ID}. Subscript t represents time; n describes the number of lags (0, …, k); and γ, δ, and θ are parameters to be estimated.

$$\Delta lnP_{ID\,t} = \sum\nolimits_{n=1}^{k} \gamma_{1_n} \Delta lnP_{ID_{t-n}} + \delta_1 \Delta lnP_{W_{t-n}} + \theta_1 ect_{t-1} \qquad (11a)$$

$$\Delta lnP_{W\,t} = \sum\nolimits_{n=1}^{k} \gamma_{2_n} \Delta lnP_{ID_{t-n}} + \delta_2 \Delta lnP_{W_{t-n}} + \theta_2 ect_{t-1} \qquad (11b)$$

and

$$\Delta lnP_{JB\,t} = \sum\nolimits_{n=1}^{k} \gamma_{3_n} \Delta lnP_{JB_{t-n}} + \delta_3 \Delta lnP_{ID_{t-n}} + \theta_3 ect_{t-1} \qquad (12a)$$

$$\Delta lnP_{ID\,t} = \sum\nolimits_{n=1}^{k} \gamma_{4_n} \Delta lnP_{JB_{t-n}} + \delta_4 \Delta lnP_{ID_{t-n}} + \theta_4 ect_{t-1} \qquad (12b)$$

Additionally, the VECM can be briefly presented in matrix notation, as presented below. Equations 19a and 19b represent the two-pair time series relationships without a SB, where the long-run equation is inserted as ect within the short-run equation. Matrices A and B denote the effects of prices in the previous periods. Matrix ε denotes normally distributed errors. Equations 20a and 20b define the two-pair time series relationships with SB, where there is a level shift in the model, while equations 21a and 21b define where there is a regime shift in the model. Those equations are differed into parts with a dummy 0 (before SB or t ≤ breakpoint) and dummy 1 (after SB or t > breakpoint).

First, one cointegration vector model allowing for a SB is chosen between two; thus, there is only one model left representing the SB (eq. 20a and 20b or 21a and 21b). Then, that model is compared to the model without the SB (eq. 19a and 19b) to confirm that the effect of SB is legitimate. Again, to do so, we compare the model-selection criteria value for both models: the lower the value, the better the model. Also, the higher the log-likelihood value, the better the model. Another criterion is that when all the GH cointegration test possibilities provide significant results, it is most likely that the model with the SB fits best.

$$\begin{bmatrix}\Delta lnP_{ID}\\ \Delta lnP_W\end{bmatrix} = \overbrace{\sum_{n=1}^{k}\begin{bmatrix}\gamma_{1n} & \delta_1\\ \gamma_{2n} & \delta_2\end{bmatrix}\begin{bmatrix}\Delta lnP_{ID_{t-n}}\\ \Delta lnP_{W_{t-n}}\end{bmatrix}}^{\mathbf{A}} + \begin{bmatrix}\theta_{1_1}\\ \theta_{2_1}\end{bmatrix}\underbrace{\left[lnP_{ID} - \alpha_{1_1} - \beta_1.lnP_W\right]}_{ect} + \overbrace{\begin{bmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\end{bmatrix}}^{\boldsymbol{\varepsilon}} \tag{19a}$$

$$\begin{bmatrix}\Delta lnP_{JB}\\ \Delta lnP_{ID}\end{bmatrix} = \underbrace{\sum_{n=1}^{k}\begin{bmatrix}\gamma_{3n} & \delta_3\\ \gamma_{4n} & \delta_4\end{bmatrix}\begin{bmatrix}\Delta lnP_{JB_{t-n}}\\ \Delta lnP_{ID_{t-n}}\end{bmatrix}}_{\mathbf{B}} + \begin{bmatrix}\theta_{3_1}\\ \theta_{4_1}\end{bmatrix}\left[lnP_{JB} - \alpha_{1_4} - \beta_4.lnP_{ID} - \xi_1.ET - \rho_1.TL\right] + \begin{bmatrix}\varepsilon_{3t}\\ \varepsilon_{4t}\end{bmatrix} \tag{19b}$$

;

$$\begin{bmatrix}\Delta lnP_{ID}\\ \Delta lnP_W\end{bmatrix} = \begin{cases} \mathrm{A} + \begin{bmatrix}\theta_{1_{2a}}\\ \theta_{2_{2a}}\end{bmatrix}\left[lnP_{ID} - \alpha_{1_{2a}} - \alpha_{2_{1a}}SB - \beta_{2a}.lnP_W\right] + \varepsilon, & \mathrm{SB} = 0\\ \mathrm{A} + \begin{bmatrix}\theta_{1_{2b}}\\ \theta_{2_{2b}}\end{bmatrix}\left[lnP_{ID} - \alpha_{1_{2b}} - \alpha_{2_{1b}}SB - \beta_{2b}.lnP_W\right] + \varepsilon, & \mathrm{SB} = 1\end{cases} \tag{20a}$$

$$\begin{bmatrix}\Delta lnP_{JB}\\ \Delta lnP_{ID}\end{bmatrix} = \begin{cases} \mathrm{B} + \begin{bmatrix}\theta_{3_{2a}}\\ \theta_{4_{2a}}\end{bmatrix}\left[lnP_{JB} - \alpha_{1_{5a}} - \alpha_{2_{3a}}SB - \beta_{5a}.lnP_{ID} - \xi_{2a}.ET - \rho_{2a}.TL\right] + \varepsilon, & \mathrm{SB} = 0\\ \mathrm{B} + \begin{bmatrix}\theta_{3_{2b}}\\ \theta_{4_{2b}}\end{bmatrix}\left[lnP_{JB} - \alpha_{1_{5b}} - \alpha_{2_{3b}}SB - \beta_{5b}.lnP_{ID} - \xi_{2b}.ET - \rho_{2b}.TL\right] + \varepsilon, & \mathrm{SB} = 1\end{cases} \tag{20b}$$

;

$$\begin{bmatrix}\Delta lnP_{ID}\\ \Delta lnP_W\end{bmatrix} = \begin{cases} \mathrm{A} + \begin{bmatrix}\theta_{1_{3a}}\\ \theta_{2_{3a}}\end{bmatrix}\left[lnP_{ID} - \alpha_{1_{3a}} - \alpha_{2_{2a}}SB - \alpha_{3_{1a}}SB.lnP_W - \beta_{3a}.lnP_W\right] + \varepsilon, & \mathrm{SB} = 0\\ \mathrm{A} + \begin{bmatrix}\theta_{1_{3b}}\\ \theta_{2_{3b}}\end{bmatrix}\left[lnP_{ID} - \alpha_{1_{3b}} - \alpha_{2_{2b}}SB - \alpha_{3_{1b}}SB.lnP_W - \beta_{3b}.lnP_W\right] + \varepsilon, & \mathrm{SB} = 1\end{cases} \tag{21a}$$

$$\begin{bmatrix}\Delta lnP_{JB}\\ \Delta lnP_{ID}\end{bmatrix} = \begin{cases} \mathrm{B} + \begin{bmatrix}\theta_{3_{3a}}\\ \theta_{4_{3a}}\end{bmatrix}\left[lnP_{JB} - \alpha_{1_{6a}} - \alpha_{2_{4a}}SB - \alpha_{3_{2a}}SB.lnP_{ID} - \beta_{6a}.lnP_{ID} - \xi_{3a}.ET - \rho_{3a}.TL\right] + \varepsilon, & \mathrm{SB} = 0\\ \mathrm{B} + \begin{bmatrix}\theta_{3_{3b}}\\ \theta_{4_{3b}}\end{bmatrix}\left[lnP_{JB} - \alpha_{1_{6b}} - \alpha_{2_{4a}}SB - \alpha_{3_{2b}}SB.lnP_{ID} - \beta_{6b}.lnP_{ID} - \xi_{3b}.ET - \rho_{3b}.TL\right] + \varepsilon, & \mathrm{SB} = 1\end{cases} \tag{21b}$$

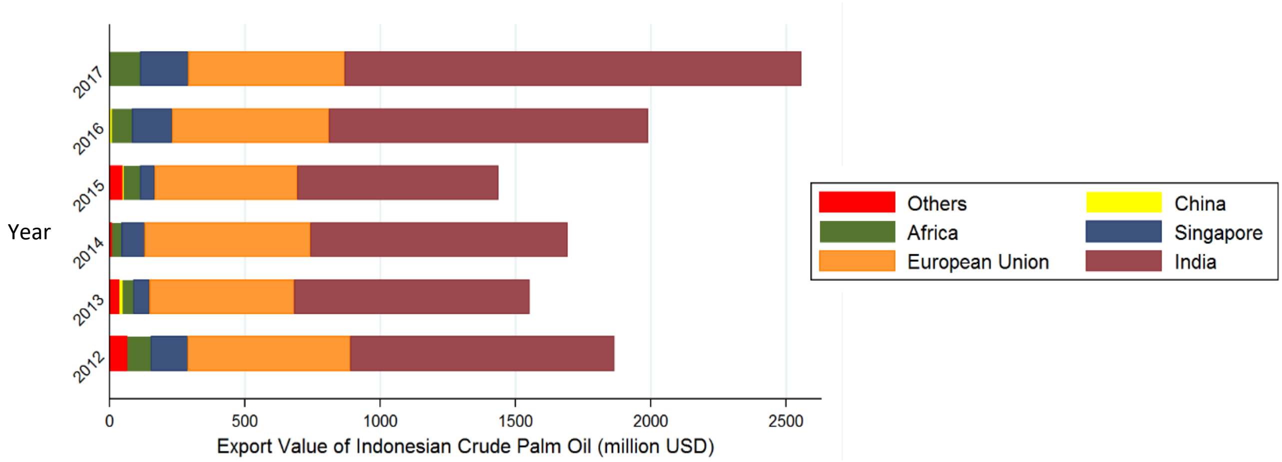
At last, if the SB effect is legitimate, we compare the full model (also called the restricted model) which allows for the presence of the SB (eq. 20 or eq. 21) to the unrestricted model (also called as separated model). The unrestricted model represents the separation of equation 19 into before and after the breakpoint, thus we will have two long-run relationships (two-unrestricted model). To do so, a Likelihood Ratio (LR) test is required, since the VECM model determination employs the log-likelihood function. The log-likelihood discrepancy between a full model and the two-unrestricted model determines the LR value (eq. 22), which is then compared with a chi-square (χ^2) distribution (Wooldridge, 2013). The two-unrestricted model is better than the full model if we can reject the null hypothesis.

$$LR = 2\,(L_{ur} - L_r) \tag{22}$$

2.4. Data

We use data on world CPO price (P_W), Indonesian CPO price (P_{ID}), and Jambi FFB price (P_{JB}) at a weekly frequency. P_W and P_{ID} are obtained from DataStream Navigator by Thomson Reuters (2019a, 2019b), while P_{JB} data are gathered from the Estate Crop Office of the Jambi Province (2019). The series starts in October 2011, when the data is most recently available, and ends in November 2018, when the EU biodiesel AD imposition ended. It is expected that within that time period, the effect of the duty imposition can be analyzed.

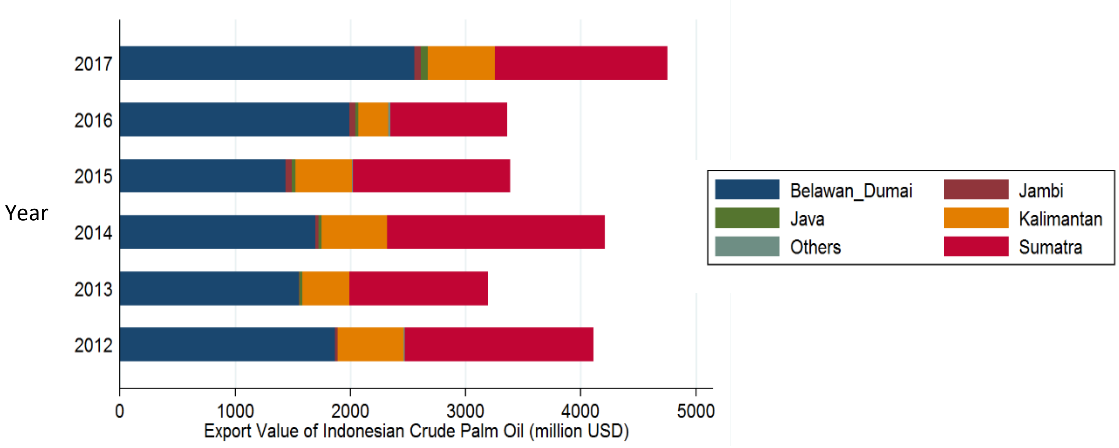
We utilized CPO Cost, using Insurance and Freight (CIF) Rotterdam Price as a proxy for the P_W. Rotterdam is considered the main export entrance for the EU countries. Its price frequently influences the domestic price of exporting countries. Based on Figure 2. 9, the EU is the second largest Indonesian CPO importer, and EU countries absorbed around 25 % of total Indonesian CPO export quantity in between 2012-2017. Meanwhile, India remains the largest importing country, consuming more than 60% of the total Indonesian CPO export quantity in 2017.



Source: Own production based on (Statistics Indonesia, 2018)

Figure 2. 9 Share of Indonesian CPO Export Value based on Importing Countries

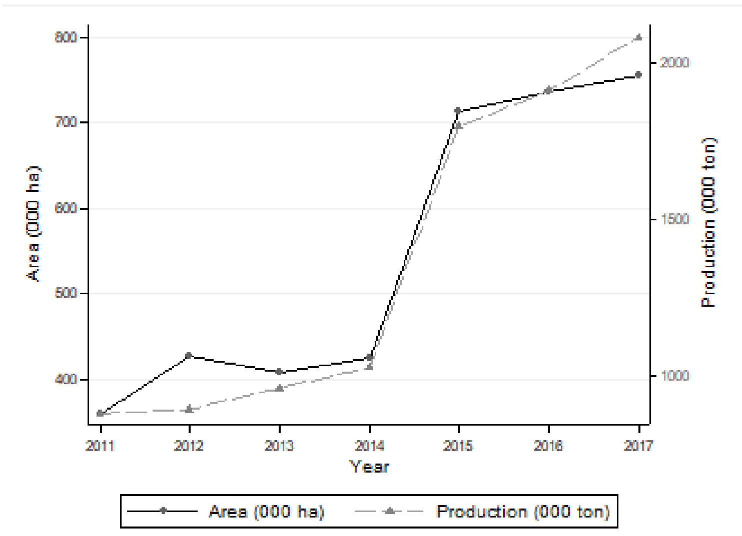
We used CPO Free on Board (FOB) price in the Indonesian ports of Dumai and Belawan as a proxy for P_{ID}, as these are the main ports for CPO export activities. They accommodate more than 50% of total Indonesian CPO export quantity in 2017 (Figure 2. 10). Those ports are located in Sumatra island, where the majority of Indonesian CPO production originates. They are also easily accessible from the Jambi province.



Source: Own production based on (Statistics Indonesia, 2018)

Figure 2. 10 Share of Indonesian CPO Export Value based on Ports' Location

We use Jambi province to represent local Indonesian areas. The province widely expanded the development of both oil palm land area and production from 2011-2017 (Figure 2. 11), and the number of oil palm farmers in the province increased 20% during this period(Directorate General of Estate Crops, 2015, 2016a). Oil palm accounted for nearly 12% of Indonesian CPO export value in 2017 (Statistics Indonesia, 2018). The local price, P_{JB}, is the price of oil palm FFBs, which are freshly harvested and delivered on the same day to prevent any deterioration in quality received by farmers at the factory level (Estate Crops Office, 2019)..



Source: (Directorate General of Estate Crops, 2015, 2016a)

Figure 2. 11 Area and Production of Oil Palm Plantation in the Jambi Province

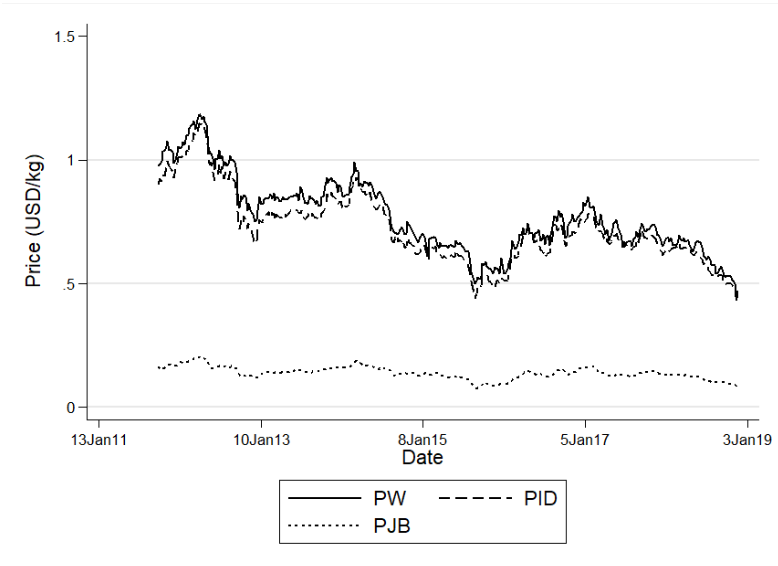
Summary statistics of these price variables in USD/kg are presented in Table 2. 2. We employ weekly price data, and thus have 373 observations. The P_{JB} restricts any higher of a data frequency[12], which would have been preferable, since it is determined once per week[13] by the Jambi Governmental Office of Plantations[14].

Table 2. 2 Summary Statistics of Price Variables (USD/kg)

Variables	Obs	Mean	Std. Dev.	Min	Max
FFB - Jambi price (P_{JB})	373	0.14	0.03	0.08	0.21
CPO FOB - Indonesia price (P_{ID})	373	0.72	0.15	0.43	1.15
CPO CIF - World price (P_W)	373	0.77	0.15	0.44	1.19

Source: Own production based on (Estate Crops Office, 2019; Thomson Reuters, 2019a, 2019b).

As expected, the mean price P_W is higher than that of other prices. The large gap between Indonesian and World CPO prices and P_{JB} is due to CPO processing costs and the input-output ratio[15]. Similarly, the standard deviation of both P_{ID} and P_W is higher than that of P_{JB}, implying that both prices fluctuate more than P_{JB} does. The time series plot of variables can be seen in Figure 2. 12.



Source: Own production based on (Estate Crops Office, 2019; Thomson Reuters, 2019a, 2019b).

Figure 2. 12 Time Series Plot of Price Variables

Other additional data gathered are the value of export tariffs and levies imposed during the period of interest (Figure 2. 13). The regulation concerning the stipulation of CPO export tariffs was replaced on July 14, 2015 (Minister of Finance of the Republic of

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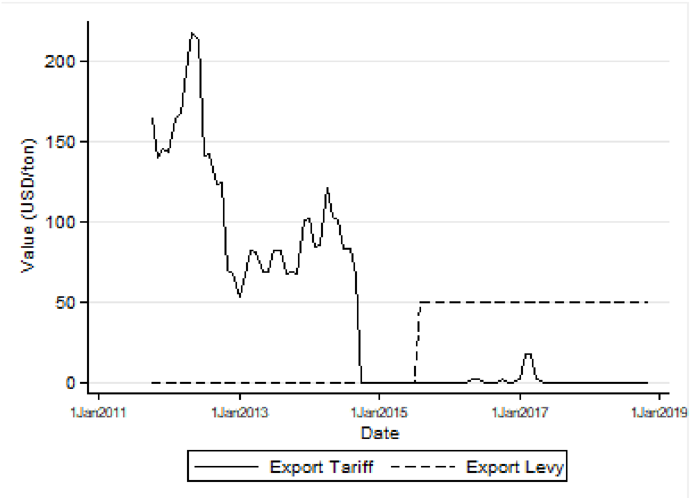
[12] Other prices were adjusted to the frequency level of P_{JB}

[13] We attended the weekly meeting where all palm oil stakeholders can come.

[14] P_{JB} determination is based on CPO local, CPO export, and Kernel local price.

[15] An interview to the one of CPO factories mentioned that the processing cost can reach more than 50% of the CPO price.

Indonesia, 2011, 2015a). Another regulation imposing a CPO export levy of $50 USD/ton was instituted on July 16, 2015 (Minister of Finance of the Republic of Indonesia, 2015b). The government claims that the goal of the export levy was to provide funds for the development of sustainable plantation businesses, encourage the development of downstream plantation industries, increase the optimization of the use of plantation products, and improve the welfare and sustainability of smallholder plantations (Directorate General of Customs and Excise, 2015). Another reason for the tariff was that the CPO price was below the threshold to be recognized by the export tariff for some time, causing losses in government revenue.



Source: Own production based on data from Minister of Trade of the Republic of Indonesia (2019) and Ministry of Finance of the Republic of Indonesia (2019).

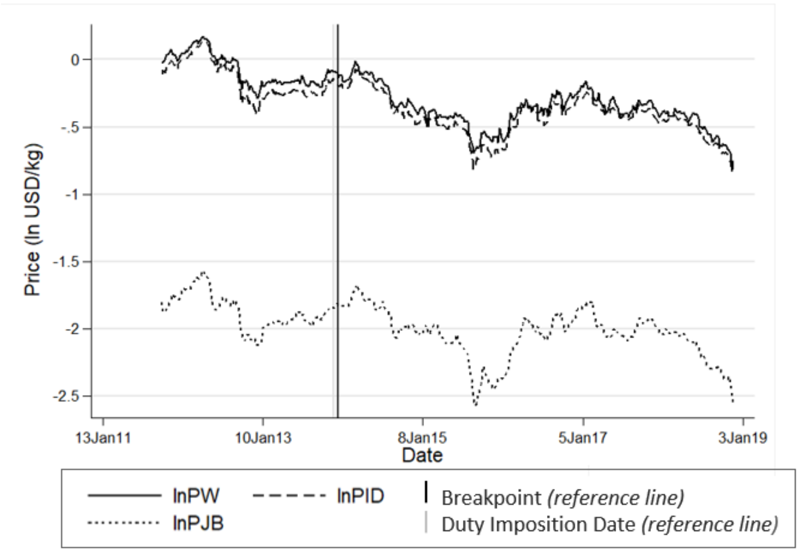
Figure 2. 13 Value of Export Tariff and Levy (USD/ton) of Indonesian CPO

2.5. Result and Discussion

We employ a series of unit root tests (Appendix 2. 1). All test-statistic values are higher than their critical values and the null hypothesis cannot be rejected, indicating that variables have unit root and are not stationary. Meanwhile, we can reject the null hypothesis at first difference indicating these have no unit root and are stationary on I (1). Additionally, the ZA test results support ADF and PP test results due to robustness motivation. Results show that SB exist in each variable, which may indicate that a SB also exist in the long-run relationships.

We also perform a Johansen cointegration test. As the trace statistic values are less than the critical values, we cannot reject the null hypothesis that there is a one or fewer cointegration equation (Appendix 2. 2 and 2. 3). We also compare the maximum statistics test result and determine that values are less than their critical values here as well. This supports the result that we cannot reject the null hypothesis. Also, some model selection criteria suggest that there is a lag of price which may influence both two-pair long-run relationships.

We then employ a GH cointegration test to consider the presence of a SB in the cointegration vector. Several suggestions appear on the result (Appendix 2. 4 and 2. 5). We evaluate two model possibilities to find the best estimated model. Models allowing for a change in regime suggest December 19, 2013 to be the breakpoint for both two-pair relationships (Figure 2. 14) and provide the lowest value of test statistics. Even though the model with a change in level in the relationship between P_{JB} and P_{ID} suggests a similar breakpoint date, the same model used to analyze the relationship between P_{ID} and P_{W} does not suggest the same, making this model option less robust. Model selection criteria are also considered. All tests indicate lag 1 to be the optimal lag used in further estimations.



Source: Own production based on (Estate Crops Office, 2019; Thomson Reuters, 2019a, 2019b).

Figure 2. 14 Time Series Plot with Structural Break

We currently have two two-pair models to be compared, i.e. models without a SB (Appendix 2. 10 and 2. 14) and models allowing for a SB (Appendix 2. 11 and 2. 15). As stated before, lower model selection criteria values (AIC, BIC, and HQIC) and higher log-likelihood values indicate a better model. Thus, models allowing for the SB provide the best fit. Since SB models seem to be the best fit, we compare full/restricted models (Appendix 2. 11 and 2. 15) with unrestricted models, separating by breakpoint (Appendix 2. 12-2. 13 and 2. 16-2. 17). To do so, we employ the LR test (eq. 22).

Table 2. 3. Log-likelihood Values of Restricted and Unrestricted Models

Model	P_{ID} and P_W		P_{JB} and P_{ID}	
	Log-likelihood Value	df	Log-likelihood Value	df
Restricted	1811.8278	371 – 4 = 367	1761.7651	371 – 6 = 365
Unrestricted	583.80093 + 1415.2962 = 1999.09713	(114–2) + (255 – 2) = 365	535.81993 + 1220.6718 = 1756.49173	(114–3) + (255–4) = 362

Source = Own production based on Appendix 2. 11-2. 17

We calculate the computed and critical LR test[16] according to the data in Table 2. 3. Since the computed LR_1 test > the critical LR_1 test, the null hypothesis can be rejected; thus, the unrestricted model fits best for long-run relationship between P_{ID} and P_W. In contrast, since the computed LR_2 test < the critical LR_2 test, the null hypothesis cannot be rejected; thus, the restricted model fits best for a long-run relationship between P_{JB} and P_{ID}. The final estimations to be interpreted for both two-pair relationships are:

a. VECM estimation between P_{ID} and P_W before the breakpoint

$$lnP_{ID} = -0.06 + 1.17\ lnP_W + ect \tag{23a}$$

$$\Delta lnP_{ID\ t} = -0.11\ \Delta lnP_{ID_{t-n}} + 0.16\ \Delta lnP_{W_{t-n}} + 0.08\ ect_{t-1} \tag{23b}$$

$$\Delta lnP_{W\ t} = 0.07\ \Delta lnP_{ID_{t-n}} - 0.05\ \Delta lnP_{W_{t-n}} + 0.40^{**}\ ect_{t-1} \tag{23c}$$

b. VECM estimation between P_{ID} and P_W after the breakpoint

$$lnP_{ID} = -0.04 + 1.00\ lnP_W + ect \tag{24a}$$

$$\Delta lnP_{ID\ t} = 0.06\ \Delta lnP_{ID_{t-n}} + 0.10\ \Delta lnP_{W_{t-n}} - 0.02\ ect_{t-1} \tag{24b}$$

$$\Delta lnP_{W\ t} = 0.16\ \Delta lnP_{ID_{t-n}} - 0.02\ \Delta lnP_{W_{t-n}} + 0.37^{***}\ ect_{t-1} \tag{24c}$$

c. VECM estimation between P_{JB} and P_{ID} with SB

$$lnP_{JB} = -1.44 + 0.06\ SB - 0.10\ SB.lnP_{ID} + 1.44\ lnP_{ID} - 1.48\ ET - 0.04\ TL + ect \tag{25a}$$

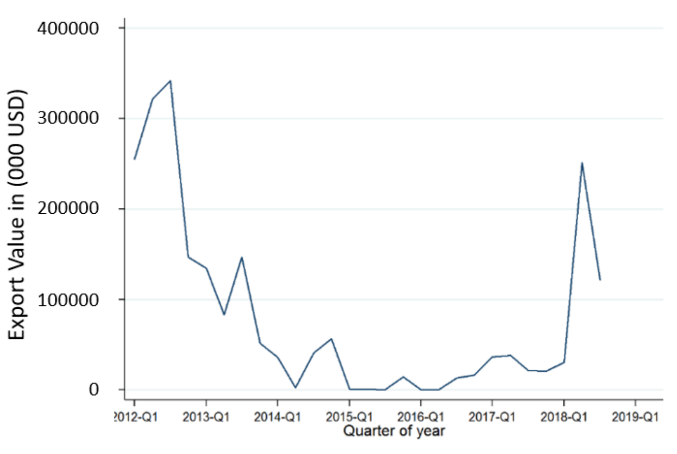
$$\Delta lnP_{JB\ t} = 0.19^{***}\ \Delta lnP_{JB_{t-n}} + 0.38^{***}\ \Delta lnP_{ID_{t-n}} - 0.22^{***}\ ect_{t-1} \tag{25b}$$

$$\Delta lnP_{ID\ t} = 0.11^{**}\ \Delta lnP_{JB_{t-n}} + 0.21^{***}\ \Delta lnP_{ID_{t-n}} + 0.13^{***}\ ect_{t-1} \tag{25c}$$

The breakpoint identified in the econometric analysis occurs three weeks after the biodiesel EU AD imposition date on November 27, 2013 (European Commission, 2013a). Export trade agreements are generally made in advance; thus, the effect of the duty cannot be expected to be observed in the same week, but rather with a time lag. The period during which we find empirical effects provides a very plausible explanation for a causal interpretation. As previously mentioned, even though the policy was intended to impose a

16 $LR_{1\ computed} = 2\ (1999.09713 - 1811.8278) = 374{,}53866$; $LR_{1\ critical} = \chi 2\ (0.95, (367 - 365)) = \chi 2\ (0.95, 2) = 5.991465$; $LR_{2\ computed} = 2\ (1756.49173 - 1761{,}7651) = -10{,}54674$; $LR_{2\ critical} = \chi 2\ (0.95, (365 - 362)) = \chi 2\ (0.95, 3) = 7.814728$

higher duty on biodiesel imported from Indonesia, Indonesian CPO prices may be affected, since CPO is the main raw material for biodiesel production in Indonesia. However, the effects on EU biodiesel import demand from Indonesia can be seen in Figure 2. 15; we see a clear decline in export value as Indonesia faces a challenge in replacing the EU as their most valuable biodiesel importer.



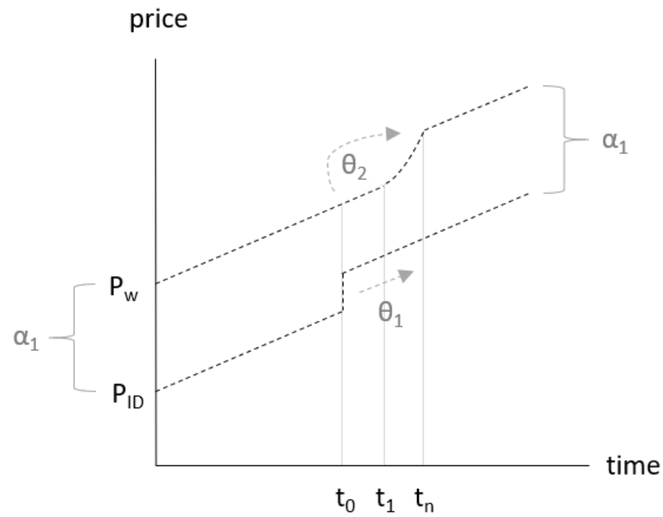
Source: Own production based on Trade Map (2019)

Figure 2. 15 Export Value of Biodiesel from Indonesia to the EU (USD thousand)

Our theoretical considerations yield ambiguous results as to whether decreasing demand for Indonesian biodiesel results in beneficial or detrimental effects on Indonesian domestic CPO demand. It benefits Indonesia when the EU domestic biodiesel companies require more raw materials in the production of biodiesel; therefore P_{ID} may increase. In contrast, it harms the Indonesian CPO demand when Indonesian biodiesel companies' demand decreases, as illustrated in Figure 2. 8, which causes P_{ID} to decrease.

Empirical results show that the duty results in a lower price of CPO received by Indonesia (eq. 23a and 24a). In previous periods, an increase in P_W by 1 % was followed by an increase in P_{ID} of approximately 1.17 %, whereas after the breakpoint an increase in P_W by 1 % results in an increase in P_{ID} of approximately 1 %. Decreasing Indonesian CPO demand leads to a demand shift, resulting in a price reduction. This indicates that the detrimental effect has a stronger effect to the model. Thus, the duty imposition negatively affects the Indonesian CPO price.

Furthermore, both VECM short-run estimations between P_{ID} and P_W (eq. 23b-c and 24b-c) show interesting and significant results as to how P_W adjust to any disequilibrium-causing, while the P_{ID} does not. Visualization of this phenomenon can be seen in Figure 2. 2. 16, where θ_2>0 and θ_1=0 when there is a shock in t_0. A high contribution of Indonesian biodiesel to the world market causes P_W to react more in periods following a shock. Indeed, P_W has a slower reaction to disequilibrium after the breakpoint, which indicates that P_W gains more power due to the imposition of duties. It reduces from a 40% to a 37% correction of any deviation from long-run equilibrium per period, in this case in another week. A lower biodiesel quantity imported by the EU makes it less dependent on Indonesia.



Source: Own illustration

Figure 2. 16 Visualization of VECM estimation between P_{ID} and P_W

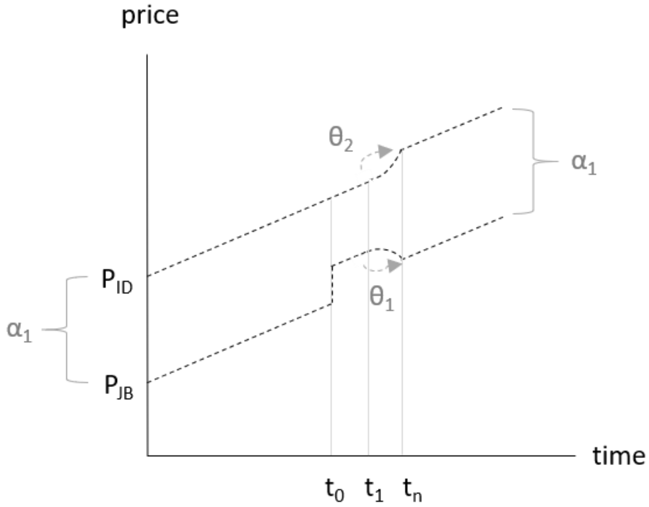
The VECM estimation result of the relationship between P_{JB} and P_{ID} allows for a interpretation. We could separate the long-run VECM estimation into periods before and after the breakpoint. To do so, we include SB=0 when t ≤ breakpoint and SB=1 when t > breakpoint to Estimation 25a, which can be seen below:

$$lnP_{JB} = -1.44 + 1.44\, lnP_{ID} - 1.48\, ET - 0.04\, TL + ect \ , \ SB = 0 \qquad (25a0)$$

$$lnP_{JB} = -1.38 + 1.34\, lnP_{ID} - 1.48\, ET - 0.04\, TL + ect \ , \ SB = 1 \qquad (25a1)$$

Similarly, results show that the duty creates a lower FFB price received by oil palm farmers in Indonesia (eq. 25a0 and 1). Decreases in demand for Indonesian CPO lead to a decrease in demand for Jambi FFB among Indonesian CPO producers. Previously, an increase in P_{ID} by 1 % was followed by an increase in P_{JB} of approximately 1.44 %, whereas after the breakpoint, an increase in P_{ID} by 1 % is followed by an increase in P_{JB} of approximately 1,34 %. This demand shift causes a price reduction. Thus, the duty imposition also negatively affects the Jambi FFB price.

However, in the short run, there is only one pair of estimations (eq. 25b and c) to interpret, where there is an adjustment from both P_{JB} and P_{ID} if any disequilibrium exists. Visualization of this phenomenon can be seen in Figure 2. 17, where θ_2>0 and θ_1<0 when there is a shock in t_0. Both adjustments are clearly visible and significant, where P_{JB} corrects 22% per period from the long-run deviation to return to the equilibrium when any shocks appear, while P_{ID} corrects 13% per period. Since P_{ID} corrects slower than P_{JB} does, we assume that P_{ID} acts more as a leader, while P_{JB} acts more as a follower. In total, there will be around 35% correction when a shock occurs in the short-run.



Source: Own illustration

Figure 2. 17 Visualization of VECM estimation between P_{ID} and P_W

2.6. Conclusion

The imposition of the EU biodiesel AD generated a SB in the cointegration estimation between Indonesian and world CPO prices, and between Jambi FFB and Indonesian CPO prices. This could indicate that the duty had an effect on the price after the breakpoint. Results show that the duty negatively affected the Indonesian CPO and local Jambi FFB price, whereas the world CPO market gained more power after the duty implementation. Decreases in Indonesian CPO demand due to decreased demand for imported biodiesel by the EU lead to a price reduction caused by a shifting of demand.

Chapter 3

Fight or Flight: Factors Affecting Local Traders' Decisions to Remain in or Exit the Market

Rakhma Melati Sujarwo , Thomas Kopp , Bernhard Brümmer

3.1. Introduction

Traders play a significant and often underestimated role in agricultural trading activities and can be decisive actors in agricultural marketing channels. In the agricultural sector, traders are often able to bridge the gap between factory and farmer by mediating issues with geographical distance and logistics, gaps in capital, and supply chain continuity, which can be difficult for farmers to remedy. Furthermore, Coughlan, Anderson, Stern, & El-Ansary (2006) explains that the right intermediaries must be considered in order for a product to be marketed and sold through the optimal channel.

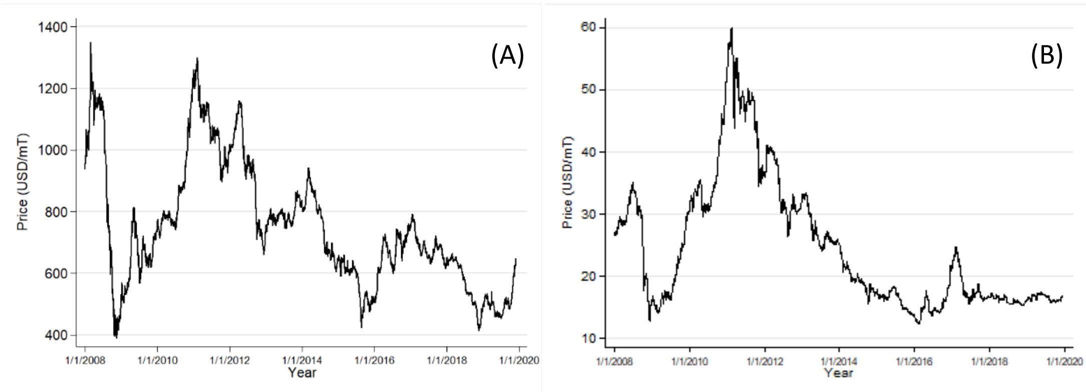
Having more traders in the market is favourable for competition, as farmers have better options for selling their products to the preferred trader of their choice. If there are only few traders available in the area, traders could gain more market power as a result (Mas-Colell, Whinston and Green, 1995). However, existing market power structures within agricultural markets are not easily overcome. In Indonesian rubber value chains, there exist a significant amount of trader market power (Kopp & Brümmer, 2017), particularly in remote areas and in smaller markets. Nevertheless, the traders' role remains considered.

Additionally, agricultural products have specific handling requirements, in terms of shipping and distribution, which set them apart from other products, mainly due to their inherent perishability and bulkiness. Fluctuating prices, differences in capital requirements, and differences in post-harvest handling all may become significant obstacles for traders, and addressing these obstacles is necessary in understanding the trader's behaviour in the market. In the presence of some influential economic divergence, for example a falling price in the traded product, traders' behaviours will likely diverge as a result. Some may remain in the market and some may exit, which can in turn alter the market's overarching structure. Understanding this situation is relevant for policy makers in predicting fluctuations in agricultural market structures.

To study these issues further, we focus on the case of oil palm and rubber traders in the Jambi province, Indonesia. Indonesia has a strong agricultural sector which accounted for nearly 13% of total national Gross Domestic Product in 2018 (Statistics Indonesia, 2019), and the Indonesian oil palm and rubber trade provide a significant contribution to the country's foreign exchange (Directorate General of Estate Crops, 2017a, 2017b).

The Jambi province is located in Sumatra island in western Indonesia. Recently, oil palm and rubber plantations in the province have rapidly expanded, resulting in a number of indirect land use change issues (Directorate General of Estate Crops, 2015, 2016a, 2016b, 2017a, 2017b), and most relevant stakeholders are benefiting from higher incomes due to the expansion of the sector (Bou Dib et al., 2018). The Indonesian palm oil and rubber industries have also created many new employment opportunities for the country, and there was an increase in labor usage in the Palm Oil and Rubber industries of about 36 % and 7 %, respectively, from 2013 to 2018 (Directorate General of Estate Crops, 2015, 2016a, 2016b, 2017a, 2017b). This unique contrast makes studying the palm oil and rubber industries particularly appealing for researchers and national governments alike.

Oil palm and rubber traders in Jambi face different obstacles to survive. Palm oil and rubber prices have both fluctuated rather unexpectedly over the past few years (Figure 3. 1); however, palm oil has seen more pronounced fluctuations than rubber, on average. Rubber prices have been constantly declining since 2012, whereas palm oil prices have more promising situation where there are times that prices go up momentarily.



Source: Own Production based on Thomson Reuters (2019b, 2019a)

Figure 3. 1 Price Volatility of Palm Oil and Rubber Price (2008-2019)

Another issue to consider is the perishability of the products being traded. Oil palm fresh fruit bunches are more perishable than rubber, therefore prompt delivery is essential in preventing quality deterioration. Meanwhile, the lower the water content in rubber, the higher the rubber quality, so storing rubber will not be a problem. Differences in bulkiness between goods can also lead to different handling requirements when shipping products to the factory, and conveyances such as trucks, pickup trucks, or even motorbikes can all play a role in alleviating these issues. These challenges all have an impact on traders' ability to survive in the market.

Bearing in mind these considerations, this study focuses on trader's decisions to remain in or exit the market, and the various factors influencing this decision. To analyse the probability of remaining in the market, we employ a binary logistic regression method to variables obtained from 3-rounds of primary data collection in Jambi.

Studies of traders' adaptations to economic divergence have been limited in the literature. Some studies have focused on how financial market traders survive in the presence of market competition (Benos, 1998; Kogan, Ross, & Westerfield, 2006), but none have focused on agricultural product traders, thus the required approaches may be quite different. Those studies have pointed out that risk-taker traders are expected to have higher profits than risk-averse traders, and thus are more likely to remain in the market. However, numerous studies of similar behaviour among farmers have analysed which factors affect farmers' decisions to remain in or exit the market (Bragg & Dalton, 2004; Ferjani, Zimmermann, & Roesch, 2015; Kimhi & Bollman, 1999; Nag et al., 2018; Stiglbauer & Weiss, 2000)

These are the most relevant studies in the literature, since, to the best of our knowledge, trader- level studies of agricultural products have not been undertaken. Therefore, this study is intended to fill this gap and to further diversify the existing research on the topic.

The study is structured as follows: the next few sections provide an overview of the role of local traders in Jambi. The model specification section describes the methodology implemented and is followed by a description of the data used in the study. We then discuss the results before summarizing our study in the conclusion section.

3.2. Role of Local Traders in Jambi

3.2.1 The Importance of Traders

It is important to understand the crucial role traders play in several different marketing functions in agricultural markets. Traders serve as intermediaries, performing many transactional and exchange-related activities, such as "*buying, selling, and risk taking*" (Kerin, Hartley, & Rudelius, 2013). In terms of physical/logistical functions, intermediaries may also undertake tasks such as "*assorting, storing, sorting, and transporting*" of agricultural products (Kerin et al., 2013). Additionally, intermediaries may partake in important "facilitating" functions, like "*financing, grading, and marketing information and research*" (Kerin et al., 2013).

From a demand perspective, there are 2 important advantages to the existence of intermediaries: their ability to facilitate demand connections between producers and end-users, and their ability to fulfill the demand requirement of end-buyers by sorting products (Coughlan et al., 2006). Moreover, Kerin, Hartley and Rudelius (2013) outlined 4 consumer benefits gained from the existence of intermediaries, namely time, place, form and possession utilities. On the supply-side, there are also two advantages provided by intermediaries: reducing producers' distribution costs by arranging frequent transactions, and reducing transaction or contact costs incurred by producers (Coughlan et al., 2006). Indeed, intermediaries increase profits on both the demand-side and the supply-side.

Zúñiga-Arias (2007) noted that traders have substantial knowledge of important marketing information not available to farmers (Kopp et al., 2014) like price, quality, quantity, and various purchasing requirements of end-buyers. Therefore, traders could help to bridge the information gap between farmers and end-buyers.

Moreover, traders have superior access to transportation (Zúñiga-Arias, 2007). This is an important factor, especially in developing countries, where smallholder farmers are often located in remote areas like Jambi Province, where location and capital constraints can affect farmers' choices of an appropriate channel destination for their products (Kopp et al., 2014). Less capital-constrained, traders may have more ready access to vehicles, which can aid farmers in distributing products to end-buyers.

Furthermore, if producers have difficulties in meeting market requirements, traders can help them find alternative channels (Zúñiga-Arias, 2007). Another important role played by the trader is in value-added generation through grading, packing, and in certain cases treating products. Also, with their relatively higher working capital, traders are better able to increase the value-added of agricultural products. In Jambi, traders may also act as informal financiers for producers or other intermediary traders. Indeed, traders may arguably be the best facilitators in bridging the gap between the production and marketing sides of the marketing chain (Zúñiga-Arias, 2007), and this is likely true in the case of Jambi province.

3.2.2 Rubber and Oil Palm Fresh Fruit Bunch (OPFFB) Trading Activities in Jambi

There was a decline in the number of rubber and oil palm fresh fruit bunch traders between 2012 and 2015 due to rubber and palm oil falling price. This decrease in rubber prices was due to an over-supply of rubber and a decline in crude oil price (Aidenvironment, 2016), which led to lower prices of synthetic rubber, a common substitute for natural rubber. The same situation occurred in the oil palm market as well (Abd, Nambiappan, Palm, & Board, 2013).

When we returned to Jambi to collect data for second round, we faced many rejections and a cynical attitude from locals, who initially thought we were debt collectors. Many would first hide from us and have another family member say that they were out of town, and only after we explained that we were from an educational institution would their views change, and they be willing to be interviewed. This fearful response illustrates the challenging situation that many faced due to weak prices during that time period, in which trader populations declined by 19.7% in the survey area. These declines continued until round 3, where we observed losses of around 5% of the total trader population compared to round 2 (Table 3. 1).

Table 3. 1 Number of All Active Traders in the Survey Area

	Year		
	2012	2015	2018
Rubber	309	197	185
Rubber + OPFFB	15	19	26
OPFFB	127	109	119
Total	451	362	342

Source: Own production

In detail, we can see that the number of both rubber and palm oil traders decreased from 2012 to 2015. Meanwhile, there was an increase in the number of oil palm traders between 2015-2018, while the number of rubber traders decreased during that same period. A plausible explanation for this situation is that the palm oil sector may be more profitable and promising than the rubber industry.

Table 3. 2 Transition Matrix of Traders in Period 1 (2012-2015)

		2015			
		Rubber	Rubber + OPFFB	OPFFB	Exit
2012	Rubber	213	4	2	90
	Rubber + OPFFB	-	13	1	1
	OPFFB	-	-	74	53
	Enter	28	2	35	

Source: Own production

Table 3. 2 and 3. 3 present the transition matrix of products traded between a certain period, divided into two periods. The first took place in between 2012-2015, where traders were interviewed first in 2012 and then recalled back in 2015 to observe whether they remained in or exited the market. The same procedure was performed for the second period, from 2015-2018. Both tables illustrate whether traders who remained in the market traded the same product or not, where in most cases, traders remained to trade the same product.

Table 3. 3 Transition Matrix of Traders in Period 2 (2015-2018)

		2018			
		Rubber	Rubber + OPFFB	OPFFB	Exit
2015	Rubber	167	8	1	65
	Rubber + OPFFB	2	14	1	2
	OPFFB	-	3	77	32
	Enter	28	1	40	

Source: Own production

Table 3. 4 Average Income of Traders Existing both in 2012 and 2015 (million IDR)

2012 \ 2015	Oil Palm	Rubber	Both	Unobserved
Oil Palm	10.9 → 8.5	21.4 → 6.0	1.0 → 3.0	20.5 → 0.0
Rubber	4.8 → 5.3	25.7 → 6.8	9.5 → 22.3	18.3 → 0.0
Both	0	0	26.0 → 8.0	12.5 → 0.0

Source: Own production

The dynamics of trader's incomes are presented in aggregate in Table 4 and 5. The figures illustrate that traders generally earned less in 2015 compared to 2012 and earned more still in 2018 compared to 2015. These income increases may be due to more stable market conditions overall, or due to traders generally being more adaptable to the market situation than they were before.

Table 3. 5 Average Income of Traders Existing both in 2015 and 2018 (million IDR)

2015 \ 2018	Oil Palm	Rubber	Both	Unobserved
Oil Palm	9.9 → 24.6	0	2.7 → 40.9	9.4 → 0.0
Rubber	1.5 → 3.0	6.3 → 11.5	3.9 → 21.1	7.1 → 0.0
Both	4.5 → 5.7	7.5 → 26.6	15.6 → 16.2	12.0 → 0.0

Source: Own production

3.4. Model Specification

3.4.1 Determinants in Exiting the Market

As mentioned in section 3.1, several studies have sought to determine which factors affect financial market traders' decisions on whether to remain in or exit the market (Benos, 1998; Kogan et al., 2006). One of the key findings was that risk-taker traders are more willing to remain in the market while anticipating higher future profits than their risk-averse counterparts. Even though this was observed only in the financial market, it can be adopted into our study. Another study was performed to investigate trader behavior in the off-farm labor market using panel data from Austrian farm households. A probability model was utilized, and it was found that an increase in wages increases the probability that a worker will change their status from full-timer to part-time worker (Weiss, 1997).

Comparable studies (Bragg & Dalton, 2004; Ferjani et al., 2015; Kimhi & Bollman, 1999; Nag et al., 2018; Stiglbauer & Weiss, 2000) have also been performed to observe which factors affect farmers' decisions in remaining in or exit the agricultural sector. A study found that large farms tend to stay in the sector, since they have more assets. Also, younger farmers in Canada and Israel were found to exit the market more than their older counterparts (Kimhi & Bollman, 1999).. This could also represent the determinants in exiting the market by traders. For this reason, a probit model is used.

Table 3. 6 Definition of Variables

Variables	Definition	Expected Sign
Dependent Variable		
$remain$	Dummy variable: remain in (1) in or exit (0) from the market	
Independent Variables		
Factor 1: Human Capital		
edu	Dummy variable of trader's education: having at least primary school education (1) or not (0)	-
exp	Traders' experience in trading (in number of year)	+
$func$	Dummy variable of trader's function in the village: having at least one village's function (such as a village head) (1) or not (0)	+
$info$	Dummy variable of knowledge in price information: having the access to get the price information (1) or not (0)	+
Factor 2: Trading Structure		
tp	Dummy variable of traded product: only rubber or both rubber & OPFFB (1) or only OPFFB (0)	-
$stat$	Dummy variable of trader's status: a larger trader (1) or a village-level trader (0)	+
$vehic$	Dummy variable of operational vehicle ownership: having operational vehicle (1) or not (0)	+
num	Number of workers	+
$comp$	Dummy variable of computer ownership: having computer (1) or not (0)	+
$smph$	Dummy variable of smartphone ownership: having smartphone (1) or not (0)	+
$cred$	Dummy variable of credit provision by traders: credit provider (1) or not (0)	-
$land$	Land area owned by traders (in ha)	-
Factor 3: Structural Environment		
$supp$	Number of suppliers	+
com	Number of competitors	-
Factor 4: Socioeconomic		
$trans$	Dummy variable of transmigration's status: part of the transmigration scheme (1) or not (0)	+
$trrev$	Trading revenue (in million IDR)	+
loc	Distance measured by how long it takes to travel by vehicle from trader's location to the closest factory (in minutes)	-

Source: Own production

Bragg and Dalton (2004) sought to determine which factors affect farmers' decisions to exit dairy farming markets, employing a binary logistic regression model. They found that older producers, higher off-farm income, lower variable cost, and greater diversification of farm income led to an increase in the probability of farmers exiting the market. Nag *et al.*

(2018) also employed a binary logit regression to observe the factors affecting Indian rural farm youths' decision to remain in or exit the agricultural sector.

Another study examines the determinants of farmer exit from farming markets in Western Europe (Breustedt & Glauben, 2007). They determined that farm characteristics and policy environment both affect the decisions of farmers to exit or remain in the industry. Ferjani, Zimmermann, and Roesch (2015), who analyzed determinants of farmer exit in agriculture markets in Switzerland, provide a better structure to be adjusted and utilized in our study. They employed a logit estimation and considered four factors influencing the farm exit decision, which we adapt to our study: human capital, trading structure, structural environment, and socioeconomic factors (Table 3. 6). Grouping and expected signs are based on the abovementioned studies and relevant assumptions according to the condition in the survey area.

3.4.2 Binary Logistic Regression and Marginal Effect

In order to analyse determinants affecting traders' decisions to remain in or exit the market, a Binary Logistic Regression (logit) model is employed. The model is applied by determining and implementing relevant dummy dependent variables (Cameron & Trivedi, 2005); in this case a binary variable equal to 1 for traders' remaining in the market, and 0 for traders' exiting the market. Within this model we observe the probability, y_i, of those traders' preferences. The following equation explains the probability, characterized by

$$y_i = \Pr(Y_i = 1|x_i) = \frac{\exp(\beta_0 + \beta_i x_i)}{1 + \exp(\beta_0 + \beta_i x_i)} = F(x_i \beta_i) \tag{1}$$

where x_i is constructed by all explanatory variables considered in the model and β_i represents all parameters estimated.

It is worth noting that marginal effects are used to obtain a straightforward interpretation in logistic models (Cameron & Trivedi, 2005). In the case of a linear regression model, marginal effect can be directly implied from the coefficient (β), where the marginal effect of

$$\mathrm{E}[\mathrm{y}|\mathrm{x}] = x'\beta \tag{2}$$

is

$$\frac{\partial \mathrm{E}[\mathrm{y}|\mathrm{x}]}{\partial \mathrm{x}} = \beta \tag{3}$$

meanwhile, in the case of a logistic regression model, it can be illustrated that, E[y|x] is in the form of $\Pr(Y_i = 1|x_i)$. Therefore, the marginal effect will be:

$$\frac{dy_i}{dx_i} = \frac{\exp(\beta_0 + \beta_i x_i)}{1 + \exp(\beta_0 + \beta_i x_i)^2} \beta_i \tag{4}$$

Furthermore, a marginal effect estimation must be performed in logistic regression models in order to obtain β_i. To do so, we employ the Average Marginal Effect (AME) estimation directly after performing a logit model estimation.

Using the statistical model illustrated above, the new form of statistical model is developed (Eq. 5) based on Equation 1. Aligned with this study, the linear predictors are customized by all explanatory variables (Table 3. 6). The new model formed is:

$$\begin{aligned} y_i = \Pr(Y_i = 1|x_i) = \beta_0 + \beta_1\, edu + \beta_2 exp + \beta_3 func + \beta_4 info + \beta_5 tp \\ + \beta_6 stat + \beta_7 vehic + \beta_8 num + \beta_9 comp + \beta_{10} smph + \beta_{11} cred \\ + \beta_{12} land + \beta_{13} supp + \beta_{14} com + \beta_{15} trans + \beta_{16} trrev + \beta_{17} loc + \varepsilon \end{aligned} \tag{5}$$

3.4.3 Goodness of Fit and Logit Postestimation

The logit estimation examines whether all variables combination effect differ from zero, proved by its significant value (Prob>chi2) using log likelihood chi-square test (Cameron & Trivedi, 2005; UCLA, 2020a). Unlike the OLS regression estimation, the logit model employs a Pseudo R^2 measurement of McFadden (Cameron & Trivedi, 2005) to observe the goodness of fit of the model, which is

$$Pseudo\ R^2 = 1 - \left(\frac{ll_{model}}{ll_{null}}\right) \tag{18}$$

where ll_{model} represents the log-likelihood of the model and ll_{null} represents the log-likelihood of the intercept-only model. The log-likelihood based Pseudo-R^2 value provides the interpretation that higher values of Pseudo-R^2 mean better improvements in the new model compared to the null model (Hemmert, Schons, Wieseke, & Schimmelpfennig, 2018; McFadden, 1973).

As part of the logit postestimation, we are required to verify the absence of multicollinearity among independent variables in the model. VIF and tolerance value of all variables are examined, where anything close to 1 indicates that the variable is uncorrelated to each other (UCLA, 2020a).

We employ another test observe the existence of specification error in the model. Specification error occurs either when the logit is not the proper function for the model, or when all relevant variables are not considered in the model. To test for this, the linktest command in Stata is employed after the logit command. This command constructs the predicted value and predicted value squared from the model, where the predicted value must be significant, while the predicted value squared must not. If the significances turn to be the other way around, this is an indication of model specification error (UCLA, 2020a).

3.4.4 Statistical Test

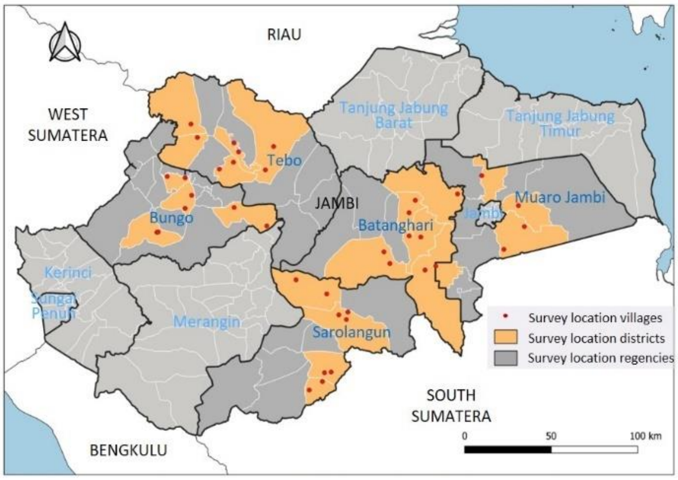
We perform a statistical test to examine the difference between groups of existing traders and new traders using the round 3 (2018) dataset. Initially we observe the type of variables considered (Table), then we divide the variables into metric and nominal variables. We test the metric variables for normality using a Shapiro-Wilk Normality Test (Royston, 1992) to decide which test can be performed. Since none of the variables are normally distributed, we pursue the Wilcoxon-Mann-Whitney test as non-parametric test for equality between groups based on their median values (Mann & Whitney, 1947; Wilcoxon, 1947). We then employ a Pearson's Chi-square test to deal with nominal (dummy) variables by group (UCLA, 2020b). The tabulate command in Stata is used to examine the test statistics and p-values.

3.5. Data

Data collection was performed in 3 rounds, taking place at the end of 2012, 2015, and 2018. The data collection was part of the Collaborative Research Centre (CRC) project in Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems in the Jambi province, Indonesia, a joint project between the University of Goettingen and 3 Indonesian Universities (IPB University, Jambi University, and Tadulako University).

Five regencies - Sarolangun, Batanghari, Muaro Jambi, Tebo, and Bungo - were selected purposefully[17] to determine the survey location (Figure 3. 2). Later, stratified random sampling was applied in selecting districts and villages. An advantage to using stratified random sampling is that it minimizes survey costs without compromising accuracy (Cameron & Trivedi, 2005). Initially, 22 districts and 40 villages were chosen in 2012 (Appendix 3. 1). However, due to time constraints and traders' unwillingness to be interviewed, the number of villages was reduced to 38 in the following rounds.

[17] Performed by Krishna and Euler, members of CRC's team, and also stated on the EFForTS Discussion Paper by Faust *et al.* (2013).



Source: Village map-geoprocessed[18] from BPS-Statistics of Jambi Province (2018)

Figure 3. 2 Map of Jambi

Data was obtained directly from respondents, using interview questionnaires[19] to administered to active small traders of oil palm fresh fruit bunches and rubber within the survey area. All active traders were attempted to be contacted for interviews. Table 3. 7 illustrates the final number of individuals reached in each survey round: a final sample of 295, 292, and 325 observations were obtained for further analysis from round 1, 2, and 3, respectively. We were unable to obtain 100% of the population for our sample due to time constraints and traders' unwillingness to participate, as well as some irreplaceable missing values and outliers. Nevertheless, the number of observations is still suitable for a representative analysis.

Table 3. 7 Number of All Active Traders in the Survey Area

	2012		2015		2018	
	Population	Sample	Population	Sample	Population	Sample
Rubber	309	207	234	196	197	185
Rubber + OPFFB	15	5	19	13	26	24
OPFFB	127	83	109	83	119	116
Total	451	295	362	292	342	325
% of population		65%		81%		95%

Source: Own production

.

We also employed data from 2018 to compare individual characteristics of existing traders and new traders. All available variables were examined to observe which factors specifically characterize new traders. In table 3. 3, we can see that 58% of new traders choose

[18] Supported by Purnama Dept. Forest Inventory and Remote Sensing – Univ. Goettingen
[19] Similar questionnaire with the one used by (Kopp and Brümmer (2017)

to trade OPFFB, indicating that this product may be currently more attractive and promising to traders.

3.6. Result and Discussion

3.6.1 Remainers versus Leavers

A logit estimation is initially employed to determine which variables affect traders' decisions to remain in or exit the market, with marginal effect estimations subsequently applied. Results are divided into two periods based on data observation round (Table 3. 8). The period 1 logit estimation converges to the log-likelihood of -173.537, while the period 2 logit estimation converges to the log-likelihood of -157.614. The iteration process begins from iteration 0, represented by the intercept-only model. The iteration log performed by both estimations exhibits convergence in 4 iterations (Appendix 3. 5 and 3. 7); such a prompt convergence may indicate that both estimation models are less prone to multicollinearity issues (Cameron & Trivedi, 2010).

The estimation examines whether the combined effect of all variables considered in the model differs from zero or not. This is supported by the significance values (Prob>chi2) of both estimations, which supports the expectation that the model has relevant explanatory power. As mentioned earlier, higher values of Pseudo-R2 indicate improvements in the new model compared to the null model (Hemmert et al., 2018; McFadden, 1973); thus, both estimations provide improvements over the intercept-only model of 15.1% and 11.8% for period 1 and 2, respectively.

In order to verify the absence of multicollinearity among independent variables in the model, we examine the VIF and tolerance value of all variables subsequent to logit estimation (Appendix 3. 11 and 3. 12). Both the VIF and the tolerance values of each variable are close to 1, indicating that all variables are uncorrelated with each other. Another test, called a link test, is applied to examine the possible existence of specification error (Table 3. 8). Both logit estimations provide variable _hat, representing the predicted value from the model, which is required to be statistically significant. Thus, it can be assumed that the considered predictors are meaningful. Additionally, the insignificant variable _hatsq represents the predicted value squared. This variable is not required to be significant or to have a high predictive power (UCLA, 2020a), as expected, hence we can assume that there is no indication of model specification error.

As mentioned previously, we employed AME estimation after logit estimation to obtain a more informative output. The coefficient value resulting from logit estimation cannot be interpreted directly. In the logit estimation, the marginal effect of the function was weighted by both the estimator and the regressors (Cameron & Trivedi, 2005). However, the variables' coefficient signs resulting from logit estimation remain consistent with those gained from the marginal effect estimation (Table 3. 8). Meanwhile, some variables are found to have different response in term of significance.

Unexpectedly, even though rubber price drops worse than OPFFB price, we found that rubber traders tend to remain in the market more often than OPFFB traders. This interesting behavior occurs both in period 1 and in period 2, where we see 16.7% and 13.5% increases in the probability of remaining in the market among rubber traders in both periods, respectively. A plausible reason for this is that, technically, rubber traders are able to store their *bokar*[20] as long as desired, much longer than OPFFB traders; some rubber traders reported having stored *bokar* for more than 6 months while anticipating a rubber price increase. Meanwhile, storage is not an option for OPFFB traders, as traders risk quality losses from storage which can affect the prices they receive or result in rejection from buyers. Thus, the effects of falling prices of rubber and palm oil are more visible in the OPFFB market than in rubber trading activities.

Another variable which has a significant effect on the decision of traders to remain in or exit the market in both periods is education. We observe 21.5% and 12.8% decreases in the probability of remaining in the market, in periods 1 and 2, respectively, if traders have not completed their primary school education. Having no education leaves traders no other option in finding another job. Interestingly, the number of agricultural worker in Jambi province decreased by 16.9% between August 2017 and August 2018, while the number of non-agricultural worker increased by 19.5% during the same period (Statistics Jambi Province, 2019).

More experienced traders tend to remain in the market, as shown in the period 2 estimation, and we observe a 0.8% increase in the probability of remaining in the market for every one-year increase in trader experience. This probability increase is illustrated in Figure 3. 3. It's possible that traders' experiences in period 1 make them more capable of facing difficult situations related to persistently weak prices in period 2. 62.3% of traders remaining

[20] *bokar* is a common thicker form of rubber slab produced by local farmers

in the market have 3 or more years of trading experience, which means that they have previously experienced price reduction in period 1.

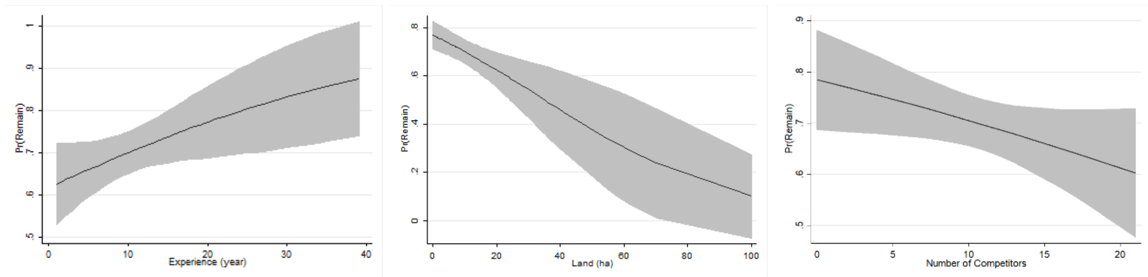
Table 3. 8 Result of Logit and Marginal Effect Estimation

Remain	Period 1 (2012-2015)				Period 2 (2015-2018)			
	Logit est.		Marginal Effect est.		Logit est.		Marginal Effect est.	
	Coef.	SE	dy/dx	SE	Coef.	SE	dy/dx	SE
Variables								
tp	0.813 **	0.314	0.167 ***	0.063	0.721 **	0.337	0.135 **	0.064
edu	-1.110 *	0.643	-0.215 *	0.112	-0.783 *	0.452	-0.128 **	0.065
exp	-0.008	0.018	-0.002	0.004	0.043 *	0.024	0.008 *	0.004
func	-0.410	0.337	-0.083	0.068	0.540	0.434	0.092	0.068
info	-0.107	0.280	-0.022	0.057	0.092	0.307	0.017	0.055
stat	0.603 *	0.338	0.121 *	0.066	0.439	0.363	0.077	0.061
num	0.012	0.027	0.002	0.005	0.007	0.042	0.001	0.008
cred	-1.726 ***	0.328	-0.356 ***	0.057	0.752 **	0.334	0.147 **	0.068
land	0.005	0.011	0.001	0.002	-0.040 ***	0.013	-0.007 ***	0.002
vehic	0.071	0.366	0.014	0.074	0.797 **	0.381	0.157 **	0.079
comp	-0.367	0.301	-0.074	0.061	-0.633	0.489	-0.123	0.099
smph	0.033	0.348	0.007	0.070	-0.150	0.394	-0.028	0.073
supp	0.002	0.004	0.000	0.001	0.000	0.006	0.000	0.001
com	-0.000	0.026	-0.000	0.005	-0.048 *	0.028	-0.009 *	0.005
trans	0.834 **	0.357	0.168 **	0.069	0.044	0.340	0.008	0.065
trrev	-0.012	0.005	-0.002	0.002	0.053 *	0.027	0.010 **	0.005
loc	-0.000	0.005	-0.000	0.001	0.002	0.005	0.000	0.001
_cons	1.394	0.909			-0.271	0.808		
Goodness of Fit Measures								
Obs.	295				292			
LL	-173.537				-157.614			
LR chi2(17)	61.720				42.190			
Prob>chi2	0.000				0.001			
Pseudo R^2	0.151				0.118			
Specification Error								
_hat	0.985 ***	0.146			1.246 ***	0.266		
_hatsq	0.187	0.123			-0.149	0.107		
_cons	-0.149	0.163			-0.004	0.192		

Source: Own production (Appendix 3. 5 – 3. 10)
Note: [a] *** p<0.01, **p<0.05, *p<0.1

Smaller, village-level traders tend to exit the market more often, as shown in our period 1 estimation, and we observe a 12.1% higher probability of remaining in the market among larger traders. A plausible reason for this is that larger traders are often more effective in managing their trading costs to obtain higher profits. Also, they often have more assets (such as bigger storage, in the case of rubber traders), more savings, and other sources of income; we found that larger traders gain significantly higher farming revenues than smaller, village-level traders (Appendix 3. 13). Most traders, 88.81% of the sample, are also farmers.

One of our most compelling results is the influence a trader's credit provision has on their decision in remaining in or exit the market. This effect is found to be significant in both periods; however, the signs are different. Traders who provide credit to suppliers tend to exit the market more often in period 1, and we observe a 35.6% decrease in the probability of remaining in the market among credit-providers during this period. Meanwhile, these traders tend to remain in the market more often in period 2, and we observe a 14.7% increase in the probability of remaining in the market among this group. Traders in 2012 experienced higher rubber prices and OPFFB prices, and thus many of them do not hesitate to provide credit for suppliers, and in fact 71.53% of the sample were found to provide credit. However, a drastic decrease in prices after 2012 caused many traders and farmers to experience sudden losses, resulting in many bad loans. Thus, providing credit may ultimately lead to traders deciding to exit the market. During the 2015 survey round, in which traders from the first round were recalled, many initially refused to be interviewed because they thought we were debt collectors. Additionally, the traders in period 2 became more careful in providing credit, and we observed traders using their ability to provide credit as a way of maintaining a continuous supply from farmers. We employed a further study related to this matter in the next chapter and found that rubber traders providing credit offer higher price for *bokar* than those providing no credit (Table 4. 9). However, they tend to offer less amount of credit due to reduction in risk of loss.



Source: Own production

Figure 3. 3 Illustration of the Increase of Probability per Unit Variable

Other variables significantly influencing the traders' decision to remain in or exit the market during period 2 are land area and status and type of operational vehicle ownership among traders. The more land area owned by traders, the less likely traders are to remain in the market, and we observed a 0.7% decrease in the probability of traders remaining in the market for every hectare increase in land area. This increase in probability is illustrated in

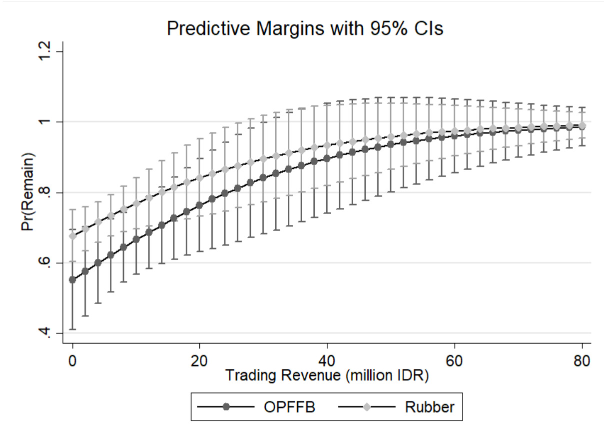
Figure 3. 3. Traders have an option to focus on farming activities when they own more land, since trading activities are no longer profitable for them. They also have the option of renting the land as a profitable investment, while working in a different sector. On the other hand, traders who own an operational vehicle are 15.7% more likely to remain in the market. Owning an operational vehicle can allow traders to pick up of products from suppliers and/or deliver products to buyers, reducing traders' transaction cost and making it is easier for them to adapt to falling prices.

Having fewer competitors makes traders more likely to remain in the market, as shown in period 2 estimation; we see a 0.9% decrease in the probability of remaining in the market for every one-unit increase in traders' competitors (see Figure 3.3). Having fewer competitors is associated with an increase in market power among traders, who are able to maximize their profit without fear of losing their potential suppliers. Suppliers, likewise, have an already limited choice of potential buyers (traders).

The last significant effect observed in period 1 is that transmigrant traders have a 16.8% higher likelihood of remaining in the market compared to their non-transmigrant peers. Since transmigrant traders are typically sponsored by their government (Leinbach & Smith, 1994), they tend to be more settled in their farming and trading activities. Agricultural extension programs and other supporting activities are routinely provided by the government and help them to overcome this challenging situation; therefore, they tend to remain in the market.

Traders with higher trading revenues tend to remain in the market, as observed in period 2. There is a 1.0% increase in the probability of remaining in the market for everyone million IDR increase in trader revenue. Higher trading revenues are generally related to higher profits; therefore, it is understandable that traders with higher revenues would be more adaptable to difficult conditions than others. The mean trading revenue of traders who remain in the market are higher than those of traders who leave the market and were observed to be 6.83 million IDR and 4.61 million IDR, respectively (Appendix 3. 14)).

We construct an interaction between trading revenues and the type of product traded and observe the resulting change in the probability of remaining in the market. Initially, we found that the interaction between trading revenue and rubber traded product increases the probability of remaining in the market. However, we identified that at a certain level of trading revenue, the type of product traded has no further influence, and the probability is only affected by trading revenue (Figure 3. 4).



Source: Own production

Figure 3. 4 Illustration of the Increase of Probability per Unit Interacted Variable

It is intriguing that some variables are only significant in particular periods but not in others. This is due to overall market situations and resulting trading behavior fluctuating over time. One example of this is in period 1, where the trading revenue variable turns insignificant. The mean trading revenue in 2015 was calculated to be much less than that in 2012 (Appendix 3. 14), even adjusting for inflation. Therefore, it is most likely that the trader revenues from period 2 respondents are closer to the threshold of traders' decision to remain in or exit the market. On the other hand, the price situation in period 1 is very profitable for traders. They may collectively have higher trading revenues; thus, variance in trading revenues does not affect their decision to remain in or exit the market.

3.6.2 New versus Existing Traders

In this section, characteristics between new and existing traders (Figure 3. 5) are compared. The results illustrate the differences in characteristics between both groups. As mentioned in the model specification section, we initially performed a Shapiro-Wilk normality test for our metric variables to decide on the appropriate test of differences between groups. However, we found that not all metric variables are normally distributed; therefore, a Wilcoxon rank-sum (Mann-Whitney) non-parametric test is performed to test for equality between groups based on their median values (Table 3. 9) (Mann & Whitney, 1947; Wilcoxon, 1947).

Results imply that the number of workers, land area owned (ha) and trading revenues (million IDR) of the existing traders are significantly higher than those of new traders. This is very plausible, as new traders face challenges in adapting to their new trading competition. They usually start small, with limited resources; thus, they employ fewer workers and gain just enough revenue for living.

Table 3. 9 New and Existing Traders' Characteristics in 2018

Variables	Existing Trader actual rank sums		New Trader actual rank sums		Sign.
Number of workers	44231.0	>	8744.0	<	***
Land Area	44718.5	>	8256.5	<	***
Number of suppliers	42455.0	>	10520.0	<	
Number of competitors	41840.0	<	11135.0	>	
Trading revenue	43588.0	>	9387.0	<	**
Location	42112.0	>	10863.0	<	
expected rank sums	42054.0		10921.0		
number of obs.	258		67		

Source: Own production (Appendix 3. 16)
Note: *** p<0.01, **p<0.05, *p<0.1

To test for independence between two nominal (dummy) variables, we employ a Pearson's chi-square test (Appendix 3. 17), which will determine whether each categorical value of variables within a two-way table are independent of one another. We found the combination of type of product traded and type of trader to be statistically significantly independent of each other. Interestingly, 58.2% of the new traders chose OPFFB as the traded product. Even though one of the determinants of remaining in the market is having rubber as the traded product, newcomers seem to choose OPFFB as their traded product of choice. A plausible explanation for this is that a higher stability of prices and the need for quick delivery of OPFFB may lead to a faster profit turnover among traders.

Source: Own production

Figure 3. 5 Frequency of Existing and New Traders by Traded Product

3.7. Conclusion

Many traders changed their activities due to falling oil palm and rubber prices during the period of study. These price fluctuations seem to raise uncertainty among traders, affecting their decisions to remain in or exit the market. In light of this evidence, it is clear that human capital (education and experience), trading structure (traded product, credit provision, land area, operational vehicle ownership, and trader status), structural environment (number of competitors), and socioeconomic (trading revenue) factors affect the decisions of traders to remain in or exit the market. It is also interesting that some variables are only significant in particular periods but not in others, due to different situations and different trader behavior over time.

Chapter 4

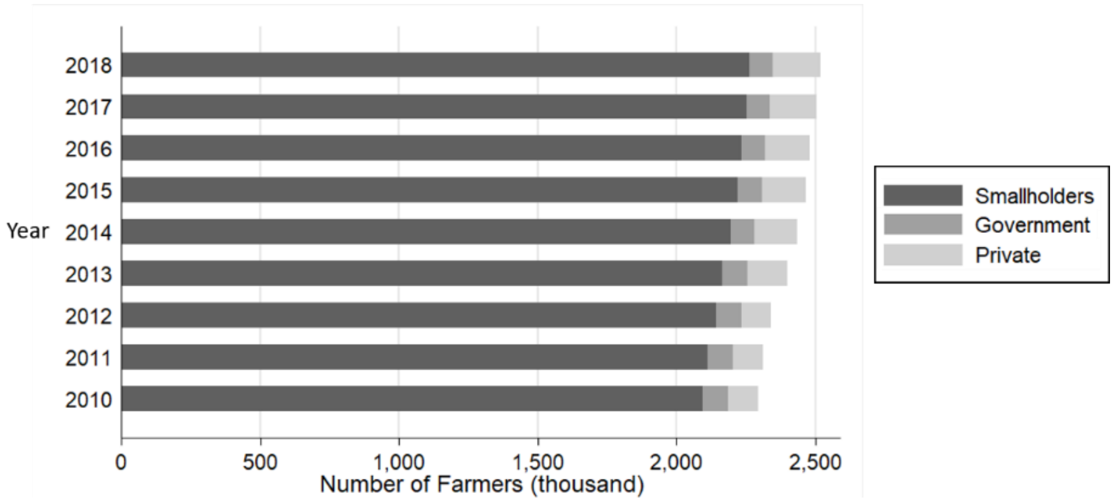
The Perils of a Loan: Interdependency between Rubber Quality and Farmer's Debt in Buying Choices among Local Rubber Traders in Jambi Province, Indonesia

Rakhma Melati Sujarwo , Bernhard Brümmer

4.1. Introduction

Many smallholder farmers depend on loans, not only for farming activities but also for their daily needs. Carranza and Niles (2019) found that food, agricultural and livestock inputs, and medical expenses are the main loan-dependent expenses among smallholder farmer households. Loans can be obtained from both formal and informal financial institutions; however the latter may be more desirable for smallholder farmers because of lower transaction costs and risk (Guirkinger, 2008). The source of the loan may be related to how the loan is spent. Informal loans are mostly spent on food, while formal loans are generally utilized for agricultural inputs (Carranza & Niles, 2019). Additionally, the level of a farmers education, income, and age are factors which may affect a farmer's decision to ask for a loan or not (Oni, Oladele, & Oyewole, 2005).

These conditions are all very relevant to rubber farmers in Indonesia, the second largest rubber producer[21] in the world (Jegede, 2019). The majority of rubber farmers in Indonesia are smallholder farmers (Figure 4. 1). With the largest rubber plantation area in Indonesia, Sumatera island accounts for 68% of the total number of Indonesian smallholder farmers (Directorate General of Estate Crops, 2018). Jambi province in Sumatra is currently experiencing a rapid development in its rubber production industry, which increased 20.41% from 2014 to 2018. The number of rubber farmers in the area increased by 7.10% during the same period (Directorate General of Estate Crops, 2018), and the majority of these new farmers are smallholder farmers.



Source: Own production based on Directorate General of Estate Crops (2018)

Figure 4. 1 Number of Farmers by Ownership

[21] Indonesia contributes to 27.3% of the total rubber production in the world (Jegede, 2019)

49.64% of Jambi rubber smallholder farmers require either formal or informal loans, and 32.95% of those requiring loans take a loan from rubber traders, considered to be informal financial institutions[22]. Obtaining an informal loan from a trader is quite different from obtaining a formal loan and can induce a reciprocal seller-buyer relationship; when a farmer is indebted to a trader, the farmer feels obligated to sell their rubber to the trader. Based on our initial survey in 2018, 82.38% of all rubber trader respondents provide credit for their suppliers, and 79.77% require their suppliers to sell their rubber to them. This is also proved by the study in the previous chapter that showed that credit is one of the main factors influencing the decision of rubber traders to remain in the market. This shows that credit can secure the constant supply of rubber for traders, giving traders leverage in their relationships with farmers.

In Jambi rubber trading, there is a common local term called *basi*. This is defined as the percentage of impurities of a *bokar* - a common thicker form of rubber slab produced by local farmers - which will then be transferred as a percentage of price reduction from the current asking price. The *basi* value is determined solely by the trader, and thus many factors may affect its value other than simple impurities. A supporting study showed that 11.8% of respondents overestimated the *basi* value for indebted suppliers (Kopp & Brümmer, 2017). We also performed a serial study applying the unrelated question randomized response model to capture possible hidden responses due to a particularly sensitive question, where we assume that manipulating *basi* estimation is an improper action. As expected, it captures a higher proportion of respondents, showing that they give lower *basi* to debt-free farmers than to indebted farmers. It reaches 86.62% of the proportion. The high number of respondents demonstrates that there is another factor besides quality affecting *basi*, namely debt. Both studies will be explained in more detail in the next section. Additionally, the approaches cannot capture how much *basi* traders are willing to charge when a farmer has a certain amount of debt.

Thus, due to the fact that the *basi* is influenced not only by rubber quality but also by farmer's debt, further studies to understand how much they influence price reduction are particularly appealing. To investigate this further, we test whether price reduction, rubber quality, and farmers' debt influence traders' preferences in buying rubber, and estimate how much of a price reduction, traders are willing to charge to obtain higher quality or lower

[22] Based on survey collected by C07, as part of the CRC project in Jambi, Indonesia, in 2015.

debt. We also measure the impact of the respondents' socio-demographic characteristics and the interaction variables between those characteristics and the main attributes.

We implement a method called a Discrete Choice Experiment (DCE), which is broadly used to asses consumer preference and willingness to pay for certain products with different attributes (Asante-Addo & Weible, 2019; Gao & Schroeder, 2009; Hasselbach & Roosen, 2015). This method can disguise questions that are slightly sensitive and illicit a more candid response. DCE was initially performed in the literature on marketing and transport economics (Louviere & Hensher, 1982; Louviere & Woodworth, 1983). A random utility model (Manski, 1977), influenced by Lancaster's characteristics theory of value (Lancaster, 1966), is the theoretical background for this method (Bennett & Birol, 2010).

First, by comparing the conditional and mixed logit method as part of the estimation strategy, we will test for the existence of heterogeneity in the model, thus forming a model with the best fit (Asante-Addo & Weible, 2019; Cameron & Trivedi, 2010; Elshiewy, Guhl, & Boztug, 2017; Hensher, Rose, & Greene, 2005). In this step we capture how price reduction, rubber quality, and farmers' debt affect the traders' preference in rubber buying choice. Then, to observe how much price reduction traders are willing to charge (WTC) when a farmer offers a certain quality and has a certain amount of debt, we employ a willingness to pay (WTP) measurement approach (Elshiewy et al., 2017; Hensher et al., 2005), which is derived from the result of the conditional and mixed logit model. To the best of our knowledge, there are no studies implementing DCE to capture agricultural traders' or middlemen's behavior in buying decisions and, no studies using price reduction (WTC) as a replacement for WTP; therefore, the methods applied in this study are a novel approach in the literature.

The subsequent sections provide an overview of *basi* manipulation captured by Kopp and Brümmer (2017) and our supporting study, as well as the difference between *basi* and price reduction. The next section provides the theoretical background of the DCE and is followed by the estimation strategy and data sections. Results and a discussion will be provided in detail, before we summarize our findings in the conclusion section.

4.2. Overview: *Basi* versus Price Reduction

Rubber farmers tap rubber directly from rubber trees. The sap is collected and coagulated, and dries into a material called *bokar*, which is a common, thicker form of rubber slab produced by local farmers. Bokar may contain contamination in three forms. First, it may contain impurities known known as *tatal* caused by a contamination of dirt from dust, tree bark, or tree branches during the process of making the *bokar*. A second possible form of contamination is an introduction of water content into the bakar; the higher the water content, the worse the *bokar* quality. The third possible form of contamination is the types of coagulant that are not in accordance with the standard[23].

However, even though it has been clearly suggested by the downstream rubber buyers that farmers should reduce the *bokar* contamination to obtain higher price, the farmers still do not want to follow these requirements. In fact, they further worsen the contamination. The price obtained by farmers is based on the *bokar* weight; they believe that by increasing contamination, they will increase the *bokar* weight to get more profit than they could receive by following the requirements. This becomes a loophole farmer can use to cheat to receive a higher price.

In Jambi, this phenomenon led to the emergence of a term called *basi*, which is the percentage of contamination in *bokar*[24]. *Basi* is determined unilaterally by rubber traders, and is then transmitted to a price reduction, as a substitute for the risk of traders who will lose profits due to the selling of contaminated rubber to large traders or factories.

To determine a *basi* value, the traders choose the *bokar*, suspected to have the greatest level of contamination, and rip it apart for inspection. The *basi* value determined does not have any standard reference; it will simply serve to generalize the overall quality of rubber held by farmers at that time. Additionally, the level of contamination is often simply an estimate made without any inspection, so the *basi* and price reduction evaluation tends to be unstable and can be influenced by other factors. However, in the end, a trader's utility will increase with the higher price reduction, meaning that a higher *basi* is anyway typically preferred. Also, it should be emphasized that the *basi* system is more familiar to rubber farmers than price reductions.

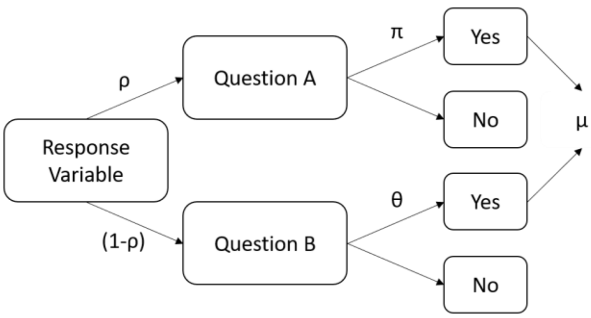
Apart from that, as previously mentioned, Kopp and Brümmer (2017) performed a rubber trader market power study in 2012 in which 11.8% of respondents were shown to have manipulated the *basi* estimation for indebted suppliers. Results indicate that the

[23] Coagulants that are in accordance with factory demand standard contains acetic acid (trademark: *Cuko 61* or *Gentong*), so that the rubber can clot perfectly. However, farmers prefer cheaper coagulants (such as plant fertilizer and floor cleaner) to the suggested one, where its use can cause the rubber does not clot perfectly and damage the rubber quality. However, the difference cannot be seen in plain view.

[24] For example, 10% *basi* from 100 kg bokar means there is 10 kg contamination in *bokar*

determination of a *basi* can indeed be influenced by a farmer's debt. However, data on the influence of debt on the *basi* was gathered by directly asking the question: "Is there an additional price reduction if farmers are in debt?", which may cause the respondent to feel intimidated, or to otherwise feel that they have done something inappropriate. With that in mind, these results may not capture the true effect. Additionally, the survey mentioned that 94.1% of all respondents provide credits to suppliers.

To further explore how many respondents, perform *basi* manipulation, and to reduce the bias of respondents who do not want to answer sensitive questions, we conducted a serial study applying Randomized Response Technique (RRT) model in 2018. RRT aims to capture hidden response due to sensitive question (Blair, Imai, & Zhou, 2015; Warner, 1965), where we assume that, for respondents, admitting to manipulating the *basi* estimation is admitting to an improper action. In the RRT model, the respondent is prompted to provide a" yes" or "no" answer to a question which appears based on random probability from two or more questions. The question selected is not revealed to the interviewer, and thus respondents feel secure and act more honestly in answering sensitive questions. There are several basic designs of RRT which develop with time, namely mirrored question, forced response, disguised response, and unrelated question design (Blair et al., 2015). The main difference among these is the probability design parameters.



Source: Own illustration based on Greenberg *et al.* (1969)

Figure 4. 2 Probability Design in Unrelated Response Randomized Response Technique

We selected the *unrelated question* design, which was developed by Greenberg *et al.* (1969). Respondents were required to role a dice; if they rolled an odd number, they were required to answer the more sensitive question: "Do you provide lower price reduction to debt-free farmers?", whereas if they rolled an even number, they were required to answer a less sensitive alternative question: "Did you consume fruits or vegetables last week?" Thus, the probability of respondent answering each question was 50% (ρ). Information about which alternative questions the respondents answered is only known by the respondent.

However, we should have prior knowledge about the probability of Yes/No answer for the alternative question. Therefore, we could have the diagram of probability answering the sensitive question (Figure 4. 2). This alternative question provides more comfort in answering questions compared to other designs; therefore, violations of instructions can be reduced (Blair et al., 2015).

The equation derived from Figure 4. 2 can be seen in Equation 1, where ρ is the probability of a respondent answering question A, π is the probability of a respondent answering "yes" to question A, and θ is the probability of a respondent answering "yes" to question B. We have found that the value of θ is 100% based on a separated question asked at different time. Later, we discovered that the value of $\boldsymbol{\mu}$ is 74.65%. At last, we calculated the value of π, representing an affirmative answer to the sensitive question, to be 86.62%. Additionally, 82.38% of all respondents provided credits to suppliers.

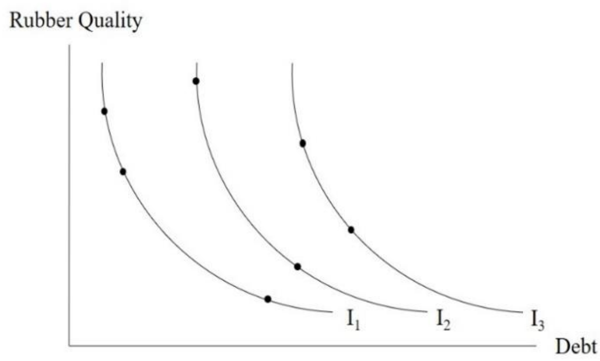
$$\mu = \rho\pi + (1-\rho)\theta \quad (\mathbf{1})$$

This high number shows that debt indeed affects the *basi* estimation. However, this calculation cannot capture how much *basi* traders are willing to charge when a farmer has a certain amount of debt. We will explore this in further sections.

4.3. Background: Random Utility Model (RUM)

In daily life, individuals make decisions by comparing possible courses of action, and selecting the best possible outcome. However, understanding which determinants influence the choice outcomes in a population is challenging, because not all related information is always available, and each individual has his/her own preferences. Some of them may have the same level of utility (I) in different combinations, which can be seen by the location of different nodes in Figure 4. 3.

The figure illustrates the assumption of rubber traders' individual preferences, where there exist distinct differences in preferences, in various combinations, for rubber quality and debt value. The combination chosen represents each individual's behavior in maximizing utility (Hensher et al., 2005). Instinctively, traders will choose better quality products and lower farmer debt value to receive higher income or maximize their utility. However, another additional attribute, such as rubber price, may provide another effect in the combination chosen. Within a population, variability in individual preferences leads to heterogeneity (Hensher et al., 2005). Maximizing the amount of measured variability can reduce the number of unobserved heterogeneities.



Source: Own illustration based on Hensher, Rose and Greene (2005)

Figure 4. 3 Illustration of rubber trader individual preferences

Equation 2 visualizes the RUM expression, representing the utility (U) of individual i and alternative j, where V_{ij} represents the utility component of individual i and alternative j, capturing all observed and measured regressors (Eq. 3). ε refers to the unobserved heterogeneity or error. (Hensher et al., 2005).

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{2}$$

$$V_{ij} = x'_{ij}\beta + z'_i\gamma_j \tag{3}$$

In this situation, regressors are divided into two types, namely case-specific and case-varying (alternative-specific) regressors (Cameron & Trivedi, 2010). Case-specific regressors, represented by vector z_i, are regressors which do not alter across alternatives, such as revenue, age, and gender. Meanwhile, alternative-specific regressors, represented by vector x_i, differ across alternatives (j), such as price and debt. Also, we further consider interaction between both type of regressors. The RUM will be modified as follows (Eq. 4):

$$U_{ij} = x'_{ij}\beta + z'_i\gamma_j + \varepsilon_{ij} \tag{4}$$

The model above becomes the reference point for analyzing unordered multinomial outcomes resulting from individual choices, with Multinomial Logit (MNL) model (Cameron & Trivedi, 2010; Greene, 2012). There are three types of MNL models which can be employed through STATA commands (Cameron & Trivedi, 2010; Greene, 2012). First, the original MNL model is applied when all regressors considered are case-specific type of regressors. Second, the Conditional Logit (CL) model is applied when all regressors are alternative-specific type of regressors. Lastly, Alternative-specific Conditional Logit (ASC-

L) model is applied when both type of regressors are considered. However, CL model can be applied as ASC-L to simplify the comprehension, in a way which is further explain in the model specification section (Cameron & Trivedi, 2010; Greene, 2012).

However, these MNL models acknowledge fixed coefficient and maintain some simplifying assumptions, which become their weakness (Rigby & Burton, 2005). The first assumption is *Independence of Choice*, which assumes that each choice is independent from the others, as if each was made by a different person (Rigby & Burton, 2005). For the purpose of our study, we consider repeated choices of data where a respondent answers several choice sets. Answers chosen by one individual are likely to be correlated. The second assumption is that of *Independence of Irrelevant Alternatives* (IIA), which assumes that the choice probability ratio for each alternative, within a random combination of attributes, is independent from other alternative(s) in the choice set (Hensher et al., 2005). Finally, the third assumption is *Homogeneity of Preferences*, which assumes that the heterogeneity of attribute preferences is limited only to individual attributes; meanwhile, there exist other attributes which are expected to influence the decision process as well (Rigby & Burton, 2005).

$$V_{ij} = x'_{ij}\beta_i + z'_i\gamma_{ji} \quad (5)$$

$$\beta_i = \beta + v_i \quad (6)$$

$$\gamma_{ij} = \gamma_j + w_{ij} \quad (7)$$

$$V_{ij} = x'_{ij}\beta + x'_{ij}v_i + z'_i\gamma_j + z'_i w_{ij} \quad (8)$$

$$U_{ij} = (x'_{ij}\beta + z'_i\gamma_j) + (x'_{ij}v_i + z'_i w_{ij} + \varepsilon_{ij}) \quad (9)$$

Another approach, the Random Parameter Logit (RPL) model, relaxes these MNL assumptions. The RPL allows for parameter β and γ to be random across individual i, and has stochastic elements that are plausibly heteroskedastic and correlated across alternatives (Cameron & Trivedi, 2010; Greene, 2012; Hensher et al., 2005). It will be defined by β's and γ's mean, and standard deviation. Equations 5 through 9 outline the modification of the RUM components. Apart from that, even though $\boldsymbol{\varepsilon_{ij}}$ itself has no correlation over alternatives, the current combination of $\boldsymbol{x'_{ij}v_i + z'_i w_{ij} + \varepsilon_{ij}}$ as error is correlated over alternatives (Cameron & Trivedi, 2010).

4.4. Model Specification

In this study, we consider three main attributes as the alternative-specific regressors, i.e. price reduction, rubber quality, and farmers' debt. We also acknowledge six socio-demographic regressors as the case-specific regressors, i.e. trading revenue, credit provision, number of suppliers, number of competitors, trader's status (whether one is a village-level trader or a larger trader), and trans-migration's status (whether one is part of the trans-migration scheme or not). Moreover, the interaction of both type of regressors are also taken into account. It is important that no attributes or regressors to be correlated (Hensher et al., 2005). Thus, we perform an initial correlation test for a nonparametric estimator for all regressors (Croux & Dehon, 2010; Spearman, 1904).

This statistical correlation test, even without a correlation between attributes, may not capture psychological aspect of decision makers, otherwise known as inter-attribute correlation (Hensher et al., 2005). For example, the decision maker may consider that a higher price is associated with a higher quality product. However, in our case, unlike palm oil, which has a clear quality grading system, there is no clear measurement of rubber quality in Jambi. The rubber quality is relatively similar across farmers and areas. Thus, the correlation between price reduction and rubber quality in our study is assumed to not be a major concern. However, considering interaction terms between case- and alternative-specific regressors will initiate another form of correlation in the estimation.

$$U1_{ij} = \beta_{01} + \beta_1\, p\_red_{ij} + \beta_2\, qual_{ij} + \beta_3\, debt_{ij} + \varepsilon_{ij} \tag{10}$$

$$\begin{gathered} U2_{ij} = \beta_{02} + \beta_4\, p\_red_{ij} + \beta_5\, qual_{ij} + \beta_6\, debt_{ij} + \beta_7\, dalt\_trrev \\ +\beta_8\, dalt\_cred + \beta_9\, dalt\_supp + \beta_{10}\, dalt\_com + \beta_{11}\, dalt\_stat + \beta_{12}\, dalt\_trans \\ +\beta_{13}\, trrev\_X\_qual + \beta_{14}\, trrev\_X\_debt + \beta_{15}\, cred\_X\_qual + \beta_{16}\, cred\_X\_debt \\ +\beta_{17}\, supp\_X\_qual + \beta_{18}\, supp\_X\_debt + \beta_{19}\, com\_X\_qual + \beta_{20}\, com\_X\_debt \\ +\beta_{21}\, stat\_X\_qual + \beta_{22}\, stat\_X\_debt + \beta_{23}\, trans\_X\_qual + \beta_{24}\, trans\_X\_debt + \varepsilon_{ij} \end{gathered} \tag{11}$$

Initially, we illustrate our estimation strategy by transforming the RUM function (Eq. 4) into Equation 10. Later, we introduce the additional socio-demographic regressors with the interaction regressors in Equation 11. All β_{0n} (n = 1, …, 5, according to the estimated model) refer to $dalt$ or the "none" option. In addition to that, β_n (n = 1, …, 48) defines all parameters estimated. All variables code used in the equations are defined in Table 4. 1.

Even though we consider both alternative- and case-specific type of regressors, we prefer to employ the CL model instead of the ASC-L model to obtain a simpler interpretation, as mentioned in the previous section. To do so, we are required to interact the case specific regressors with dummies for $m-1$ alternatives, which in this case is the $dalti$ variable

(Cameron & Trivedi, 2010). Nonetheless, we have three alternatives in total, consisting of two buying alternatives and an additional "none" option alternative, and we combine the two buying alternatives into one alternative, which we will describe further in the data section (Table 4. 2). $dalti$ itself must be included in the estimation as well.

Table 4. 1 Definition of Variables

Variables Code	Definition
Alternative-specific Regressors	
p_red	Price reduction
$qual$	Rubber quality purchased
$debt$	Farmer's debt
Constant	
$dalt$	Dummy variable where 1 means that respondents choosing any of alternative, while 0 refers to choosing the "none" option alternative
Case-specific Regressors	
$dalt\_trrev$	Trading Revenue
$dalt\_cred$	Dummy variable of credit provision by traders, whether they are credit provider (1) or not (0)
$dalt\_supp$	Number of suppliers
$dalt\_com$	Number of competitors
$dalt\_stat$	Dummy variable of trader's status, whether one is a village-level trader (0) or a larger trader (1)
$dalt\_trans$	Dummy variable of trans-migration's status, whether one is part of the trans-migration scheme (1) or not (0)
Interaction Regressors	
$trrev\_X\_qual$	Interaction between trading revenue and rubber quality purchased
$trrev\_X\_debt$	Interaction between trading revenue and farmer's debt
$cred\_X\_qual$	Interaction between credit provision and rubber quality purchased
$cred\_X\_debt$	Interaction between credit provision and farmer's debt
$supp\_X\_qual$	Interaction between number of suppliers and rubber quality purchased
$supp\_X\_debt$	Interaction between number of suppliers and farmer's debt
com_X_qual	Interaction between number of competitors and rubber quality purchased
com_X_debt	Interaction between number of competitors and farmer's debt
$stat\_X\_qual$	Interaction between trader's status and rubber quality purchased
$stat\_X\_debt$	Interaction between trader's status and farmer's debt
$trans\_X\_qual$	Interaction between trans-migration's status and rubber quality purchased
$trans\_X\_debt$	Interaction between trans-migration's status and farmer's debt

The CL model exercised in this study is introduced by McFadden (1973) and Cameron and Trivedi (2010). The general CL estimation is illustrated in Equation 12. When three main alternative-specific regressors are introduced into the equation, it is transformed into Equation 13 by considering the RUM in Equation 10, where the model estimation is later called CL_1. A similar transformation, considering the case-specific and interaction regressors in Equation 11, is also employed, where CL_2 will be the model estimation.

$$P_{ij} = \frac{exp(x_{ij}'\beta)}{\sum_{l=1}^{m} exp(x_{il}'\beta)}, \qquad j = 1, \ldots, m \tag{12}$$

$$P_{ij} = \Pr[y_i = j] = \frac{exp(\beta_{01} + \beta_1\, p\_red_{ij} + \beta_2\, qual_{ij} + \beta_3\, debt_{ij})}{\sum_{l=1}^{3} exp(\beta_{01} + \beta_1\, p\_red_{ij} + \beta_2\, qual_{ij} + \beta_3\, debt_{ij})}, \qquad j = 1, \ldots, 3 \tag{13}$$

As a comparison, we exercised the ML model (Eq. 16) (Cameron & Trivedi, 2010) as part of the RPL, which is expressed in Equation 14 and 15. The difference is that we consider only rubber quality and farmer's debt to be random across individual i. This model's objective is to relax the assumptions of fixed coefficient in MNL model (Hensher et al., 2005; Rigby & Burton, 2005).

$$U3_{ij} = \beta_{03} + \beta_{25}\, p\_red_{ij} + \beta_{26i}\, qual_{ij} + \beta_{27i}\, debt_{ij} + \varepsilon_{ij} \tag{14}$$

$$\begin{aligned} U4_{ij} = {} & \beta_{04} + \beta_{28}\, p\_red_{ij} + \beta_{29i}\, qual_{ij} + \beta_{30i}\, debt_{ij} + \beta_{31}\, dalt\_trrev \\ & + \beta_{32}\, dalt\_cred + \beta_{33}\, dalt\_supp + \beta_{34}\, dalt\_com + \beta_{35}\, dalt\_stat + \beta_{36}\, dalt\_trans \\ & + \beta_{37}\, trrev\_X\_qual + \beta_{38}\, trrev\_X\_debt + \beta_{39}\, cred\_X\_qual + \beta_{40}\, cred\_X\_debt \\ & + \beta_{41}\, supp\_X\_qual + \beta_{42}\, supp\_X\_debt + \beta_{43}\, com\_X\_qual + \beta_{44}\, com\_X\_debt \\ & + \beta_{45}\, stat\_X\_qual + \beta_{46}\, stat\_X\_debt + \beta_{47}\, trans\_X\_qual + \beta_{48}\, trans\_X\_debt + \varepsilon_{ij} \end{aligned} \tag{15}$$

Additionally, we do not consider p_red to be random, since it will become an obstacle in measuring WTP when its β distribution is close to zero (Rigby & Burton, 2005). Also, other regressors are not considered to be random. These assumptions might lead to inconsistency in preference heterogeneity. However, model simplicity will be the main reason behind these assumptions (Cameron & Trivedi, 2010; Hasselbach & Roosen, 2015).

$$P_{ij} = \frac{exp(x_{ij}'\beta + x_{ij}'v_i)}{\sum_{l=1}^{m} exp(x_{il}'\beta + x_{ij}'v_i)}, \qquad j = 1, \ldots, m \tag{16}$$

$$P_{ij} = \Pr[y_i = j] = \frac{exp(\beta_{03} + \beta_{19}\, p\_red_{ij} + \beta_{20i}\, qual_{ij} + \beta_{21i}\, debt_{ij})}{\sum_{l=1}^{3} exp(\beta_{03} + \beta_{19}\, p\_red_{ij} + \beta_{20i}\, qual_{ij} + \beta_{21i}\, debt_{ij})}, \qquad j = 1, \ldots, 3 \tag{17}$$

Similar regressors are introduced into the equation (Eq. 16), as in Equation 17, by considering the RPL in Equation 14: here the model estimation is called ML_1. A similar transformation considering the interaction regressors in Equation 15 is also employed, where ML_2 will be the model estimation. The last model estimation, called ML_3, introduces cross-correlation among random attribute parameters, in the form of a Cholesky matrix, to the ML_2 estimation. Thus, we would have the true standard deviation of the random parameters (Asante-Addo & Weible, 2019; Hensher et al., 2005).

The model chosen between CL and ML models will be based on Pseudo-R^2 value, the model selection criteria (Akaike and Bayesian information criterion (AIC and BIC)), and the log-likelihood values. The log-likelihood based Pseudo-R^2 value (Equation 17) provides the interpretation that higher values of Pseudo-R^2 mean better improvements in the new model compared to the null model (Hemmert et al., 2018; McFadden, 1973).

$$Pseudo\ R^2 = 1 - \left(\frac{ll_{model}}{ll_{null}}\right) \tag{18}$$

Typically, lower criterion values indicate a better model. The difference between criterions lies in how the number of estimated parameters and observations are penalized (Mills & Prasad, 1992). Meanwhile, even though the general rule is that higher log-likelihood values indicate a better model, we could also apply the Likelihood Ratio (LR) test (Equation 18), wherein UR refers to unrestricted (new) model and R defines otherwise, to be then compared with a chi-square (χ^2) distribution (Hensher et al., 2005; Wooldridge, 2013). The new model fits best when we reject the null hypothesis, i.e. the computed LR > critical LR. To get the critical value of the chi-square (χ2) distribution, we have to define the degree of freedom of the particular model by subtracting the number of observations in a sample by the number of independent constraints or β-parameters estimated (Hensher et al., 2005).

$$LR = 2\,(L_{UR} - L_R) \tag{19}$$

At last, the main objective of this study is to observe how much price reduction traders are willing to charge (WTC) when a farmer with a certain amount of debt or quality offers a product. To do so, we employed a WTP measurement approach (Hensher et al., 2005), derived from choosing the best result between all model estimations. It is based on the ratio of the two parameters involved, where β_p refers to p_red parameter, while n represents parameter of other regressors. It is important to obtain significant regressors to measure the WTC, otherwise no valuable measurement can be determined (Hensher et al., 2005). Additionally, a common supporting Krinsky Robb bootstrap method to measure WTP is employed (Hasselbach & Roosen, 2015; Hole, 2007a).

$$WTC_n = -\frac{\beta_n}{\beta_p} \tag{20}$$

Additional normality and non-parametric equality test are conducted to obtain supporting data based on the socio-demographic respondent characteristics. A Shapiro-Wilk Normality Test is employed to perform normality test for variables required (Royston, 1992), meanwhile Wilcoxon rank-sum (Mann-Whitney) non-parametric test is exercised to obtain equality test between groups based on their median values (Mann & Whitney, 1947; Wilcoxon, 1947).

4.5. Data

4.5.1 Data Source

The data used in this study is part of the data collected from the Collaborative Research Centre (CRC) in Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems in the Jambi province, Indonesia in 2018. Five regencies, namely Sarolangun, Batang Hari, Muaro Jambi, Tebo, and Bungo Regency, were selected purposefully[25]. Then, stratified random sampling was applied in order to select districts and villages. One advantage of using stratified random sampling is that it minimizes survey costs without compromising accuracy (Cameron & Trivedi, 2010). Next, twenty-two districts and thirty-seven villages were chosen, and respondents were formed by selecting all active, small rubber traders in the selected villages, and excluding those who could not be reached due to absence or rejection. We conducted direct interviews with respondents to gather information about their socio-demographic characterises. Also, we performed an interactive experiment to obtain our DCE data as our main research objectives.

4.5.2 Choice Experimental Design

We decided to consider in the study three main attributes related to the core research question: price reduction, rubber quality, and farmer's debt. All were included as alternative specific regressors. Each attribute is presented in different levels. Attributes and levels used in this study are described in Table 4. 2. Combinations of attributes, each with unique levels, are named alternative. There is no label identification for the alternative in this study, commonly called an unlabelled experiment, which is beneficial because there is less of a possibility of a correlation between alternatives and a reduced bias in considering attributes, since decision makers may hold initial assumption by reading the alternative's label (Hensher et al., 2005).

To have an efficient experimental design, all alternatives, attributes, attribute levels and attribute-level labels have to be well-identified and refined before a design is formed (Hensher et al., 2005). It is thought that the presence of too many choice sets may reduce the response reliability. Therefore, even though, theoretically, more information is gained by having more levels of attributes, reducing the number of attribute levels is preferred. Another way is to reduce the size of the experimental design while still considering the concept of

[25] Performed by Krishna and Euler, members of CRC's team, and also stated on the EFForTS Discussion Paper by Faust *et al*. (2013)

orthogonality, where all attributes are statistically independent of one another (Hensher et al., 2005).

Table 4. 2 Attributes, Levels and Descriptions

Attribute	Level	Description
Quality	Bad (0), good (1)	illustrating the rubber quality whether it is in bad or good quality.
Debt	0 IDR, 350,000 IDR, 750,000 IDR	illustrating the loan amount borrowed by the indebted suppliers.
Basi	5%, 10%, 15%	referring the price reduction in percentage determined by traders.

In this study, the design of the choice experiment was automatically generated by JMP Statistical Discover from SAS. It will automatically consider the number of alternatives, attributes, attribute levels, and choice sets desired, by still considering the orthogonality concept, called the orthogonal fractional factorial design. We consider a combination of three attributes within a choice set containing two alternatives and a "none" option for each set (Table 4. 3). Also, we include 10 choice sets per survey, from three surveys and over 180 expected respondents. These considerations were then input into the software to randomly generate a design.

Table 4. 3 An example of a Choice Set (simplification)

Set 1	Choice A	Choice B	Choice C
Quality	Bad Quality	Good Quality	
Debt	750,000 IDR	0 IDR	Neither
Basi	5%	15%	

Note: A sample of choice set is presented in Appendix 4. 1.

A preliminary pilot study was performed where we interviewed actual rubber traders outside the survey area as well as experts who understand the behaviour of traders. Their choice outcomes and feedbacks provided improvement for the final choice design. It is necessary to detect potentially relevant attributes, so that all combination used in the survey are realistic for the respondents. the type of choice data employed in this study is known as

Revealed Preference (RP)[26] data, where the choice is based on actual market condition (Hensher et al., 2005).

At the end of survey, we interviewed 210 respondents who were then randomly and evenly divided into three groups to perform different surveys. Each respondent was confronted with choice sets shown in sequence. They were asked to choose one of the alternatives presented in the choice set. The choice concerned 100 kg of "*bokar*" and 8,000 IDR/kg and was mentioned in the beginning of survey.

To provide a sense of realism, we prefer to use term *basi* rather than "price reduction" in the choice set, since it is better known by both rubber farmers and traders. Also, it is in the common form of price reduction (in percentage) used on the field. It is then transformed into Indonesian Rupiah (IDR) which must be in accordance with our assumption. Keep in mind that, in the end, we are looking for WTC *basi* instead of WTP. Additionally, we divide debt by one million to adjust for the many zeros when dealing with IDR currency.

4.5.3 Descriptive Statistics of Socio-Demographic Characteristic Data

Descriptive statistics for key socio-demographic variables relating to the respondents are described in Appendix 4. 2. Key variables include the size, number of competitors, socio-human capital, and credit provision of rubber traders. In an initial assessment of trading activities, of the majority of rubber traders dealt in rubber alone, whereas 12.38% of respondents reported also trading in oil palm.

Table 4. 4 Village and Larger Traders' Characteristics

Variables	Village Trader *actual rank sums*		Larger Trader *actual rank sums*		Sign.
Trading revenue	13041.0	<	9114.0	>	***
Quantity purchased	12479.5	<	9675.5	>	***
Number of workers	13083.5	<	9071.5	>	***
Number of suppliers	12459.5	<	9695.5	>	***
Number of competitors	15792.5	>	6362.5	<	***
expected rank sums	14559.0		7596.0		
number of obs.	138		72		

Source: Own production (Appendix 4. 4)
Note: *** p<0.01, **p<0.05, *p<0.1

[26] Another type of choice data is Stated Preference (SP) data, where a choice is based on hypothetical condition.

To capture the relative "size" of traders, we divide traders into village and larger traders, finding that 65.71% of respondents are village traders. To compare characteristics between village and larger traders, we performed the Wilcoxon rank-sum (Mann-Whitney) non-parametric test of both groups in total trading revenue, quantity of rubber purchased, number of workers, number of suppliers and number of competitors (Table 4. 4 and Appendix 4. 4). We initially conducted Shapiro-Wilk Normality Test for the variables compared (Appendix 4. 3), however those are not normally distributed thus we considered the rank-sum test to compare variables medians of both groups. Results show that the median of trading revenue, quantity purchased, number of workers, and number of suppliers variables of larger traders are significantly higher than those of village traders, but otherwise for the number of competitors variable. This is very plausible, because when there is a larger trader in an area, the challenge to become a competitor in that region will be greater due to capital required.

In terms of measuring traders' competition, 54.75% of respondents reported having 10-16 competitors in their village. Furthermore, when analysing socio-human capital characteristics of traders, we determined that 7.14% of respondents reported having a leadership title within the village, like village official, teenage leader, or religious leader; 14.76% of respondents reported being transmigrant[27], and 84.26% of respondents attained a basic education, and were at least primary or secondary school graduates.

Table 4. 5 Credit Providers and Traders not Providing Credit Characteristics

Variables	Provide no Credit *actual rank sums*		Provide Credit *actual rank sums*		Sign.
Trading revenue	3612.5	<	18542.5	>	
Quantity purchased	3501.0	<	18654.0	>	
Number of workers	3391.0	<	18764.0	>	
Number of suppliers	2845.0	<	19310.0	>	***
Number of competitors	4164.5	>	17990.5	<	
expected rank sums	3903.5		18251.5		
number of obs.	37		173		

Source: Own production (Appendix 4. 4)
Note: *** p<0.01, **p<0.05, *p<0.1

At last, we observed the traders' credit provision, where 82.38 % of respondents provided credits to suppliers, and 79.77% of them felt that indebted suppliers had the

[27] Those have followed a transmigration program from Indonesian government, with the aim of equal distribution of Indonesian population. The program is fully subsidized by the government.

obligation to sell their rubber to them. We also divide the respondents into two groups based on credit availability (Table 4. 5 and Appendix 4. 4). To compare both groups, we also performed the Wilcoxon rank-sum (Mann-Whitney) non-parametric test for median difference of the same variables as in Table 4. 4. Results show that the “median number of supplier” variable is significantly higher among credit providers than those traders not providing credit. One plausible reason for this is that more suppliers depend on credits offered by traders.

4.6. Result and Discussion

We analysed the choice experiment data using conditional and mixed logit model in STATA 14.2. Three main alternative-specific attributes and six additional socio-demographic regressors are considered, as well as their interaction. A separate initial Spearman’s rank correlation test (Appendix 4. 5) was carried out for all variables in all estimations where there is no correlation among three main attributes found; meanwhile, some interaction variables indicate otherwise. These are understandable since main attributes are counted in the interaction variables. However, we also considered cross-correlation among random attribute parameters in the last model estimation to anticipate different responses once random characteristics are introduced for some main attributes.

There are five models we considered in obtaining the best fitted model (Appendix 4. 6). The most general model represented by CL_1 introduced fixed coefficients for the main attributes, which do not vary across respondents, while CL_2 introduced additional socio-demographic characteristics and their interaction regressors to CL_1. Both models were estimated using conditional logit estimation. The last three models were estimated using a mixed logit model, allowing for variation in the main attribute’s coefficients, except for the price reduction and “none” option. ML_1 considers only main attributes in the estimation, while ML_2 considers main attributes as well as additional socio-demographic characteristics and their interaction regressors. We then introduced cross-correlation to ML_3 to ensure that the random attributes are still random after allowing for correlation among them. The cross-correlation information is captured as Cholesky Matrix (Hole, 2007b) which is represented by the lower-triangular matrix in ML_3. The matrix is part of the covariance matrix in Appendix 4. 13. Additionally, all mixed logit models are estimated using 500 Halton draws to find better result accuracy (Hole, 2007b).

We compare the goodness of fit measures in order to find the best model. Estimation statistics of all model estimations are shown in Table 4. 6. The first measure is the log-likelihood measure, where, generally, a higher log-likelihood value indicates a better model, shown by ML_3. However, it is also necessary to prove this with a log-likelihood ratio test, which determines the ML_2 model to be the best fit (Table 4. 7). The second measure utilized is the pseudo-R^2 by McFadden (1973), wherein a higher value of Pseudo-R^2 indicates a better improvement of the new model compared with the null modeln (Hemmert et al., 2018; McFadden, 1973). It can be seen that the ML_2 and ML_3 have similar and high Pseudo-R^2 values. The last measures considered are the AIC and BIC value, where a lower value indicates a better model. ML models provide lower criterion values than those of CL models. It was determined that the ML_2 model fit best based on AIC while ML_1 fit best based on BIC. Overall, ML models improve the model estimation, especially the model ML_2.

Table 4. 6 Estimation Statistics of All Model Estimations

Model	Obs	Log-likelihood Value		df	AIC	BIC	Pseudo R^{2} [b)]
		ll-null [a)]	ll-model				
CL_1	6300	-2307.09	-1450.42	4	2908.84	2935.83	0.37
CL_2	6300	-2307.09	-1396.03	22	2836.07	2984.53	0.39
ML_1	6300	-1450.42	-1179.90	6	2371.81	2412.29	0.49
ML_2	6300	-1396.03	-1154.40	24	2356.81	2518.77	0.50
ML_3	6300	-1396.03	-1153.59	25	2357.18	2525.88	0.50

Source: Own production (Appendix 4. 7-4. 11)
Note: [a)] The ll-null values for ML estimations equal to ll-model values for CL estimations, thus we replace the ll-null values for ML estimations with ll-null values for CL estimations to calculate the true Pseudo R^2. [b)] Calculation is based on Equation 17.

Even though model ML_3 is not the best model, the estimation result appears similar, which can reflect a quite robust result. All models provide consistent result in term of parameter signs, although number of significant regressors are reduced (Appendix 4. 6). However, the main three attributes are all significant and specify persistent parameter signs.

Based on the ML_2 model estimation, as expected, respondents tend to obtain higher price reductions to increase their utility (Table 4. 8). Theoretically, price attributes should be statistically significant and negative (Elshiewy et al., 2017; Hensher et al., 2005), while in our study, we replace the price attribute with the price reduction attribute which should respond in the opposite direction. Having a higher price reduction allows rubber traders to increase their profit per unit.

Table 4. 7 Log-likelihood Ratio Test

Models Compared	Computed Value [b)]		Critical Value		Model Chosen [c)]
ML_3 vs ML_2	2 (-1153.59 - (-1154.40)) =	1.64	$\chi2$ (0.95,1) =	3.84	ML_2
ML_3 vs ML_1	2 (-1153.59 - (-1179.90)) =	52.62	$\chi2$ (0.95,37) =	52.19	ML_3
ML_3 vs CL_2	2 (-1153.59 - (-1396.03)) =	484.88	$\chi2$ (0.95,25) =	37.65	ML_3
ML_3 vs CL_1	2 (-1153.59 - (-1450.42)) =	593.66	$\chi2$ (0.95,43) =	59.30	ML_3
ML_2 vs ML_1	2 (-1154.40 - (-1179.90)) =	51.00	$\chi2$ (0.95,36) =	50.99	ML_2
ML_2 vs CL_2	2 (-1154.40 - (-1396.03)) =	483.24	$\chi2$ (0.95,24) =	36.42	ML_2
ML_2 vs CL_1	2 (-1154.40 - (-1450.42)) =	592.02	$\chi2$ (0.95,42) =	58.12	ML_2
ML_1 vs CL_2 [a)]	2 (-1179.90 - (-1396.03)) =	432.26	-		ML_1
ML_1 vs CL_1	2 (-1179.90 - (-1450.42)) =	541.04	$\chi2$ (0.95,6) =	12.59	ML_1
CL_2 vs CL_1	2 (-1396.12 - (-1450.42)) =	108.60	$\chi2$ (0.95,18) =	28.87	CL_2

Source: Own production (Appendix 4. 8-4. 12)
Note: [a)] Degree of freedom (df) of ML_1 is less than that of CL_2, thus critical value is unmeasured. However, we consider both models are not better than ML_2 and ML_3 based on other calculations. [b)] Based on Equation 18. [c)] The new model fits best when we reject the null hypothesis, i.e. the computed value > critical value.

Further, the results indicate that respondents tend to choose higher rubber quality to increase their utility. Having a higher quality product surely increases the probability to obtain higher selling price. Also, it shows that respondents tend to select lower farmer's debt to minimize the risk of losing money to suppliers who default on their debt. Based on ML_2 model, farmer's debt has the highest marginal utility among main attributes. On the other hand, "none" option parameter turns to be not significant, since it is currently interacted with the socio-demographic regressors, unlike in the model ML_1.

Evidently, traders having higher trading revenue, credit provision, less suppliers and transmigrant traders prefer to choose any alternative option to the "none" option. It implies that attributes presented in alternatives matter for those criteria. Regarding the interaction regressors, good quality is preferred over bad quality for larger traders and traders having higher number of competitors.

Additionally, Table 4. 8 presents the significance outcomes for random parameters. It implies that there exits heterogeneity among traders for the related attributes, since their estimates are significantly different from zero. Each trader preference differs from others as well as their WTC. Table 4. 9 shows the ML_2 WTC value which influences the respondents' utility. It can be deduced that there is no WTC for any non-significant regressors. WTC value comparisons among all models are presented in Appendix 4. 14. We assumed a prevailing rubber price of 8,000 IDR/kg and divided the debt value by one million to provide a more intuitive interpretation.

Table 4. 8 Parameter Estimates from the ML_2 Model Estimation

Attributes	Coefficient a)		SE
Mean Estimates			
p_red	0.0007	***	(0.0001)
qual	1.6480	*	(0.9059)
debt	-1.9086	**	(0.9488)
dalt b)	-0.1110		(0.4054)
dalt_trrev	0.0094	*	(0.0050)
dalt_cred	0.8596	***	(0.2840)
dalt_supp	-0.0085	***	(0.0032)
dalt_com	0.0215		(0.0253)
dalt_stat	-0.3790		(0.2636)
dalt_trans	0.6552	*	(0.3402)
trrev_*x*_qual	-0.0124		(0.0109)
trrev_ *x* _debt	0.0052		(0.0105)
cred_ *x* _qual	-0.0272		(0.6658)
cred_ *x* _debt	1.0145		(0.6876)
supp_ *x* _qual	0.0126		(0.0077)
supp_ *x* _debt	-0.0036		(0.0071)
com_ *x*_qual	0.1018	*	(0.0550)
com_ *x* _debt	0.0294		(0.0555)
stat_ *x* _qual	1.9702	***	(0.6022)
stat_ *x* _debt	-0.0283		(0.5876)
trans_ *x* _qual	-1.0488		(0.7122)
trans_ *x* _debt	-0.3422		(0.7190)
Standard Deviation of Random Parameter Distributions			
qual	2.8441	***	(0.2936)
debt	2.6058	***	(0.2755)
Goodness of Fit Measures			
Log-likelihood	-1154.4063		
Pseudo-R^2	0.4996		
AIC	2356.8130		
BIC	2518.7720		
Number of observations	6300		
Number of respondents	210		

Source: Own production (Appendix 4. 10)
Note: a) *** p<0.01, **p<0.05, *p<0.1 ; b) Dummy variable for choosing any alternative (1) or "none" opt (0)

An increase in quality from bad to good, is followed by a decrease in price reduction by 2,397.48 IDR/kg, *ceteris paribus,* which is 29.97% of the assumed price. This is in accordance with our expectation, because the price of *bokar* of very poor quality can reach 40% of the prevailing price. Meanwhile, *bokar* with prices of up to 10% of the prevailing price are considered to be of good quality[28]. Furthermore, an increase in farmer's debt by 1 million IDR leads to an increase in price reduction by 2,776.54 IDR/kg, *ceteris paribus,* which is 34.71 % of the assumed price. The most common farmer's debt values are below 1 million IDR, with an average of 0.5 million IDR[29], and these loans are often used for daily needs. In other words, mostly price reduction due to farmer's debt value is below 2,776.54 IDR/kg. Also, the farmer's reason for having the debt is in accordance with a study finding that informal loans are mostly spent on food (Carranza & Niles, 2019).

Table 4. 9 Rubber Traders' Willingness to Charge Price Reduction for Rubber Attributes

Attributes	WTC [a)]		Min.	Max.
Alternative-specific regressors				
qual	-2,397.48	*	-5,763.19	-149.19
debt	2,776.54	**	-84.55	6,285.63
Socio-demographic regressors				
dalt_trrev	-13.64	*	-32.62	0.73
dalt_cred	-1,250.49	***	-2,538.36	-410.00
dalt_supp	12.42	***	3.33	25.88
dalt_com	-31.24		-115.25	40.39
dalt_stat	551.36		-200.98	1,514.28
dalt_trans	-953.11	*	-2,222.23	25.99
Interaction regressors				
trrev_*x*_qual	18.03		-13.82	55.70
trrev_ *x* _debt	-7.62		-41.76	23.84
cred_ *x* _qual	39.51		-2,007.59	2,146.49
cred_ *x* _debt	-1,475.85		3,992.40	510.05
supp_ *x* _qual	-18.38		-46.99	4.15
supp_ *x* _debt	5.23		-16.11	28.13
com_ *x*_qual	-148.05	*	-356.51	7.32
com_ *x* _debt	-42.83		-221.74	126.85
stat_ *x* _qual	-2,866.18	***	-5,620.40	-1,106.14
stat_ *x* _debt	41.19		-1,757.88	1,860.62
trans_ *x* _qual	1,525.72		-473.64	4,118.37
trans_ *x* _debt	497.85		-1,622.50	2,812.17

Source: Own production (Appendix 4. 18), with Confidence Interval 95%
Note: [a)] *** p<0.01, **p<0.05, *p<0.1

As the second part of the WTC result, from the socio-demographic characteristic perspective, we observe a positive WTC for the "number of suppliers" regressor as well as

[28] Based on interview with one of the rubber factories in Jambi.
[29] Based on interview with rubber traders in Jambi.

negative WTC for the “trader revenue”, “credit provision”, and “transmigrant status” regressors. The average buyer respondent is willing to increase his/her price reduction by 12.42 IDR/kg for an increase of one unit of suppliers, *ceteris paribus,* which is 0.16% of the assumed price. A plausible reason for this phenomenon is that traders with more suppliers feel less at risk of supply shortages resulting from increasing price reduction.

The average buyer respondent is willing to reduce his price reduction by 13.64 IDR/kg for an increase of a million-trading revenue, *ceteris paribus,* which is 0.17% of the assumed price. With higher trading revenue, the trader can loosen his desire to take advantage of price reduction, which makes perfect sense. Further, a buyer respondent with credit provision has his WTC unexpectedly decrease by 1,250.49 IDR/kg, *ceteris paribus,* which is 15.63% from the assumed price. This means that traders providing credit offer higher prices for their rubber than traders providing no credit. The plausible reason is that they would like to provide credit to maintain supply continuity from farmers. That is also one of the factors influencing the trader to remain in the market, based on the previous chapter. Meanwhile, transmigrant trader’s WTC decreases by 953.11 IDR/kg, which is 11.91% of the assumed price, *ceteris paribus*. We found that transmigrant traders purchase more rubber than non-transmigrant traders in term of quantity (Appendix 4. 20). This can explain that the transmigrant traders may focus more in purchasing rubber rather than pursuing higher margin gained from price reduction.

At last, there are two interaction regressors providing significant effects on the respondent’s utility. An initial interpretation for this is that having one additional competitor leads to a respondent’s WTC for quality decreasing by 148.05 IDR/kg, which is 1.85% of the assumed price. A trader with more competitors seeks to achieve higher quality by reducing price reduction, to attract suppliers selling their better-quality rubber to them instead of their competitors. Secondly, a larger trader’s WTC decreases by 2,866.18 IDR/kg for good quality, which is 35.83% of the assumed price, *ceteris paribus*. The plausible reason is that they may be more efficient in trading activity than the village traders and thus are able to give more incentive to suppliers selling high quality rubber.

4.7. Conclusion

The Discrete Choice Experiment (DCE) method has successfully helped us to answer the research questions of this study. We found that a mixed logit model, which considers heterogeneity of the random parameters, provides the best fitted model with the highest value of log-likelihood and the lowest value of AIC.

There are significant results showing that price reduction, rubber quality and farmer’s debt influence traders’ preference in buying rubber, where increased price reduction, higher rubber quality, and lower farmer’s debt will increase the trader’s utility. Some interaction variables between those main attributes and some respondents’ socio-demographic characteristics also influence the traders’ preference. These include the interaction between number of competitors and rubber quality, and whether a trader is a larger trader or village trader and rubber quality. Afterwards, we employ a WTP measurement approach and find a WTC by traders for all significant regressors. An increase in quality from bad to good is associated with a 29.97% price reduction from the assumed price. Further, an increase in farmer’s debt of 1 million IDR is followed by an increase in 34.71% price reduction off of the assumed price.

Chapter 5

General Conclusion

Based on results of all chapters regarding the initial research objectives, we can conclude that there are effects of an importing country trade policy to price in a targeted exporting country, which in this case the EU AD duty affects the Indonesian CPO and local Jambi FFB price. Also, we found that there are factors affecting OPFFB and rubber local traders to remain in or exit the market. Those are human capital, trading structure, structural environment, and socioeconomic factors. Lastly, we found that rubber farmer's debt influences the rubber traders' preference in buying rubber. The summary of each chapter's conclusion is presented as follows.

The first paper explains that the imposition of the EU biodiesel AD generated a SB in the cointegration estimation between Indonesian and world CPO prices, and between Jambi FFB and Indonesian CPO prices. This could indicate that the duty had an effect on the price after the breakpoint. Results show that the duty negatively affected the Indonesian CPO and local Jambi FFB price, whereas the world CPO market gained more power after the duty implementation. Decreases in Indonesian CPO demand due to decreased demand for imported biodiesel by the EU lead to a price reduction caused by a shifting of demand.

From the second paper we could summarize that many traders leave their activities due to falling oil palm and rubber prices in the period of study. This price fluctuation raise uncertainty to traders to remain in the market. In light of this evidence, it is clear that human capital, trading structure, structural environment, and socioeconomic factors affect the decision of traders in remaining in or exiting the market. It is also interesting that some variables are only significant in particular period but not significant in the other, due to different situation and behavior, formed over time.

Lastly, the third paper concludes that there are significant results showing that price reduction, rubber quality and farmer's debt influence traders' preference in buying rubber, where increased price reduction, higher rubber quality, and lower farmer's debt will increase the trader's utility. Some interaction variables between those main attributes and some respondents' socio-demographic characteristics also influence the traders' preference. These include the interaction between number of competitors and rubber quality, and whether a trader is a larger trader or village trader and rubber quality. Afterwards, we employ a WTP measurement approach and find a WTC by traders for all significant regressors. An increase in quality from bad to good is associated with a decrease of 29.97% price reduction of the assumed price. Further, an increase of farmer's debt by 1 million IDR, is followed by an increase in 34.71% price reduction of the assumed price.

Bibliography

Abd, A., Nambiappan, B., Palm, M., & Board, O. (2013). Impact of Palm Oil Supply and Demand on Palm Oil Price Behaviour. *Oil Palm Industry Economic Journal*, *13*(1). Retrieved from https://www.researchgate.net/publication/324561688_Impact_of_Palm_Oil_Supply_and_Demand_on_Palm_Oil_Price_Behaviour

Aidenvironment. (2016). *Low Prices Drive Natural Rubber Producers into Poverty*. Retrieved from http://www.aidenvironment.org/wp-content/uploads/2016/10/Rubber-study-FRA.pdf

Andarani, P., Nugraha, W. D., & Wieddya. (2017). Energy balances and greenhouse gas emissions of crude palm oil production system in Indonesia (Case study: Mill P, PT X, Sumatera Island). *AIP Conference Proceedings*, *1823*. https://doi.org/10.1063/1.4978137

Asante-Addo, C., & Weible, D. (2019). Is there hope for domestically produced poultry meat? A choice experiment of consumers in Ghana. *Agribusiness*, (July). https://doi.org/10.1002/agr.21626

Asche, F. (2001). Testing the effect of an anti-dumping duty: The US salmon market. *Empirical Economics*, *26*(2), 343–355. https://doi.org/10.1007/s001810000043

Asteriou, D., & Hall, S. G. (2016). *Applied Econometrics* (3rd Ed). London: Macmillan Publishers Ltd.

Avşar, V. (2013). *Trade Effects of Turkey's Antidumping Duties*. *XXXII*(1), 1–10.

Bennett, J., & Birol, E. (2010). The roles and significance of choice experiments in developing country contexts. In J. Bennett & E. Birol (Eds.), *Choice Experiments in Developing Countries* (pp. 1–13). Cheltenham: Edward Elgar Publishing Limited.

Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *International Social Work*, 353–383. https://doi.org/10.1177/002087288602900206

Blair, G., Imai, K., & Zhou, Y. Y. (2015). Design and Analysis of the Randomized Response Technique. *Journal of the American Statistical Association*, *110*(511), 1304–1319. https://doi.org/10.1080/01621459.2015.1050028

Bou Dib, J., Krishna, V. V., Alamsyah, Z., & Qaim, M. (2018). Land-use change and livelihoods of non-farm households: The role of income from employment in oil palm and rubber in rural Indonesia. *Land Use Policy*, *76*(March), 828–838. https://doi.org/10.1016/j.landusepol.2018.03.020

Bourguignon, D. (2015). Briefing EU biofuels policy. In *European Parliamentary Research Service*.

BPS-Statistics of Jambi Province. (2018). *Jambi Province in Figures 2018*. Jambi: BPS-Statistics of Jambi Province.

Bragg, L. A., & Dalton, T. J. (2004). Factors affecting the decision to exit dairy farming: A two-stage regression analysis. *Journal of Dairy Science*, *87*(9), 3092–3098. https://doi.org/10.3168/jds.S0022-0302(04)73444-X

Brambilla, I., Porto, G., & Tarozzi, A. (2012). Adjusting to Trade Policy: Evidence from

U.S. Antidumping Duties on Vietnamese Catfish. *The Review of Economics and Statistics*, *94*(1), 304–319.

Breustedt, G., & Glauben, T. (2007). Driving forces behind exiting from farming in Western Europe. *Journal of Agricultural Economics*, *58*(1), 115–127. https://doi.org/10.1111/j.1477-9552.2007.00082.x

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics, Methods and Applications*. Cambridge: Cambridge University Press.

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics Using Stata* (Revised). Texas: Stata Press.

Carranza, M., & Niles, M. T. (2019). Smallholder Farmers Spend Credit Primarily on Food: Gender Differences and Food Security Implications in a Changing Climate. *Frontiers in Sustainable Food Systems*, *3*(July). https://doi.org/10.3389/fsufs.2019.00056

Chandra, P., & Long, C. (2013). Anti-dumping Duties and their Impact on Exporters: Firm Level Evidence from China. *World Development*, *51*, 169–186. https://doi.org/10.1016/j.worlddev.2013.05.018

Cheong, D. (2007). The impact of Antidumping on EU Trade. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.575.3592

Corzine, M. N. (2008). *An Analysis of Import Tariff Escalation: A Case of Maize Trade between Sout Africa and Mozambique* (Michigan State University). https://doi.org/10.1017/CBO9781107415324.004

Coughlan, A. T., Anderson, E., Stern, L. W., & El-Ansary, A. I. (2006). *Marketing Channel* (7th ed.). New Jersey: Pearson Prentice Hall.

Croezen, H. J., Bergsma, G. C., Otten, M. B. J., & van Valkengoed, M. P. J. (2010). *Biofuels: Indirect land use change and climate impact*. Retrieved from https://www.ce.nl/publicaties/download/944

Croux, C., & Dehon, C. (2010). Influence functions of the Spearman and Kendall correlation measures. *Statistical Methods and Applications*, *19*(4), 497–515. https://doi.org/10.1007/s10260-010-0142-z

Cuyvers, L., & Dumont, M. (2005). EU anti-dumping measures against ASEAN countries: Impact on trade flows. *Asian Economic Journal*, *19*(3), 249–271. https://doi.org/10.1111/j.1467-8381.2005.00212.x

Directorate General of Customs and Excise. (2015, September). Export Tariff and Levy for CPO and Its Derivative Products (in Indonesian). *Warta Bea Cukai (Customs News), Directorate General of Customs and Excise of the Republic of Indonesia*, *47*(9), 1–64.

Directorate General of Estate Crops. (2015). *Tree Crop Estate Statistics Of Indonesia 2013-2015 Palm Oil* (Y. Soependi & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Directorate General of Estate Crops. (2016a). *Tree Crop Estate Statistics Of Indonesia 2015-2017 Palm Oil* (D. Hendaryati & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Directorate General of Estate Crops. (2016b). *Tree Crop Estate Statistics of Indonesia 2015-2017 Rubber* (D. Hendaryati & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Directorate General of Estate Crops. (2017a). *Tree Crop Estate Statistics Of Indonesia 2016-2018 Palm Oil* (D. Hendaryati & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Directorate General of Estate Crops. (2017b). *Tree Crop Estate Statistics of Indonesia 2016-2018 Rubber* (D. Hendaryati & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Directorate General of Estate Crops. (2018). *Tree Crop Estate Statistics of Indonesia 2017-2019 Rubber* (D. Hendaryati & Y. Arianto, Eds.). Retrieved from http://ditjenbun.pertanian.go.id

Elamin, N., & Khaira, H. (2003). Tariff Escalation in Agricultural Commodity Markets. In *Commodity Market Review 2003-2004*. Retrieved from http://www.fao.org/3/a-y5117e.pdf#page=107

Elshiewy, O., Guhl, D., & Boztug, Y. (2017). Multinomial Logit Models in Marketing - From Fundamentals to State-of-the-Art. *Marketing ZFP*, *39*(3), 32–49. https://doi.org/10.15358/0344-1369-2017-3-32

Estate Crops Office. (2019). *Oil Palm Fresh Fruit Bunch Price Data - requested data*.

European Commission. Directive 2003/30/EC pf the European Parliament and of the Council. , Pub. L. No. 2003/30/EC, Official Journal of the European Union 42 (2003).

European Commission. *Procedures Relating to the Implementation of the Common Commercial Policy*. , Pub. L. No. 2012/C 260/04, 8 (2012).

European Commission. *Council Implementing Regulation (EU) No 1194/2013*. , Pub. L. No. 1194/2013, 2 (2013).

European Commission. (2013b). *EU to impose definitive anti-dumping duties on biodiesel from Argentina and Indonesia*. Retrieved from http://europa.eu/rapid/press-release_IP-13-1140_en.htm

European Commission. Directive (EU) 2018/2001 of the European Parliament and of the Council. , Pub. L. No. 2018/2001, Official Journal of the European Union 82 (2018).

European Commission. Commssion Delegated Regulation (EU) 2019/807. , Pub. L. No. 2019/807, L133 Official Journal of the European Union 1 (2019).

European Union External Action. (2018). *EU Anti-Dumping Duties on Biodiesel from Indonesia*. Retrieved from https://eeas.europa.eu/sites/eeas/files/20180323_biodiesel_fact_sheet_en_1.pdf

Faust, H., Schwarze, S., Beckert, B., Brümmer, B., Dittrich, C., Euler, M., … Wollni, M. (2013). *Assessment of socio-economic functions of tropical lowland transformation systems in Indonesia - sampling framework and methodological approach*. Göttingen.

Feenstra, R. C., & Taylor, A. C. (2014). *International Trade* (3rd Ed). Ney York: Worth Publishers.

Ferjani, A., Zimmermann, A., & Roesch, A. (2015). Determining factors of farm exit in agriculture in Switzerland. *Agricultural Economics Review*, *16*(1), 59–72.

Flach, B., Lieberz, S., Lappin, J., & Bolla, S. (2018). *EU Biofuels Annual 2018*. The Hague.

Flach, B., Lieberz, S., Rondon, M., Williams, B., & Wilson, C. (2016). *EU Biofuels Annual 2016*. Retrieved from http://gain.fas.usda.gov/Recent GAIN Publications/Biofuels Annual_Buenos Aires_Argentina_7-6-2012.pdf

Gao, Z., & Schroeder, T. C. (2009). Effects of label information on consumer willingness-to-pay for food attributes. *American Journal of Agricultural Economics*, *91*(3), 795–809. https://doi.org/10.1111/j.1467-8276.2009.01259.x

Greenberg, B. G., Abul-Ela, A.-L. A., Simmons, W. R., & Horvitz, D. G. (1969). *The Unrelated Question Randomized Response Model : Theoretical Framework*. *64*(326), 520–539.

Greene, W. H. (2012). *Econometric Analysis* (7th ed.). Boston: Pearson Education Limited.

Gregory, A. W., & Hansen, B. E. (1996). Residual-based tests for cointegration with regime shifts in models with regime shifts. *Journal of Econometrics*, *70*, 99–126. Retrieved from file:///C:/Users/ellasujarwo/Downloads/1-s2.0-0304407669416857-main (1).pdf

Guirkinger, C. (2008). Understanding the Coexistence of Formal and Informal Credit Markets in Piura, Peru. *World Development*, *36*(8), 1436–1452. https://doi.org/10.1016/j.worlddev.2007.07.002

Hasselbach, J. L., & Roosen, J. (2015). Consumer Heterogeneity in the Willingness to Pay for Local and Organic Food. *Journal of Food Products Marketing*, *21*(6), 608–625. https://doi.org/10.1080/10454446.2014.885866

Hemmert, G. A. J., Schons, L. M., Wieseke, J., & Schimmelpfennig, H. (2018). Log-likelihood-based Pseudo-R2 in Logistic Regression: Deriving Sample-sensitive Benchmarks. *Sociological Methods and Research*, *47*(3), 507–531. https://doi.org/10.1177/0049124116638107

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied Choice Analysis A Primer* (1st ed.). Cambridge: Cambridge University Press.

Hole, A. R. (2007a). A Comparison of Approaches to Estimating Confidence Intervals for Willingness to Pay Measures. *Health Economics*, *16*, 827–840. https://doi.org/10.1002/hec

Hole, A. R. (2007b). Fitting mixed logit models by using maximum simulated likelihood. *Stata Journal*, *7*(3), 388–401. https://doi.org/10.1177/1536867x0700700306

Jabbour, L., Tao, Z., Vanino, E., & Zhang, Y. (2009). The good, the bad and the ugly: Chinese import, EU anti-dumping measurs and firm performance. *Research Paper Series. Globalisation, Productivity and Technology*.

Jegede, A. (2019). Top 10 Largest Farmers Producing Countries in the World. Retrieved February 27, 2020, from The Daily Records website: http://www.thedailyrecords.com/2018-2019-2020-2021/world-famous-top-10-list/world/largest-rubber-producing-countries-world-10-top/6857/

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*, 231–254. https://doi.org/10.1016/0165-1889(88)90041-3

Kerin, R. A., Hartley, S. W., & Rudelius, W. (2013). *Marketing* (11th ed.). USA: McGraw-Hill Irwin.

Kimhi, A., & Bollman, R. (1999). Family farm dynamics in Canada and Israel: The case of farm exits. *Agricultural Economics*, *21*(1), 69–79. https://doi.org/10.1016/S0169-5150(99)00015-8

Kogan, L., Ross, S. A., & Westerfield, M. M. (2006). The Price Impact and Survival of Irrational Traders. *The Journal of Finance*, *LXI*(1), 1–35. Retrieved from https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1540-6261.2006.00834.x

Konings, J., & Vandenbussche, H. (2013). Antidumping protection hurts exporters: Firm-level evidence. *Review of World Economics*, *149*(2), 295–320. https://doi.org/10.1007/s10290-013-0151-8

Kopp, T., Alamsyah, Z., Fatricia, R. S., & Brümmer, B. (2014). *Have Indonesian Rubber Processors Formed a Cartel? Analysis of Intertemporal Marketing Margin Manipulation* (No. EFForTS Discussion Paper Series, No. 3). Retrieved from https://econpapers.repec.org/paper/zbwcrc990/3.htm

Kopp, T., & Brümmer, B. (2017). Traders' market power along Indonesian rubber value chains. *China Agricultural Economic Review*, *9*(2), 169–187. https://doi.org/10.1108/CAER-07-2015-0080

Lancaster, K. (1966). *A New Approach to Consumer Theory*. *74*(2), 132–157.

Leinbach, T. R., & Smith, A. (1994). Off-Farm Employment , Land , and Life Cycle : Transmigrant Households in South Sumatra , Indonesia. *Economic Geography*, *70*(3), 273–296.

Lindsey, B., & Ikenson, D. J. (2003). *Antidumping Exposed: the devilish details of unfair trade law*. Washington D.C.: The Cato Institute.

Louviere, J. J., & Hensher, D. A. (1982). Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modelling. In *Attitudes, Perceptions, and Constraints on Travel* (pp. 11–17). Washington, D.C.: National Academy of Sciences.

Louviere, J. J., & Woodworth, G. (1983). Design and Analysis of Simulated Consumer Choice Experiments or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, *20*, 350–367.

Lu, Y., Tao, Z., & Zhang, Y. (2013). How do exporters respond to antidumping investigations? *Journal of International Economics*, *91*, 290–300. https://doi.org/10.1016/j.jinteco.2013.08.005

Mann, H. B., & Whitney, D. R. (1947). On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *The Annals of Mathematical Statistics*, *18*(1), 50–60.

Manski, C. F. (1977). The Structure of Random Ultility Models. *ProQuest*, *8*(3), 229. Retrieved from https://search.proquest.com/docview/1303217712/fulltextPDF/D4F85BFF40AE403APQ/1?accountid=11144

Mas-Colell, A., Whinston, M. D., & Green, J. R. (1995). *Microeconomic Theory*. New York: Oxford University Press, Inc.

Matsuda, H., & Takeuchi, K. (2018). Biofuels and Approach to Biofuel Issues from the Perspective of Sustainability Science Studies. In K. Takeuchi, H. Shiroyama, O. Saito,

& M. Matsuura (Eds.), *Biofuels and Sustainability* (pp. 11–15). Japan: Springer Open.

McFadden, D. (1973). Conditional logit analysis of quality choice behaviour. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105–142). https://doi.org/10.1080/07373937.2014.997882

Mills, J. A., & Prasad, K. (1992). A comparison of model selection criteria. *Econometric Reviews*, *11*(2), 201–234. https://doi.org/10.1080/07474939208800232

Minister of Finance of the Republic of Indonesia. *Regulation of the Minister of Finance concerning the Stipulation of Export Goods subject to Export Duties and Export Duty Tariff.* , Pub. L. No. 128 / PMK.011 / 2011 (2011).

Minister of Finance of the Republic of Indonesia. *Regulation of the Minister of Finance concerning the Stipulation of Export Goods subject to Export Duties and Export Duty Tariff.* , Pub. L. No. 136 / PMK.010 / 2011 (2015).

Minister of Finance of the Republic of Indonesia. *Regulation of the Minister of Finance of the Republic of Indonesia concerning Service Tariff of the General Service Board, the Oil Palm Plantation Fund Management Board in the Ministry of Finance (in Indonesian).* , Pub. L. No. 133/PMK.05/2015 (2015).

Minister of Trade of the Republic of Indonesia. (2019). Regulation of the Minister of Trade of the Republic of Indonesia concerning the Designation on Export Standard Price of Exported Goods Charged with Export Duty in 2009-2018 (in Indonesian). Retrieved November 25, 2019, from Documentation Network and Legal Information website: http://jdih.kemendag.go.id/peraturan

Ministry of Finance of the Republic of Indonesia. (2019). Decree of the Minister of Finance of the Republic of Indonesia concerning the Designation on Export Standard Price for Export Duty Determination of Agricultural and Forestry Products in 2009-2018 (in Indonesian). Retrieved November 25, 2019, from Documentation Network and Legal Information website: https://jdih.kemenkeu.go.id/#/

Nag, A., Jha, S. K., Mohammad, A., Maiti, S., Gupta, J., Gosain, D. K., … Mohanty, T. K. (2018). Predictive factors affecting Indian rural farm youths' decisions to stay in or leave agriculture sector. *Journal of Agricultural Science and Technology*, *20*(2), 221–234.

Nogués, J. (2011). *Agricultural Export Barriers and Domestic Prices: Argentina during the last Decade*. (June), 1–49. Retrieved from http://www.ucema.edu.ar/conferencias/download/2012/06.15AN.pdf

Oni, O. A., Oladele, O. I., & Oyewole, I. K. (2005). Analysis of Factors Influencing Loan Default Among Poultry Farmers in Ogun State Nigeria. *Journal of Central European Agriculture*, *6*(4), 619–624. https://doi.org/10.5513/jcea.v6i4.344

Patterson, K. (2000). *An Introduction to Applied Econometrics: a time series approach*. London: Macmillan Press Ltd.

Pierce, J. R. (2011). Plant-level responses to antidumping duties: Evidence from U.S. manufacturers. *Journal of International Economics, 85*(2), 222–233. https://doi.org/10.1016/j.jinteco.2011.07.006

Reed, R. R. (2001). *International Trade in Agricultural Products* (1st ed.). New Jersey: Prentice Hall.

Rigby, D., & Burton, M. (2005). Preference heterogeneity and GM food in the UK. *European Review of Agricultural Economics*, *32*(2), 269–288. https://doi.org/10.1093/eurrag/jbi009

Royston, P. (1992). Approximating the Shapiro-Wilk W-test for non-normality. *Statistics and Computing*, *2*(3), 117–119. https://doi.org/10.1007/BF01891203

Sheehan, J., Camobreco, V., Duffield, J., Graboski, M., & Shapori, H. (1998). *An Overview of Biodiesel and Petroleum Diesel Life Cycles*. Retrieved from https://www.nrel.gov/docs/legosti/fy98/24772.pdf

Smith, P. L. (2018). Biodiesel From Argentina and Indonesia: Antidumping Duty Orders. *Federal Register*, *83*(81), 18278–18279. https://doi.org/10.1016/0196-335x(80)90058-8

Spearman, C. (1904). The Proof and Measurement of Association between Two Things. *The American Journal of Psychology*, *15*(1), 72–101. https://doi.org/10.1037/h0065390

Statistics Indonesia. (2018). *Export Dataset - purchased data*.

Statistics Indonesia. (2019). *Indonesian Gross Domestic Product according to Business Sector, 2014-2019*. Retrieved from https://www.bps.go.id/dynamictable/2015/05/06/826/-seri-2010-pdb-triwulanan-atas-dasar-harga-berlaku-menurut-lapangan-usaha-miliar-rupiah-2014-2019.html

Statistics Jambi Province. (2019). *The status of employment in Jambi province in August 2019*. Jambi.

Stiglbauer, A., & Weiss, C. R. (2000). Family and Non-Family Succession in the Upper-Austrian Farm Sector Family and Non-Family Succession. *Cahiers d'Economie et de Sociologie Rurales*, *54*, 6–26.

Thomson Reuters. (2019a). *Palm Oil, ID CPO Free on Board United States Dollar per Metric Tonne - Datastream*.

Thomson Reuters. (2019b). *Palm Oil Crude MAL Cost Insurance Freight Rotterdam United States Dollar per Metric Tonne - Datastream*.

Thomson Reuters. (2019c). *Rubber, Indonesia Origin Technically Specified Rubber Grade 20 New York UC/Pound - Datastream*.

Tiseo, I. (2019). Biofuels consumption for transport in the European Union (EU-28) 2015-2018. Retrieved November 13, 2019, from https://www.statista.com/statistics/613238/biofuels-consumption-transport-eu/

Trade Map. (2019). List of importing markets for a product exported by Indonesia - Biodiesel. Retrieved November 13, 2019, from https://www.trademap.org/Index.aspx

UCLA. (2020a). Lesson 3 Logistic Regression Diagnostics. Retrieved April 15, 2020, from Institute for Digital Research and Education, Statistical Consulting website: https://stats.idre.ucla.edu/stata/webbooks/logistic/chapter3/lesson-3-logistic-regression-diagnostics-2/

UCLA. (2020b). What Statistical Analysis Should I Use? Statistical Analyses Using Stata. Retrieved April 15, 2020, from Institute for Digital Research and Education, Statistical Consulting website: https://stats.idre.ucla.edu/stata/whatstat/what-statistical-analysis-should-i-usestatistical-analyses-using-stata/

UFOP. (2017, September). EU-28 Biodiesel Imports Likely to Increase Significantly. Retrieved from Biodiesel Magazine website: http://biodieselmagazine.com/articles/2516142/eu-28-biodiesel-imports-likely-to-increase-significantly

UN Comtrade. (2019). List of importing markets for a product exported by Indonesia. Retrieved November 13, 2019, from https://comtrade.un.org/data/

Waheed, M., Alam, T., & Ghauri, S. P. (2007). *Structural breaks and unit root : evidence from Pakistani macroeconomic time series*. Retrieved from https://mpra.ub.uni-muenchen.de/1797/1/mpra_paper_1797.pdf?origin=publication_detail

Warner, S. L. (1965). Randomized Response : A Survey Technique for Eliminating Evasive Answer Bias. *Journal of the American Statistical Association*, *60*(309), 63–69.

Weiss, C. R. (1997). Do they come back again? The symmetry and reversibility of off-farm employment. *European Review of Agricultural Economics*, *24*(1), 65–84. https://doi.org/10.1093/erae/24.1.65

Wilcoxon, F. (1947). Probability Tables for Individual Comparisons by Ranking Methods. *Biometrics*, *3*(3), 119–122.

Wooldridge, J. M. (2013). *Introductory Econometrics A Modern Approach* (5th ed.). South-Western, Cengage Learning.

World Trade Organization. *Article VI Anti-dumping and Countervailing Duties*. , Pub. L. No. The General Agreement on Tariffs and Trade (GATT), 219 (1994).

World Trade Organization. (2018). European Union – Anti-Dumping Measures on Biodiesel from Indonesia. In *WTO Report of the Panel*. https://doi.org/10.1017/s1474745617000106

World Trade Organization. (2019). *Anti-dumping Initiations: By Reporting Member 01/01/1995 - 31/12/2018*. Retrieved from https://www.wto.org/english/tratop_e/adp_e/AD_InitiationsByRepMem.pdf

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, *10*(3), 251–270. https://doi.org/10.1080/07350015.1992.10509904

Zúñiga-Arias, G. E. (2007). *Quality management and strategic alliances in the mango supply chain from Costa Rica* (Wageningen University). Retrieved from https://edepot.wur.nl/2476

Appendices

Appendix 2. 1 Unit Root Tests

Price Variables	ADF test		PP test		ZA test			
					Level		1st Diff	
	Level	1st Diff	Level	1st Diff	Break	Min t-stat	Break	Min t-stat
lnP_W	-0.910	-19.744***	-0.812	-19.767***	21Jan16	-4.206	3Sep15	-20.145***
lnP_{ID}	-0.499	-16.992***	-0.836	-17.090***	28Jan16	-4.051	3Sep15	-17.560***
lnP_{JB}	-0.201	-12.300***	-1.195	-12.383***	4Feb16	-3.574	10Sep15	-9.339***

Note: ADF dan PP (Z(t)) test Critical Values: 1%: -3.450, 5%: -2.875, 10%: -2.570; ZA test Critical Values: 1%: -5.34, 5%: -4.80, 10%: 4.58 via TTest

Appendix 2. 2 Johansen Cointegration Test between Indonesian and World CPO Prices

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	66.344	15.410	20.040	66.086	14.070	18.630
1	0.163	**0.258****	3.760	6.65	**0.258**	3.760	6.650
2	0.001						

Note: lags=1

Appendix 2. 3 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	32.379	15.410	20.040	31.765	14.070	18.630
1	0.082	**0.614****	3.760	6.65	**0.614**	3.760	6.650
2	0.002						

Note: Lags = 1

Appendix 2. 4 Gregory-Hansen Cointegration Test between Indonesian and World CPO Prices

GH Test	Test Statistics	Breakpoint	Asymptotic Critical Value		
			1%	5%	10%
Model: Change in Level (lags = 1, AIC & BIC)					
ADF	-7.57***	Feb 20, 2014	-5.13	-4.61	-4.34
Zt	-9.30***	Jan 02, 2014	-5.13	-4.61	-4.34
Za	-147.38***	Jan 02, 2014	-50.07	-40.48	-36.19
Model: Change in Regime (lags = 1, AIC)					
ADF	-7.94***	Jan 16, 2014	-5.47	-4.95	-4.68
Zt	-9.72***	Dec 19, 1013	-5.47	-4.95	-4.68
Za	-157.73***	Dec 19, 1013	-57.17	-47.04	-41.85

Appendix 2. 5 Gregory-Hansen Cointegration Test between Jambi FFB and Indonesian CPO Prices

GH Test	Test Statistics	Breakpoint	Asymptotic Critical Value		
			1%	5%	10%
Model: Change in Level (lags = 1, BIC)					
ADF	-5.93***	Oct 21, 2013	-5.13	-4.61	-4.34
Zt	-6.56***	Dec 19, 1013	-5.13	-4.61	-4.34
Za	-83.18***	Dec 19, 1013	-50.07	-40.48	-36.19
Model: Change in Regime (lags = 1, BIC)					
ADF	-6.51***	Dec 26, 1013	-5.47	-4.95	-4.68
Zt	-7.30***	Dec 19, 1013	-5.47	-4.95	-4.68
Za	-97.25***	Dec 19, 1013	-57.17	-47.04	-41.85

Appendix 2. 6 Johansen Cointegration Test between Indonesian and World CPO Prices before the Breakpoint

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	66.697	15.410	20.040	66.214	14.070	18.630
1	0.228	**0.484****	3.760	6.65	**0.484**	3.760	6.650
2	0.002						

Note: lags=1

Appendix 2. 7 Johansen Cointegration Test between Indonesian and World CPO Prices after the Breakpoint

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	31.456	15.410	20.040	30.205	14.070	18.630
1	0.146	**1.251****	3.760	6.65	**1.251**	3.760	6.650
2	0.005						

Note: lags=1

Appendix 2. 8 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices before the Breakpoint

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	75.732	15.410	20.040	74.730	14.070	18.630
1	0.082	**1.002****	3.760	6.65	**1.002**	3.760	6.650
2	0.002						

Note: Lags = 1

Appendix 2. 9 Johansen Cointegration Test between Jambi FFB and Indonesian CPO Prices after the Breakpoint

Max Rank	Eigenvalue	Trace statistics	Critical Values		Max Statistics	Critical Values	
			5%	1%		5%	1%
0	.	**17.954***	15.410	20.040	16.940	14.070	18.630
1	0.082	**1.015****	3.760	6.65	**1.015**	3.760	6.650
2	0.002						

Note: Lags = 1

Appendix 2. 10. VECM Estimation between Indonesian and World CPO Prices

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2018-12-05 (T = 371)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_ID	1.0000
	(0.00000)
lnP_W	-1.0179
	(0.019549)
const	0.058648
	(0.0066206)

alpha (adjustment vectors)

lnP_ID	-0.062430
lnP_W	0.18768

Log-likelihood = 1768.6987
Determinant of covariance matrix = 2.4783124e-007
AIC = -9.4916
BIC = -9.4072
HQC = -9.4581

Equation 1: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
d_lnP_ID_1	0.0678890	0.0877177	0.7739	0.4395
d_lnP_W_1	0.0682527	0.0789647	0.8643	0.3880
EC1	−0.0624297	0.0611156	−1.022	0.3077

Mean dependent var	−0.002030	S.D. dependent var	0.027859
Sum squared resid	0.281688	S.E. of regression	0.027705
R-squared	0.024262	Adjusted R-squared	0.016286
rho	−0.007055	Durbin-Watson	2.010929

Equation 2: d_lnP_W

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_ID_1	0.230024	0.0995170	2.311	0.0214	**
d_lnP_W_1	−0.150547	0.0895866	−1.680	0.0937	*
EC1	0.187677	0.0693365	2.707	0.0071	***

Mean dependent var	−0.001994	S.D. dependent var	0.032059
Sum squared resid	0.362567	S.E. of regression	0.031431
R-squared	0.050246	Adjusted R-squared	0.042482
rho	−0.013784	Durbin-Watson	2.019377

Cross-equation covariance matrix:

	lnP_ID	lnP_W
lnP_ID	0.00075927	0.00070298
lnP_W	0.00070298	0.00097727

determinant = 2.47831e-007

Appendix 2. 11 VECM Estimation between Indonesian and World CPO Prices allowing Structural Break

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2018-12-05 (T = 371)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_ID	1.0000
	(0.00000)
lnP_W	-1.3667
	(0.032649)
const	0.045589
	(0.0048494)
SB	0.011194
	(0.0090282)
SBxlnP_W	0.36334
	(0.036856)

alpha (adjustment vectors)

lnP_ID	0.23468
lnP_W	0.53378

Log-likelihood = 1811.8278
Determinant of covariance matrix = 1.9641815e-007
AIC = -9.7241
BIC = -9.6397
HQC = -9.6906

Equation 1: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_ID_1	−0.0947447	0.0850806	−1.114	0.2662	
d_lnP_W_1	0.242923	0.0764682	3.177	0.0016	***
EC1	0.234683	0.0496388	4.728	<0.0001	***

Mean dependent var	−0.002030	S.D. dependent var	0.027859
Sum squared resid	0.266230	S.E. of regression	0.026970
R-squared	0.077807	Adjusted R-squared	0.067728
rho	0.033346	Durbin-Watson	1.931993

Equation 2: d_lnP_W

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_ID_1	0.0203581	0.0881360	0.2310	0.8175	
d_lnP_W_1	0.0746029	0.0792143	0.9418	0.3469	
EC1	0.533776	0.0514214	10.38	<0.0001	***

Mean dependent var	−0.001994	S.D. dependent var	0.032059
Sum squared resid	0.285694	S.E. of regression	0.027939
R-squared	0.251615	Adjusted R-squared	0.243436
rho	0.131929	Durbin-Watson	1.730852

Cross-equation covariance matrix:

	lnP_ID	lnP_W
lnP_ID	0.00071760	0.00059681
lnP_W	0.00059681	0.00077007

determinant = 1.96418e-007

Appendix 2. 12 VECM Estimation between Indonesian and World CPO Prices before the Breakpoint

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2014-01-01 (T = 114)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_ID	1.0000
	(0.00000)
lnP_W	-1.1660
	(0.029409)
const	0.060600
	(0.0041074)

alpha (adjustment vectors)

lnP_ID	0.082717
lnP_W	0.39578

Log-likelihood = 583.80093
Determinant of covariance matrix = 1.2216715e-007
AIC = -10.1018
BIC = -9.9098
HQC = -10.0238

Equation 1: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_ID_1	−0.108847	0.218097	−0.4991	0.6187	
d_lnP_W_1	0.161486	0.228673	0.7062	0.4816	
EC1	0.0827171	0.189608	0.4363	0.6635	

Mean dependent var	−0.001045	S.D. dependent var	0.029274
Sum squared resid	0.096425	S.E. of regression	0.029607
R-squared	0.005509	Adjusted R-squared	-0.021614
rho	0.004652	Durbin-Watson	1.982445

Equation 2: d_lnP_W

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_ID_1	0.0724771	0.209683	0.3457	0.7303	
d_lnP_W_1	−0.0464685	0.219851	−0.2114	0.8330	
EC1	0.395777	0.182293	2.171	0.0321	**

Mean dependent var	−0.001089	S.D. dependent var	0.028930
Sum squared resid	0.089128	S.E. of regression	0.028465
R-squared	0.058918	Adjusted R-squared	0.033253
rho	−0.006070	Durbin-Watson	1.991635

Cross-equation covariance matrix:

	lnP_ID	lnP_W
lnP_ID	0.00084583	0.00073425
lnP_W	0.00073425	0.00078183

determinant = 1.22167e-007

Appendix 2. 13 VECM Estimation between Indonesian and World CPO Prices after the Breakpoint

VECM system, lag order 2
Maximum likelihood estimates, observations 2014-01-22-2018-12-05 (T = 255)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

P_ID	1.0000
	(0.00000)
P_W	-0.99705
	(0.021038)
const	0.037280
	(0.014820)

alpha (adjustment vectors)

P_ID	-0.018372
P_W	0.37791

Log-likelihood = 1415.2962
Determinant of covariance matrix = 5.1787548e-008
AIC = -11.0376
BIC = -10.9265
HQC = -10.9929

Equation 1: d_P_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_P_ID_1	0.0597548	0.0995838	0.6000	0.5490	
d_P_W_1	0.0996565	0.0817413	1.219	0.2239	
EC1	−0.0183715	0.0769050	−0.2389	0.8114	

Mean dependent var	−0.001564	S.D. dependent var	0.017447
Sum squared resid	0.075347	S.E. of regression	0.017326
R-squared	0.033224	Adjusted R-squared	0.021669
rho	−0.006639	Durbin-Watson	2.002533

Equation 2: d_P_W

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_P_ID_1	0.160427	0.125197	1.281	0.2012	
d_P_W_1	−0.0170034	0.102765	−0.1655	0.8687	
EC1	0.377912	0.0966851	3.909	0.0001	***

Mean dependent var	−0.001647	S.D. dependent var	0.022589
Sum squared resid	0.119091	S.E. of regression	0.021782
R-squared	0.086014	Adjusted R-squared	0.075090
rho	−0.004889	Durbin-Watson	1.997934

Cross-equation covariance matrix:

	P_ID	P_W
P_ID	0.00029548	0.00029361
P_W	0.00029361	0.00046702

determinant = 5.17875e-008

Appendix 2. 14 VECM Estimation between Jambi FFB and Indonesian CPO prices

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2018-12-05 (T = 371)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_JB	1.0000
	(0.00000)
lnP_ID	-1.3558
	(0.063101)
const	1.4346
	(0.032321)
ET	1.7910
	(0.22217)
TL	0.022204
	(0.016798)

alpha (adjustment vectors)

lnP_JB	-0.15886
lnP_ID	0.020219

Log-likelihood = 1745.9297
Determinant of covariance matrix = 2.8019667e-007
AIC = -9.3689
BIC = -9.2844
HQC = -9.3354

Equation 1: d_lnP_JB

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.177914	0.0408673	4.353	<0.0001	***
d_lnP_ID_1	0.440617	0.0526689	8.366	<0.0001	***
EC1	−0.158856	0.0285240	−5.569	<0.0001	***

Mean dependent var	−0.001851	S.D. dependent var	0.029854
Sum squared resid	0.169197	S.E. of regression	0.021501
R-squared	0.488879	Adjusted R-squared	0.483293
rho	−0.142773	Durbin-Watson	2.283819

Equation 2: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.110650	0.0526172	2.103	0.0362	**
d_lnP_ID_1	0.102648	0.0678119	1.514	0.1310	
EC1	0.0202186	0.0367250	0.5505	0.5823	

Mean dependent var	−0.002030	S.D. dependent var	0.027859
Sum squared resid	0.280476	S.E. of regression	0.027683
R-squared	0.028458	Adjusted R-squared	0.017840
rho	−0.008245	Durbin-Watson	2.014206

Cross-equation covariance matrix:

	lnP_JB	lnP_ID
lnP_JB	0.00045606	0.00025413
lnP_ID	0.00025413	0.00075600

determinant = 2.80197e-007

Appendix 2. 15 VECM Estimation between Jambi FFB and Indonesian CPO allowing Structural Break

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2018-12-05 (T = 371)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_JB	1.0000
	(0.00000)
lnP_ID	-1.4356
	(0.062597)
const	1.4839
	(0.025909)
ET	1.4846
	(0.15469)
TL	0.042258
	(0.010304)
SB	-0.065405
	(0.018591)
SBx lnP_ID	0.090191
	(0.056691)

alpha (adjustment vectors)

lnP_JB	-0.22305
lnP_ID	0.12994

Log-likelihood = 1761.7651
Determinant of covariance matrix = 2.5726986e-007
AIC = -9.4543
BIC = -9.3698
HQC = -9.4207

Equation 1: d_lnP_JB

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.187357	0.0405341	4.622	<0.0001	***
d_lnP_ID_1	0.382961	0.0567833	6.744	<0.0001	***
EC1	−0.223049	0.0368110	−6.059	<0.0001	***

Mean dependent var	−0.001851	S.D. dependent var	0.029854
Sum squared resid	0.166761	S.E. of regression	0.021375
R-squared	0.496237	Adjusted R-squared	0.489337
rho	−0.125469	Durbin-Watson	2.249512

Equation 2: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.112848	0.0520537	2.168	0.0308	**
d_lnP_ID_1	0.211365	0.0729209	2.899	0.0040	***
EC1	0.129943	0.0472726	2.749	0.0063	***

Mean dependent var	−0.002030	S.D. dependent var	0.027859
Sum squared resid	0.275015	S.E. of regression	0.027449
R-squared	0.047374	Adjusted R-squared	0.034324
rho	−0.014566	Durbin-Watson	2.027326

Cross-equation covariance matrix:

	lnP_JB	lnP_ID
lnP_JB	0.00044949	0.00027555
lnP_ID	0.00027555	0.00074128

determinant = 2.5727e-007

Appendix 2. 16 VECM Estimation between Jambi FFB and Indonesian CPO before the Breakpoint

VECM system, lag order 2
Maximum likelihood estimates, observations 2011-11-02-2014-01-01 (T = 114)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_JB	1.0000
	(0.00000)
lnP_ID	-1.3186
	(0.11053)
const	1.5235
	(0.051871)
ET	1.2885
	(0.31794)

alpha (adjustment vectors)

lnP_JB	-0.21157
lnP_ID	0.15544

Log-likelihood = 535.81993
Determinant of covariance matrix = 2.8348578e-007
AIC = -9.2600
BIC = -9.0680
HQC = -9.1821

Equation 1: d_lnP_JB

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.191262	0.0789317	2.423	0.0170	**
d_lnP_ID_1	0.263705	0.0962188	2.741	0.0072	***
EC1	−0.211573	0.0679147	−3.115	0.0023	***

Mean dependent var	0.000367	S.D. dependent var	0.027960
Sum squared resid	0.055390	S.E. of regression	0.022440
R-squared	0.373086	Adjusted R-squared	0.355988
rho	−0.069435	Durbin-Watson	2.133894

Equation 2: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.214220	0.100875	2.124	0.0359	**
d_lnP_ID_1	0.0813139	0.122968	0.6613	0.5098	
EC1	0.155437	0.0867956	1.791	0.0761	*

Mean dependent var	−0.001045	S.D. dependent var	0.029274
Sum squared resid	0.090469	S.E. of regression	0.028678
R-squared	0.066935	Adjusted R-squared	0.041487
rho	−0.009036	Durbin-Watson	2.002806

Cross-equation covariance matrix:

	lnP_JB	lnP_ID
lnP_JB	0.00048588	0.00031953
lnP_ID	0.00031953	0.00079359

determinant = 2.83486e-007

Appendix 2. 17 VECM Estimation between Jambi FFB and Indonesian CPO after the Breakpoint

VECM system, lag order 2
Maximum likelihood estimates, observations 2014-01-22-2018-12-05 (T = 255)
Cointegration rank = 1
Case 2: Restricted constant
beta (cointegrating vectors, standard errors in parentheses)

lnP_JB	1.0000
	(0.00000)
lnP_ID	-1.3512
	(0.037368)
const	1.4216
	(0.019997)
ET	1.3963
	(0.18839)
TL	0.036912
	(0.010764)

alpha (adjustment vectors)

lnP_JB	-0.26788
lnP_ID	0.038235

Log-likelihood = 1220.6718
Determinant of covariance matrix = 2.3832027e-007
AIC = -9.5112
BIC = -9.4001
HQC = -9.4665

Equation 1: d_lnP_JB

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.184076	0.0457755	4.021	<0.0001	***
d_lnP_ID_1	0.410339	0.0689450	5.952	<0.0001	***
EC1	−0.267875	0.0438832	−6.104	<0.0001	***

Mean dependent var	−0.002869	S.D. dependent var	0.030774
Sum squared resid	0.103071	S.E. of regression	0.020305
R-squared	0.575223	Adjusted R-squared	0.568426
rho	−0.138180	Durbin-Watson	2.275964

Equation 2: d_lnP_ID

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
d_lnP_JB_1	0.0622092	0.0612367	1.016	0.3107	
d_lnP_ID_1	0.191260	0.0922318	2.074	0.0391	**
EC1	0.0382349	0.0587052	0.6513	0.5154	

Mean dependent var	−0.002551	S.D. dependent var	0.027345
Sum squared resid	0.184455	S.E. of regression	0.027163
R-squared	0.037259	Adjusted R-squared	0.021855
rho	−0.010216	Durbin-Watson	2.011778

Cross-equation covariance matrix:

	lnP_JB	lnP_ID
lnP_JB	0.00040420	0.00023250
lnP_ID	0.00023250	0.00072335

determinant = 2.3832e-007

Appendix 3. 1 Name of Regencies, Districts and Villages of Survey Location

Regencies	Districts	Villages
1. SAROLANGUN	1. Pelawan	1. Pematang Kolim 2. Batu Putih
	2. Singkut	1. Bukit Murau 2. Payo Lebar
	3. Pauh	1. Pauh 2. Semaran 3. Danau Serdang
	4. Air Hitam	1. Baru 2. Pematang Kabau
2. BATANGHARI	1. Bathin XXIV	1. Simpang Karmeo 2. Jangga
	2. Muara Bulian	1. Sridadi 2. Simpang Terusan
	3. Bajubang	1. Bungku
	4. Maro Sebo Ilir	1. Bulian Jaya 2. Bukit Sari
	5. Pemayung	1. Pulau Raman
3. MUARO JAMBI	1. Sungai Bahar	1. Mulya Jaya
	2. Kumpeh Ulu	1. Tarikan
	3. Sungai Gelam	1. Ladang Panjang 2. Parit
	4. Maro Sebo	1. Tanjung Katung
4. TEBO	1. Sumay	1. Teriti 2. Muara Sekalo
	2. Rimbo Ilir	1. Giriwinangun 2. Sepakat Bersatu
	3. Tebo Ulu	1. Pulau Panjang 2. Rantau Langkap
	4. VII Koto	1. Aur Cino
	5. Rimbo Ulu	1. Sumber Sari
5. BUNGO	1. Pelepat Ilir	1. Muara Kuamang 2. Maju Jaya
	2. Bathin III Ulu	1. Lubuk Beringin 2. Laman Panjang
	3. Muko Muko Bathin VII	1. Tebing Tinggi 2. Tanjung Agung
	4. Tanah Sepenggal	1. Teluk Pandak 2. Tenam

Appendix 3. 2 Stata Output of Variable Descriptive Statistics Year 2012

```
. sum tp edu exp func info stat num cred land vehic comp smph supp com trans trrev loc
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tp	295	.7186441	.4504248	0	1
edu	295	.9457627	.2268702	0	1
exp	295	8.872881	8.054551	1	47
func	295	.2	.4006797	0	1
info	295	.6169492	.4869566	0	1
stat	295	.7762712	.4174505	0	1
num	295	6.027119	6.064221	0	35
cred	295	.7152542	.4520601	0	1
land	295	11.28534	15.00797	0	95
vehic	295	.8237288	.3816982	0	1
comp	295	.2983051	.4582915	0	1
smph	295	.1864407	.3901237	0	1
supp	295	34.09492	34.48846	2	250
com	295	11.68814	5.289352	0	21
trans	295	.1728814	.3787872	0	1
trrev	295	12.38375	20.25782	.3	150
loc	295	64.67458	29.39114	4	155

Appendix 3. 3 Stata Output of Variable Descriptive Statistics Year 2015

```
. sum tp edu exp func info stat num cred land vehic comp smph supp com trans trrev loc
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tp	293	.7167235	.4513604	0	1
edu	292	.8561644	.3515254	0	1
exp	292	10.22432	7.139397	1	39
func	292	.1472603	.3549735	0	1
info	292	.3287671	.4705716	0	1
stat	292	.260274	.4395373	0	1
num	293	4.003413	4.068336	0	32
cred	292	.7842466	.4120502	0	1
land	293	10.33993	12.51335	0	100
vehic	292	.8458904	.3616736	0	1
comp	292	.0787671	.2698374	0	1
smph	292	.1575342	.3649291	0	1
supp	292	30.65753	31.15033	3	250
com	292	10.57534	5.184348	0	21
trans	292	.1986301	.3996539	0	1
trrev	292	6.159683	9.220843	.15	80
loc	292	67.13014	27.65305	4	155

Appendix 3. 4 Stata Output of Variable Descriptive Statistics Year 2018

```
. sum tp edu exp func info stat num cred land vehic comp smph supp com trans trrev loc
```

Variable	Obs	Mean	Std. Dev.	Min	Max
tp	325	.6430769	.4798306	0	1
edu	325	.9107692	.2855161	0	1
exp	325	10.52154	6.797977	1	38
func	325	.08	.2717115	0	1
info	325	.6215385	.4857514	0	1
stat	325	.3261538	.4695273	0	1
num	325	4.901538	4.8096	0	34
cred	325	.8369231	.3700055	0	1
land	325	9.771415	10.7516	0	70
vehic	325	.8738462	.3325347	0	1
comp	325	.16	.3671714	0	1
smph	325	.4523077	.4984877	0	1
supp	325	38.60308	45.32468	3	325
com	325	11.72	5.606302	0	25
trans	325	.1384615	.3459163	0	1
trrev	325	12.0911	19.48656	.2	160
loc	325	66.28923	25.67898	4	155

Appendix 3. 5 Stata Output of Logit Estimation Year 2012

```
. logit remain i.tp i.edu exp i.func i.info i.stat num i.cred land i.vehic i.comp
>  i.smph supp com i.trans trrev loc

Iteration 0:   log likelihood = -204.39536
Iteration 1:   log likelihood = -173.67216
Iteration 2:   log likelihood = -173.53673
Iteration 3:   log likelihood = -173.53656
Iteration 4:   log likelihood = -173.53656

Logistic regression                               Number of obs     =        295
                                                  LR chi2(17)       =      61.72
                                                  Prob > chi2       =     0.0000
Log likelihood = -173.53656                       Pseudo R2         =     0.1510
```

remain	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.tp	.8131209	.3137939	2.59	0.010	.1980962	1.428146
1.edu	-1.110443	.6432386	-1.73	0.084	-2.371168	.1502812
exp	-.0080335	.0181582	-0.44	0.658	-.043623	.0275559
1.func	-.4094667	.3370509	-1.21	0.224	-1.070074	.2511409
1.info	-.1065286	.2804224	-0.38	0.704	-.6561464	.4430892
1.stat	.6028337	.3381714	1.78	0.075	-.05997	1.265637
num	.0122727	.0268905	0.46	0.648	-.0404318	.0649771
1.cred	-1.726172	.3279802	-5.26	0.000	-2.369001	-1.083343
land	.0046163	.0105949	0.44	0.663	-.0161492	.0253819
1.vehic	.0714405	.3663748	0.19	0.845	-.6466409	.7895219
1.comp	-.3666151	.3013363	-1.22	0.224	-.9572234	.2239931
1.smph	.0327894	.3476114	0.09	0.925	-.6485165	.7140953
supp	.0017558	.0039365	0.45	0.656	-.0059595	.0094711
com	-.0000885	.0260642	-0.00	0.997	-.0511734	.0509964
1.trans	.8341763	.3574204	2.33	0.020	.1336452	1.534707
trrev	-.0117783	.007595	-1.55	0.121	-.0266642	.0031077
loc	-.0002076	.0047592	-0.04	0.965	-.0095355	.0091204
_cons	1.394381	.9084701	1.53	0.125	-.3861874	3.17495

Appendix 3. 6 Stata Output of Marginal Effect Estimation Year 2012

```
. margin, dydx(*)

Average marginal effects                        Number of obs     =        295
Model VCE    : OIM

Expression   : Pr(remain), predict()
dy/dx w.r.t. : 1.tp 1.edu exp 1.func 1.info 1.stat num 1.cred land 1.vehic
               1.comp 1.smph supp com 1.trans trrev loc
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.tp	.1667961	.0629113	2.65	0.008	.0434922	.2900999
1.edu	-.2150113	.1119647	-1.92	0.055	-.434458	.0044354
exp	-.0016187	.0036545	-0.44	0.658	-.0087814	.005544
1.func	-.0826901	.0675675	-1.22	0.221	-.2151199	.0497398
1.info	-.0215217	.0567604	-0.38	0.705	-.13277	.0897265
1.stat	.1212588	.0664524	1.82	0.068	-.0089854	.2515031
num	.0024728	.0054124	0.46	0.648	-.0081352	.0130809
1.cred	-.3564509	.0573524	-6.22	0.000	-.4688595	-.2440422
land	.0009302	.0021323	0.44	0.663	-.003249	.0051093
1.vehic	.0143873	.0737221	0.20	0.845	-.1301054	.1588799
1.comp	-.0744092	.0610855	-1.22	0.223	-.1941346	.0453163
1.smph	.0066041	.0699823	0.09	0.925	-.1305586	.1437668
supp	.0003538	.0007923	0.45	0.655	-.001199	.0019066
com	-.0000178	.0052517	-0.00	0.997	-.010311	.0102754
1.trans	.1676354	.0688033	2.44	0.015	.0327835	.3024873
trrev	-.0023732	.0015101	-1.57	0.116	-.0053329	.0005864
loc	-.0000418	.0009589	-0.04	0.965	-.0019213	.0018377

Note: dy/dx for factor levels is the discrete change from the base level.

Appendix 3. 7 Stata Output of Logit Estimation Year 2015

```
. logit remain i.tp i.edu exp i.func i.info i.stat num i.cred land i.vehic i.comp
>  i.smph supp com i.trans trrev loc

Iteration 0:   log likelihood = -178.70999
Iteration 1:   log likelihood = -158.60336
Iteration 2:   log likelihood =  -157.6246
Iteration 3:   log likelihood = -157.61431
Iteration 4:   log likelihood =  -157.6143

Logistic regression                             Number of obs     =        292
                                                LR chi2(17)       =      42.19
                                                Prob > chi2       =     0.0006
Log likelihood =  -157.6143                     Pseudo R2         =     0.1180
```

remain	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.tp	.7210577	.3368864	2.14	0.032	.0607724	1.381343
1.edu	-.7833169	.45212	-1.73	0.083	-1.669456	.1028221
exp	.043068	.0237277	1.82	0.070	-.0034374	.0895733
1.func	.5399779	.4343338	1.24	0.214	-.3113007	1.391257
1.info	.0920677	.3064726	0.30	0.764	-.5086077	.692743
1.stat	.4390833	.3627313	1.21	0.226	-.271857	1.150024
num	.00742	.0415288	0.18	0.858	-.0739748	.0888149
1.cred	.7516832	.3335158	2.25	0.024	.0980043	1.405362
land	-.0394647	.0128783	-3.06	0.002	-.0647057	-.0142237
1.vehic	.7971226	.3807064	2.09	0.036	.0509518	1.543293
1.comp	-.6330536	.4886475	-1.30	0.195	-1.590785	.3246779
1.smph	-.1504273	.3943546	-0.38	0.703	-.9233481	.6224935
supp	.0001396	.005962	0.02	0.981	-.0115456	.0118249
com	-.0482794	.0281207	-1.72	0.086	-.103395	.0068362
1.trans	.0440653	.3595999	0.12	0.902	-.6607377	.7488682
trrev	.053066	.027339	1.94	0.052	-.0005175	.1066494
loc	.0018053	.0052247	0.35	0.730	-.0084349	.0120455
_cons	-.2708329	.8076663	-0.34	0.737	-1.85383	1.312164

Appendix 3. 8 Stata Output of Marginal Effect Estimation Year 2015

```
. margin, dydx(*)

Average marginal effects                        Number of obs     =        292
Model VCE    : OIM

Expression   : Pr(remain), predict()
dy/dx w.r.t. : 1.tp 1.edu exp 1.func 1.info 1.stat num 1.cred land 1.vehic
               1.comp 1.smph supp com 1.trans trrev loc
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.tp	.1351579	.0635813	2.13	0.034	.0105408	.2597749
1.edu	-.1282899	.0648282	-1.98	0.048	-.2553508	-.001229
exp	.0077974	.0042191	1.85	0.065	-.0004718	.0160666
1.func	.0918167	.0682762	1.34	0.179	-.0420021	.2256355
1.info	.0165978	.0549871	0.30	0.763	-.0911748	.1243705
1.stat	.077089	.0610766	1.26	0.207	-.0426189	.196797
num	.0013434	.0075172	0.18	0.858	-.0133901	.0160769
1.cred	.1468276	.0678224	2.16	0.030	.0138981	.2797572
land	-.007145	.0021976	-3.25	0.001	-.0114522	-.0028379
1.vehic	.1572627	.0787475	2.00	0.046	.0029205	.3116049
1.comp	-.1228838	.0993739	-1.24	0.216	-.317653	.0718853
1.smph	-.0276224	.0733514	-0.38	0.706	-.1713885	.1161437
supp	.0000253	.0010794	0.02	0.981	-.0020903	.0021409
com	-.0087409	.0050068	-1.75	0.081	-.0185541	.0010722
1.trans	.0079459	.0645757	0.12	0.902	-.1186202	.134512
trrev	.0096075	.0048551	1.98	0.048	.0000917	.0191233
loc	.0003268	.0009453	0.35	0.730	-.0015259	.0021796

Note: dy/dx for factor levels is the discrete change from the base level.

Appendix 3. 9 Stata Output of Specification Error Year 2012

```
. linktest

Iteration 0:   log likelihood = -204.39536
Iteration 1:   log likelihood = -172.81972
Iteration 2:   log likelihood =  -172.3811
Iteration 3:   log likelihood = -172.38062
Iteration 4:   log likelihood = -172.38062

Logistic regression                               Number of obs     =        295
                                                  LR chi2(2)        =      64.03
                                                  Prob > chi2       =     0.0000
Log likelihood = -172.38062                       Pseudo R2         =     0.1566
```

remain	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.9852397	.1461047	6.74	0.000	.6988797	1.2716
_hatsq	.1870438	.1225771	1.53	0.127	-.053203	.4272906
_cons	-.1491667	.1627824	-0.92	0.359	-.4682144	.169881

Appendix 3. 10 Stata Output of Specification Error Year 2015

```
. linktest

Iteration 0:   log likelihood = -178.70999
Iteration 1:   log likelihood = -157.20941
Iteration 2:   log likelihood = -156.82042
Iteration 3:   log likelihood =  -156.8169
Iteration 4:   log likelihood =  -156.8169

Logistic regression                               Number of obs     =        292
                                                  LR chi2(2)        =      43.79
                                                  Prob > chi2       =     0.0000
Log likelihood =  -156.8169                       Pseudo R2         =     0.1225
```

remain	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	1.24622	.265599	4.69	0.000	.7256556	1.766785
_hatsq	-.1493225	.1069492	-1.40	0.163	-.3589391	.0602941
_cons	-.0035206	.1915014	-0.02	0.985	-.3788564	.3718152

Appendix 3. 11 Stata Output of Collinearity Diagnostics Year 2012

```
. collin tp edu exp func info stat num cred land vehic comp smph supp com trans trrev loc
(obs=295)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
        tp      1.14    1.07    0.8741      0.1259
       edu      1.05    1.03    0.9504      0.0496
       exp      1.34    1.16    0.7488      0.2512
      func      1.08    1.04    0.9302      0.0698
      info      1.11    1.05    0.9012      0.0988
      stat      1.12    1.06    0.8966      0.1034
       num      1.49    1.22    0.6712      0.3288
      cred      1.14    1.07    0.8766      0.1234
      land      1.58    1.26    0.6343      0.3657
     vehic      1.15    1.07    0.8720      0.1280
      comp      1.12    1.06    0.8931      0.1069
      smph      1.13    1.06    0.8873      0.1127
      supp      1.16    1.08    0.8620      0.1380
       com      1.11    1.05    0.9024      0.0976
     trans      1.12    1.06    0.8903      0.1097
     trrev      1.11    1.06    0.8969      0.1031
       loc      1.12    1.06    0.8939      0.1061
----------------------------------------------------
  Mean VIF      1.18

                           Cond
        Eigenval          Index
---------------------------------
    1    10.7564          1.0000
    2     1.1291          3.0865
    3     0.9862          3.3026
    4     0.7236          3.8554
    5     0.7099          3.8925
    6     0.6305          4.1305
    7     0.5975          4.2429
    8     0.4563          4.8555
    9     0.3606          5.4616
    10     0.3248          5.7551
    11     0.2923          6.0666
    12     0.2821          6.1747
    13     0.1978          7.3748
    14     0.1733          7.8776
    15     0.1660          8.0506
    16     0.1296          9.1099
    17     0.0657         12.7930
    18     0.0184         24.1701
---------------------------------
 Condition Number        24.1701
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)    0.2394
```

Appendix 3. 12 Stata Output of Collinearity Diagnostics Year 2015

```
. collin tp edu exp func info stat num cred land vehic comp smph supp com trans trrev loc
(obs=292)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
        tp      1.20    1.10    0.8305      0.1695
       edu      1.12    1.06    0.8904      0.1096
       exp      1.31    1.14    0.7631      0.2369
      func      1.08    1.04    0.9245      0.0755
      info      1.12    1.06    0.8930      0.1070
      stat      1.16    1.08    0.8625      0.1375
       num      1.38    1.17    0.7265      0.2735
      cred      1.10    1.05    0.9090      0.0910
      land      1.32    1.15    0.7579      0.2421
     vehic      1.14    1.07    0.8782      0.1218
      comp      1.06    1.03    0.9460      0.0540
      smph      1.09    1.04    0.9169      0.0831
      supp      1.38    1.17    0.7251      0.2749
       com      1.14    1.07    0.8743      0.1257
     trans      1.09    1.04    0.9165      0.0835
     trrev      1.34    1.16    0.7481      0.2519
       loc      1.06    1.03    0.9439      0.0561
----------------------------------------------------
  Mean VIF      1.18

                           Cond
        Eigenval          Index
---------------------------------
    1     9.9544          1.0000
    2     1.0816          3.0338
    3     0.9483          3.2399
    4     0.8715          3.3797
    5     0.8431          3.4362
    6     0.7894          3.5510
    7     0.6648          3.8697
    8     0.5846          4.1265
    9     0.5116          4.4110
    10     0.3635          5.2330
    11     0.2940          5.8188
    12     0.2814          5.9479
    13     0.1995          7.0635
    14     0.1662          7.7401
    15     0.1553          8.0073
    16     0.1417          8.3803
    17     0.1250          8.9222
    18     0.0242         20.2788
---------------------------------
 Condition Number        20.2788
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)    0.2273

.
```

Appendix 3. 13 Stata Output of Wilcoxon Rank-sum (Mann-Whitney Test of Farming Revenue by Traders' Status

```
. ranksum frrev , by (stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |       66      8302.5        9768
           1 |      229     35357.5       33892
-------------+---------------------------------
    combined |      295       43660       43660

unadjusted variance   372812.00
adjustment for ties    -1396.82
                     ----------
adjusted variance     371415.18

Ho: frrev(stat==0) = frrev(stat==1)
             z =  -2.405
    Prob > |z| =   0.0162
```

Appendix 3. 14 Stata Output of Trading Revenue Summary Statistics by Remain Year 2015

```
. sum trrev if remain==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
trrev	204	6.826593	10.42516	.15	80

```
. sum trrev if remain==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
trrev	88	4.613665	5.228212	.28	30

Appendix 3. 15 Stata Output of Trading Revenue Summary Statistics Year 2012 and 2015

```
. *2012

. sum trrev
```

Variable	Obs	Mean	Std. Dev.	Min	Max
trrev	295	12.38375	20.25782	.3	150

```
. *2015

. sum trrev
```

Variable	Obs	Mean	Std. Dev.	Min	Max
trrev	292	6.159683	9.220843	.15	80

Appendix 3. 16 Wilcoxon rank-sum (Mann-Whitney) non-parametric test

```
. ranksum num, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258       44231       42054
           1 |       67        8744       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties    -5098.88
                      ----------
adjusted variance     464504.12

Ho: num(nt==0) = num(nt==1)
             z =   3.194
    Prob > |z| =   0.0014
```

```
. ranksum land, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258     44718.5       42054
           1 |       67      8256.5       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties    -1259.92
                      ----------
adjusted variance     468343.08

Ho: land(nt==0) = land(nt==1)
             z =   3.893
    Prob > |z| =   0.0001
```

```
. ranksum supp, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258       42455       42054
           1 |       67       10520       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties    -2169.70
                      ----------
adjusted variance     467433.30

Ho: supp(nt==0) = supp(nt==1)
             z =   0.587
    Prob > |z| =   0.5575
```

```
. ranksum com, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258       41840       42054
           1 |       67       11135       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties    -5390.59
                      ----------
adjusted variance     464212.41

Ho: com(nt==0) = com(nt==1)
             z =  -0.314
    Prob > |z| =   0.7535
```

```
. ranksum trrev, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258       43588       42054
           1 |       67        9387       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties     -701.70
                      ----------
adjusted variance     468901.30

Ho: trrev(nt==0) = trrev(nt==1)
             z =   2.240
    Prob > |z| =   0.0251
```

```
. ranksum loc, by (nt)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

          nt |      obs    rank sum    expected
-------------+---------------------------------
           0 |      258       42112       42054
           1 |       67       10863       10921
-------------+---------------------------------
    combined |      325       52975       52975

unadjusted variance   469603.00
adjustment for ties    -1155.11
                      ----------
adjusted variance     468447.89

Ho: loc(nt==0) = loc(nt==1)
             z =   0.085
    Prob > |z| =   0.9325
```

Appendix 3. 17 Pearson Chi2 test

```
. tab tp nt, chi2

           |          nt
        tp |         0          1 |     Total
-----------+----------------------+----------
         0 |        77         39 |       116 
         1 |       181         28 |       209 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =  18.6427   Pr = 0.000

. tab edu nt, chi2

           |          nt
       edu |         0          1 |     Total
-----------+----------------------+----------
         0 |        24          5 |        29 
         1 |       234         62 |       296 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.2215   Pr = 0.638

. tab func nt, chi2

apakah_and |
a_memiliki |
_fungsi_ja |          nt
         b |         0          1 |     Total
-----------+----------------------+----------
         0 |       237         62 |       299 
         1 |        21          5 |        26 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.0331   Pr = 0.856

. tab info nt, chi2

           |          nt
      info |         0          1 |     Total
-----------+----------------------+----------
         0 |        96         27 |       123 
         1 |       162         40 |       202 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.2158   Pr = 0.642

. tab stat nt, chi2

           |          nt
      stat |         0          1 |     Total
-----------+----------------------+----------
         0 |       172         47 |       219 
         1 |        86         20 |       106 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.2935   Pr = 0.588

. tab cred nt, chi2

apakah_and |
a_menyedia |
kan_kredit |          nt
        _k |         0          1 |     Total
-----------+----------------------+----------
         0 |        39         14 |        53 
         1 |       219         53 |       272 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   1.3016   Pr = 0.254

. tab vehic nt, chi2

           |          nt
     vehic |         0          1 |     Total
-----------+----------------------+----------
         0 |        31         10 |        41 
         1 |       227         57 |       284 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.4085   Pr = 0.523

. tab comp nt, chi2

           |          nt
      comp |         0          1 |     Total
-----------+----------------------+----------
         0 |       215         58 |       273 
         1 |        43          9 |        52 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.4139   Pr = 0.520

. tab smph nt, chi2

apakah_and |
a_memiliki |
_telepon_p |          nt
        in |         0          1 |     Total
-----------+----------------------+----------
         0 |       144         34 |       178 
         1 |       114         33 |       147 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   0.5514   Pr = 0.458

. tab trans nt, chi2

apakah_and |
a_transmig |          nt
      rasi |         0          1 |     Total
-----------+----------------------+----------
         0 |       219         61 |       280 
         1 |        39          6 |        45 
-----------+----------------------+----------
     Total |       258         67 |       325 

          Pearson chi2(1) =   1.6925   Pr = 0.193
```

Appendix 4. 1 A Choice Set

KUALITAS KURANG BAIK
(basah dan banyak kotoran)

PINJAMAN : Rp. 750,000,-

BASI : 5%

1A

KUALITAS BAIK
(kering dan bersih)

PINJAMAN : Rp. 0,-

BASI : 15%

1B

Tidak Memilih

1C

Bad Quality
(wet and lots of dirt)

Loan : 750,000 IDR

Price Reduction : 5%

1A

Good Quality
(dry and clean)

Loan : 0 IDR

Price Reduction : 15%

1B

Neither

1C

Appendix 4. 2 Descriptive Statistics of Respondents (n=210)

No	Variable	Mean	SD	Min	Max	Type	Unit
1	traded_products	1.1238	0.3302	1	2	Categoric	1= rubber 2=rubber & palm oil
2	age	45.1762	10.5632	23	75	Cont.	years
3	education	1.9857	0.3971	1	3	Categoric	1=no education 2=prim/secondary 3=under/post-grad
4	experience	12.2119	7.0327	1	38	Cont.	years
5	transmigrant	0.1442	0.3521	0	1	Categoric	yes/no
6	family_number	4.1190	1.1197	1	9	Cont.	person
7	village_function	0.0714	0.2582	0	1	Categoric	yes/no
8	trader_status	0.3429	0.4758	0	1	Categoric	yes/no
9	ownership	1.0238	0.1528	1	2	Cont.	person
10	worker_number	4.9190	5.0564	0	34	Cont.	person
11	credit_availability	0.8238	0.3819	0	1	Categoric	yes/no
12	obligation_to_sell	0.6571	0.4758	0	1	Categoric	yes/no
13	price_information	0.6286	0.4843	0	1	Categoric	yes/no
14	suppliers_number	39.8381	51.6029	3	500	Cont.	person
15	competitors_number	11.2905	4.6839	0	25	Cont.	person
16	product_source	0.8761	0.3302	0	1	Categoric	yes/no
17	land_ownership	10.4690	11.0861	0	70.0000	Cont.	ha
18	operational_vehicle	0.8333	0.3736	0	1	Categoric	yes/no
19	computer_ownership	0.1667	0.3736	0	1	Categoric	yes/no
20	smartphone_ownership	0.4333	0.4967	0	1	Categoric	yes/no
21	total_revenue	24.7000	63.0000	1.00	782.00	Cont.	million IDR
22	total_trade_revenue	12.3000	32.1000	1.00	400.00	Cont.	million IDR
23	quantity_purchased	15.3857	33.7164	0.20	300.00	Cont.	ton

Appendix 4. 3 Stata Output of Shapiro-Wilk Normality Test

```
. swilk trrev
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
trrev	210	0.30198	108.659	10.813	0.00000

```
. swilk quan
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
quan	210	0.42277	89.856	10.375	0.00000

```
. swilk num
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
num	210	0.84788	23.680	7.299	0.00000

```
. swilk supp
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
supp	210	0.55182	69.767	9.792	0.00000

```
. swilk com
```

Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
com	210	0.96838	4.922	3.676	0.00012

Appendix 4. 4 Stata Output of Wilcoxon Rank-sum (Mann-Whitney) Test by Traders' Status (left) and Credit Provision Status (right)

```
. ranksum trrev , by(stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |      138       13041       14559
           1 |       72        9114        7596
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   174708.00
adjustment for ties     -352.59
                     ----------
adjusted variance     174355.41

Ho: trrev(stat==0) = trrev(stat==1)
             z =  -3.635
    Prob > |z| =   0.0003

. ranksum quan , by(stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |      138     12479.5       14559
           1 |       72      9675.5        7596
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   174708.00
adjustment for ties     -656.29
                     ----------
adjusted variance     174051.71

Ho: quan(stat==0) = quan(stat==1)
             z =  -4.984
    Prob > |z| =   0.0000

. ranksum num , by(stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |      138     13083.5       14559
           1 |       72      9071.5        7596
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   174708.00
adjustment for ties    -2011.76
                     ----------
adjusted variance     172696.24

Ho: num(stat==0) = num(stat==1)
             z =  -3.551
    Prob > |z| =   0.0004

. ranksum supp , by(stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |      138     12459.5       14559
           1 |       72      9695.5        7596
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   174708.00
adjustment for ties     -811.36
                     ----------
adjusted variance     173896.64

Ho: supp(stat==0) = supp(stat==1)
             z =  -5.035
    Prob > |z| =   0.0000

. ranksum com , by(stat)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        stat |      obs    rank sum    expected
-------------+---------------------------------
           0 |      138     15792.5       14559
           1 |       72      6362.5        7596
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   174708.00
adjustment for ties    -3982.44
                     ----------
adjusted variance     170725.56

Ho: com(stat==0) = com(stat==1)
             z =   2.985
    Prob > |z| =   0.0028
```

```
. ranksum trrev , by(cred)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        cred |      obs    rank sum    expected
-------------+---------------------------------
           0 |       37      3612.5      3903.5
           1 |      173     18542.5     18251.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   112550.92
adjustment for ties     -227.15
                     ----------
adjusted variance     112323.77

Ho: trrev(cred==0) = trrev(cred==1)
             z =  -0.868
    Prob > |z| =   0.3852

. ranksum quan , by(cred)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        cred |      obs    rank sum    expected
-------------+---------------------------------
           0 |       37        3501      3903.5
           1 |      173       18654     18251.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   112550.92
adjustment for ties     -422.80
                     ----------
adjusted variance     112128.12

Ho: quan(cred==0) = quan(cred==1)
             z =  -1.202
    Prob > |z| =   0.2294

. ranksum num , by(cred)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        cred |      obs    rank sum    expected
-------------+---------------------------------
           0 |       37        3391      3903.5
           1 |      173       18764     18251.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   112550.92
adjustment for ties    -1296.02
                     ----------
adjusted variance     111254.89

Ho: num(cred==0) = num(cred==1)
             z =  -1.537
    Prob > |z| =   0.1244

. ranksum supp , by(cred)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        cred |      obs    rank sum    expected
-------------+---------------------------------
           0 |       37        2845      3903.5
           1 |      173       19310     18251.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   112550.92
adjustment for ties     -522.70
                     ----------
adjusted variance     112028.22

Ho: supp(cred==0) = supp(cred==1)
             z =  -3.162
    Prob > |z| =   0.0016

. ranksum com , by(cred)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

        cred |      obs    rank sum    expected
-------------+---------------------------------
           0 |       37      4164.5      3903.5
           1 |      173     17990.5     18251.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance   112550.92
adjustment for ties    -2565.58
                     ----------
adjusted variance     109985.34

Ho: com(cred==0) = com(cred==1)
             z =   0.787
    Prob > |z| =   0.4313
```

Appendix 4. 5 Stata Output of Spearman's Rank Correlation Coefficients

```
. spearman p_red qual debt none dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat dalt_trans  trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X_debt com_X_qual com_X_debt stat_X_qual stat_X_debt t
> rans_X_qual trans_X_debt
(obs=6300)
```

	p_red	qual	debt	none	dalt_t~v	dalt_c~d	dalt_s~p	dalt_com	dalt_s~t	dalt_t~s	trrev_~l	trrev_~t	cred_X~l	cred_X~t	supp_X~l	supp_X~t	com_X_~l	com_X_~t	stat_X~l	stat_X~t	trans_~l	trans_~t
p_red	1.0000																					
qual	0.4060	1.0000																				
debt	0.5027	0.2345	1.0000																			
none	-0.8470	-0.4727	-0.5890	1.0000																		
dalt_trrev	0.7075	0.3892	0.4816	-0.8323	1.0000																	
dalt_cred	0.6629	0.3627	0.4484	-0.7805	0.6704	1.0000																
dalt_supp	0.7089	0.3897	0.4813	-0.8326	0.8128	0.7256	1.0000															
dalt_com	0.6980	0.3959	0.4994	-0.8315	0.6492	0.6296	0.6629	1.0000														
dalt_stat	0.3254	0.1810	0.2257	-0.3849	0.4490	0.3108	0.4985	0.2166	1.0000													
dalt_trans	0.1948	0.1113	0.1415	-0.2336	0.1738	0.2136	0.2757	0.2661	0.0993	1.0000												
trrev_X_qual	0.3987	0.9778	0.2270	-0.4622	0.4596	0.3600	0.4116	0.3757	0.2102	0.1044	1.0000											
trrev_X_debt	0.4964	0.2422	0.9381	-0.5814	0.6095	0.4542	0.5280	0.4731	0.2769	0.1323	0.2689	1.0000										
cred_X_qual	0.3588	0.8705	0.2012	-0.4115	0.3501	0.5273	0.3780	0.3349	0.1614	0.1142	0.8574	0.2133	1.0000									
cred_X_debt	0.4336	0.2043	0.8464	-0.5084	0.4298	0.6514	0.4618	0.4193	0.1939	0.1445	0.2009	0.8128	0.3096	1.0000								
supp_X_qual	0.3986	0.9779	0.2258	-0.4623	0.4112	0.3735	0.4598	0.3791	0.2218	0.1309	0.9731	0.2473	0.8728	0.2066	1.0000							
supp_X_debt	0.4974	0.2392	0.9460	-0.5814	0.5277	0.4749	0.6036	0.4798	0.2953	0.1731	0.2455	0.9466	0.2202	0.8388	0.2631	1.0000						
com_X_qual	0.3948	0.9749	0.2351	-0.4609	0.3677	0.3482	0.3699	0.4686	0.1512	0.1278	0.9467	0.2374	0.8425	0.2022	0.9478	0.2357	1.0000					
com_X_debt	0.4928	0.2412	0.9662	-0.5794	0.4597	0.4365	0.4627	0.5966	0.1872	0.1676	0.2303	0.9076	0.2053	0.8160	0.2302	0.9162	0.2685	1.0000				
stat_X_qual	0.2098	0.5143	0.1223	-0.2431	0.2819	0.1911	0.3105	0.1376	0.6316	0.0632	0.5483	0.1617	0.4530	0.0933	0.5641	0.1680	0.4669	0.1038	1.0000			
stat_X_debt	0.2487	0.1241	0.4716	-0.2923	0.3400	0.2238	0.3710	0.1673	0.7593	0.0753	0.1470	0.5213	0.0958	0.4025	0.1514	0.5436	0.1046	0.4195	0.4596	1.0000		
trans_X_qual	0.1321	0.3274	0.0847	-0.1548	0.1160	0.1403	0.1839	0.1771	0.0655	0.6625	0.3138	0.0833	0.3096	0.0900	0.3516	0.1077	0.3467	0.1025	0.1769	0.0433	1.0000	
trans_X_debt	0.1548	0.0838	0.2945	-0.1843	0.1388	0.1680	0.2178	0.2100	0.0763	0.7887	0.0794	0.2796	0.0882	0.2809	0.0980	0.3297	0.0959	0.3238	0.0430	0.1512	0.5137	1.0000

Appendix 4. 6 Results across Different Model Estimations

Attributes	CL_1			CL_2			ML_1			ML_2			ML_3		
	Coeff.		SE	Coeff.		SE	Coeff.		SE	Coeff.		SE	Coeff.		SE
Mean															
p_red	0.0003	***	(0.0001)	0.0003	***	(0.0001)	0.0007	***	(0.0001)	0.0007	***	(0.0001)	0.0007	***	(0.0001)
qual	1.7486	***	(0.0675)	0.8894	***	(0.2573)	3.5872	***	(0.3143)	1.6480	*	(0.9059)	1.6750	*	(0.9003)
debt	-0.2605	**	(0.1134)	-0.7371	*	(0.4259)	-0.9105	***	(0.2609)	-1.9086	**	(0.9488)	-1.9484	**	(0.9621)
dalt (opt-out)	0.6771	***	(0.1290)	-0.1508		(0.3598)	0.5837	***	(0.1549)	-0.1110		(0.4054)	-0.1559		(0.4059)
dalt_trrev				0.0075	*	(0.0040)				0.0094	*	(0.0050)	0.0094	*	(0.0050)
dalt_cred				0.9987	***	(0.2484)				0.8596	***	(0.2840)	0.8623	***	(0.2828)
dalt_supp				-0.0070	**	(0.0027)				-0.0085	***	(0.0032)	-0.0085	***	(0.0032)
dalt_com				0.0213		(0.0230)				0.0215		(0.0253)	0.0228		(0.0253)
dalt_stat				-0.3030		(0.2371)				-0.3790		(0.2636)	-0.3650		(0.2631)
dalt_trans				0.5529	*	(0.3037)				0.6552	*	(0.3402)	0.6495	*	(0.3381)
trrev_X_qual				-0.0064	**	(0.0029)				-0.0124		(0.0109)	-0.0118		(0.0110)
trrev_X_debt				-0.0015		(0.0051)				0.0052		(0.0105)	0.0054		(0.0107)
cred_X_qual				-0.1140		(0.1857)				-0.0272		(0.6658)	-0.0438		(0.6723)
cred_X_debt				0.2847		(0.3070)				1.0145		(0.6876)	1.0095		(0.7012)
supp_X_qual				0.0058	***	(0.0021)				0.0126		(0.0077)	0.0134	*	(0.0080)
supp_X_debt				-0.0003		(0.0036)				-0.0036		(0.0071)	-0.0037		(0.0072)
com_X_qual				0.0543	***	(0.0156)				0.1018	*	(0.0550)	0.0989	*	(0.0540)
com_X_debt				0.0324		(0.0255)				0.0294		(0.0555)	0.0269		(0.0561)
stat_X_qual				1.0452	***	(0.1766)				1.9702	***	(0.6022)	1.9841	***	(0.6056)
stat_X_debt				-0.1418		(0.2832)				-0.0283		(0.5876)	-0.0391		(0.5915)
trans_X_qual				-0.3663	*	(0.1908)				-1.0488		(0.7122)	-1.0172		(0.7219)
trans_X_debt				-0.4365		(0.3231)				-0.3422		(0.7190)	-0.3400		(0.7202)
Standard Deviation of Random Parameters Distribution															
qual							3.0088	***	(0.3101)	2.8441	***	(0.2936)	2.8724	***	(0.2976)
debt							2.6674	***	(0.2717)	2.6058	***	(0.2755)	2.6344	***	(0.2786)
Cholesky Matrix															
/111													2.8728	***	(0.2967)
/121													-0.3835		(0.3014)
/122													2.6063	***	(0.2746)
Goodness of fit Measures															
Log-likelihood	-1450.4206			-1396.0336			-1179.9023			-1154.4063			-1153.5881		
Pseudo-R^2	0.3713			0.3949			0.4886			0.4996			0.5000		
AIC	2908.8410			2836.0670			2371.8050			2356.8130			2357.1760		
BIC	2935.8340			2984.5300			2412.2940			2518.7720			2525.8840		
Number of obs.	6300			6300			6300			6300			6300		
Number of resp:	210			210			210			210			210		

Note: Based on model estimations result on Appendix 8-12 ; *** $p<0.01$, **$p<0.05$, *$p<0.1$

Appendix 4. 7 Stata Output of CL_1 Model Estimation

```
. clogit choice p_red qual debt dalt, group (obs)

Iteration 0:   log likelihood = -1533.6217
Iteration 1:   log likelihood = -1470.0796
Iteration 2:   log likelihood = -1450.4495
Iteration 3:   log likelihood = -1450.4206
Iteration 4:   log likelihood = -1450.4206

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      6,300
                                                LR chi2(4)        =    1713.33
                                                Prob > chi2       =     0.0000
Log likelihood = -1450.4206                     Pseudo R2         =     0.3713
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p_red	.0003025	.0001026	2.95	0.003	.0001014	.0005037
qual	1.748577	.0674592	25.92	0.000	1.616359	1.880794
debt	-.2604909	.1133757	-2.30	0.022	-.4827031	-.0382787
dalt	.6771401	.1290243	5.25	0.000	.4242571	.9300232

```
. estimate stats

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	6,300	-2307.086	-1450.421	4	2908.841	2935.834

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Appendix 4. 8 Stata Output of CL_2 Model Estimation

```
. clogit choice p_red qual debt dalt dalt_trrev dalt_cred dalt_supp dalt_com dal
> t_stat dalt_trans trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qua
> l supp_X_debt com_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans
> _X_debt, group (obs)

Iteration 0:   log likelihood = -1481.5575
Iteration 1:   log likelihood = -1442.7173
Iteration 2:   log likelihood = -1396.4945
Iteration 3:   log likelihood = -1396.0344
Iteration 4:   log likelihood = -1396.0336
Iteration 5:   log likelihood = -1396.0336

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      6,300
                                                LR chi2(22)       =    1822.10
                                                Prob > chi2       =     0.0000
Log likelihood = -1396.0336                     Pseudo R2         =     0.3949
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p_red	.0003099	.0001041	2.98	0.003	.0001059	.0005139
qual	.8894306	.2573292	3.46	0.001	.3850748	1.393787
debt	-.7371133	.4259414	-1.73	0.084	-1.571943	.0977164
dalt	-.1508277	.359752	-0.42	0.675	-.8559286	.5542732
dalt_trrev	.0075275	.0040298	1.87	0.062	-.0003708	.0154258
dalt_cred	.998677	.2483933	4.02	0.000	.5118351	1.485519
dalt_supp	-.0069533	.0027	-2.58	0.010	-.0122452	-.0016614
dalt_com	.0212922	.0230138	0.93	0.355	-.023814	.0663983
dalt_stat	-.3029766	.2370865	-1.28	0.201	-.7676577	.1617045
dalt_trans	.5528894	.3036693	1.82	0.069	-.0422915	1.14807
trrev_X_qual	-.0064198	.0029041	-2.21	0.027	-.0121117	-.0007279
trrev_X_debt	-.0015306	.0050574	-0.30	0.762	-.011443	.0083818
cred_X_qual	-.1139548	.1856843	-0.61	0.539	-.4778894	.2499798
cred_X_debt	.284663	.307034	0.93	0.354	-.3171127	.8864387
supp_X_qual	.0058436	.0021168	2.76	0.006	.0016947	.0099924
supp_X_debt	-.0002788	.0035751	-0.08	0.938	-.0072859	.0067282
com_X_qual	.0543091	.0155613	3.49	0.000	.0238094	.0848088
com_X_debt	.0323736	.025548	1.27	0.205	-.0176996	.0824469
stat_X_qual	1.045158	.1766074	5.92	0.000	.699014	1.391302
stat_X_debt	-.1417844	.2832108	-0.50	0.617	-.6968673	.4132984
trans_X_qual	-.3662978	.1908374	-1.92	0.055	-.7403323	.0077367
trans_X_debt	-.4365248	.3231352	-1.35	0.177	-1.069858	.1968086

```
. estimate stats

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	6,300	-2307.086	-1396.034	22	2836.067	2984.53

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Appendix 4. 9 Stata Output of ML_1 Model Estimation

```
. mixlogit choice p_red dalt, group( obs ) rand( qual debt) id( id ) nrep(500)

Iteration 0:   log likelihood = -1445.6391  (not concave)
Iteration 1:   log likelihood = -1209.0481
Iteration 2:   log likelihood = -1188.9008
Iteration 3:   log likelihood = -1180.1933
Iteration 4:   log likelihood = -1179.9032
Iteration 5:   log likelihood = -1179.9023
Iteration 6:   log likelihood = -1179.9023

Mixed logit model                               Number of obs     =      6,300
                                                LR chi2(2)        =     541.04
Log likelihood = -1179.9023                     Prob > chi2       =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean						
p_red	.0006768	.000138	4.91	0.000	.0004064	.0009473
dalt	.5837059	.1548747	3.77	0.000	.2801571	.8872547
qual	3.587235	.3142988	11.41	0.000	2.97122	4.203249
debt	-.9105175	.2609395	-3.49	0.000	-1.42195	-.3990855
SD						
qual	3.008825	.3101383	9.70	0.000	2.400965	3.616684
debt	2.66735	.2717045	9.82	0.000	2.134819	3.199881

```
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive

. estimate stats

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	6,300	-1450.421	-1179.902	6	2371.805	2412.294

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Appendix 4. 10 Stata Output of ML_2 Model Estimation

```
. mixlogit choice p_red dalt dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat d
> alt_trans trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X
> _debt com_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans_X_debt
> , group( obs ) rand( qual debt) id( id ) nrep(500)

Iteration 0:   log likelihood = -1391.7069  (not concave)
Iteration 1:   log likelihood = -1183.1023
Iteration 2:   log likelihood = -1165.6366
Iteration 3:   log likelihood = -1154.9686
Iteration 4:   log likelihood =   -1154.41
Iteration 5:   log likelihood = -1154.4063
Iteration 6:   log likelihood = -1154.4063

Mixed logit model                               Number of obs     =      6,300
                                                LR chi2(2)        =     483.25
Log likelihood = -1154.4063                     Prob > chi2       =     0.0000
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Mean						
p_red	.0006874	.0001381	4.98	0.000	.0004167	.0009581
dalt	-.1110411	.4053591	-0.27	0.784	-.9055303	.683448
dalt_trrev	.0093766	.0050174	1.87	0.062	-.0004573	.0192105
dalt_cred	.8595852	.2839714	3.03	0.002	.3030114	1.416159
dalt_supp	-.0085387	.00317	-2.69	0.007	-.0147518	-.0023256
dalt_com	.0214721	.0252976	0.85	0.396	-.0281103	.0710546
dalt_stat	-.3790035	.2635615	-1.44	0.150	-.8955745	.1375676
dalt_trans	.6551674	.3402414	1.93	0.054	-.0116935	1.322028
trrev_X_qual	-.0123972	.0109305	-1.13	0.257	-.0338207	.0090263
trrev_X_debt	.0052378	.0104514	0.50	0.616	-.0152467	.0257223
cred_X_qual	-.0271561	.6658068	-0.04	0.967	-1.332113	1.277801
cred_X_debt	1.0145	.687557	1.48	0.140	-.3330873	2.362087
supp_X_qual	.0126331	.0077494	1.63	0.103	-.0025555	.0278217
supp_X_debt	-.0035955	.0071231	-0.50	0.614	-.0175566	.0103656
com_X_qual	.1017665	.0549536	1.85	0.064	-.0059407	.2094736
com_X_debt	.0294384	.0554837	0.53	0.596	-.0793077	.1381845
stat_X_qual	1.970207	.6021886	3.27	0.001	.789939	3.150475
stat_X_debt	-.0283131	.5876455	-0.05	0.962	-1.180077	1.123451
trans_X_qual	-1.048777	.7121806	-1.47	0.141	-2.444625	.3470715
trans_X_debt	-.3422247	.7189553	-0.48	0.634	-1.751351	1.066902
qual	1.648026	.9058799	1.82	0.069	-.1274661	3.423518
debt	-1.908593	.9488355	-2.01	0.044	-3.768277	-.0489099
SD						
qual	2.844126	.2936468	9.69	0.000	2.268589	3.419663
debt	2.605781	.2754901	9.46	0.000	2.065831	3.145732

```
The sign of the estimated standard deviations is irrelevant: interpret them as
being positive

. estimate stats

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	6,300	-1396.034	-1154.406	24	2356.813	2518.772

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Appendix 4. 11 Stata Output of ML_3 Model Estimation

```
. *ML_3
. mixlogit choice p_red dalt dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat d
> alt_trans trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X
> _debt com_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans_X_debt
> , group( obs ) rand( qual debt ) id( id ) corr nrep(500)

Iteration 0:   log likelihood = -1390.2818  (not concave)
Iteration 1:   log likelihood = -1301.8695  (not concave)
Iteration 2:   log likelihood = -1251.2342  (not concave)
Iteration 3:   log likelihood = -1185.6029
Iteration 4:   log likelihood = -1159.8604
Iteration 5:   log likelihood = -1153.6664
Iteration 6:   log likelihood = -1153.5884
Iteration 7:   log likelihood = -1153.5881
Iteration 8:   log likelihood = -1153.5881

Mixed logit model                               Number of obs     =      6,300
                                                LR chi2(3)        =     484.89
Log likelihood = -1153.5881                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       p_red |   .0006992   .0001388     5.04   0.000     .0004272    .0009712
        dalt |  -.1559398   .4059133    -0.38   0.701    -.9515152    .6396357
  dalt_trrev |   .0093595   .0050024     1.87   0.061     -.000445     .019164
   dalt_cred |   .8623129   .2828246     3.05   0.002     .3079869    1.416639
   dalt_supp |  -.0085206   .0031565    -2.70   0.007    -.0147072   -.0023339
    dalt_com |   .0227997    .025283     0.90   0.367    -.0267541    .0723535
   dalt_stat |   -.364986   .2631487    -1.39   0.165    -.8807479     .150776
  dalt_trans |   .6494959   .3381495     1.92   0.055    -.0132649    1.312257
trrev_X_qual |  -.0118474    .010979    -1.08   0.281    -.0333658     .009671
trrev_X_debt |   .0053506   .0106809     0.50   0.616    -.0155836    .0262847
 cred_X_qual |  -.0437669   .6722502    -0.07   0.948    -1.361353    1.273819
 cred_X_debt |   1.009514   .7011863     1.44   0.150    -.3647861    2.383814
 supp_X_qual |   .0133936   .0080232     1.67   0.095    -.0023317    .0291188
 supp_X_debt |  -.0036986   .0071631    -0.52   0.606    -.0177381    .0103409
  com_X_qual |   .0988924   .0539771     1.83   0.067    -.0069007    .2046855
  com_X_debt |   .0269374   .0561479     0.48   0.631    -.0831104    .1369852
 stat_X_qual |   1.984133    .605622     3.28   0.001     .7971358     3.17113
 stat_X_debt |  -.0390676   .5915439    -0.07   0.947    -1.198472    1.120337
trans_X_qual |  -1.017195   .7219418    -1.41   0.159    -2.432175     .397785
trans_X_debt |  -.3400208   .7201954    -0.47   0.637    -1.751578    1.071536
        qual |   1.674987   .9003226     1.86   0.063    -.0896131    3.439587
        debt |  -1.948405   .9621451    -2.03   0.043    -3.834175   -.0626355
-------------+----------------------------------------------------------------
        /l11 |   2.872426   .2966539     9.68   0.000     2.290995    3.453857
        /l21 |  -.3834505   .3014198    -1.27   0.203    -.9742226    .2073215
        /l22 |   2.606308   .2746322     9.49   0.000     2.068039    3.144577
------------------------------------------------------------------------------

. mixlcov, sd

        qual:  sqrt([l11]_b[_cons]*[l11]_b[_cons])
        debt:  sqrt([l21]_b[_cons]*[l21]_b[_cons] + [l22]_b[_cons]*[l22]_b[_cons
> ])

------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        qual |   2.872426   .2966539     9.68   0.000     2.290995    3.453857
        debt |   2.634364    .278576     9.46   0.000     2.088365    3.180363
------------------------------------------------------------------------------

. estimate stats

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |      6,300 -1396.034  -1153.588      25    2357.176   2525.884
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.
```

Appendix 4. 12 The Cholesky Factorization of the Covariance Matrix

	qual	debt
qual	2.8724	
debt	-0.3835	2.6063

Appendix 4. 13 Stata Output of the ML_3 Random Coefficients Covariance Matrix

```
. mixlcov

        v11:  [l11]_b[_cons]*[l11]_b[_cons]
        v21:  [l21]_b[_cons]*[l11]_b[_cons]
        v22:  [l21]_b[_cons]*[l21]_b[_cons] + [l22]_b[_cons]*[l22]_b[_cons]
```

choice	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
v11	8.250829	1.704232	4.84	0.000	4.910595	11.59106
v21	-1.101433	.8887921	-1.24	0.215	-2.843434	.6405674
v22	6.939874	1.467741	4.73	0.000	4.063154	9.816595

Appendix 4. 14 Summary of Rubber Traders' WTC Price Reduction for All Attributes across Different Model Estimations

Attributes	CL_1			CL_2			ML_1			ML_2			ML_3		
	WTC	Min.	Max.	WTC	Min.	Max.	WTC	Min.	Max.	WTC	Min.	Max.	WTC	Min.	Max.
qual	-5,779.57 ***	-16,427.93	-3,428.13	-2,869.82 ***	-8,510.64	-1,115.09	-5,300.05 ***	-8,813.71	-3,660.01	-2,397.48 *	-5,763.19	-149.19	-2,395.48 *	-5,680.84	92.77
debt	861.00 ***	116.26	2,768.26	2,378.36 *	-360.18	8,300.65	1,345.27 ***	583.77	2,546.99	2,776.54 **	-84.55	6,285.63	2,786.50 **	86.98	6,278.60
dalt_trrev				-24.29 *	-82.86	1.71				-13.64 *	-32.62	0.73	-13.39 *	-31.79	0.71
dalt_cred				-3,222.32 ***	-9,667.04	-1,376.92				-1,250.49 ***	-2,538.36	-410.00	-1,233.23 ***	-2,485.45	-410.02
dalt_supp				22.44 **	4.91	71.06				12.42 ***	3.33	25.88	12.19 ***	3.29	25.22
dalt_com				-68.70	-317.72	86.40				-31.24	-115.25	40.39	-32.61	-115.26	37.52
dalt_stat				977.58	-548.43	3,913.49				551.36	-200.98	1,514.28	521.98	-217.66	1,450.35
dalt_trans				-1,783.94 *	-6,059.25	176.80				-953.11 *	-2,222.23	25.99	-928.87 *	-2,159.26	26.57
trrev_x_qual				20.71 **	1.54	68.23				18.03	-13.82	55.70	16.94	-14.45	53.86
trrev_x_debt				4.94	-35.51	51.64				-7.62	-41.76	23.84	-7.65	-42.03	24.00
cred_x_qual				367,68	-1,000.33	2,181.72				39.51	-2,007.59	2,146.49	62.59	-1,961.10	2,150.77
cred_x_debt				-918.49	-4,319.78	1,223.27				-1,475.85	3,992.40	510.05	-1,443.75	-3,930.93	532.89
supp_x_qual				-18.85 ***	-58.02	-4.68				-18.38	-46.99	4.15	-19.15 *	-48.13	3.56
supp_x_debt				0.90	-26.93	31.70				5.23	-16.11	28.13	5.29	-15.99	27.48
com_x_qual				-175.23 ***	-514.08	-66.40				-148.05 *	-356.51	7.32	-141.43 *	-340.45	9.05
com_x_debt				-104.46	-401.73	69.98				-42.83	-221.74	126.85	-38.52	-218.01	129.49
stat_x_qual				-3,372.29 ***	-9,538.08	-1,748.31				-2,866.18 ***	-5,620.40	-1,106.14	-2,837.60 ***	-5,555.25	-1,088.06
stat_x_debt				457,48	-1,707.48	3,124.85				41.19	-1,757.88	1,860.62	55.87	-1,734.02	1,853.19
trans_x_qual				1,181.89 *	-21.80	3,944.20				1,525.72	-473.64	4,118.37	1,454.74	-544.34	4,005.18
trans_x_debt				1,408.48	-692.10	5,383.38				497.85	-1,622.50	2,812.17	486.28	-1,586.82	2,737.23

Note: Based on WTC result on Appendix 16-20 ; *** $p<0.01$, **$p<0.05$, *$p<0.1$

Appendix 4. 15 WTC Stata Output of CL_1 Model Estimation

```
. wtp p_red qual debt , krinsky reps (10000)

           qual        debt
wtp  -5779.5708   861.00059
 ll  -16427.933   116.25767
 ul  -3428.1263   2768.2577
```

Appendix 4. 16 WTC Stata Output of CL_2 Model Estimation

```
. wtp p_red qual debt dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat dalt_tra
> ns trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X_debt c
> om_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans_X_debt, krinsk
> y reps (10000)

             qual          debt    dalt_trrev     dalt_cred     dalt_supp
wtp    -2869.8234     2378.3586    -24.288141    -3222.3161     22.435346
 ll    -8510.6425    -360.18141    -82.857362    -9667.0423     4.9081522
 ul     -1115.089     8300.6505     1.7093009    -1376.9215     71.064892

         dalt_com     dalt_stat    dalt_trans  trrev_X_qual  trrev_X_debt
wtp    -68.700965     977.57962    -1783.9445     20.713999     4.9386766
 ll    -317.72482    -548.43268    -6059.2511     1.5383881    -35.506952
 ul     86.401528     3913.4891     176.79724     68.234635     51.642945

      cred_X_qual   cred_X_debt   supp_X_qual   supp_X_debt    com_X_qual
wtp     367.68494     -918.4893    -18.854795     .89967518    -175.23297
 ll     -1000.326    -4319.7761    -58.022752    -26.931238    -514.07808
 ul      2181.724     1223.2717    -4.6809837     31.696756    -66.400511

       com_X_debt   stat_X_qual   stat_X_debt  trans_X_qual  trans_X_debt
wtp    -104.45625    -3372.2912     457.47951     1181.8909     1408.4842
 ll    -401.73025    -9538.0835    -1707.4845    -21.804664    -692.09677
 ul     69.977112    -1748.3108     3124.8454     3944.1984     5383.3834
```

Appendix 4. 17 WTC Stata Output of ML_1 Model Estimation

```
. wtp p_red qual debt , krinsky reps (10000)

           qual        debt
wtp  -5300.0507   1345.2672
 ll  -8813.7074   583.76868
 ul   -3660.015   2546.9928
```

Appendix 4. 18 WTC Stata Output of ML_2 Model Estimation

```
. wtp p_red qual debt dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat dalt_tra
> ns trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X_debt c
> om_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans_X_debt, krinsk
> y reps (10000)

            qual         debt   dalt_trrev    dalt_cred    dalt_supp
wtp   -2397.4807    2776.5436   -13.640672   -1250.4893    12.421798
 ll     -5763.19    84.548628    -32.61855   -2538.3588    3.3340584
 ul    149.19242    6285.6279    .73449223   -409.99973    25.884108

        dalt_com    dalt_stat   dalt_trans trrev_X_qual trrev_X_debt
wtp     -31.2368    551.35877   -953.11081    18.034944   -7.6197354
 ll   -115.24758   -200.98047   -2222.2301   -13.823633   -41.757385
 ul    40.387888    1514.2768    25.987509    55.703638    23.839381

     cred_X_qual  cred_X_debt  supp_X_qual  supp_X_debt   com_X_qual
wtp    39.505521   -1475.8527   -18.378116    5.2305822   -148.04567
 ll   -2007.5935   -3992.3978    -46.98688   -16.108645   -356.50866
 ul    2146.4934     510.0531    4.1493358    28.132794    7.3163255

      com_X_debt  stat_X_qual  stat_X_debt trans_X_qual trans_X_debt
wtp   -42.825819   -2866.1764    41.188672    1525.7175    497.85445
 ll   -221.74057   -5620.3983   -1757.8764   -473.63704   -1622.4994
 ul     126.8477   -1106.1434    1860.6154    4118.3659    2812.1698
```

Appendix 4. 19 WTC Stata Output of ML_3 Model Estimation

```
. wtp p_red qual debt dalt_trrev dalt_cred dalt_supp dalt_com dalt_stat dalt_tra
> ns trrev_X_qual trrev_X_debt cred_X_qual cred_X_debt supp_X_qual supp_X_debt c
> om_X_qual com_X_debt stat_X_qual stat_X_debt trans_X_qual trans_X_debt, krinsk
> y reps (10000)

            qual         debt   dalt_trrev    dalt_cred    dalt_supp
wtp   -2395.4765    2786.5049   -13.385411   -1233.2338    12.185643
 ll   -5680.8444    86.976805   -31.794771   -2485.4526     3.287972
 ul    92.774808    6278.5978    .70640345   -410.01716    25.216756

        dalt_com    dalt_stat   dalt_trans trrev_X_qual trrev_X_debt
wtp   -32.606901    521.98338   -928.87434    16.943526   -7.6521076
 ll   -115.26274   -217.66204   -2159.2577   -14.445075   -42.026748
 ul    37.520813     1450.353    26.572476    53.863794    24.000661

     cred_X_qual  cred_X_debt  supp_X_qual  supp_X_debt   com_X_qual
wtp    62.593025   -1443.7526   -19.154765    5.2895524   -141.43059
 ll   -1961.1018   -3930.9332   -48.130365   -15.986124   -340.44811
 ul    2150.7686    532.89306    3.5649008    27.477563    9.0451465

      com_X_debt  stat_X_qual  stat_X_debt trans_X_qual trans_X_debt
wtp   -38.524436    -2837.601    55.872366    1454.7377    486.27953
 ll   -218.00867   -5555.2467    -1734.018   -544.33697   -1586.8164
 ul    129.49391   -1088.0583    1853.1851    4005.1761    2737.2305
```

Appendix 4. 20 Stata Output of Wilcoxon Rank-sum (Mann-Whitney) Test of Rubber Quantity Purchased Variable by Transmigrant Status

```
. ranksum quan , by(trans)

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

       trans |      obs    rank sum    expected
-------------+---------------------------------
           0 |      179       18145     18884.5
           1 |       31        4010      3270.5
-------------+---------------------------------
    combined |      210       22155       22155

unadjusted variance    97569.92
adjustment for ties     -366.52
                     ----------
adjusted variance      97203.40

Ho: quan(trans==0) = quan(trans==1)
             z =  -2.372
    Prob > |z| =   0.0177

. codebook quan if trans==1

-------------------------------------------------------------------------------
quan                                                                (unlabeled)
-------------------------------------------------------------------------------

                  type:  numeric (float)

                 range:  [.6,120]                     units:  .1
         unique values:  25                       missing .:  0/31

                  mean:   19.6065
              std. dev:   29.0579

           percentiles:        10%       25%       50%       75%       90%
                                .8         5       9.5        24        35

. codebook quan if trans==0

-------------------------------------------------------------------------------
quan                                                                (unlabeled)
-------------------------------------------------------------------------------

                  type:  numeric (float)

                 range:  [.2,300]                     units:  .1
         unique values:  46                       missing .:  0/179

                  mean:   14.6547
              std. dev:   34.4793

           percentiles:        10%       25%       50%       75%       90%
                                 1         2         4        10        30
```

Curriculum Vitae

_ not available _

Declaration

1. I, hereby, declare that this Ph.D. dissertation has not been presented to any other examining body either in its present or a similar form.

   Göttingen, ……………………………………………….

   ……………………………………………….
   (Signature)

   ……………………………………………….
   (Name in block capitals)

2. I hereby, solemnly declare that this dissertation was undertaken independently and without any unauthorized aid.

   Göttingen, ……………………………………………….

   ……………………………………………….
   (Signature)

   ……………………………………………….
   (Name in block capitals)