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Networks and Transaction Costs

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In general, one can distinguish two different pathways for how social networks influence individual behavior and social outcomes: the impact of networks on cooperation and the impact of networks on beliefs (Jackson 2008). Regarding the first, economic and social exchange is often plagued by opportunistic behavior. Ensuring honest compliance with an explicit or implicit contract requires institutions to detect and punish cheating. In modern and developed economies, a well-functioning state legal system performs these functions. However, even within a well-functioning legal system, opportunistic behavior generally still occurs. Thus, self-governance has been studied as a form of governance, which complements rule-based systems (Dixit 2003). Self-governance corresponds to relation-based governance, i.e. the fact that cooperation is sustained via specific structures of interactions among actors.

Self-governance among a group of actors with repeated exchange among different partners can work if communication within the group permits a collective memory of cheating and group members punish cheaters by refusing to trade with them. Kandori (1992) developed a pioneering theoretical approach, which was elaborated on by Greif (1994) and more recently by Dixit (2003). Moreover, in sociology, a well-established literature on social exchange and networks exists (Cook and Emerson 1978; Raub and Weesie 1990; Buskens 2003). However, despite these seminal contributions, it is fair to conclude that research on networks and cooperation is still in its infancy. In particular, existing economic studies focus on rather abstract models of relation-based self-governance. These models do not permit derivation of explicit hypotheses regarding how specific network structures impact cooperation (Dixit 2003; Greif 1994). Moreover, existing studies mostly analyze the impact of network structure on cooperation or defection as a binary variable, while the degree of cooperation, or the costs of achieving cooperation, have hardly been studied as yet.

In this context, this article sets out (1) to develop a simple game-theoretical model in which transaction costs are derived from the risk of opportunistic behavior in repeated multilateral trade relations, (2) to demonstrate that individual transaction costs are determined by the structure of an agent's egocentric (personal) business network, and (3) to estimate empirically the impact of business network structures on farms' transaction costs observed for different input and output markets. Estimation results based on a sample of Polish farms imply a significant influence of social network structures on farms' transaction costs.

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Theory

A simple trading world

Consider a simple trading world comprising two buyers and three sellers located in two regions. Let $b = 1,2$ denote the buyers, while $s = 3,4,5$ denote the sellers.

Sellers and buyers are matched and can exchange two commodities, A and B. For a given exchange rate v, sellers are willing to exchange a specific quantity t of commodity A in return for a quantity $v \cdot t$ of commodity B. Sellers are defined as the agents who move first, while buyers, by definition, always respond. Thus, exchange is considered as a one-sided prisoner's dilemma game (OSPD), where only buyers can display opportunistic behavior. Let $\Pi^s(t,v) = v \cdot t - C(t)$ and $\Pi^b(t,v) = (1-v)t \; \forall \; t \leq \hat{t}_b$, $\Pi^b(t,v) = 0 \; \forall \; t > \hat{t}_b$ denote the payoff functions of sellers and buyers, respectively. $C(.)$ is a convex function, which reflects increasing marginal costs of production for commodity A. Quantity $\hat{t}_b$ is understood as buyer b's maximum trading capacity.

Matches

The game is played in two periods. In the first period, buyers can decide whether they want to behave honestly or cheat. The appropriate reward or punishment for their behavior occurs in the second period, which is, as usual, interpreted as the reduced form of a longer future (Dixit 2003, p. 1296). In each period, both buyers are randomly matched with sellers, where m_{bs} denotes the probability that buyer b is matched with seller s. The matches are assumed to have the following properties:

MI1. Independence: In each period, matches of buyer 1 and 2 are independent of each other. Further, the actual match in period 1 does not affect the probabilities of matches in period 2—an assumption to make the analysis more tractable. In reality, buyers and sellers may build reputation and preserve matches that have had good outcomes. But as long as there is some exogenous probability of separation due to death or retirement of trading partners, qualitative results will be unaffected by this assumption (see also Dixit 2003).

MI2. Matching technology: In each period, each buyer b meets exactly one seller s. Hence $\sum_s m_{bs} = 1$, $b \in (1,2)$. However, a seller can meet one, two or no buyer, i.e. $\sum_b m_{bs} \leq 1 \; \forall \; s$. The latter assumption implies that trading involves search costs for sellers, which can differ among sellers.

MI3. Spread of information: If a buyer in a match cheats the seller, the seller can inform other sellers. We denote the probability that information sent by seller s is received by seller s' by $i_{ss'}$. Information transmission is symmetric: $i_{ss'} = i_{s's}$. Obviously $i_{ss} = 1$.

Player types, information, strategies, and payoffs

Following Dixit (2003) there are two behavioral types of buyers: normal buyers (N-type) and Machiavellian buyers (M-type). The M-type buyers should be thought of as especially skillful cheaters. In period 1 types are unknown, where nature independently draws the type of each buyer, with ε being the probability that a buyer is of type M. The probability ε is assumed to be very small. In each period, four different matching scenarios are possible for each seller. We denote these by $g = 0,1,2,3$: no match ($g = 0$), meeting buyer 1 ($g = 1$), meeting buyer 2 ($g = 2$), or meeting both buyers ($g = 3$). With given matching probabilities, it is straightforward to calculate the probability that a specific matching scenario occurs for each seller. We denote these probabilities by W_{sg}.

If a seller is matched with a buyer he may know the buyer's history of cheating, if any, given the information mechanism described under MI3. For each matching scenario g, the stage game of matched sellers and buyers is as follows:

G1. Matched players simultaneously choose whether to play or not. The payoff of the outside opportunity for each player is normalized to zero.

G2. If a seller and a buyer choose to play, they play the following one-sided prisoner's dilemma game (OSPD^g).

Seller s formulates an exchange proposal (t_{bs}, v_{bs}), $0 \leq t_{bs} \leq \hat{t}_b$ and $v_{bs} \in (v_c, v)$. Buyer b can agree with this proposal, or reject. If b rejects, the game is over and both players receive their outside payoff of zero. If b agrees, then seller s delivers t_{bs} units of commodity A to the buyer. After receiving t_{bs}, the buyer can choose to be honest, i.e. return $v \cdot t_{bs}$ units of commodity B to the seller, or the buyer can cheat and only return $v_c \cdot t_{bs}$ units, with $0 < v_c < v$. Hence, we assume that trading does not occur in a completely lawless environment, i.e. there is a limit to cheating, with a minimum degree of contract fulfillment being guaranteed by the state legal system at least for N-type buyers.

If b is honest, he receives payoff $\Pi^b(t_{bs}, v_{bs})$ which is always lower than, or equal to, his payoff from cheating $\Pi^b(t_{bs}, v_c)$. Seller s's payoff depends on the matching scenario g. If a seller meets only one buyer, his payoff is $\Pi^s(t_{bs}, v_{bs})$ if the buyer is honest and $\Pi^s(t_{bs}, v_c)$ if the buyer cheats. However, if seller s meets both buyers his possible payoffs from the game played with buyer b are conditional on his trade proposal made to the other buyer t_{-bs}, i.e. $\sum_b t_{bs} v_{bs} - C(t_{bs} + t_{-bs})$ if b is honest and $t_{bs} v_c + t_{-bs} v_{-bs} - C(t_{bs} + t_{-bs})$ if b cheats, respectively. Thus, under scenario $g = 3$, a seller simultaneously plays two OSPD games, one with each of the two buyers. To formulate some further restrictions regarding the payoff functions of players, we define $t_s^o = \operatorname{argmax} \Pi^s(t,v)$ and $t_s^c = \operatorname{argmax} \Pi^s(t,v_c) < t_s^o$ as seller s's maximum trading volumes given prices v and v_c, respectively.

If a buyer meets an M-type player, the latter always cheats. In particular, we assume that even if a seller proposes the state guaranteed exchange rate v_c, M-type buyers still have sufficient cheating skills to reduce this price, while N-types pay v_c. We thus assume that seller s will always make a loss, $L > 0$, when playing against an M-type buyer. Therefore, knowing that b is an M-type buyer implies that s will choose not to play. If s proposes the higher exchange rate v, cheating of any buyer will always imply the price v_c, independently of the buyer's type.

We make two further assumptions:

P1. It holds for any seller that $(1-\varepsilon)\Pi^s(t_s^c, v_c) - \varepsilon L > 0$, which implies that every seller prefers to play when matched with a random buyer, where in period 2 sellers will always propose the minimal trading contract (t_s^c, v_c) to any unknown buyer they meet under matching scenarios 1 and 2, while they will propose $(0.5t_s^c, v_c)$ to each single buyer under matching scenario 3.

P2. It holds for any buyer that $\Pi^b(\hat{t}_b, v_c) - \Pi^b(\hat{t}_b, v) < c_b^{hs}\ \forall s$, where, as defined below, c_b^{hs} is the expected payoff of an N-type player in period 2 who played honestly with seller s in period 1. P2 says that in a world where cheating is detected with certainty, no N-type buyer will choose to cheat. Thus, N-type buyers will only be tempted to cheat if there is a positive probability that cheating in period 1 will not be detected by future trading partners.

Equilibrium

Instead of a full derivation of equilibrium strategies, we focus on characterizing the equilibrium behavior of sellers and buyers, where a formal proof is available from the authors. The general solution concept is an imperfect Bayesian Nash equilibrium. By assumption, M-type players always choose to play, and if they play, they always cheat. Thus, the relevant strategies to be characterized are those of the sellers and N-type buyers.

The crucial point is that in equilibrium, N-type buyers will only play honestly in period 1 if their total expected payoff from playing honestly is higher than the payoff received from cheating. Given a trading proposal (t_{bs}, v), cheating results in a profit gain of $t_{bs}(v - v_c)$ in period 1, while the cost of cheating results from the fact that in period 2 future trading partners might be informed about a buyer's cheating and refuse to play. Let c_b^{hs} and c_b^{cs} denote the expected payoffs of buyer b in period 2 if he played honestly with seller s and if he cheated in period 1, respectively. Thus, the cost of cheating equals $c_b^{hs} - c_b^{cs}$. It holds: $c_b^{hs} = \sum_{s'} m_{bs'} c_{bs'}$, where $c_{bs'} = t_{s'}^c (1 - v_c)[1 - 0.5 m_{-bs'}(1 - m_{-bs'}\varepsilon)]$. Accordingly, it holds $c_b^{cs} = \sum_{s'} m_{bs'}(1 - i_{ss'}) c_{bs'}$. Overall, buyers play honestly as long as the gains from cheating are lower or equal to the costs of cheating, i.e. $t_{bs}(v - v_c) \le c_b^{hs} - c_b^{cs}$.

Hence, for each seller and each buyer, a maximum trading volume, $\bar{t}_{bs} = Q_{bs}/(v - v_c)$, exists that guarantees honesty in equilibrium and is determined by the given matching and information technology MI1–MI3, where $Q_{bs} = c_b^{hs} - c_b^{cs} = \sum_{s'} m_{bs'} i_{ss'} c_{bs'}$ are the costs of cheating. Accordingly, given this equilibrium strategy of N-type buyers, a seller s's Bayesian updating on the information that a currently matched buyer cheated in period 1 results in the belief that this buyer is an M-type player. Therefore, choosing not to play with this buyer in period 2 is optimal.

Overall, in equilibrium, each seller has a trading strategy in period 1, $t_{sg}^* = (t_{bsg}^*), v_{sg}^* = (v_{bsg}^*)$, for each matching scenario $g = 0,1,2,3$ which maximizes his expected profit. Assuming Q_{bs} is sufficiently large so that sellers always cooperate in the first period[1], equilibrium strategy can be characterized as follows:[2] $t_{1sg}^* = 0, g = 0,2$; $t_{1sg}^* = \min\{\bar{t}_{1s}, \hat{t}_1, t_s^o\}, g = 1,3$; $t_{2sg}^* = 0, g = 0,1$; $t_{2sg}^* = \min\left\{\bar{t}_{2s}, \hat{t}_2, t_s^o - t_{1sg}^*\right\}, g = 2,3$.

Transaction costs and networks

Obviously, as long as $\sum_b t_{bsg}^* < t_s^o$, trading will be restricted from the view point of a seller, where trade restrictions are caused by a commitment problem of matched buyers to play honestly ($\bar{t}_{bs} < t_s^o$), or due to search costs. In our simple trading game, commitment power of a buyer b vis-à-vis a seller s is exactly captured by the term Q_{bs}, while search costs result from the fact that a seller is not matched

[1] If Q_{bs} is below a specific threshold, sellers will cease to cooperate, i.e. make a non-cooperative trading proposal, (t_s^c, v_c) even in period 1.

[2] Please note that under scenario 3 there might be multiple trading proposals (t_{bs}) that maximize seller s's payoff. For simplicity, guaranteeing a unique solution, we assume that sellers always suggest a maximum trading quantity to buyer 1 without changing main implications of our analyses.

with a buyer, or is matched with a buyer who has limited trading capacities ($\hat{t}_b < t_s^o$).

In reality, firms often have to make production decisions before actually knowing which trading deals they can make. In this case, sellers have to make their production decision under uncertainty, i.e. they do not know which trading scenario $g = 0,1,2,3$ will be realized. Assuming that non-sold quantities of commodity A have value v_s^0 to the seller, his expected profit maximization with ex ante uncertainty of trading scenarios can be stated as follows:

$$
\text{(1)} \qquad t_s^* = \underset{t}{\operatorname{argmax}}\ \Pi^s(t) - TC^s(t)
$$

$$
TC^s(t) = \sum_g W_{sg}\Big[I_{t>\hat{t}_{sg}}(v - v_s^0)(t - \hat{t}_{sg}) + \varepsilon \cdot \hat{t}_{sg}(v - v_c)\Big],
$$

where t_s^* denotes seller s's optimal production decision, $\hat{t}_{sg} = \sum_b t_{bsg}^*$ are the equilibrium trading volumes resulting from our simple trading game, and $I_{t>\hat{t}_{sg}}$ is an indicator function that is one if $t > \hat{t}_{sg}$ and zero otherwise. Obviously, $TC^s(t)$ can be interpreted as seller s's transaction costs of using the trading regime (MI1–MI3) reflecting inherent commitment and search problems. Further, $TC^s(t)$ is increasing stepwise in t, where the discontinuous jumps of the transaction costs occur at the equilibrium trade volumes of each trading scenario g ($t = \hat{t}_{sg}$). Accordingly, the concrete specification of seller s's transaction cost function depends on the matching and information mechanism MI1–MI3.

How can we relate transaction costs of relation-based trading regimes with actual network structures of underlying interactions? In more specific terms, how can we relate a firm's personal, so-called ego-centric, network structures to its individual transaction costs, which result from commitment problems of trading partners?

To understand this relation intuitively, please note that both the matching and the information mechanisms are defined by a network of dyadic trading and information exchange relations among the set of traders. Accordingly, an ego-centric network of an individual trader i (EGO) is defined as the subset of all dyadic relations among traders in the neighborhood of EGO, where the latter is defined as the subset of all traders which have a direct trading or information exchange relation with trader EGO.

Assume business occurs in separated small local trading worlds. In this case, it follows that small and dense ego-centric business networks increase commitment power of firms and hence reduce c.p. their transaction costs. To see this, consider a small local trading world comprising only one buyer and three sellers, where a seller s has a strong and direct information link to the two other sellers, i.e. $i_{ss'}$ is close to 1, while all sellers have a strong trading link with the buyer b, say $m_{s'b} = 0.33$ for all s'. Hence, the ego-centric business network of s is small with a size of 3 and dense, with a density of $2/3 = 0.67$. Moreover, it follows that Q_{bs} almost equals c_b^{hs}, that is cheating is detected with almost certainty and thus seller s has almost full commitment power vis-à-vis buyer b.

In a large global trading world, however, a seller meets many different buyers with a low matching frequency for a specific buyer. Hence, in a large trading world, a seller would need to form a large number of information ties to be able to commit all matched buyers. But, network ties are costly and hence the number of ties per firm is restricted. Accordingly, in a global trading world, a seller can only reach a large set of other trading partners via indirect information ties. It is well known in quantitative network theory (Rapoport 1953) that the probability that information spreads from any node i to any other node j in a large network is determined by global network structures, i.e. the global network density and the global clustering of the network. Analogously, at the micro level, the probability that information sent by EGO will reach an average node in the network increases with size and decreases with density of the EGO's network (Henning and Saggau 2010).

Thus, in a global trading world, large and sparse ego-centric business networks imply higher values of Q_{bs}, which increase the commitment power of firms and lower their transaction costs. Compared to small local trading worlds, transaction costs are ceteris paribus higher, as information transmission is less efficient in large, as opposed to small networks. Moreover, please note that as long as business occurs in separated small trading worlds, large and sparse networks, including traders of different local trading worlds, are quite inefficient at committing to a specific local trader.

Empirical Framework

Overall, our theory implies that relation-based self-governance of trading involves commitment problems implying firm-specific non-linear transaction costs. Moreover, the density and size of a firm's ego-centric business network should have a significant impact on the firm's absolute and marginal transaction costs.

To test our theory empirically, we undertake an econometric estimation of the impact of social networks on transaction costs in commodity markets. Our starting point is the following Lagrangian for maximizing a farm's risk-adjusted profit including transaction cost:

$$\Lambda = \sum_{i=1}^{N} \left[p_i y_i - T_i^y(y_i) - R_i^y \right] - \sum_{k=1}^{K} \left[w_k x_k + T_k^x(x_k) \right] - \lambda F(\boldsymbol{y}, \boldsymbol{x}) \tag{2}$$

where $\boldsymbol{y} = (y_1, \ldots, y_N)'$ is a vector of N output quantities, $\boldsymbol{x} = (x_1, \ldots, x_K)'$ is a vector of K input quantities, p_i is the price of the ith output, w_k is the price of the kth input, T_i^y are transaction costs for selling the ith output, T_k^x are transaction costs for purchasing the kth input, R_i^y is a risk premium due to price volatility of the ith output, λ is a Lagrangian multiplier, and $F(\boldsymbol{y}, \boldsymbol{x})$ denotes the transformation function with $F(\boldsymbol{y}, \boldsymbol{x}) = 0$ if the output quantities $\boldsymbol{y}$ can be produced from the input quantities $\boldsymbol{x}$. The first-order conditions are

$$\frac{\partial \Lambda}{\partial y_i} = p_i - \tau_i^y - r_i^y - \lambda F_i^y = 0 \; \forall \, i; \tag{3}$$

$$\frac{\partial \Lambda}{\partial x_k} = -w_k - \tau_k^x - \lambda F_k^x = 0 \; \forall \, k \tag{4}$$

with $\tau_i^y = \partial T_i^y / \partial y_i$ being marginal transaction costs for selling the ith output, $r_i^y = \partial R_i^y / \partial y_i$ are marginal risk premiums due to price volatility of the ith output, $F_i^y = \partial F(.)/\partial y_i$ are partial derivatives of the transformation function with respect to the ith output, $\tau_k^x = \partial T_k^x / \partial x_k$ are marginal transaction costs for selling the kth input, and $F_k^x = \partial F(.)/\partial x_k$ are partial derivatives of the transformation function with respect to the kth input. Some calculus leads to

$$\frac{F_i^y}{F_1^y} = \frac{p_i}{p_1} \, \frac{1 - \dfrac{\tau_i^y}{p_i} - \dfrac{r_i^y}{p_i}}{1 - \dfrac{\tau_1^y}{p_1} - \dfrac{r_1^y}{p_1}} \; \forall \, i \geq 2; \tag{5}$$

$$-\frac{F_{x_k}}{F_{y_1}} = \frac{w_k}{p_1} \, \frac{1 + \dfrac{\tau_k^x}{w_k}}{1 - \dfrac{\tau_1^y}{p_1} - \dfrac{r_1^y}{p_1}} \; \forall \, k. \tag{6}$$

Given a specified farm technology, $F(\boldsymbol{y}, \boldsymbol{x})$, the transaction costs function can be estimated econometrically based on firms' observed inputs and outputs, observed farm-specific input and output prices, as well as further farm characteristics.

Econometric models

In the first step we estimate $F(\boldsymbol{y}, \boldsymbol{x})$ as a flexible translog multiple-output stochastic Ray production frontier, as suggested by Löthgren (2000). The key idea of this approach is to represent the vector of output quantities $\boldsymbol{y}$ by a distance component $l(\boldsymbol{y}) = \|\boldsymbol{y}\|$ (its Euclidean norm) and a direction measure $\boldsymbol{m}(\boldsymbol{\theta}(\boldsymbol{y}))$, i.e. the polar coordinates with $\|\boldsymbol{m}(\boldsymbol{\theta}(\boldsymbol{y}))\| = 1$.

In the second step, we estimate transaction cost parameters based on eq. (5) and (6). Taking the logarithm and replacing the logarithmic terms on the right-hand side by first-order Taylor series approximations yields after re-arrangements (Henning, Henningsen, and Henningsen 2010):

$$\ln\left(\frac{F_i^y}{F_1^y}\right) - \ln\left(\frac{p_i}{p_1}\right) = -\frac{\tau_i^y}{p_i} - \frac{r_i^y}{p_i} + \frac{\tau_1^y}{p_1} + \frac{r_1^y}{p_1} \; \forall \, i \geq 2 \tag{7}$$

$$\ln\left(-\frac{F_{x_k}}{F_{y_1}}\right) - \ln\left(\frac{w_k}{p_1}\right) = \frac{\tau_k^x}{w_k} + \frac{\tau_1^y}{p_1} + \frac{r_1^y}{p_1} \; \forall \, k. \tag{8}$$

Given our theoretical results, we assume that the transaction costs T_i^y and T_k^x can be approximated by the quadratic functions

$$T_i^y = \psi_i^y + \alpha_i^y y_i + \beta_i^y y_i^2 \; \forall \, i; \tag{9}$$

$$T_k^x = \psi_k^x + \alpha_k^x x_k + \beta_k^x x_k^2 \; \forall \, k, \tag{10}$$

where ψ_i^y, α_i^y, β_i^y, ψ_k^x, α_k^x, and β_k^x are unknown parameters.

To estimate the influence of network parameters on transaction costs, we further parameterize the parameters of the transaction cost functions by

$$\alpha_i^y = \delta_i^y + \boldsymbol{\zeta}_i^y \boldsymbol{z} \; \forall \, i; \quad \alpha_k^x = \delta_k^x + \boldsymbol{\zeta}_k^x \boldsymbol{z} \; \forall \, k \tag{11}$$

$$\beta_i^y = \kappa_i^y + \boldsymbol{\eta}_i^y \boldsymbol{z} \; \forall \, i; \quad \beta_k^x = \kappa_k^x + \boldsymbol{\eta}_k^x \boldsymbol{z} \; \forall \, k, \tag{12}$$

where δ_i^y, δ_k^x, κ_i^y, and κ_k^x are unknown parameters, $\boldsymbol{\zeta}_i^y$, $\boldsymbol{\zeta}_k^x$, $\boldsymbol{\eta}_i^y$, and $\boldsymbol{\eta}_k^x$ are vectors of unknown parameters, and $\boldsymbol{z}$ denotes a vector of network structural parameters. Finally, we assume that the risk premium due to volatility of output prices can be approximated by the functions $R_i^y = \mu_i^y v_i^y y_i$, where μ_i^y is an unknown parameter and v_i^y is the price volatility of the ith output.

$$(13)\quad Y_i^y = \delta_i^y\left(-\frac{1}{p_i}\right) + \boldsymbol{\zeta}_i^y\left(-\frac{\mathbf{z}}{p_i}\right) + \kappa_i^y\left(-2\cdot\frac{y_i}{p_i}\right) + \boldsymbol{\eta}_i^y\left(-2\cdot\mathbf{z}\frac{y_i}{p_i}\right) + \mu_i^y\left(-\frac{v_i^y}{p_i}\right)$$
$$+\delta_1^y\left(\frac{1}{p_1}\right) + \boldsymbol{\zeta}_1^y\left(\frac{\mathbf{z}}{p_1}\right) + \kappa_1^y\left(2\cdot\frac{y_1}{p_1}\right) + \boldsymbol{\eta}_1^y\left(2\cdot\mathbf{z}\frac{y_1}{p_1}\right) + \mu_1^y\left(\frac{v_1^y}{p_1}\right) + \varepsilon_i^y\;\forall\, i\geq 2$$

$$(14)\quad Y_k^x = \delta_k^x\left(\frac{1}{w_k}\right) + \boldsymbol{\zeta}_k^x\left(\frac{\mathbf{z}}{w_k}\right) + \kappa_k^x\left(2\cdot\frac{x_k}{w_k}\right) + \boldsymbol{\eta}_k^x\left(2\cdot\mathbf{z}\frac{x_k}{w_k}\right)$$
$$+\delta_1^y\left(\frac{1}{p_1}\right) + \boldsymbol{\zeta}_1^y\left(\frac{\mathbf{z}}{p_1}\right) + \kappa_1^y\left(2\cdot\frac{y_1}{p_1}\right) + \boldsymbol{\eta}_1^y\left(2\cdot\mathbf{z}\frac{y_1}{p_1}\right) + \mu_1^y\left(\frac{v_1^y}{p_1}\right) + \varepsilon_k^x\;\forall\, k,$$

Given the above model specifications, we can derive the system of structural equations as given in eq. (13) and eq. (14), where $Y_i^y = \ln\left(\frac{F_i^y}{F_1^y}\frac{p_1}{p_i}\right)\;\forall\, i\geq 2$, $Y_k^x = \ln\left(-\frac{F_k^x}{F_1^y}\frac{p_1}{w_k}\right)\;\forall\, k$, and $\varepsilon_i^y\;\forall\, i\geq 2$ as well as $\varepsilon_k^x\;\forall\, k$ are stochastic error terms.

Data and estimation

For the econometric estimation of the above structural equations, we use accountancy data and data of ego-centric networks of Polish farms collected in an farm-household survey in 2007, conducted by the authors (Henning, Henningsen, and Henningsen 2010). We have a sample of 315 observations entering the first step of the estimation. However, at the second step, we had to disregard between 215 and 232 observations due to missing price data (see table 2). We distinguish two aggregate outputs, aggregate crop production including 12 individual crops and aggregate livestock production including 10 individual animal products, as well as six inputs, labor, land, capital, intermediate inputs for crop production, intermediate inputs for livestock production, and general intermediate inputs. Furthermore, we include four variables in the model as explanatory variables for the inefficiency term, education (1 = low to 4 = high), experience (measured in years worked in agriculture), a dummy variable for mixed (non-specialized) farms, and the farmers' attitude to risk (1 = risk neutral to 4 = strong risk aversion). The multi-output stochastic ray production frontier model was estimated enforcing monotonicity in inputs applying a three-step estimation procedure proposed by Henningsen and Henning (2009) using the *R* package *frontier* (Coelli and Henningsen 2010). Estimated parameters of the unrestricted and restricted model are provided in Henning, Henningsen, and Henningsen (2010).

Using the parameters of the adjusted restricted model, we compute the dependent variables for the second step of our estimation procedure, i.e. equations (13) and (14). In this step, we consider transaction costs on five markets, crop products, animal products, intermediate inputs for crop production, intermediate inputs for animal production, and general intermediate inputs, while we consider labor, land, and capital as quasi-fixed production factors. Following our theoretical hypothesis, we use two network parameters, density (z_1) and size (number of business contacts, z_2), calculated from farmers' ego-centric business networks. Following the state-of-the-art approach in quantitative network theory, we use three name generators to collect ego-centric business network data, i.e. we asked farm managers to name up to five most important suppliers of inputs and demanders of their outputs, as well as to name up to five most important other firms with whom they exchange valuable business information (Henning, Henningsen, and Henningsen 2010). Following the approach of Krackhardt (Wasserman and Faust 1994), we further ask farm managers to describe the relations between named business partners ranging from 0 = no relation to 3 = very close relation.

We denote crop products as first output ($i = 1$) so that the corresponding variables are used for the normalization in equations (13) and (14). Hence, we estimate a system of four equations—one equation (13) (with $i = 2$ for livestock products) and three equations (14) (with $k = 1$ for intermediate inputs for crop production, $k = 2$ for intermediate inputs for livestock production, and $k = 3$ for general intermediate inputs)—by seemingly unrelated regressions (SUR) using the *R* package *systemfit* (Henningsen and Hamann 2007).

Given the parameter estimates of the second stage, we can calculate the estimated normalized marginal transaction costs by

$$(15) \quad \frac{\tau_i^y}{p_i} = \frac{\delta_i^y + \zeta_{i,1}^y z_1 + \zeta_{i,2}^y z_2 + 2\kappa_i^y y_i}{p_i} + \frac{2\eta_{i,1}^y y_i z_1 + 2\eta_{i,2}^y y_i z_2}{p_i} \quad \forall\, i$$

$$(16) \quad \frac{\tau_k^x}{w_k} = \frac{\delta_k^x + \zeta_{k,1}^x z_1 + \zeta_{k,2}^x z_2 + 2\kappa_k^x x_k}{w_k} + \frac{2\eta_{k,1}^x x_k z_1 + 2\eta_{k,2}^x x_k z_2}{w_k} \quad \forall\, k.$$

To analyze estimated network effects on normalized marginal transaction costs, we take the partial derivatives of eqs. (15) and (16) with respect to density (z_1) and size (z_2).

Results

Summary statistics and estimated transaction cost parameters are presented in tables 1 and 2. Overall, estimation results can be summarized in the following points. First, as can be seen from table 3, we find considerable marginal transaction costs ranging from 32 % to 59 % of the corresponding input and output prices. Second, a significant influence of network parameters on both marginal proportional (ζ-parameters) and non-proportional (η-parameters) transaction costs results. However, single parameters are only significant at the 5%-level for network size (z_2, see t-values for parameters $\zeta_{i2}^y, \zeta_{k2}^x, \eta_{i2}^y, \eta_{k2}^x$), but not for network density (z_1, see t-values for parameters $\zeta_{i1}^y, \zeta_{k1}^x, \eta_{i1}^y, \eta_{k1}^x$ in table 1).

Third, on average, the following pattern of the impact of network parameters on transaction costs can be observed from table 3. While density lowers transaction costs on input markets and raises transaction costs on output markets, the opposite effect can be observed for network size.

How can these patterns be explained? Based on our above theoretical analysis, it follows that for globally traded goods, transaction costs are lower the larger and less clustered the business network of a firm.

By contrast, for locally traded goods, firms with dense and locally clustered business networks face comparatively low transaction costs, since they can better constrain their local business partners via direct contacts to their local clients.

Interestingly, in our farm sample, inputs mainly comprise fodder and seeds, which are partly self-produced, as well as machinery services, fertilizers, and pesticides, which are traded mostly with other farms or small enterprises in the neighborhood. Hence, inputs are usually traded 'locally', while outputs are usually sold to commercial traders operating 'globally', i.e. across communities. Thus, the estimated patterns of network effects tend to support our theory.

Conclusion

We see two contributions of this article to the emerging field of networks and economics. First, the article extends the theory by introducing transaction costs into existing network models of multilateral exchange. Second, we submit our extended theory to a comprehensive econometric empirical estimation of farms' marginal transaction costs. We find a significant quantitative impact of ego-centric network structures on these costs. This not only adds to the established theory of farm behavior and transaction costs, but also suggests future research on how policy intervention can be designed to change a farm's business networks to lower transaction costs.

References

Buskens, V. 2003. "Trust in Triads: Effects of Exit, Control, and Learning." *Games and Economic Behavior* 42:235–252.

Coelli, T., and A. Henningsen. 2010. *frontier: Stochastic Frontier Analysis*. R package version 0.996, `http://CRAN.R-project.org/package=frontier`.

Cook, K.S., and R.M. Emerson. 1978. "Power, Equity, and Commitment in Exchange Networks." *American Sociological Review* 43:721–739.

Dixit, A. 2003. "Trade Expansion and Contract Enforcement." *Journal of Political Economy* 111:1293–1317.

Greif, A. 1994. "Cultural beliefs and the organization of society: a historical and theoretical reflection on collectivist and individualist societies." *Journal of Political Economy* 102:912–950.

Henning, C.H.C.A., G. Henningsen, and A. Henningsen. 2010. "Networks and Transaction Costs: Theory and Empirical Estimation." Working Papers of Agricultural Policy No. 10, Department of Agricultural Economics, University of Kiel.

Henning, C.H.C.A., and V. Saggau. 2010. "Information Networks and Knowledge Spillovers: Simulations in an Agent-Based Model Framework." In N. Salvadori, ed. *Institutional and so-*

Table 1. Parameters Estimated on the 2nd Step

Coefficient	Estimate	t value	Coefficient	Estimate	t value
δ_1^y	0.80456314	2.3240	$\zeta_{1,2}^x$	0.04102752	1.6079
$\zeta_{1,1}^y$	0.48501037	0.8573	κ_1^x	-0.00000373	-1.8032
$\zeta_{1,2}^y$	-0.22042459	-2.9761	$\eta_{1,1}^x$	-0.00000593	-1.5396
κ_1^y	0.00000410	4.6660	$\eta_{1,2}^x$	0.00000009	0.1935
$\eta_{1,1}^y$	0.00000106	0.3474	δ_2^x	0.08015138	1.0440
$\eta_{1,2}^y$	-0.00000012	-0.5614	$\zeta_{2,1}^x$	-0.30235091	-1.3487
μ_1^y	-0.12894477	-1.7863	$\zeta_{2,2}^x$	0.05193221	1.9735
δ_2^y	0.09574413	0.3026	κ_2^x	-0.00000045	-0.7926
$\zeta_{2,1}^y$	0.13505684	0.1623	$\eta_{2,1}^x$	0.00000167	1.4934
$\zeta_{2,2}^y$	-0.18270195	-2.3449	$\eta_{2,2}^x$	-0.00000034	-2.0020
κ_2^y	0.00000112	0.3938	δ_3^x	0.20119201	0.7349
$\eta_{2,1}^y$	0.00000107	0.2761	$\zeta_{3,1}^x$	-0.92568881	-1.0514
$\eta_{2,2}^y$	0.00000030	0.5616	$\zeta_{3,2}^x$	0.22630664	3.1923
μ_2^y	-0.01044592	-0.1447	κ_3^x	-0.00000995	-1.8383
δ_1^x	0.11524579	1.1466	$\eta_{3,1}^x$	0.00000938	0.5748
$\zeta_{1,1}^x$	0.10241470	0.3176	$\eta_{3,2}^x$	-0.00000121	-1.1524

Table 2. Summary Statistics of the 2nd-Step Estimation

	N	DF	R^2	adj. R^2
Y_2^y (livestock products)	97	83	0.4616	0.3772
Y_1^x (intermediate inputs crop)	98	85	0.6710	0.6245
Y_2^x (intermediate inputs livestock)	83	70	0.4096	0.3084
Y_3^x (general intermediate inputs)	100	87	0.4382	0.3607

Table 3. Relative Transaction Costs and Effects of Network Parameters (Median Values)

	relative TAC	effect of density	effect of size
Input Crops	0.3563	-0.0580	0.1020
Input Livestock	0.2659	-0.4769	0.0785
Input General	0.5905	-0.8188	0.2131
Output Crops	0.5167	0.6414	-0.2523
Output Livestock	0.3232	0.1930	-0.1587

cial dynamics of growth and distribution. Edward Elgar, pp. 253–288, 414.

Henningsen, A., and J.D. Hamann. 2007. "systemfit: A Package for Estimating Systems of Simultaneous Equations in R." *Journal of Statistical Software* 23:1–40.

Henningsen, A., and C.H.C.A. Henning. 2009. "Imposing Regional Monotonicity on Translog Stochastic Production Frontiers with a Simple Three-Step Procedure." *Journal of Productivity Analysis* 32:217–229.

Jackson, M.O. 2008. *Social and Economic Networks*. Princeton University Press.

Kandori, M. 1992. "Social Norms and Community Enforcement." *Review of Economic Studies* 59:63–80.

Löthgren, M. 2000. "Specification and estimation of stochastic multiple-output production and technical inefficiency." *Applied Economics* 32:1533–1540.

Rapoport, A. 1953. "Spread Of Information Through A Population With Socio-Structural Bias: II. Various Models With Partial Transitivity." *Bulletin Of Mathematical Biophysics* 15:535–546.

Raub, W., and J. Weesie. 1990. "Reputation and Efficiency on Social Interactions: An Example of Network Effects." *American Journal of Sociology* 96:626–654.

Wasserman, S., and K. Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press.