Journal of Economic Dynamics & Control 117 (2020) 103944

Contents lists available at ScienceDirect

Journal of Economic Dynamics & Control

journal homepage: www.elsevier.com/locate/jedc

How traders influence their neighbours: Modelling social evolutionary processes and peer effects in agricultural trade networks

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ARTICLE INFO

Article history:
Received 21 February 2019
Revised 7 February 2020
Accepted 11 June 2020
Available online 15 June 2020

Keywords:
Agent-based modelling
Complex adaptive systems
Networks
Rubber
Indonesia
Agricultural trade

ABSTRACT

Marketing channel choices in agricultural trade networks affect the networks' overall performance and influence rural livelihoods. This study identifies key determinants of these choices among natural rubber traders in Indonesia to evaluate four policy scenarios and their potential effects on rural incomes.

Since traders' marketing decisions are based on past interactions, resulting trade networks are formed in recursive processes and can be understood as complex adaptive systems. Due to inherent endogeneity in these systems, process-based approaches such as agent-based modelling (ABM) can be effective in understanding them. Using a self-gathered primary dataset from Jambi Province, Indonesia, we implement and parameterise an ABM to simulate the formation of the rubber trading network and analyse the effects on rural livelihoods of four hypothetical policy scenarios: improved micro-credit availability, increased access to education, better infrastructure and transportation capacity, and market information availability. The model is calibrated through a genetic algorithm which maximises the similarity between the simulated network and the actual network observed in the data.

Results indicate that sellers' decisions on a buyer are primarily determined by debt obligations and past peer-interactions. The most influential sellers have a similar level of formal education as their peers and live in close physical proximity. Results of the policy scenario analysis suggests that policies aimed at reducing sellers' dependence on credit from buyers and increasing education are the most effective policies for improving value chains and reducing poverty in the region under consideration.

1. Introduction

Small-scale traders play a large role in agricultural value chains in economically less developed countries (Piyapromdee et al., 2014; Subramanian and Qaim, 2011). Their marketing channel decisions largely shape the structure of local trading networks, which in turn impacts the effectiveness of rural policies aimed at strengthening the performance of such

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https://doi.org/10.1016/j.jedc.2020.103944
0165-1889/

networks (Sujarwo et al., 2014). Understanding the value-chain decisions of small-scale farmers is therefore crucial in enacting effective policies to develop strong trading networks in developing countries and improve the welfare of the rural poor (Barrett, 2008).[1] However, the analysis of these processes is challenging, since models of such marketing decisions are characterised by feedback loops from repeated buyer-seller transactions and peer interactions, especially in small rural communities (Iftekhar and Tisdell, 2016). A prime example of these processes at work is in rubber market value chains in rural Indonesia. Here, small-scale village traders buy raw rubber from smallholder farms and sell at arms' length to larger traders at the district level. Previous studies have shown that market imperfections exist at several stages of this value chain (Kopp and Brümmer, 2017; Martini et al., 2010).

In this paper, we simulate different rural development policies through a parameterised agent-based model (ABM) in order to evaluate their potential effects. The unique construction of this ABM allows for a representation of complex interactions among rubber traders in Jambi province, Indonesia, by modelling the effects of social closeness and peer interaction on participants' marketing decisions. The model is calibrated to fit a rich data set gathered through in-field surveys conducted in the region.

Complex adaptive systems (CAS) exhibit evolutionary dynamics which arise from a) interactions amongst stakeholders, interactions between stakeholders and the environment, and a learning process through which the results of these interactions feed back into the decision-making processes in future periods. This results in a permanent adjustment of the matrix of combined decisions of all stakeholders to the environment (Potgieter et al., 2005; Rammel et al., 2007).

Feedback loops are a source of high-degree complexity in CAS and endogeneity is omnipresent (van den Bergh and Gowdy, 2003). This poses drawbacks to econometric approaches such as regression analysis in modelling these processes (Holland, 2006). Also, whenever observations are only available for one point in time it is difficult to assess how knowledge spreads between stakeholders. Process-based approaches are better suited to study CAS since they can capture endogenous processes and multiple feedback loops. To this end, agent-based modelling (ABM) approaches can circumvent endogeneity issues (Zhang and Brorsen, 2010).

One example of CAS at work in the field of economics is in the marketing networks of natural rubber traders in Jambi Province, Indonesia.[2] In this region, rubber is predominately produced by small-scale farmers and then distributed via a network of agricultural traders to domestic processors, the crumb rubber factories. Traders vary in size and capacity; smaller village traders sell the rubber to larger district traders, who then sell either to a processor or to still another trader (Kopp and Brümmer, 2017). Several studies point to shortcomings in these value chains, primarily in terms of inadequate infrastructure (Martini et al., 2010; Peramune and Budiman, 2007), a lack of access to fair credit (Akiefnawati et al., 2010; Kopp and Brümmer, 2017), and a lack of market transparency (Peramune and Budiman, 2007). In Jambi, rural incomes lie significantly below the national average (Kopp et al., 2017). Given the importance of the rubber market in Indonesia's national economy, policies aimed at improving the performance of the trade networks might be a promising way to effectively address these problems (Iftekhar and Tisdell, 2016). This paper seeks to determine *which policy options can be effective in improving trade network performance and increasing rural welfare.*

To answer this question, while accounting for the complex and dynamic nature of a multi-agent decision-making environment, we develop the agent-based model RUBNET, which models each agent's selling decision as a recursive process. The model is designed to allow for the simulation of previously developed policy scenarios. To take the CAS properties of the trading network into account, we employ an agent-based, pattern-oriented modelling approach to generate a hypothetical outcome under certain assumptions, represented as global model parameters (Grimm et al., 2005). RUBNET predicts trading connections of model agents based on these global parameter values and compares the emerging network to the network that was empirically observed in the field. The global parameters are then systematically changed in order to maximise the similarities between the simulated and the observed trading network. The predicted decisions in the model are influenced by individual buyer and seller characteristics, characteristics of bilateral relationships between sellers and buyers, as well as relationships between sellers. Data was gathered from a representative, multi-stage micro survey of small and medium-scale agricultural traders in Jambi Province, Indonesia in 2012. The parametrised model is then used to simulate the effects of different policy scenarios on the performance of the trading network.

The basic logic of the modelling process is as follows: A seller ranks all potential buyers based on individual characteristics, as well as their existing relationships to the prospective buyer and then selects the buyer with the highest rank.[3] This procedure allows for heterogeneous effects based on individual characteristics. The selling decisions made by each seller's peers also affect his or her decision-making process in future periods. To quantify the importance of peer influence on marketing decisions, a matrix of all other sellers' decisions in the previous period enters the model as a possible determinant of the decision in the current period. The resulting seller-specific lists order all potential buyers according to each individual seller's propensity to engage in trade with them. After each iteration, descriptive metrics of the predicted network are saved.

[1] "Network performance" captures three qualities of the trading networks under consideration, namely prices paid to farmers, value chain length, and size of network components. These qualities are defined more precisely in Section 3.3.

[2] While the CAS framework is most often applied to biological processes, Markose (2005) argues that socio-economic systems like markets may well be understood as CAS, too.

[3] To avoid confusion, when differentiating between selling traders and their buyers, who can be traders, too, the remainder of this paper refers to "buyers" and "sellers" throughout.

This process is then repeated until the metrics converge. An optimisation algorithm is used to determine the values of the global parameters which maximise the number of correctly predicted trading links.

To the best of the authors' knowledge, this is the first paper to employ an ABM approach based on the theory of CAS to predict agricultural traders' marketing channel choices. The model includes an innovative approach of multiplying a social matrix with a weighting vector, to allow for heterogeneous effects based on individual characteristics. This enables the researcher to identify individuals whose decisions are disproportionally influential. The policy scenarios that are simulated based upon the parameterised model provide insights for policy makers on which policies are most effective in value chain improvement and subsequently poverty reduction in the region under consideration. The tools developed in this analysis are also applicable to similar situations in other countries and markets where the identification of drivers of trading network structures is desired. These include, firstly, the simulation of seller-trader relationships through agent-based modelling to predict agricultural traders' marketing channel choices. Second is the systematic evaluation of policy scenarios based on the parameterised network. The study builds upon and shows the value of a unique data set of sellers' and buyers' data from a multi-stage field survey with agricultural traders.

The paper is structured as follows: the literature review in Section two gives an overview of ABM approaches used in the economics literature so far. Section three presents the ABM RUBNET, and applies it to the natural rubber trade network in Indonesia. Section four presents and discusses the results, and Section five concludes. An elaborate appendix lays out the details of the ABM developed in this paper.

2. ABM and CAS in agricultural economics literature

While agent-based modelling is increasingly being applied in the (agricultural) economics literature (Utomo et al., 2018), virtually no empirical work has been undertaken to model marketing decisions at the micro level in general and at the stage of traders in particular. This section provides an overview of existing ABM applications in the literature so far and identifies gaps in the research.

In the last two decades a growing number of authors in the applied economics literature argued that ABM approaches are more appropriate than econometrics in specific situations. A recent meta study by Utomo et al. (2018) provides an extensive overview of the use of ABMs in analysing Agri-food networks. Klos and Nooteboom (2001) analyse transaction costs with an ABM to explicitly account for the impact of mutual trust and heterogeneity of stakeholders on buyer-seller transactions, challenging the assumption of efficient outcomes. Alfarano and Milakovic (2009) use an ABM approach to analyse macro-level financial market outcomes as result of stakeholder behaviour at the micro level. Zhang and Brorsen (2010, p. 1182) argue that agent-based computational economics (ACE) "can be used to study problems with behavioural assumptions that are too difficult to analyse with mathematical methods. ACE is more economical and time efficient compared with experiments with human subjects (e.g. Ward et al., 1999) and is more controllable.".

In the CAS literature, Markose (2005) provides an overview of ABM approaches in analysing CAS in economics. These are required in situations that deviate from the basic assumptions typically made in economics; for example, when understanding processes such as "innovation, competitive co-evolution, persistent heterogeneity, increasing returns, the error-driven processes behind market equilibria, herding, crashes and extreme events such as in the business cycle or in stock markets" (Markose, 2005, p. 159). Butler (2016) reviews the literature on applications of complex systems to agricultural economics. He concludes that (agricultural) markets are generally too complicated for regression analysis, which assumes the emergence of equilibria, because markets need to be understood as complex systems "in which economic agents [...] continually adjust and react to market behaviour of others" (Butler, 2016, p. 2). Feedback loops and "neighbour effects" add to the complexity of such systems and likely affect seller's decisions. Chen and Yeh (2001) analyse the behaviour of traders on an artificial stock-market with an ABM. They find that while traders may behave as if they do not believe in the efficient market hypothesis, their aggregate behaviour results in an efficient capital market.

In the agricultural economics literature the majority of ABM studies model farm-level production decisions, such as investment decisions (Feil and Musshoff, 2013; Resende-Filho and Buhr, 2008), adoption of new technologies (Schreinemachers et al., 2009), participation in certification schemes (Latynskiy and Berger, 2017), farm-level climate change adaptation (Troost and Berger, 2014), or breeders' responses to price shocks (Zhang and Brorsen, 2010). Latynskiy and Berger (2017) model decision making within coffee farmer cooperatives to understand the processes of collective action in voluntary sustainability certifications. On a similar track, Iftekhar and Tisdell (2016) model the participation of farmers in conservation programs subject to constraints on land-use and existing social networks. Boyer and Brorsen (2013) analyse processors' market power by including the US Livestock Mandatory Price Reporting Act into an auction-based ABM.

The present study adds to the literature by modelling the marketing decisions of agricultural traders. Decision processes at this stage of the value chain have so far received little attention in the majority of studies in the economics or the agricultural economics literature. The same is true for marketing decisions made by any stakeholder in the value chain.

3. Methodology

RUBNET is implemented in NetLogo version 6.0.3 (Wilensky, 1999). The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual-based models (Grimm et al., 2006; 2010) and the ODD+D extension for ABMs including human decision-making (Müller et al., 2013). This section provides the *overview*, while *design*

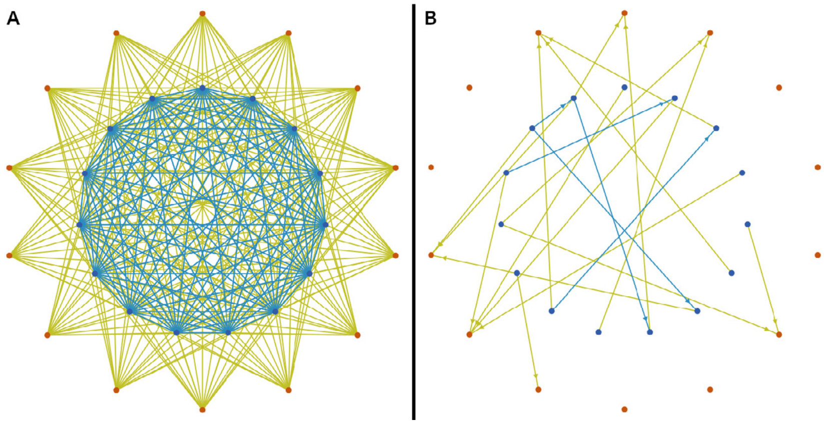

Fig. 1. Graphical representation of all agents and links. Orange dots indicate buying agents (buyers), blue dots indicate selling agents (sellers). Yellow lines represent trading connections between selling and buying agents. Blue lines represent social connections between selling agents. A: example network showing all potential trading and social connections, irrespective of connection activity. B: example of a realised network, showing only active connections, i.e. yellow links represent chosen trading connections and blue links indicate peer recommendations within social networks. Note that there are no yellow connections between blue dots, i.e. the sellers are not modelled to be able to sell to each other, which is confirmed by the observed data. Also note that there are no yellow connections between orange dots, i.e. RUBNET considers the first transaction of the rubber trading chain but no trading on higher levels, such as trading amongst buyers. The total number of agents has been reduced for this illustration. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

concepts and *details* are provided in Appendix Section B2. In the remainder of this section we first explain the general modelling logic behind RUBNET, the ABM used to simulate policy options and evaluate the corresponding scenarios. The second subsection describes the calibration of RUBNET to the natural rubber value chain in Indonesia, before the policy scenarios are developed in the third subsection.

3.1. Model description

The general purpose of RUBNET is to reconstruct the channel choice behaviour of selling agents within an empirical context to simulate the outcomes of different policy scenarios. The first step of this first application of RUBNET is to identify which factors determine marketing channel choices among rubber traders in the Jambi Province in Sumatra, Indonesia. The model parameters are identified in an optimisation scenario using genetic algorithms which vary the model parameters in order to maximise the proportion of correctly predicted trading links (Kumar et al., 2010).[4] To identify policies with the potential to increase the trading network's performance, we then utilise this parametrised model to simulate the effects of four policy scenarios which were developed based on findings from previous studies. These are the introduction of a microcredit scheme, improvements in the education system, a subsidy of transport capacity, and the introduction of a price information system. Each scenario manipulates initial characteristics of the network agents which would be affected by the aforementioned policy measures in a real-life situation.

3.1.1. Agents and links

The main entities of RUBNET are the trading agents, represented by network nodes, and their potential interactions, represented by network links. Trading agents are grouped into two categories: selling agents (seller) and buying agents (buyer). All selling agents are interconnected via social links, which represent the potential social interactions of these agents. Each selling agent is further connected to every buying agent via trading links, which represent potential trading connections (Fig. 1). All of these links are created during model initialisation. However, not all links are considered active, which is indicated by a state variable of the links. Inactive links still exist in the model but are not shown in the visual output or considered for output measurements. Each agent and link is characterised by a set of state variables (see Tables A.1, A.2, and A.3). The agent and link variables, such as locations, social characteristics, and information on trade flows are derived from empirical data. Thus, our model agents represent the original survey data distribution of agents and their characteristics. These properties (including prices offered by buying agents) do not change during model execution.[5]

[4] The optimisation procedure is elaborated in Section 3.2.2.

[5] Predicting price changes accurately, for example, is generally associated with high levels of uncertainty, given that these are determined by many factors. In the given context, the prices are set by the buyers. (Note that the agents whose behaviour is assumed to change are the sellers.) Their decisions are determined by a) processes occurring downstream the value chain, such as changes in their own selling prices and b) processes occurring upstream. The agents in RUBNET constitute only a fraction of the latter group, given that the buyers buy not only from the sellers observed in this study but from (many) more. This nourishes the conclusion that the subjects of analysis in the present studies, all rubber sellers in the representative villages, cause only relatively little effect on the actions of their respective buyers.

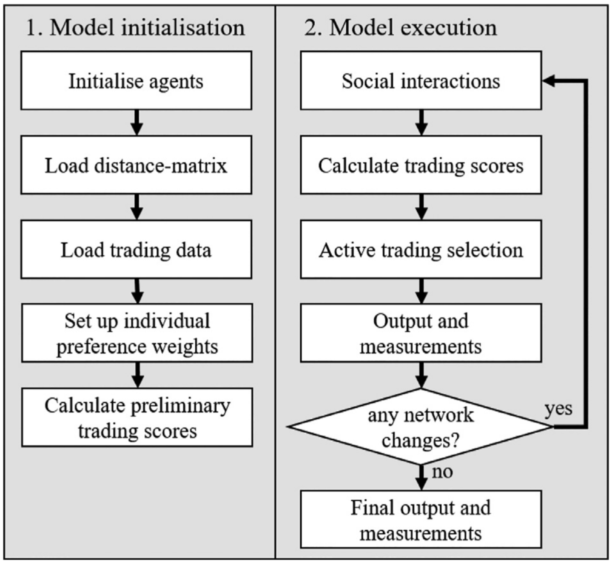

Fig. 2. Flowchart of model processes. Main procedures during model initialisation and model execution.

3.1.2. Execution

First, the model is initialised (see Fig. 2; for details on initialisation, see Appendix Section B2.1) by inputting empirical buyer and seller data from an extensive survey of rubber traders (Section 3.2.1), creating "seller" and "buyer" model agents with specific agent IDs. Directed "social links" from each selling agent to each other selling agent are generated, as well as directed "trading links" from the selling agents to each buying agent. Geographical distances between agents are loaded from a distance matrix that provides Euclidean distances for all agent-ID pairs. These distances are stored as link state variables. In order to initialise the state variables pertaining to trade links between agents, trading data from the survey are loaded into the model. The data provides actual trading connections, including variables such as amount of rubber traded, prices, debts between selling and buying agents, and social characteristics of agents. After all agents and links are initialised, preliminary sub scores for price, distance between traders, and debt between traders are calculated for each outgoing trading link of each selling agent.

The selection of buying agents by the selling agents is performed by calculating resulting weighted scores for the criteria distance, price, and debt. So-called *global weights* for all selling agents are provided as global parameters (see Table A.4), and are modified by the optimisation approach. Additionally, each selling household has a set of *individual weight* preferences that are determined based upon the selling agents' individual properties (see Table A.1). These preferences are constant and used to modify the global weights for final trading link score calculation.

For each initial weighting criterion a weighted score is calculated by multiplying the criterion score with its corresponding global weight (w_p for price, w_{di} for distance, w_{de} for debts) and the selling agents' corresponding weight preferences (see Eq. (1)). The sum of these weighted scores is then divided by the sum of all weights, multiplied with the corresponding weight preferences.[6]

$$l\_score = \frac{s_p * w_p * p_p + s_{di} * w_{di} * p_{di} + s_{de} * w_{de} * p_{de}}{w_p * p_p + w_{di} * p_{di} + w_{de} * p_{de}} \tag{1}$$

The model execution process involves four main procedures: determining social interactions, calculating final trading scores, selecting active trading connections, and calculating output metrics (see Fig. 2).

To measure the influence of social interactions on channel choice, a social influence score is calculated for each social link, based on the properties of the connected selling agents (for details see Appendix Section B2.3). Depending on the global parameter *n_social*, each selling agent sets the most n influential incoming social links to "active" ($n = n\_social$). The combination of these active social links is then considered the "social network" of interactions between selling agents.

The implementation of feedback mechanisms resulting from learned results of past interactions between socially connected sellers is implemented in an iterative loop that does not incorporate temporal scales explicitly. The final social score of each social link is then calculated by weighting the social sub-scores with the global weight parameters for the social matrix (see Eq. (2)). Since a social link is created from each selling agent to each other selling agent, there exist two links between each pair of selling agents. From each pair of social links between the same agents, only the social link with the

[6] Details on score calculation and determination of individual weights are provided in Appendix Section B2.1.

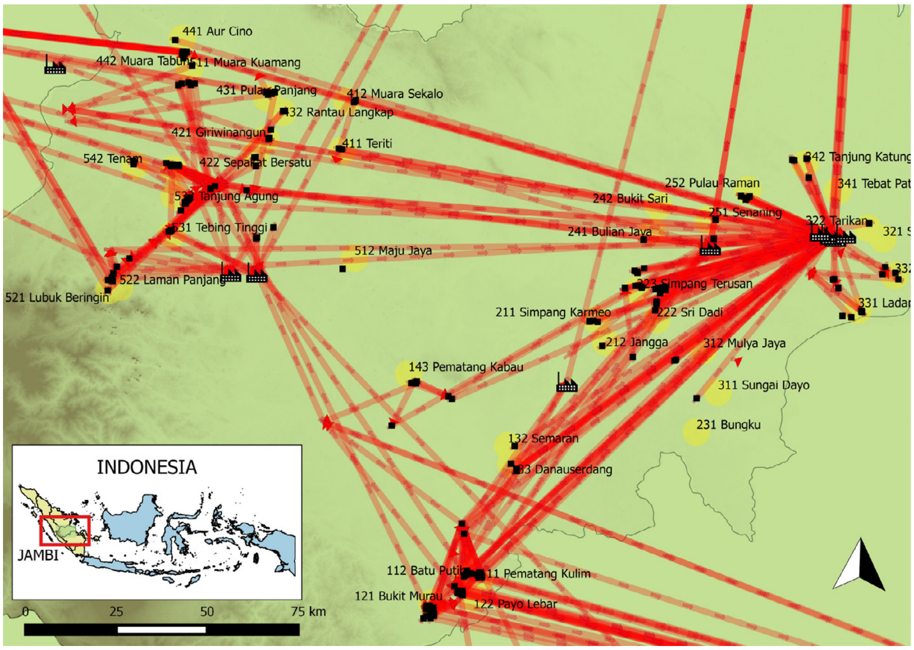

Fig. 3. Trader Network in Jambi. Black squares represent traders, red arrows are trade flows. Yellow circles are survey villages and the factory icons represent rubber processors. On its way from farmers to processors, agricultural output passes on average 3.1 traders. *Source:* Kopp and Brümmer (2017), based on original survey data, collected in a representative survey with rubber traders in 40 villages in the Jambi Province (Sumatra, Indonesia) as well as with the downstream traders that the initial respondents named as their buyers. Further information on the sampling procedure is provided in Section 3.2. Borders of Jambi and Sumatra were obtained from the Center for International Forestry Research, and the surface of Jambi from NASA/EOSDIS. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

higher social score is kept in the model.

$$l\_score_{soc} = \frac{s_{prox} * w_{s,prox} + s_{educ} * w_{s,educ} + s_{eth} * w_{s,eth} + s_{group} * w_{s,group} + s_{job} * w_{s,job}}{w_{s,proximity} + w_{s,educ} + w_{s,eth} + w_{s,group} + w_{s,job}} \quad (2)$$

Afterwards, final scores for each trading link are calculated. In contrast to the preliminary scores, these final scores also incorporate the trading decisions of socially connected selling agents. The final trading score for each trading link is then calculated based on the initial sub-scores calculated during initialisation (distance, price, debts) and the social score indicating trading preferences within the selling agents' active social network (see Eq. (3)).

$$l\_score = \frac{s_p * w_p * p_p + s_{di} * w_{di} * p_{di} + s_{de} * w_{de} * p_{de} + s_{soc} * w_{soc} * p_{soc}}{w_p * p_p + w_{di} * p_{di} + w_{de} * p_{de} + w_{soc} * p_{soc}} \quad (3)$$

Finally, active trading connections are selected based on the final trading scores, and output metrics of the emerging trading network are calculated. The main simulation procedure is repeated until a stable network solution is found. These iterations of the main simulation procedure do not represent a temporal progression with a distinct temporal resolution.

To assess network stability, we calculate the number of changing trading links between each iteration. As soon as the mean number of changes of the previous 10 iterations drops below 1.0, a stable network is reached. To prevent endless loops, a second exit option stops the current iteration if no stable network is reached after 10,000 iterations.

3.2. Model application

3.2.1. Study region and data

RUBNET is applied to the value chain for natural rubber in the Jambi Province in Sumatra, Indonesia. Here, rubber is produced by smallholders and transported along a chain of successive agricultural traders before finally being purchased by processors, the crumb rubber factories (Kopp and Brümmer, 2017). Unlike many other agricultural products, rubber is extremely durable and can be stored for long periods of time, enabling the formation of value chains consisting of relatively many stakeholders and extensive trading networks, as illustrated in Fig. 3. In many developing countries, agricultural traders also offer other crucial services such as the transportation of farm output, the reduction of information asymmetries (for example on prices), and the lending of credit to farmers (Subramanian and Qaim, 2011). A prime example of this is in the rubber market value chain in Jambi Province where traders provide all of these services (Kopp and Brümmer, 2017).

Data for the study was gathered from a 2012 two-stage survey with agricultural traders in Jambi.[7] For the first stage, 40 villages were chosen through a random sampling procedure, stratified on a sub-district level. 180 traders enter the analysis, which constitutes 58 percent of the total population (i.e., the total number of agricultural traders in each village, which was identified via a snowball-like search). These respondents are referred to as "sellers" throughout this study. During the first stage interviews, these sellers were asked to whom they sell their output. The individuals named by the sellers – hereby referred to as "buyers" in this analysis – were subsequently identified, contacted, and then interviewed in the second stage of the survey campaign.

The selection of the variables that enter RUBNET was determined by previous studies on the area. Existing debts between a seller and potential buyers was chosen as the first possible determinant of traders' channel choice. According to Kopp and Brümmer (2017), agricultural traders play a key role as informal lenders in Jambi province, and debt obligations have an effect on farmers' marketing channel choice, which may also be true at the interface between village traders and their buyers. Next, Hernández et al. (2015) and Natawidjaja et al. (2014) demonstrate the importance of distance between agents in the choice of Indonesian farmers' marketing channel choice. To allow selling agents to account for this criterion within the model, RUBNET includes the distances between a seller and all potential buyers. The third indicator is the price offered by all potential buyers. To account for the effects of peer interaction, as motivated in Section two, several characteristics that determine the social closeness between each seller and all peers (*i.e.*, other sellers) are included. These include similarity in education, ethnicity, and active membership in a village group, as well as employment in a prestigious job and the physical distance between peers. An overview of the variables entering the simulation, as well as further details on the data set, are provided in Appendix Section B2.2.

3.2.2. Parameterisation

We follow a pattern-based parameter calibration approach to identify model parameter combinations explaining network patterns in the survey data (Grimm et al., 2005). In order to maximise predictive power of the model, our approach aims to find optimal values for the number of socially connected peers, the four global weight parameters, and the five weight parameters of the social matrix within the interval [0–100] (see global parameters in Table A.4). To perform the model parameterisation, we applied a genetic algorithm using the R-package *nlrx* (Kumar et al., 2010; Salecker et al., 2019; Willighagen and Ballings, 2015). Genetic algorithms are iterative optimisation algorithms that are initialised with a starting *population* of individuals, wherein each individual represents a random parameterisation of the model. A fitness function is then used to determine the fitness of each individual (parameterisation) of the population. Individuals with higher fitness have a higher chance to be selected as *parents* for the following *generation* (iteration). The individuals for the following *generation* are then created from these *parents* by generating *childs* that carry a random combination of the *parents* properties (parameters). In between *generations*, individuals also have a certain chance to be *mutated* (slightly modified) to prevent solutions to be stuck in local minima. A genetic algorithm is typically performed over a defined number of *generations* or executed until a specific fitness values is reached. We initialised the genetic algorithm with a *population* of 200 individuals, *i.e.* parameterisations, and a mutation chance of 1%. Our fitness function is simply defined as the proportion of correctly predicted trading connections in comparison to the survey data. We define a maximum number of 200 *generations* (iterations). Finally, we store the parameterisation and trading network of the final iteration with the highest proportion of correctly predicted trading connections.

3.2.3. Model validation

Utomo et al. (2018) show that model validation has become the norm in the ABM literature. The most common approach to assess the validity of an ABM is to estimate the relation between observed and simulated values through ordinary least squares (Berger, 2001), where an estimation coefficient close to unity and an R^2 close to 100% indicate high predictive quality of the model. Troost and Berger (2014), however, argue that "achieving a perfect fit to reality is not the primary concern for a process-based model and is not necessarily an indicator of model validity" (Troost and Berger, 2014, p. 841). Apart from Troost and Berger's reservations for theoretical reasons, the approach of fitting an OLS to observed and simulated results is only applicable to analyses in which the dependent/simulated variable is continuous, i.e., where there is a clear qualitative ordering of simulated values for the cases in which they are not identical to the observed one. This is where this simulation differs from all other studies found in the literature: the dependent variable, the seller's choice of a marketing channel, is a non-ordered categorical variable, *i.e.* out of all possible choices for a buyer, only one is "correct" and all others are (equally) incorrect. From this it follows that the metric for each observation is binary (correct or incorrect), while the metric used most commonly in the literature is continuous ("correct", "slightly wrong", "very wrong", etc.).

As an alternative to the regression approach of model validation, we compare the validity of the fully parameterised RUBNET model to a number of null models. The first null model assigns each seller a random buyer (*random*). Second, a set of null models is simulated in which only one characteristic enters the analysis, namely *debts* (by setting the debts weight to 100 and all other weights to 0), *distance* (by setting the distance weight to 100 and all other weights to 0), and *price* (by setting the price weight to 100 and all other weights to 0). The third set of null models includes a distance restriction and only considers the closest 25% of buyers, referred to as *random & distance, debts & distance* and *price & distance*.

[7] Data from subproject C01 of Collaborative Research Centre 990 https://www.uni-goettingen.de/en/310995.html.

In order to assess the stability of the parameterised model, we calculate parameter sensitivity indices by applying a local sensitivity analysis (one-at-a-time method) (Pianosi et al., 2016). We increase and decrease the number of socially connected peers, the four global weight parameters, and the five weight parameters of the social matrix by 25% one at a time while keeping all other parameters constant. This allows us to investigate the effect of different parameterisations on the properties of the resulting trading network.

3.3. Policy scenarios

To identify policies with the potential to increase the trading network's performance, the effects of four sets of policy options are simulated based upon the parameterised RUBNET. These policy scenarios are developed based upon the shortcomings of this value chain diagnosed in previous studies, own observations in the field, as well as possible solutions suggested in the literature.

The outcomes of these scenarios are evaluated against three indicators of network quality which are based upon the Structure-Conduct-Performance approach (Perloff et al., 2007): the *performance* is captured by a) the mean prices paid in the resulting network and the *structure* by b) the mean length of active trading links and c) the total number of buyers being chosen, which corresponds to the number and size of network components, i.e. number and size of independent sub-networks.[8] a) is of interest because a possible price increase realised by sellers would be passed on to small-scale farmers, even if only partially, increasing province-wide standards of living. The distance between buyers and sellers, b), is decisive for the transaction costs to be incurred per sales instance (Santosa and Joewono, 2005). The number and size of network components c) is interesting because it measures market structure, which is found by Kopp and Brümmer (2017) to be a determinant of market power: on average, buyers located in villages with fewer competitors are more likely to exercise oligopsonistic market power than those in villages with more competitors, *ceteris paribus*.

3.3.1. Micro credits

The literature on farmer-trader relations shows a clear link between credit and output markets (Subramanian and Qaim, 2011). Since many farmers in the global South are credit-constrained due to lack of collateral because of limited formalised land titles (Barnett et al., 2008), agricultural traders commonly act as informal lenders to smallholders. This puts farmers into a lock-in situation with their creditor, leading to traders exercising market power over farmers (Piyapromdee et al., 2014). According to Kunz et al. (2016), the lack of formal land titles is indeed a problem for smallholders in the Jambi province, and Kopp and Brümmer (2017) find evidence for traders' market power over credit constrained farmers due to producer lock-in in that region. The same study further provides anecdotal evidence showing that village traders (the sellers in this analysis) reportedly use credit as a tool to foster dependence in their providers (i.e., smallholder farmers) and further ensure repeat sales. It is unclear, however, whether this also happens at the next downstream seller-buyer nexus, where both the seller and the buyer are traders. If the sellers in our analysis are indeed shown to be beholden to credit relations and are therefore limited in their decisions on to whom sell to (e.g. to the buyer offering the highest price), it would be useful for policy-makers to know how policies aimed at reducing informal credit relations could lessen this limitation on trading decisions.[9]

As a potential solution to this problem at the farmers stage, Peramune and Budiman (2007) suggest micro credit systems as instruments for reducing farmers' dependence on credit from prospective buyers. This might also be effective in increasing network performance further downstream. We model this scenario by reducing the state variable "debt" between sellers and buyers by 50% (scenario S_{A1}) or 100% (scenario S_{A2}). However, micro credits are often offered at very high interest rates in developing and emerging economies due to the relatively small loan size in relation to the fixed transaction and processing costs incurred by formal institutions when issuing credit (Banerjee et al., 2015). To allow for this, a third scenario (S_{A3}) is simulated that accounts for the hypothetical interest that the farmer would have to pay for a micro credit. The cost of formal micro credit is accounted for by a price deduction that each seller currently taking out loans from his or her buyer would receive. The price deduction is calculated based on the typical microcredit interest rate in this region (23.3% in Asia, Rosenberg et al., 2013), the loan size of the sellers, and their mean sales quantity.

3.3.2. Education

It has been established in the literature that improving access to education is a key measure for poverty reduction and rural development (Gasperini, 2003; Hanif and Arshed, 2016; Kayani et al., 2017) as it increases the capacity for rational decision making (Fan, 2017; Klein, 1999). However, no study was found that analyses whether there is a transmission channel between education and rural development through agricultural traders' marketing decisions. In Jambi, education is generally low. 19.4% of the population over 15 years old have not completed a primary education, and only 29.4% have finished an education beyond primary school (Statistics of Jambi Province, 2013, p. 153, table 3.2.2). This is also true for the sellers in

[8] The equivalent of *conduct* is the actual behaviour of agents that is simulated by RUBNET.

[9] In the long run a reduction in debt might also be followed by an increase of prices offered by low-pay-buyers. To isolate the consequences of a reduction in debt, this scenario does not manipulate the prices paid. Such a reaction is captured in the scenario *D* (see below), which assumes an increase of the lowest prices offered in the region.

this analysis who are only slightly better educated: 12.8% did not finish primary school, and 30.2% finished their education after primary school (see Table B.3). While Peramune and Budiman (2007, p. 38) suggest improving education for "key farmers", village traders might also be effective in acting as multipliers.[10] A second transmission channel between traders' education levels and rural incomes is the effect of education on social closeness amongst the traders. If peer effects prove to be important, then improving social ties has the potential to increase network performance. However, policy makers have limited tools available to affect social relations. The only characteristic within the social matrix they can influence is the level of schooling. The second set of simulated scenarios therefore increase educational levels. This is modelled by either increasing the sellers' education from 1 and 2 to 3, i.e. ensuring primary education for all (scenario S_{B1}), or increasing the education to the highest level in each village, i.e. ensuring that everybody visits the schools that already exist (scenario S_{B2}).

3.3.3. Transport capacity

Road infrastructure is poor in the Jambi province (Kopp and Brümmer, 2017), a problem common to many tropical environments in which long rainy seasons put high stress on paved roads. The World Bank finds that the per capita stock of public capital in Indonesia is 33% of that of other emerging economies. The Bank further estimates that "Indonesia faces an estimated gap in infrastructure assets of USD 1.5 trillion" (The World Bank, 2017, p. 35). According to Santosa and Joewono (2005, Fig. 4), road density in Jambi is around 17 km/km^2, ranking Indonesia 79th out of 125 countries listed (Metcalve et al., 2019). The same paper finds a "road performance" indicator of 0.5 (Santosa and Joewono, 2005, Fig. 5), listing 50% of all roads in Jambi as being in "unstable condition". Improving road conditions is a difficult task in Jambi, however, where a long rainy season and a tropical landscape make maintenance of paved roads expensive (Arns and Hellmig, 2018; Harding et al., 2017). An alternative would be to empower stakeholders within the rubber value chain to adopt to the weak infrastructure. Peramune and Budiman (2007), for example, suggest helping farmers by "providing infrastructure support such as small truck (1 to 1.5 MT) to farmer groups" as a development policy. However, qualitative interviews with members of farmers groups in 2012 showed that there is a lot of mismanagement in farmer groups which often do not emerge from a bottom-up process but are rather set up by the government in a top-down manner. Therefore, this intervention might be more successful when targeting village traders rather than farmer groups.[11] This policy is modelled by setting the transport capacity of the lower half of the population to the mean value to predict the results of a policy that subsidises transportation (scenario S_C).

3.3.4. Price information system

Asymmetric information on market prices of agricultural output has been identified as a key determinant of market power among small-scale farmers by previous authors (Asongu et al., 2016; Bergemann et al., 2015), and increasing farmers' access to market information can in turn increase their bargaining position (Wollni and Zeller, 2007). Price information systems have been suggested as a means to tackle this issue (Mittal and Mehar, 2012), and the introduction of such systems can be beneficial for small-scale farmers (De Silva et al., 2012). For the farmer-trader nexus, empirical evidence on the price-increasing effect of a price information system through increased bargaining power on the farmers' side has been provided by Mittal and Mehar (2012) for rural India and by Karugu (2010) for Kenya. The effects measured by these authors for the farmers-traders nexus can be expected to be qualitatively the same at the interface between small-scale village traders and their respective buyers. In the case of Jambi, a lack of market transparency at this stage of the value chain is indicated by large variation in prices paid between traders. The introduction of a price information system would likely lead to an increase in the sellers' bargaining power, as they can sell to other buyers if these are known to offer better prices.[12] This will drive up prices offered by the buyers who pay the lowest prices. In the simulations, this is captured by the sellers' decision on whom to sell to (which can be different from the decisions observed in reality). The increase of the lowest prices would reduce the variation in the prices offered by potential buyers to each seller. We model this policy (scenario S_D) by adjusting the price paid by each buyer in the sample in such a way that the difference between the buyers' prices and the median price over all buyers is reduced by 50%.

To summarise, the following policy scenarios are evaluated:

- S_{A1}: All debts between sellers and buyers are halved (S_{A2}: set to zero), representing a policy to increase the share of credit that is taken from formal lending institutions. Scenario S_{A3} accounts for the relatively high interest rates on micro credits. These costs are implemented via a perceived price reduction on the individual seller's level, specific to the debt and mean sales quantity of each selling agent.
- S_{B1}: Increase the level of education of sellers with education levels 1 (never went to school) and 2 (dropped out of primary school) to level 3 (completing primary school), i.e. ensuring primary education for all. In scenario S_{B2} we increase sellers' education levels to the highest level in each village, i.e. ensure that everybody visits existing schools.

[10] We agree with one reviewer's point that such as measure would have to be undertaken with caution, as it might have adverse effects by creating a new source of traders' market power.

[11] Again, such a measure would have to be undertaken with caution, as it might have adverse effects by creating a new source of market power for traders.

[12] This implicitly assumes that alternative traders are able and willing to accommodate additional quantity offered by sellers, which appears plausible, given that 87.8% of all rubber traders surveyed replied positively to the question if they would buy rubber from additional suppliers if given the chance to.

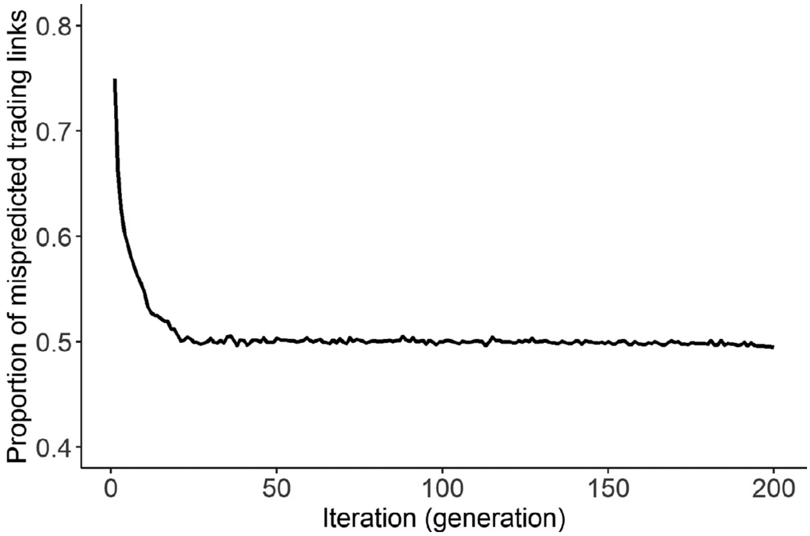

Fig. 4. Fitness of optimisation algorithm over 200 generations (iterations). The vertical axis represents the share of falsely predicted trading links, so the decrease over iterations represents an increasing fit.

Table 1
Results of the optimisation scenario using genetic algorithms.

Parameter name	Parameter value
n_social	04.50
w_price	00.94
w_dist	11.51
w_debts	73.55
w_social	14.00
w_social_education	28.96
w_social_ethnicity	13.03
w_social_activegroup	14.96
w_social_prestigious_job	01.86
w_social_proximity	41.19

Start values for each parameter were chosen randomly within the weight interval [0–100] by applying a genetic algorithm. The genetic algorithm was initialised with 200 random starting parameterisations and we simulated 200 iterations. The algorithm eliminates parameterisations that lead to bad results in order to maximise the proportion of correctly predicted trading links. The best-found solution resulted in 49% correctly predicted trading links.

- S_C: Homogenise transport capacity, setting the capacity of the lower half of the population to the mean value of the sample to predict the results of a policy subsidising transportation.
- S_D: Since a price information system would lead to a reduction in the variance between prices, this scenario is modelled by adjusting the price paid by each buyer in the sample in such a way that the difference between the buyers' prices and the median price over all buyers is reduced by 50%.

4. Results and discussion

4.1. Parameterised model

The solution of the genetic algorithm optimisation is sufficiently stable after 200 iterations and the best fitting parameter combination results in a proportion of 49% correctly predicted trading links (see Fig. 4). The resulting parameter values of the optimisation algorithm are depicted in Table 1.

The final weights of this simulation indicate a high weight for debts and intermediate weights for social interactions and distance, whereas the weight for the price criterion is rather small. Prices in particular do not seem to have a strong effect on sellers' decisions. According to the best-fitting parameterisation, the social matrix has a substantial effect, and

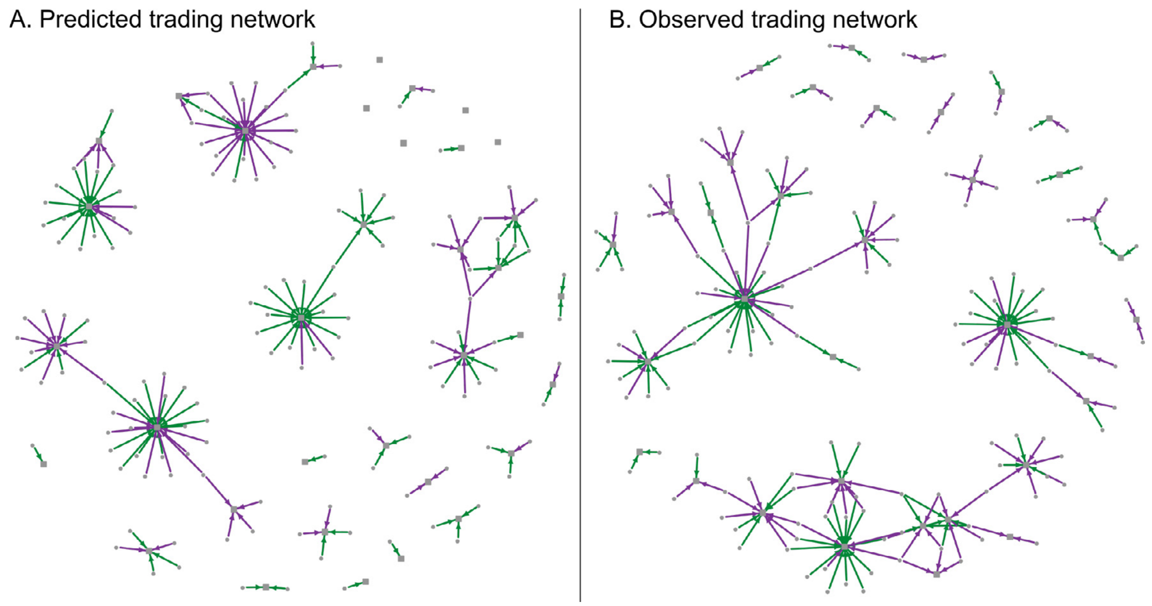

Fig. 5. A. Trading network derived from parameterised RUBNET model. B. observed trading network from survey data. Circles indicate selling agents, whereas squares indicate buying agents. Green links indicate trading links that were correctly predicted by the parameterised RUBNET model. In A., magenta links indicate predicted trading links that are not part of the observed trading network (B.). In B., magenta links indicate observed trading links that were not predicted by RUBNET. Both figures were created by applying a graph drawing algorithm, thus node and edge positions are not equivalent.

every seller is – on average – influenced by 4.5 peers. The sub-weights of the social matrix are high for proximity (same village) and education, and intermediate for ethnicity and social group membership, while having a prestigious job does not seem to make a seller disproportionally influential to his or her peers. At first it seems surprising that the price paid by potential buyers plays such a minor role, much smaller than distance between agents and existing debt between the seller and potential buyers. However, this extends the results of Kopp and Brümmer (2017), who find for the farm level that indebted sellers are often constrained in their selling decisions, to the next downstream value chain stage.

Standard graph metrics, such as number of components and component size, are used to quantify the structural differences between the predicted and observed trading network (visualisation, see Fig. 5). Compared to the observed trading network, the overall number of components is higher in the predicted network (model 25; data 17). The higher number of components is a result of five potential buying agents that have not been chosen by any selling agent. If we only consider the active trading network and ignore those agents not connected by any trading links, the predicted trading network is more compact and has a number of components similar to the actual trading network (model 20; data 17). Because both networks have the same total number of active trading links, the higher number of components in our predicted network results in lower component sizes compared to the observed trading network (mean component size model 7.2; data 10.6). Compared to the empirical trading network, the average length of the trading links and the average prices paid were well predicted by RUBNET (deviation in mean link length: -2.92% and in prices: +0.65%).

RUBNET effectively identifies the overall importance of social interactions, debts, and distance between sellers and buyers on trading channel choice. The agent-based modelling approach allows individual characteristics of sellers whose decisions can be accurately predicted by RUBNET to be compared to the characteristics of agents whose decisions cannot be predicted well. Most of the distributions of social characteristics do not differ strongly between sellers whose decisions are correctly predicted and agents with only non-matching predictions (Fig. 6). For some characteristics, however, the insights deserve mentioning: in the case of debts between sellers and buyers, RUBNET correctly predicts all trading connections of buyer-seller pairs with a long history of credit transactions. This success rate decreases to about 25% when credit is zero. The selling decisions among ethnicity 3 (Sundanese) and 4 (Melayan) can be predicted with 100% accuracy. It needs to be mentioned, though, that these two ethnic groups are especially small (5 and 3 representatives, respectively, see Table B.3), so results might suffer from limited sub-sample bias. The decisions of Javanese and autochthonous traders and the ones with unknown ethnic background (groups 1, 2, and 5, respectively), who represent the lion's share of the sample, can be predicted with average accuracy. The post-parameterisation analysis also reveals that the selling decisions of small sellers, characterised by low selling volumes, were relatively well-predictable. This can be explained by large sellers being generally indebted less often which makes them hard to predict as debt is an important criterion for the majority of the sample. On the other hand, most sellers with high transport capacities could be predicted above average. One possible explanation is that these traders form an exception to the exception, *i.e.*, that a number of traders have invested heavily in their transport capacity, which created a group of indebted traders with high sales volumes. The choices of sellers located in the North-

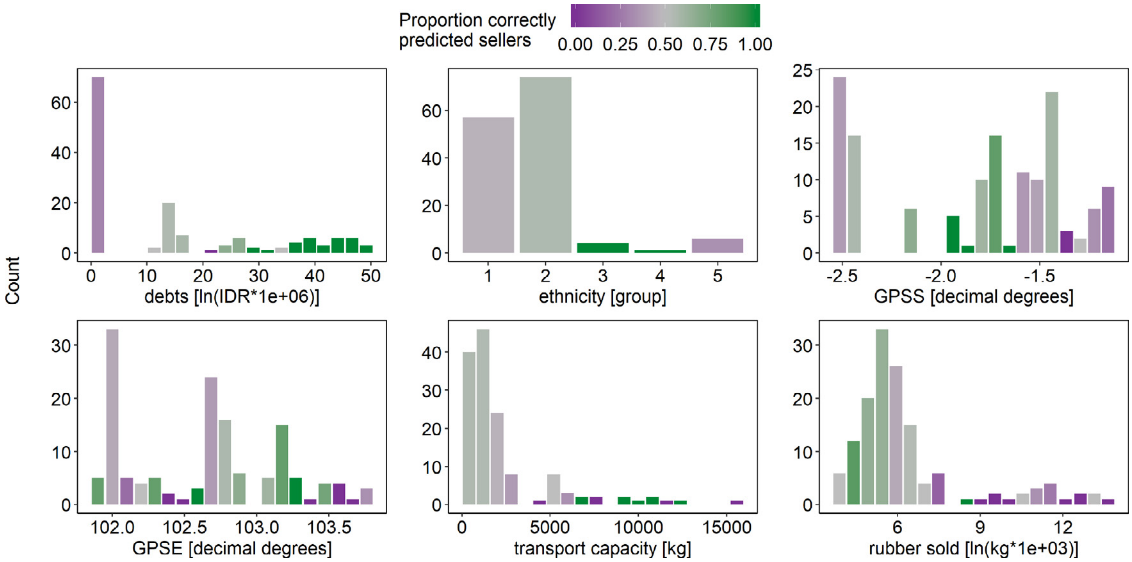

Fig. 6. Characteristics of sellers whose channel choices RUBNET predicts well/badly. The bins represent the distribution of the respondents along the characteristics depicted on the horizontal axes. The shading indicates the share of sellers whose channel choice is predicted correctly in the respective group by RUBNET (green colours) or wrongly (purple colours), depending on the characteristics captured by the horizontal axis. When the bins are grey, the number of wrongly and correctly predicted links is equal. Since RUBNETS predicts about 49% of all trading links correctly, every bin that is shaded in a greenish colour is above average and every reddish bin below average. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

West of the province, as well as in the very East can be predicted below average.[13] These are the respondents located in Tebo and Bungo districts (displayed by the sub-network in the North-West in Fig. 3), as well as the ones close to Jambi City (in the East). When differentiating along all other dimensions, the share of correctly and wrongly predicted links appear roughly symmetrical.

The analysis also indicates below average predictability of sellers located in the Tebo and Bungo districts. These two regions lie along the banks of the longest river in Sumatra, the Batanghari, and its tributaries, which – in combination with a lack of bridges and other infrastructure shortcomings – effectively splits the area in half. This is not accounted for in RUBNET due to the lack of geospatial data on the water system in the area. The high predictability of traders with high credit can be explained by the sheer importance of that variable in RUBNET.

4.2. Model validity

To assess the predictive quality of the fully parameterised RUBNET model, the predictions are compared to several null models (see Fig. 7). The complete RUBNET model that uses the combination of weights derived from the genetic algorithm, results in the correct prediction of 49% of all trading links, followed by the null model that incorporates debts only (31.3%). In the random null model, which is used as a benchmark, each selling agent is assigned links to random buying agents. It predicts 3.8% of all links correctly. The null model that only incorporates prices results in the worst prediction quality (1.6%). This follows the inherent logic of the model: if only price determines the decision, the model (falsely) predicts all selling agents to decide for the same buyer. This is below the success probability of the random model.

The overall predictive quality of RUBNET is at first sight below that of other models found in the literature. Brändle et al. (2015) report in their land use simulations mean percentage errors between 1.5% and 10.9%. Berger (2001) reports an R^2 of 99.1% in his micro-level analysis of land use decisions of smallholders, and 65.7% at the macro level. Schreinemachers et al. (2007) simulate household food intake with 87% precision, and Schreinemachers et al. (2010) report an R^2 of 95% at the highest level of aggregation, but only 23% at the household level. However, it should be kept in mind that the comparison of predictive qualities of these separate models is “apples and oranges”, as RUBNET’s predictive quality of 49% is not an R^2 but rather the share of observations that were exactly correctly predicted.[14] No other study was found for comparison which reports the share of observations whose simulated values are exactly identical to the observed ones.

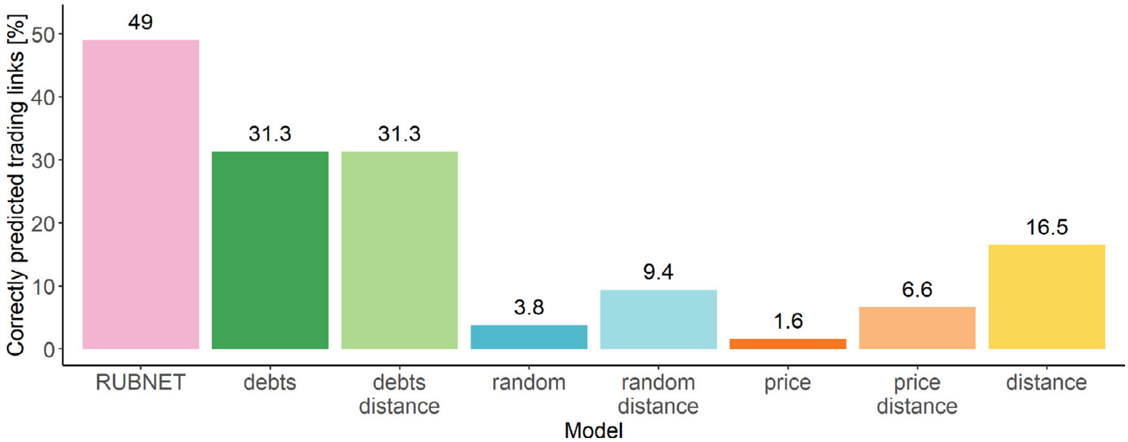

Fig. 7. Null models. The value of each bar indicates the percentage of correctly predicted trading links between seller-buyer pairs. RUBNET predictions result from applying a genetic algorithm optimisation to find the parameterisation with the highest proportion of correctly predicted trading links. Other null models are calculated by setting the weights of the specific criteria manually. In the null models that include distance (debts-distance, price-distance, and random-distance) only the 25% shortest links are allowed to be set to active.

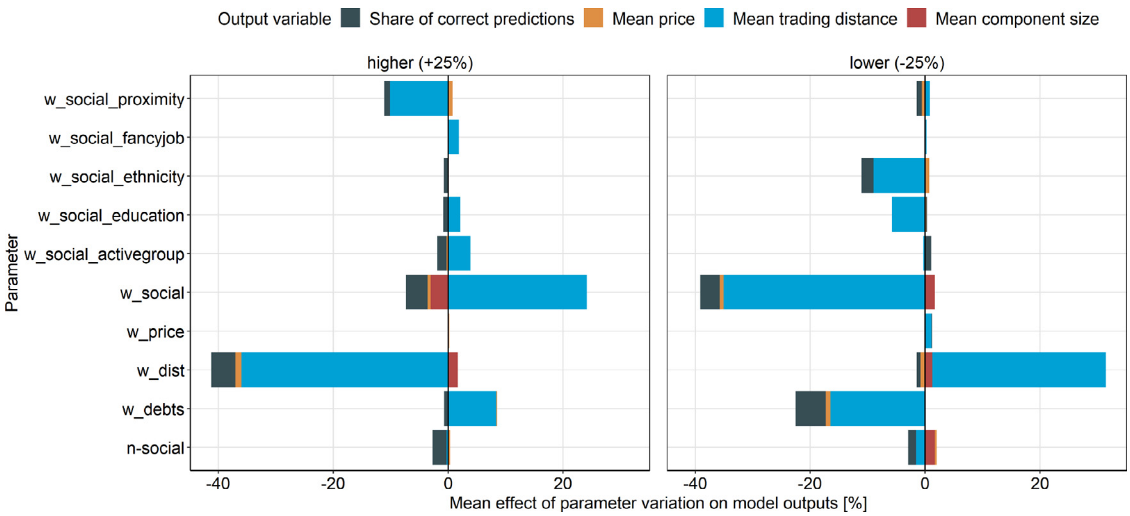

Fig. 8. Results of the local sensitivity analysis. Each paramater is varied one-at-a-time by increasing (left panel) and decreasing (right panel) the parameter value by 25% while keeping all other parameters constant. The bars indicate the mean percentage change of respective model output variables, when compared to the default parameterisation that is derived from the genetic algorithm optimisation. *Mean price* and *Mean trading distance* refer to properties of the simulated network: physical length of active trading links and mean price of realised sales. *Mean component size* refers to the mean number of nodes of independent sub-networks.

Fig. 8 displays the effect of a +/- 25%-change of each of the optimised model's parameters on the quality of the optimisation, i.e., the share of correctly predicted trading links, as well as properties of the simulated trading network, such as mean price, distance between seller and buyer, and component size. The sensitivity to a 25% change of the parameters of the optimised model parameterisation is below 5% for all parameters and outputs except the mean trading distance within the resulting trading network. The latter is relatively strongly affected by changes in the parameters *w_social* and *w_dist*. Changes in distance related weights (*w_dist*, *w_social_proximity*) result in output effects of opposite direction, whereas changes in all other weight parameters result in output effects in the same direction as the parameter change. For example, increasing distance related weights (*w_dist*, *w_social_proximity*) lead to lower mean trading distance within the resulting trading network, while increasing the weight of the social matrix (*w_social*) result in higher mean trading distance.

[13] Moving to the right on the GPSS axis indicates moving northwards and moving right on the GPSE axis means moving eastwards.

[14] The simulated network is very similar to the empirically observed data in terms of mean length of trading links (concordance: 97.08%) and the mean prices paid (concordance: 99.35%).

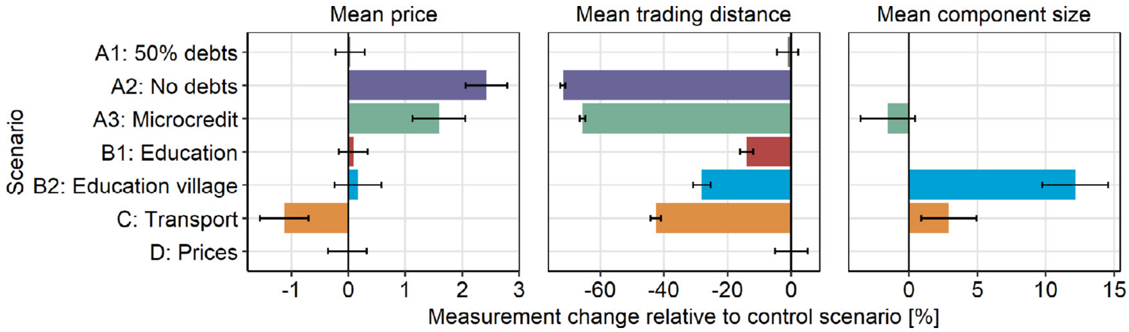

Fig. 9. Results of scenarios. Each line of bars captures the outcomes of one scenario and the three sets of bars represent the three indicators of network performance, as described in Section 3.3 and Table B.1. *Mean price* and *Mean trading distance* refer to properties of the simulated network: physical length of active trading links and mean price of realised sales. *Mean component size* refers to the mean number of nodes of independent sub-networks. The whiskers display the standard deviation between 20 simulation repetitions with different initialisation of the random number generator to control for stochasticity.

All in all, most results in terms of predictive quality are highly robust to 25%-changes in the final parameterisation. Only the mean distance in the simulated network reacts relatively sensibly to changes in the parameters for *w_distance* and *w_social*. This is not surprising, as these two parameters determine trading distance.

4.3. Evaluation of policy scenarios

The results of the policy scenarios are displayed in Fig. 9.[15] The first set of scenarios, S_{A1} and S_{A2}, simulate a respective decrease in debt of 50% and 100%, while S_{A3} simulates a 100% reduction in combination with a typical high micro-credit interest rate of 23.3%. Since the “debts” variable is the biggest determinant of sellers’ choices, modifications to its values result in the biggest expected changes. While halving every seller’s debts has no effect, the (albeit unrealistic) scenario of a complete abolition of debts leads to an increase in price and a reduction in the distances between sellers and buyers. The reason for these results is that, holding all else constant, the sellers are less restricted in their choices and therefore decide to sell to a closer buyer at a higher price. The more realistic policy of the introduction of a microcredit scheme causes higher prices as well, and even when taking into account the relatively high costs of these credits, the benefit is still significantly above zero. This price increase has a positive effect for the primary producers, as at least part of the increase can be assumed to be passed on towards the origin of the value chain. The reduction of distance is more ambiguous. While shorter travel distances between buyer and seller are likely to reduce transaction costs, it is also a key determinant of the number of stakeholders required to be in the trading chain as a whole, as shortening transaction distances may increase the number of traders through whose hands the product passes before reaching the processor. Kopp and Brümmer (2017) find that this number is positively correlated with traders’ market power over farmers, so lengthening the chain by reducing the physical distance of the predicted links will increase the combined market power that traders exercise over smallholders. The mean cluster size increases (i.e., the number of clusters decreases) what can be understood as an increasingly concentrated market structure, another possible cause of increasing market power. However, the latter indicator is not significantly different from zero. Overall, policies which reduce sellers’ dependence on credits from buyers are likely to increase the smallholders’ incomes.

The fourth and fifth scenarios (S_{B1} and S_{B2}), an alignment of the seller education levels, has an effect qualitatively similar to the abolition of all debt. However, the increases of mean prices are not significantly different from zero and the reduction in trading distances is smaller than in the previous scenarios. The reason for the reduction of mean trading distance is that the alignment in education levels increases the number of other sellers that influence the seller under consideration, resulting in the seller being informed about more attractive buyers close by. This means that policy measures which homogenise education levels within villages can emulate the effects of the much less realistic scenario of abolishing all debt in terms of reducing transaction costs, but this has little direct effects on prices. Also, in the second sub-scenario, the harmonisation of education in each village by ensuring schooling for all at existing schools increases the mean size of the network components, leading to more competition at the village level.

The increase in transport capacity of scenario S_C causes a reduction in mean prices, as well as mean trading distance. This means that for sellers, who can transport larger quantities in less time, it is more profitable to sell to buyers closer by. This is explained by the fact that larger transport capacities are the result of higher investments, making it more expensive for sellers to send their fleets on long trips, resulting in low sales frequencies and a correspondingly underutilisation of their capital investments. The solution is for them to increase sales frequency by taking shorter trips to more nearby buyers, which offsets even lower prices.

[15] Note the different scales of the x-axes in the figure.

The reduction in variation between prices that would be caused by the introduction of a price information system as modeled in scenario S_D, has no effect on any of the three indicators of network performance. This can be explained by the relatively small influence that the price offered by a buyer has on the sellers' channel choice: even if a potential buyer changes the price that he or she offers, other determinants that shape the seller's decision are more important than this new price.

These findings are relevant for policy makers who seek to effectively allocate a limited budget. To summarise, the simulations show that the introduction of policies aimed at reducing sellers' debts with buyers has a larger effect on the indicators of network performance than all other policies under consideration. This is not only true for the (rather unrealistic) scenario of a complete replacement of all loans from buyers by loans from formal lending institutions at no costs, but also when factoring in the relatively high costs of obtaining microcredits. The increase of education levels leads to a reduction of transaction costs and increases competition in villages, but has no effect on prices. While the introduction of measures to increase transport capacity has already been suggested in the literature (Peramune and Budiman, 2007), this policy comes at high costs, as the price effects are negative. If this tightening of sellers' margins is passed on to their small-scale farmer suppliers which is likely, their income situation would worsen. For the eventual decision for a specific policy, the expected effects would also have to be weighted by the costs of the respective politics.

4.4. Outlook

In order to increase the predictive quality of RUBNET, several model extensions could be implemented. Currently, RUBNET uses Euclidean distances between agents to estimate their proximity. In reality, however, road connections and barriers such as large rivers or mountain ranges affect agents' proximity and are not considered yet due to lacking road network data. In addition, the predictability of social-adaptive processes could be enhanced by incorporating more detailed data on social characteristics of trading agents. These can be easily implemented into RUBNET once such data is available.

At its current state, RUBNET does not incorporate any temporal dimension. RUBNET acknowledges the fact that the trading patterns emerge over time (through iterations of the model), but the units of time are deliberately left undefined.[16] Traders' marketing channel choices are derived for one point in time, based on empirical data. However, the model already provides detailed insights on the economic behaviour of trading agents, which is an essential step not only for future extensions of RUBNET, but also for development of other agent-based models featuring temporal dynamics, such as the economic-ecologic land-use change model EFForTS-ABM (Dislich et al., 2018). Explicit consideration of spatially explicit trading networks in a dynamic ecological-economic model will enable even more sophisticated network analyses like trading network resilience under various scenarios covering price dynamics or consolidation processes.

One huge advantage of the pattern-oriented modelling approach is that it allows the fitting of model parameters based on empirical data (Grimm et al., 2005). The resulting parametrised model can be used to predict similar trading networks based on individual characteristics of traders, without any prior knowledge of existing connections between agents. The quality of such predictions can be assessed and validated by using another empirical data set which might be available in the future.

5. Conclusions

This paper models the channel choice behaviours of agricultural traders with an agent-based model. This approach is motivated by the trading network under study being shaped by social interactions and feedback loops which hinder conventional regression analysis through problems of excessive endogeneity. The second advantage over econometric approaches is the ability to investigate how individual characteristics of agents affect their predictability. RUBNET, the ABM developed in this work, succeeds in identifying the overall impact of social interactions and other measured variables on traders' channel choice. The parameterised model has been utilised to simulate four policy scenarios. The simulations provide insights for policy makers on which policies are most effective in value chain performance improvement and subsequent poverty reduction in the region under consideration.

Results show that debt obligations between a seller and potential buyers, as well as the social closeness between sellers, are the two most important factors when simulating traders' channel choices. Within the social matrix sub-model, key drivers of peer influence are physical proximity to the peers and similarity in education levels.

Results of the policy scenario analysis indicate that the most potent and realistic policies to increase the smallholders' incomes target increases in village traders' access to formal credit, e.g., through a microcredit scheme. The scenario of abolishing all debts is even more effective in increasing prices, but deemed rather unrealistic. Policies intended to increase education levels have little effect on prices, but can positively affect the competitive situation in villages and reduce transaction costs. For the actual decision for a specific policy under functional budget constraints, these expected results would need to be weighted by the costs of implementation of said policy. It is remarkable that the changes in debt is the only set of scenarios that has a significantly positive effects on mean price levels.

[16] Incorporating time explicitly would come at a great cost in terms of highly increased complexity, because adoption can happen at various different temporal scales (both grain and extent). These costs are not justified by the potential gain, given that the exact timing of processes is not relevant for the core questions of the study.

The study further shows the value of such a data set of seller and buyer data from a multi-stage field survey with agricultural traders, which serves to motivate the generation of similar data sets for other contexts in the future.

Acknowledgements

This work was supported by the German Research Foundation (DFG) [grant number KO 5269/1-1 and in part through project number 192626868, in the framework of the collaborative German - Indonesian research project CRC990]. The funding source was not involved in study design; collection, analysis and interpretation of data; manuscript writing; or decision on submission. Stefan Moser and Matthew Rudh provided valuable research assistance. We thank seminar participants at the University of Bonn for feedback on an earlier draft. A substantial share of the work of Thomas Kopp was undertaken at the University of Göttingen.

Appendix A. Tables

Table A.1
State variables of selling agents.

State variable	Unit	Comment
h_village	-	village ID of the agents location
h_subdistrict	-	subdistrict ID of the agents location
h_district	-	district ID of the agents location
h_employees	employees	number of employees
h_GPS_S	decimal degrees	GPS southing of agents location
h_GPS_E	decimal degrees	GPS northing of agents location
h_education	education level	Education level from 1 (...) to 6 (...)
h_ethnicity	ethnicity group	Ethnicity group
h_transport	kg rubber	Transport capacity
h_prestigious_job	true/false	Important standing within social community
h_activegroup	true/false	Active in a group within the social community
h_group_count	groups	Number of groups the agent is active in
h_hhsvlg	households	Number of households in the same village
h_income	IDR	Total income of selling agent
h_age	years	Age of selling agent
h_hhsize	individuals	Number of individuals living in agents household
h_housevalue	IDR	Estate value of the selling agents house
h_debt_total_mio_log	ln(million IDR)	Amount of debts with specific trading agents
h_sell_total_ton_log	ln(kg rubber)	Total amount of rubber sold by the agent
h_n_buyer	buyers	Number of connected buying agents based on empirical data
h_w_price	-	Individual weight preference price criterion
h_w_dist	-	Individual weight preference distance criterion
h_w_debts	-	Individual weight preference debts criterion
h_w_social	-	Individual weight preference social criterion

Table A.2
State variables of buying agents.

State Variable	Unit	Comment
h_id	-	Agent ID
h_price	IDR	Average buying price of the buying agent

Table A.3
State variables of links.

State variable	Unit	Comment
l_length	meter	Real length of the connection, derived from GIS euclidean distance matrix
l_tons	tons rubber	Only trading links, amount of rubber traded via this link based on empirical data
l_price	IDR	Average buying price of this trading link, based on empirical data
l_debts	Million IDR	Amount of debts of selling agent with connected buying agent
l_social	-	Mean total score for buying agent from socially connected selling agents
l_score	-	trading links: final scores; social links: social influence
l_score_t1	-	Temporarily stores the final score for the next model iteration
l_score_price	-	Sub-score price criterion
l_score_dist	-	Sub-score distance criterion
l_score_debts	-	Sub-score debts criterion
l_score_social	-	Sub-score social criterion
l_status_model	true/false	Indicates if the link is active (=chosen) in the model
l_status_data	true/false	Indicates if the trading link exists within the empirical data

Table A.4
Global parameters.

Parameter	Comment
n_social	Maximum number of social connections of each selling agent
w_price	Weight of price criterion for trading selection
w_dist	Weight of distance criterion for trading selection
w_debts	Weight of debts criterion for trading selection
w_social	Weight of social interaction criterion for trading selection
w_social_education	Weight of education level criterion for social interaction estimation
w_social_ethnicity	Weight of ethnicity criterion for social interaction estimation
w_social_activegroup	Weight of group activity criterion for social interaction estimation
w_social_prestigious_job	Weight of job influence criterion for social interaction estimation
w_social_proximity	Weight of proximity criterion for social interaction estimation

Appendix B. Further model description: design concepts and details

B1. Design concepts

The ABM RUBNET is designed to allow for testing of the scenarios as laid out in Section 3.3.

B1.1. Basic principles

The possible determinants of an agent's decision making are displayed in Fig. B.1. Three sets of variables enter the simulation: first are the *individuals' characteristics*, which capture the probability of interaction based on individual characteristics of the sellers and the buyers, such as the location or the price offered by a buyer. The second set includes *characteristics of the buyer-seller relation* which comprise the size of a credit taken by the seller from one of the potential buyers and the

Table B.1
RUBNET observation metrics.

Variable	Type	Comment
active_tradings_n	Decision level	Number of active trading links in the network
correct_tradings_n	Decision level	Number of trading links in the current network that match empirical trading links
correct_tradings_p	Decision level	Proportion of trading links in the current network that match empirical trading links
components_n	Network structure	Number of network components (independent sub-networks) of the active trading network
components_size_mu	Network structure	Mean component size (mean number of nodes of independent sub-networks) of the active trading network
mean_trading_distance	Network properties	Mean physical length of trading links
mean_price	Network properties	Mean price of realised sales

Table B.2
Robustness check of the optimisation scenario: complete and reduced sample.

Parameter	*value.reduced*	*value.complete*
n_social	04.50	02.38
w_price	00.94	10.47
w_dist	11.51	8.11
w_debts	73.55	57.14
w_social	14.00	24.28
w_social_education	28.96	32.59
w_social_ethnicity	13.03	00.46
w_social_activegroup	14.96	01.63
w_social_prestigious_job	01.86	06.07
w_social_proximity	41.19	59.26

The right column – *value.complete* – refers to the optimisation based on the full sample while the left column – *value.reduced* – refers to results based on the reduced sample (see Section B2.2). While in the reduced sample 49% of all active trading links are predicted correctly, 44% are predicted correctly in the complete sample.

Table B.3
Descriptives: categorial variables.

Ethnicity	Freq.	Percent	Description
1	71	39.66	Javanese
2	94	52.51	Jambinese
3	5	2.79	Sundanese
4	3	1.68	Melayan
5	6	3.35	Other/unknown
Total	179	100	
Education			
1	4	2.23	Never went to school
2	19	10.61	Attended primary school (not finished)
3	54	30.17	Completed primary
4	33	18.44	Completed secondary
5	4	2.23	Completed post-secondary
6	65	36.31	Completed college
Total	179	100	
Prestigious job			
	168	94	No prestigious job
	11	6	Any kind of prestigious job
1	2	18.18	Village head
5	1	9.09	Village secretary
3	1	9.09	Village council member
4	2	18.18	Head of farmer group
2	1	9.09	Chairman of youth organisation
6	4	36.36	Teacher
Total	179	100	
Social engagement			
0	109	60.89	Not active in any village group
1	70*	39.11	Active in at least one village group
Total	179	100	

The first column displays the group number.
*Includes members of farmers groups (33), neighbourhood groups (19), religious groups (18), and 23 other groups (members in single digits).

Table B.4
Descriptives: discrete and continuous variables.

Variable	Mean	Std. Dev.	Min	Max
Number_of_employees	5.7	6.3	0	35
Transport_capacity (kg)	2219.9	2816.7	0	16,000
Debt (million IDR)	4.6	6.7	0	16.9

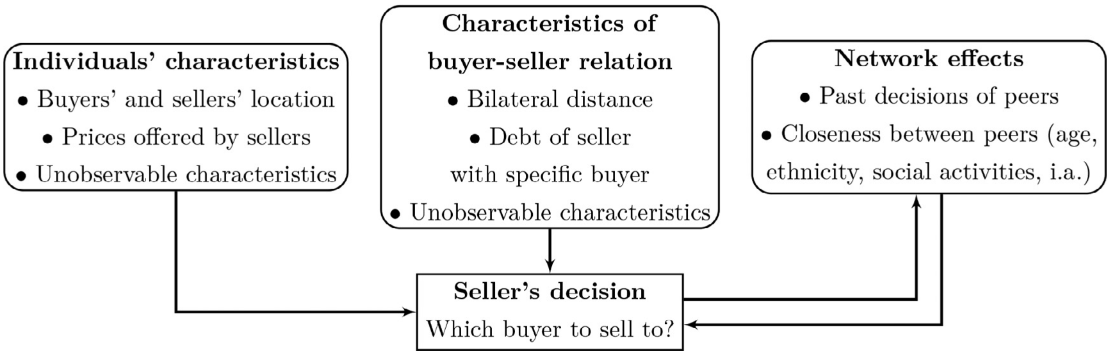

Fig. B.1. Possible determinants of decision making processes. *Source:* own design.

bilateral distance (discrete, measured as the Euclidean distance) between the seller and potential buyers. Set three captures the CAS properties of the network. These *network effects* incorporate decisions of an individual seller's peers in the past, which affect his or her decision-making process now. They are operationalised in RUBNET via a so-called *social matrix*. This matrix quantifies the social closeness between each seller and his or her peers, which determines how strongly the past decisions made by other sellers affect the channel choices of the seller under consideration. It includes plausible channels via which the decision of seller A selling to buyer X increases the probability of seller B also selling to buyer X. The characteristics accounted for in the social matrix are the characteristics of the relationship between the sellers, such as physical

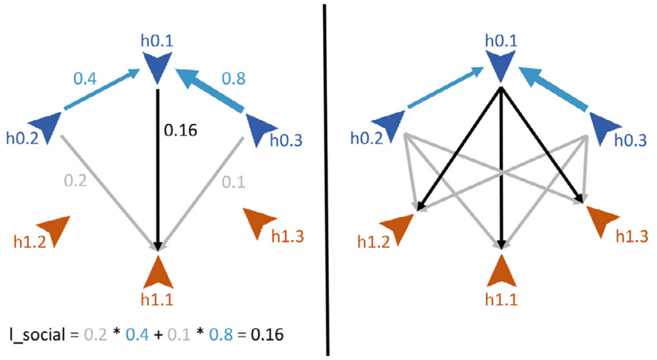

Fig. B.2. Illustration of social interactions. Blue triangles indicate selling agents (h0), while orange triangles indicate buying agents (h1). Blue links indicate directed social links (social influence). To calculate the social score of the trading link from h0.1 to h1.1, the trading scores of socially connected sellers to that same buyer are determined (grey links). These scores are then weighted with the corresponding social influence (blue links) and summed up to calculate the social score of the trading link (black link). This is repeated for all buying links for each selling agent (right panel). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table B.5
Relation between number of buyers and traded quantity.

	(1) *number_of_buyers*
ln *total_sales*	0.065***
	(0.001)
Constant	0.045**
	(0.019)
Observations	179
R^2	0.958
Standard errors in parentheses	
*** p < 0.01, ** p < 0.05, * p < 0.1	

Own production, based on survey data.

proximity,[17] the similarity in the level of education, a shared ethnicity, the membership in any village group, or whether the potential influencer works in a prestigious job apart from the trading business. The resulting matrix weighs the impact of all other sellers' decisions on each individual seller.

For the buyers' side, no decision rules have been implemented. According to data from a micro survey with agricultural traders in the same area, 28.7% of all village traders sometimes reject rubber from farmers (not from other traders, as in the study at hand) due to bad quality. However, at the stage of the natural rubber value chain that is under scrutiny in this study (from village trader to bigger wholesaler) the buyers purchase all raw rubber that is on offer. This is explained by the fact that the mean quality of the 71.3% of all village traders, who have also bought raw rubber of inferior quality, will be sufficient because the inferior quality rubber constitutes only a minor share of all purchases.

B1.2. Individual decision making

To model the trading network realistically, some assumptions are made concerning sellers' behaviour. First, the sellers are assumed to make decisions in order to maximise their profits. These decisions are influenced to a large extent by revenue and transaction costs of selling. Revenue depends on the price they receive from their buyer. Transaction costs depend on the geographic location relative to the seller and other unobserved characteristics of the buyer. The selection of a buyer therefore crucially affects the seller's profits. Second, personal relationships between stakeholders are assumed to play a central role in the decision-making process as well. They include interactions between the seller under consideration with a) potential buyers and b) with his or her peers, i.e. neighbouring sellers. The relationship between the seller and potential buyers is characterised by a) stable characteristics such as physical distance and b) time-variant characteristics such as the amount of credit the seller has taken from the buyer in previous periods. The relations between neighbouring sellers include spill over and learning effects and therefore generate feedback mechanisms. *Neighbourhood* is defined widely, i.e. along a number of dimensions such as physical proximity, ethnicity, and similarity in level of education.

[17] Note that this refers to distance between sellers, while *set two* above includes the distance between seller and potential buyers.

B1.3. Emergence

The resulting network of active trading connections emerges from the individual ranking decisions of selling agents. These decisions are influenced by the global weight parameters, individual weight preferences, and the past marketing channel choices of socially connected selling agents.

B1.4. Adaption

Trading decisions of model agents are influenced by other connected individuals based on the so-called *social matrix*. Thus, agents in RUBNET adapt their behaviour according to socially connected selling agents. RUBNET uses the social matrix parameters to rank social similarity of selling agents. Agents with similar social characteristics, such as home village, ethnicity, or education, have a higher chance of adapting trading decisions from each other, dependent upon the current social weights. The overall influence of this adaptive process on the final trading ranking of selling agents is defined by the global weight parameter *w_social*. High values increase the probability that selling agents sharing specific social characteristics will use similar trading connections.

B1.5. Spacial explicitness

RUBNET is spatially-explicit but does not utilise a discrete cell lattice with a specified grain and extent. We use the geographical coordinates of surveyed households from a vector shapefile (100×100 *m* grain) to calculate euclidean distances between all seller pairs and between all seller and buyer pairs (minimal distance between pairs is 0.1 *km*, maximum distance is 389.8 *km*). These distances are stored as a state variable of the links that connect the agents (seller, buyer) in the model. This is common practice for network models and allows to arrange agents and connections freely in space in graphical representations, without changing the spatial relations of the agents (Kaufmann and Wagner, 2001; Tamassia, 2013).

B1.6. Stochasticity

Random decisions are only made if a selling agent must decide between a set of buying agents with identical total scores. Apart from that, RUBNET is a deterministic model.

B1.7. Observation

The main observation is the network structure that emerges from the individual marketing decisions of selling agents. Several output metrics are derived from this active trading network (see Table B.1). Our application relies on the *correct_tradings_n* parameter for the optimisation scenario, and the *components_size_mu*, *trading_distance*, and *trading_price* parameters for evaluating the policy scenarios.

B2. Details

B2.1. Initialisation

The initialisation procedure contains five sub-procedures (see Fig. 2). (1) The survey input data file is loaded to create all selling and buying agents. These agents are initialised with the IDs from the survey data. Next, the input data is used to set all state variables (see Tables A.1 and A.2) of the selling and buying agents. To initialise the networks, a directed social link is created from each selling agent to each other selling agent and a directed trading link is created from each selling agent to each buying agent. All these links are initialised with an inactive model and data status. (2) The model uses a distance matrix that contains Euclidean distances for each pair of agent IDs to store the distances between agents as a link state variable. (3) The survey input data is used to indicate which trading links have been observed in reality by setting the state variable *l_status_data* to 1. (4) Individual weighting preferences are set up for each selling agent. These preferences are stored as properties of the selling agents and are used to modify the global weights for calculating final scores of trading links. By incorporating these individual weight preferences, selling agents may have different weighting priorities depending on their individual properties. The model allows for the following individual weight preferences:

- Lower distance preference (p_{di}) if the transport capacity of the selling agent is high (1 / *h_transport*)
- Lower price preference (p_p) if the selling agent is wealthy, indicated by the buying price of his/her house (1 / *h_housevalue*)
- Lower debt preference (p_{de}) if the age of the selling agent is high (1 / *h_age*)
- Lower social preference (p_{soc}) if the age of the selling agent is high (1 / *h_age*)

These preferences are first calculated individually for each selling agent. Then, in a second step, all weights of each criterion are normalised using the absolute minimum and maximum values of each preference criterion. After normalisation, all individual preferences have values between 1 and 2. For example, if the individual distance preference is 1, the global distance weight will be applied as it is. If the individual distance preference is 2, the global distance weight will be doubled, indicating a higher individual preference for the distance criterion. (5) Initial scores are calculated for each outgoing trading connection of the selling agents. Initial scores are only calculated for the distance, price, and debts criteria, because distance to buying traders, prices offered by the buying traders, and debts incurred from a specific buying trader do not change during model execution. First, for each trading link a score is calculated for each criterion (s_p for price, s_{di} for distance, s_{de} for debts). This is done by re-scaling the link values of each criterion to values between 0 and 1. For example, for the price criterion, the trading link with the highest price has a score of 1, whereas the trading link with the lowest price has a score of 0. For the distance criterion, reciprocal values are used to calculate scores, i.e. the longest trading link has a score of 0 and the shortest trading link has a score of 1. Based on these criterion scores, each selling agent calculates a preliminary score for each outgoing trading link. For each initial weighting criterion a weighted score is calculated by multiplying the criterion score with its corresponding global weight (w_p for price, w_{di} for distance, w_{de} for debts) and the selling agent's corresponding weight preferences (see Eq. B.1). The sum of these weighted scores is then divided by the sum of all weights, multiplied with the corresponding weight preferences.

$$l\_score = \frac{s_p * w_p * p_p + s_{di} * w_{di} * p_{di} + s_{de} * w_{de} * p_{de}}{w_p * p_p + w_{di} * p_{di} + w_{de} * p_{de}} \tag{B.1}$$

B2.2. Details on input data

An overview of the variables entering the simulation is provided in Tables A.1, A.2, and A.3. Further descriptive statistics can be found in Tables B.3 and B.4.

As can be seen in Fig. 3, some of the sample villages are located in close geographical proximity while others lie further apart. In areas in which the sample villages lie in closer geographical proximity, a higher share of all sellers were interviewed, which increased the probability of interviewing multiple sellers that buy from multiple sellers in the sample. In the part of the research area, in which the randomly chosen villages lie further apart, this probability is lower. In the extreme case a seller sells to a buyer whom no other seller in the sample sells to, which means that there are buyers being chosen by only one seller in the sample.[18] By construction, these links cannot be predicted by the influence of other sellers who already sell to these buyers, because there are none. This was solved by running the simulation with a sub-sample that excludes the buyers who buy from only one seller. This resulted in 66 of 246 traders being omitted (27%), which corresponds to 41 of 223 trading links (18%). As a robustness check the simulation was also carried out with the unrestricted sample (Table B.2).

The results for the main weights based on the reduced sample differ from the ones based on the full data set mainly in the parameters of the debt and the price criteria, as well as the social matrix. All changes are below 20 percentage points and the relative ordering is hardly affected by the sample reduction: the debts that a seller has with a specific buyer is most important criterion in traders' channel choice, followed by the social matrix, the indicator of the peer effects. The distance criterion is weighted at around ten percent in both samples. Only the price criterion changes strongly and becomes more important than the distance. This means that trading links to buyers, who were named by only one seller, could be well predicted by the price. Within the social matrix the two main determinants are the proximity of peers and education levels in both the full and the reduced sample. Within the three minor criteria – ethnicity, social group activity, and the prestige associated with certain jobs – the latter turns from the most to the least important determinant while the ordering of the others stay the same. However, these values are all rather small (all below 15% in both optimisations). The interpretation in the main text is based on the results from the reduced sample.

B2.3. Sub-models

Social interactions It seems plausible that sellers who are socially connected influence each other and tend to connect to similar buyers. In order to allow for these interactions, each model loop starts with the determination of social interactions between selling agents. This is done by calculating a social score for each social link that depends on several properties of the selling agents that are connected by the social link. Social link scores always indicate the influence of selling agent A on selling agent B. To determine social scores, the properties of the selling agents are compared. Each property is normalised within the [0;1] space to allow for easier comparability between the effects of the different properties.

- The *proximity* criterion has a value of 0 if agent A and B have different district IDs, a value of 0.33 if they have the same district ID, a value of 0.66 if they have the same district and subdistrict ID and a value of 1 if they have the same district, subdistrict and village ID.
- The *education* criterion has a value of 1 if agent A has the highest education (6) and a value of 0 if agent A has the lowest education (1). Values in between extremes are linearly decreasing depending on the education level (5:0.8, 4:0.6, 3:0.4, 2:0.2).
- The *ethnicity* criterion has a value of 1 if agent A and B belong to the same ethnicity, and a value of 0 if they belong to different ethnicities.
- The *group activity* criterion has a value of 1 if agent A is active in 4 groups, and a value of 0 if agent A is active in 0 groups. Values in between extremes are linearly decreasing depending on the number of active groups (3:0.75, 2:0.5, 1:0.25).
- The *prestigious job* criterion has a value of 1 if agent A has a prestigious job, and a value of 0 if agent A does not have a prestigious job.

Descriptive information on these variables are provided in Table B.3. The final social score of each social link is then calculated by weighting the social sub-scores with the global weight parameters for the social matrix (see Eq. B.2). Since a

[18] According to survey information, there are no buyers that buy from only one seller.

social link is created from each selling agent to each other selling agent, two links exist between each pair of selling agents. From each pair of social links between the same agents only the social link with the higher social score is kept in the model.

$$l\_score_{soc} = \frac{s_{prox} * w_{s,prox} + s_{educ} * w_{s,educ} + s_{eth} * w_{s,eth} + s_{group} * w_{s,group} + s_{job} * w_{s,job}}{w_{s,proximity} + w_{s,educ} + w_{s,eth} + w_{s,group} + w_{s,job}} \tag{B.2}$$

Finally, each selling agent selects the most *n_social* influential incoming social links, i.e. the incoming social links with the highest social score, to be active. These active social links are considered the social network in terms of interactions between selling agents.

Trading score calculation. The trading link sub-scores for static criteria have been calculated during initialisation (distance, price, debts). The social sub-scores of trading links are dynamic and are calculated during the procedure. This calculation is repeated in each loop iteration in the model, as trading choices may change in each iteration. Selling agents recommend buying agents to other selling agents within their social network. This is done by transferring the own individual trading scores of specific buying agents to socially connected selling agents and weighting these scores with the strength of the social influence between these two selling agents (see Fig. B.2).

For example, a selling agent h0.1 wants to determine the social score of the outgoing trading connection to buyer h1.1. First the “influencing” selling agents are determined, i.e. socially connected selling agents that have an influence on h0.1. Then the scores of the trading links of these socially connected selling agents to that same buyer (h1.1) are weighted by the social score and their sum is calculated.

This procedure is executed for all selling agents and all outgoing trading connections. Afterwards, each trading connection has a social score value that represents the weighted score of socially connected selling agents for that same buyer. Finally, the social sub-scores of all trading links are normalised to an interval between 0 and 1.

The final trading score for each trading link is then calculated based on the initial sub-scores, which were calculated during initialisation (distance, price, debts) and the social score indicating trading preferences within the selling agents' active social network (see Eq. B.3).

$$l\_score = \frac{s_p * w_p * p_p + s_{di} * w_{di} * p_{di} + s_{de} * w_{de} * p_{de} + s_{soc} * w_{soc} * p_{soc}}{w_p * p_p + w_{di} * p_{di} + w_{de} * p_{de} + w_{soc} * p_{soc}} \tag{B.3}$$

Active trading selection Within this sub-model, each selling agent decides to which buying agent he or she will connect. The total number of active trading links a selling agents chooses is defined by the parameter *h_n_buyer* which depends on the values of an agent's total sales. This relationship is found via a regression of the total sales value of each seller on the number of buyers that he/she is delivering to. The regression results can be found in Table B.5. The number of links from each seller entering the simulation are the predicted values of this regression. To select active trading connections, each selling agent simply selects the *h_n_buyer* trading links with the highest final scores and sets the *l_status_model* variables of these trading links to 1.

Output and measurements. Within this sub-model, all output observations are calculated (see Table B.1). Further, the visual output of RUBNET is updated. Inactive trading links are hidden and active trading links are displayed in different colours (see Fig. 5). These colours indicate whether a predicted active trading link has a matching trading connection within the empirically observed data.

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