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Abstract

All business transactions as well as achieving innovations take up resources, subsumed under the concept of transaction costs. One of the major factors in transaction costs theory is information. Firm networks can catalyse the interpersonal information exchange and hence, increase the access to non-public information so that transaction costs are reduced. Many resources that are sacrificed for transaction costs are inputs that also enter the technical production process. As most production data do not distinguish between these two usages of inputs, high transaction costs result in reduced observed productivity. We empirically analyse the effect of networks on productivity using a cross-validated local linear non-parametric regression technique and a data set of 384 farms in Poland. Our empirical study generally supports our hypothesis that networks affect productivity. Large and dense trading networks and dense information networks and household networks have a positive impact on a farm's productivity. A bootstrapping procedure confirms that this result is statistically significant.

Keywords: Information networks, Transaction Costs, Non-parametric estimation, Productivity analysis

JEL codes: D22, D23, D24, L14, Q12

1 Introduction

All business transactions as well as achieving innovations take up resources, subsumed under the concept of transaction costs (Williamson, 2000; Castilla et al, 2000). One major determinant in the reduction of transaction costs is access to information.

Networks can provide access to information that can reduce transaction costs (Henning et al, 2012). Access to information and consequently the impact of networks on firm performance depends on the firm's position in the network, i.e. a firm's position in the network impacts its access to information which in turn reduces transaction costs.

Firms sacrifice many resources for transactions that also enter into production, e.g. labour time, vehicles and fuel for searching information. The problem is that most production data do not distinguish between resources dedicated to transaction costs and resources entering production. In this case, input data are biased upwards resulting in firms that appear less productive than their technical production process otherwise indicates. Consequently, firms that, all else equal, access information via beneficiary network positions will spend fewer resources and seem more productive.

Employing detailed production data from a survey of 384 Polish farms, we estimate the effect of a farm's network position on its productivity, whilst controlling for other relevant factors, e.g. education, job experience, and location. We measure the farm's network position by calculating structural measures of the farm's ego-centred networks (e.g. Wasserman and Faust, 1994, p.42). To avoid specifying a parametric functional form of the unknown relationship between the explanatory variables and the dependent variable, we use a cross-validated local-linear non-parametric regression to estimate the impact of the network structure on productivity.

The paper is structured as follows: section two gives a brief overview of the concept of networks and transaction costs based on earlier studies; section three develops a simple microeconomic model to demonstrate our case; section four and five describe the econometric approach and the data, as well as the results of the analysis, respectively. Finally, section six concludes.

2 Information networks and transaction costs

Traditional neoclassical economics assumes that the exchange of goods and the search for information is costless so that—in this respect—markets are efficient and always provide goods at the lowest possible price. However, more than 75 years ago, Coase (1937) argued in his essay "The Nature of the Firm" that market transactions often involve higher costs than just the market price. Other costs (e.g. search and information costs, bargaining costs, and policing and enforcement costs) can increase the costs of procuring something from a market.

Transaction costs can be divided into two main categories: technological transaction costs and institutional transaction costs (Green and Sheshinski, 1975). Institutional transaction costs include search, negotiation, and control costs, while technological transaction costs can be separated into innovation transaction costs and physical transportation costs.

Institutional transaction costs can occur at three different stages of the transaction: *i)* contact phase, *ii)* contracting phase, and *iii)* control phase (den Butter and Mosch, 2003).

In the *contact* phase of a potential transaction, the actor is looking for information on trade partners, information on non-observable quality characteristics of her preferred product, and prices of the product (either seller or buyer prices). These searching costs occur because the search for information is not free, nor is information always complete, reliable, or easily accessible (e.g Akerlof, 1970). Searching costs are reduced if information is more easily accessible. Well functioning networks can provide their members with information on business opportunities by providing cheap access to the above mentioned information (Granovetter, 1983; Dekker, 2001; Henning and Zuckerman, 2006), whilst as a further benefit, they increase the reliability of the information. In fact, with more information available in the network, and with easier transfers to all interested members, the probability that the information is of high quality increases, i.e. the information can be trusted to be relevant and true (Casson, 1997; Fafchamps, 2001). Based on the theory of weak ties (Granovetter, 1973), Montgomery (1992) demonstrates that weak ties are positively related to higher wages and higher aggregate employment rates. Actors with many loose ties (gatekeepers) are superior regarding access to reliable information on market opportunities and perform better on the market.

The *contract* phase starts when two trade partners agree to make a deal, in this phase transaction costs take the form of negotiation costs. Both partners have to agree on how to divide potential rents from trade (Braun and Gautschi, 2000). Because of bounded rationality, a perfect contract that accounts for all eventualities is unachievable. First, not all arrangements are verifiable by third parties (verification problem). Second, many eventualities cannot be foreseen (environmental and behavioural uncertainty). The higher the *ex ante* trust level between trading partners, the lower is the need to negotiate every detail of the transaction (Portes and Sensenbrenner, 1993; Uzzi, 1996). Hence, the *ex ante* trust level can considerably reduce negotiation costs (Nee, 1998; Fafchamps, 2001). Rooks et al (2000) showed, in a vignette study, that socially well embedded transactions led a purchase manager to put less effort into the management of a transaction. In total, less time was invested in the transaction and fewer departments were involved when the *ex ante* trust level was high because of social embeddedness, which included temporal, network, and institutional embeddedness. The study shows that network embeddedness has a significant influence and reduces the amount of resources invested in a transaction.

Finally, if contracts are signed, the *control* phase starts. This consists of monitoring and enforcing the contract. Both actions can involve many resources and can induce high transaction costs. The first step is the monitoring of the partner to ensure that she meets the arrangement manifested in the contract. If one of the partners behaves opportunistically by not keeping to the agreements, the next step is enforcement of the contract. In most cases, legal procedures are troublesome, expensive, and of long duration. Informal punishment systems, such as the loss of a good reputation or exclusion from future trade possibilities (Kandori, 1992; Greif, 1994; Buskens, 1998), can reduce the costs of contract monitoring and enforcement (Ménard, 2000; Rooks et al, 2000). The better these informal mechanisms work, the lower the incentive to defect in a transaction and, hence, the lower the monitoring and enforcement costs (Buskens, 1999; Richman, 2006).

Innovation transaction costs refer to resources which are sacrificed to gather reliable information on novelties and innovative production methods and processes. Although information on innovations is accessible via public resources such as consulting or professional journals, a considerable amount of information is private (e.g. a competitor's experience with a new production method).

However, this does not mean that private information is completely unavailable. Managers might have close business partners and social contacts who possess this information and are willing to share it. Hence, the quality and quantity of relationships with other professionals and the relevance of these partners may have an important impact on a firm's innovation transaction costs (Castilla et al, 2000). It is quite straightforward that networks which allow this information to spread among entrepreneurs can have a significant impact on the productivity of the entities that have better access to the network, i.e. have better access to reliable non-public information about innovative production methods and processes (Jenssen and Koenig, 2002).

These examples show that a driving force which explains the level of transaction costs that a firm faces is information (Greif, 1994; Noorderhaven, 1996; Calvert, 1995; Levi, 2000). Both institutional as well as innovation transaction costs are therefore materially dependent on access to information. As shown above, networks can provide an efficient and opportune way of gathering especially non-publicly available information (e.g. Granovetter, 1983; Raub and Weesie, 1990; Moschandreas, 1997; Buskens, 1999; Burt, 2001; den Butter and Mosch, 2003; Wiebusch et al, 2004).

As the structure of personal and interpersonal networks differs, the ability to gather information via networks may be limited for some firms and may be amplified for others depending on their individual situation in a network (Buskens, 1999). Hence, the individual network position should have an effect on a firm's transaction costs.

The question remains which network structures are beneficial regarding the reduction of transaction costs. Apart from physical transportation which is only determined by local distance and infrastructure, all sources of transaction costs—searching, negotiation, control, and innovation costs—are related to networks. The difficulty that arises is that some structures which might be beneficial for one kind of transaction cost might be disadvantageous to others. The literature is not clear-cut on the effects of network structures on certain problems.

Beginning with searching costs, the literature suggests that beneficiary network structures are characterised by weak ties, i.e. a high number of loose contacts. In the case of negotiation and enforcement costs on the other hand, the literature states that they benefit from strong social control as a consequence of tight networks, i.e. networks with high density. The *closure argument* (Granovetter, 1985; Coleman, 1990) states that dense networks increase social control, develop common norms, and provide the possibility of punishment in the case of misbehaviour. Thus, dense networks supply their members with high levels of trust and reliable information. This hypothesis is supported by a simulation study by Buskens (1998) which shows that the level of trust increases with both the number of contacts and density. But in cases where trust is low on the dyadic level, the importance of density exceeds the influence of contact numbers.

Contrary to the closure argument, the *gossip argument* (Coleman, 1990; Burt, 2001) states that high density is not necessarily beneficial to increase the level of trust and can in fact reduce the reliability of the available information. The argument is that networks affected by the gossip effect show a tendency to self-enforcing exaggeration, which leads to very extreme positions about other actors, i.e. actors are characterised being either extremely reliable or extremely unreliable. Burt (2001) and Dekker (2001) provide empirical evidence that very dense networks are dominated by the gossip effect and reveal lower trust levels than less dense networks.

Finally, in the case of innovation costs—as in the case of search costs—Granovetter (1983) states that weak ties are the key to innovation diffusion. Loose ties between the firm's clustered core networks increase the diffusion of relevant information on innovation. According to Granovetter (1983), actors that are enclosed in a tight and locked-in network have no or minimised access to "new" information and lag behind when it comes to innovative production technology, while actors with many and loose contacts benefit from increased access to "new" information. Although Granovetter's theory is straightforward, empirical evidence is not definite. In a study among Norwegian entrepreneurs, Jenssen and Koenig (2002) find no empirical evidence to support the theory of weak ties. Contrary to what might be expected, Jenssen and Koenig (2002) show that strong ties are important channels for information and can influence entrepreneurial success.

3 Microeconomic Foundation

We assume that a firm uses a vector of n input quantities $x = (x_1, \ldots, x_n)'$ to produce the output quantity y, where the transformation of the inputs into the output can be described by the production function

$$y = f(x, T) \tag{1}$$

and depends on the state of the technology T.[1]

3.1 Production technology and innovation

We assume that the firm can use resources to improve its production technology T, where these resources can be of the same type as the inputs used for the production (e.g. labour, office supplies, IT technology, fuel). We denote these resources by $\bar{x} = (\bar{x}_1, \ldots, \bar{x}_n)'$, where the elements of $\bar{x}$ correspond to the elements of x[2] so that we can calculate the total input quantities that the firm uses for production and for improving the production technology by $x^* = x + \bar{x}$. Furthermore, the firm can utilise its network to improve its production technology by gathering information from peers, which is otherwise difficult or costly to obtain or even unavailable. We assume that these relationships can be described by the function

$$T = k(\bar{x}, z, u), \tag{2}$$

where z is a vector of network parameters characterising the firm's networks and u is a vector of other factors that might affect the firm's state of technology (e.g. the education of the management). Substituting the function in (2) for T in equation (1), we get

$$y = f(x, k(\bar{x}, z, u)) \equiv f^*(x, \bar{x}, z, u). \tag{3}$$

With respect to resources used for both production and the improvement of the production technology, data sets that are used for estimating production functions generally do not separate between input quantities used for the actual production and input quantities used to improve the production technology. Therefore, the following approximation is necessary for empirical applications:

$$y = f^*(x, \bar{x}, z, u) \approx \hat{f}^*(x + \bar{x}, z, u) = \hat{f}^*(x^*, z, u). \tag{4}$$

[1] The following derivations can also be calculated for multiple outputs, but for simplicity we only use a single output here.

[2] Of course, some elements of $\bar{x}$ might be zero (e.g. raw materials). If some inputs are only used for improving the technology, but not in the actual production (e.g. advisory services or consulting), we can add further elements to the vector x and set these elements to zero.

3.2 Transaction costs in trade

In addition to the resources required for the production x and for improving the production technology $\bar{x}$, the firm needs further resources for trading goods, i.e. purchasing the inputs and selling the output. These resources can be of the same type as the inputs used for production (e.g. labour, capital, office supplies, IT technology, fuel). We denote the vector of resources used for trading goods by $\tilde{x} = (\tilde{x}_1, \ldots, \tilde{x}_n)'$, where the elements of $\tilde{x}$ correspond to the elements of x, $\bar{x}$, and x^*.[3] Hence, we can calculate the total input quantities that the firm acquires to produce the output, improve the production technology, and to trade the goods by $x^{**} = x^* + \tilde{x} = x + \bar{x} + \tilde{x}$. We expect that the quantities of the resources required for trading goods depend on the quantities of the traded goods. Furthermore, our considerations in the previous section suggest that good networks can reduce the input quantities that are sacrificed for trading goods ($\tilde{x}$). We assume that the above mentioned relationships can be described by the (implicit) functions

$$\tilde{x}_i = g_i(x^{**}, y, z, v) \; \forall \, i, \tag{5}$$

where z is—again—the vector of network parameters and v is a vector of other factors that might influence the resources required to trade the goods (e.g. heterogeneity of goods, distance to potential sellers and buyers). Now, we rearrange the above system to get a system of implicit functions for x^*

$$x_i^{**} - x_i^* = g_i(x^{**}, y, z, v) \; \forall \, i \tag{6}$$

$$x_i^* = x_i^{**} - g_i(x^{**}, \hat{f}^*(x^*, z, u), z, v) \; \forall \, i \tag{7}$$

$$x_i^* \equiv g_i^*(x^{**}, x^*, z, u, v) \; \forall \, i, \tag{8}$$

which we can solve to get a system of explicit functions for x^*

$$x_i^* \equiv h_i(x^{**}, z, u, v) \; \forall \, i. \tag{9}$$

Substituting these functions for x^* in the production function that accounts for activities to improve the production technology (4), we get

$$y = \hat{f}^*(h(x^{**}, z, u, v), z, u) \equiv \hat{f}^{**}(x^{**}, z, u, v). \tag{10}$$

As data sets generally do not separate input quantities that are used for the actual production, for improving the production technology, and for trading goods into these three parts, production economists usually do not estimate the *real* production function $f(x)$, but an *augmented* production function $\hat{f}^{**}(x^{**}, z, u, v)$ that not only includes the pro-

[3]Of course, some elements of $\tilde{x}$ might be zero (e.g. raw materials).

duction process, but also the trading of goods and activities to improve the production technology. Hence, transaction costs and innovation costs are usually included in the estimated production technology. According to our assumptions, firms with better networks need less resources for trading goods and can improve their production technology more easily and at less cost (see discussion in the previous section). Hence, these firms should be able to produce the same amount of output (y) with smaller (total) input quantities (x^{**}), i.e. they should appear to be more productive.

4 Model and Data

If our considerations about transaction costs and networks are correct and we use a typical data set, where the input quantities include resources used for the production x, resources used to improve the production technology $\bar{x}$, and resources used for trading goods $\tilde{x}$, the production function should not only depend on the input quantities, but also on the firm's network position. Hence, we can test the hypothesis that networks influence transaction costs by estimating the *augmented* production function $\hat{f}^{**}(x^{**}, z, u, v)$ defined in (10) and testing if the network parameters z have a significant influence.

Given our microeconomic model derived above, the relationship between the total input quantities x^{**}, the network parameters z, the other factors u and v, and the output quantity y is unknown and could be rather complex. To avoid specifying a parametric functional form, we estimate this *augmented* production function by a non-parametric regression technique.[4] We apply the non-parametric local-linear estimation method for both continuous and categorical explanatory variables described in Li and Racine (2004) and Racine and Li (2004), where the second-order Epanechnikov kernel is used for continuous regressors, the kernel proposed by Aitchison and Aitken (1976, p. 29) is used for unordered categorical explanatory variables, and the kernel proposed by Wang and van Ryzin (1981) is used for ordered categorical explanatory variables. We make the frequently used assumption that the bandwidths can differ between regressors but are constant over the domain of each regressor. The bandwidths of the regressors are selected according to the expected Kullback-Leibler cross-validation criterion (Hurvich et al, 1998). The estimation was performed within the statistical software environment "R" (R Development Core Team, 2009) using the add-on package "np" (Hayfield and Racine, 2008).

[4]We estimated the *augmented* production function also using stochastic frontier analysis (SFA) with the model specification of Battese and Coelli (1995), where we assumed that the network parameters influence the firm's (in)efficiency. The results were rather similar, but the SFA approach generally returned higher marginal significance levels (smaller P-values) of the regressors than the non-parametric approach. Since the marginal significance levels of the SFA are probably incorrect due to erroneous assumptions about the parametric specification (translog function for the total input quantities x^{**}; random errors follow a normal distribution; error terms of the inefficiency model follow a truncated normal distribution, where the effect of the network parameters on the expected inefficiency is linear), we decided to only present the results of the non-parametric analysis.

In our empirical analysis, we use a data set of 384 Polish farms. The data were collected within the framework of the "Advanced-Eval" project financed by the European Union within the Sixth Framework Programme. The data set includes detailed farm accountancy data and information on the farms' ego-centred networks. We take the total value of all produced goods as output (in Zloty) and we distinguish between four inputs: labour (in working hours), land (in ha), capital (in Zloty), and intermediate inputs (in Zloty), where the last category mainly consists of seeds, fertilisers, pesticides, purchased feed, fuel, and electricity. We take the logarithm of the output and all the input quantities so that the individual values of these variables are more equally distributed within the range of observed values. If we did not do this, there would be many observations within the bandwidths for small values (farms), but only very few observations within the bandwidth for large values (farms), which usually causes problems in non-parametric regression with fixed (constant) bandwidths. Furthermore, the unknown true *augmented* production function is likely more similar to a log-linear (Cobb-Douglas) function than to a linear function (which implies perfect substitutability between inputs) so that the use of logarithmic quantities of the inputs and the output allows for larger bandwidths, which in turn increases the precision of the local-linear estimates, because the observation-specific marginal effects are based on a larger number of observations (Czekaj and Henningsen, 2013).

Since Polish farms usually have a single farm manager, we do not have to model intra-firm networks, which can play an important role in information diffusion. Hence, our data set has the advantage that we can neglect intra-firm networks when modelling networks. We apply two common network parameters for ego-centred networks to model the structure of the farms' networks, namely the number of outdegrees and the density of the network. The first network parameter refers to the total number of contacts n (*alteri*) that an *ego*—in our case the farm—has. The second network parameter, density, describes the degree of interconnectedness between *ego*'s *alteri*, $h\,/[m(m-1)/2]$, where h is the actual number of ties between the *alteri* and $m(m-1)/2$ is the number of possible ties.

The variables that might affect the firm's state of technology (u) include management characteristics, namely level of education (ordered categorical variable), work experience (in years) and attitude to risk. The latter is the average response to several questions about risk attitude, where larger positive values indicate higher risk aversion.

The region in which the farm is located (unordered categorical variable) is the only variable in our data set that might influence the resources required to trade the goods (v). Our data include farms from four different municipalities (Gminas). The municipalities Chotcza and Wieliszew are located close to urban areas, while Siemiątkowo and Kamieniec are located in remote areas. While Wieliszew and Kamieniec perform well economically, Chotcza and Siemiątkowo's economic performance is weak. Hence, the four municipalities cover all possible combinations of location and economic performance. Of course, this regional variable also accounts for differences in climate and soil, but we cannot differentiate between these effects. Whilst a separation of these effects would be interesting, it is not essential for our study.

5 Results

Table 1 presents the cross-validated bandwidths of the explanatory variables that we obtained by the method of Hurvich et al (1998). Initially, our model also included the farmer's education and his or her risk attitudes as explanatory variables but we removed these explanatory variables, because the bootstrapping method suggested by Racine (1997) and Racine et al (2006) indicated that these variables do not have a statistically significant effect. The bandwidths of the continuous explanatory variables are very large, which indicates that the relationship between these independent variables and the dependent variable is approximately linear. However, in contrast to a parametric linear regression (e.g. OLS), our non-parametric regression with large bandwidths still allows the marginal effects of the explanatory variables to differ between observations.

Table 1: Cross-validated bandwidths of the explanatory variables

Variable	Bandwidth	Scale Factor
lLabor	39601	99902
lLand	39602	70049
lCapital	271441	365861
lIntermed	710646	964351
exper	21571641	2897965
municip	0.500	1.006
outdTrade	4870849	4852258
densTrade	982087	4863543
outdInf	982088	2289227
densInf	271441	3063498
outdSoc	878408	2742619
densSoc	952187	9313730
outdHH	3428765	3477267
densHH	424369	1385528

The marginal effects (gradients) of the independent variable with respect to the explanatory variables are summarised in Table 2. This table also shows the marginal significance levels (P-values) of the explanatory variables that we obtained by the bootstrapping method suggested by Racine (1997) and Racine et al (2006) (see also Hayfield and Racine, 2008, p. 9).

All input quantities (`lLabor`, `lLand`, `lCapital`, `lIntermed`) have a positive effect on the output quantity at all observations. Hence, the monotonicity condition derived from

Table 2: Marginal effects and statistical significance of the explanatory variables

Variable	Min	Mean	Median	Max	P value	
lLabor	0.22	0.28	0.29	0.33	0.00	***
lLand	0.21	0.23	0.22	0.26	0.00	***
lCapital	0.15	0.24	0.21	0.30	0.00	***
lIntermed	0.35	0.42	0.44	0.47	0.00	***
sum: all inputs	1.12	1.16	1.15	1.24		
exper	-0.01	-0.01	-0.01	-0.00	0.04	*
municip: chot → kami	-0.35	0.19	0.22	0.54		
municip: chot → siem	-0.28	-0.01	-0.01	0.17	0.03	*
municip: chot → wiel	-0.08	0.10	0.10	0.32		
outdTrade	0.12	0.15	0.16	0.16	0.00	***
densTrade	0.06	0.32	0.44	0.47	0.04	*
outdInf	0.00	0.03	0.02	0.05	0.95	
densInf	0.67	0.74	0.72	0.81	0.07	.
outdSoc	-0.12	-0.09	-0.11	-0.04	0.66	
densSoc	-0.52	-0.47	-0.47	-0.41	0.31	
outdHH	0.02	0.04	0.04	0.05	0.24	
densHH	0.38	0.40	0.40	0.41	0.00	***

microeconomic production theory is fulfilled in our analysis even though the input quantities include transaction costs. As all input and output quantities are logarithmised, the marginal effects can be interpreted as partial production elasticities of the inputs. However, in contrast to their usual definition, they not only account for the actual production process but also for activities for improving technology and trading goods. Intermediate inputs have the largest marginal effects on output, while the marginal effects of the other three inputs are somewhat smaller. The elasticities of scale, which are equal to the sums over the four partial production elasticities, range from 1.09 to 1.17, which indicates that all farms operate under increasing returns to scale.

The effect of the farm manager's experience (`exper`) on the output is negative for most farms, where each year of experience can reduce the output by a maximum of 1%. The marginal effects of the municipalities (`municip`) describe the expected differences in output that are due to farms being located in different municipalities. We take the municipality Chotcza (`chot`) as the base for our comparison. Farms that are located in the municipality Siemiątkowo (`siem`) need on average roughly as many resources for improving technology, trading goods, and producing the same output as farms in the municipality Chotcza. In contrast, farms that are located in the municipalities Kamieniec (`kami`) and Wieliszew (`wiel`) can produce on average 19% and 10% more output, respectively, with the same amount of input and everything else being equal. Given our model and data, we cannot determine whether the above-mentioned effects of the management characteristics and the farms' location are due to differences in the production process, differences in the resources used to improve the production technology, or differences in the resources required for trade so we only analyse the combined effect.

The number of outdegrees and the density of the farm's trading network (`outdTrade` and `densTrade`, respectively) have a positive and rather large effect on the productivity of all farms. An additional contact increases the farm output on average by 15%. Increasing the density of the farm's trading network from zero (a totally loose network without any connection between the *alteri*) to one (a totally dense network with all *alteri* connected) increases the output on average by 32%.

The number of outdegrees of the farm's information network (`outdInf`) does not have a significant effect on productivity, while the effect of the density of the farm's information network (`densInf`) is large and positive but only statistically significant at the 10% level.

The farm's social network, i.e. friendships with business partners, does not have a statistically significant effect on the productivity.

The number of outdegrees of the household network (`outdHH`) does not have a statistically significant effect on the productivity. The density of the household network (`densHH`) clearly increases the output of all farms. Increasing this density from zero to one would increase the output on average by 40%.

As a complement to the marginal effects shown in table 2, we graphically illustrate the estimation results in figure 1. While the marginal effects shown in table 2 are calculated at all data points that are in the sample, the estimated relationships displayed in figure 1 are calculated by holding the other explanatory variables constant at their medians (numeric variables) or their modal values (categorical variables). Furthermore, the figure shows the 95% variability bounds obtained by bootstrapping (see Hayfield and Racine, 2008, p. 17). The findings derived from the marginal effects shown in table 2 are confirmed in figure 1, i.e. *ceteris paribus* the output monotonically increases in all inputs, slightly decreases in experience, largely increases in the outdegrees of the trade network, and slightly increases in the density of the trade, information and household networks, while the social network and the number of outdegrees of the information network and the household network are (nearly) irrelevant.

Our results confirm findings in the literature that the number of outdegrees decreases transaction costs and increases productivity for the trade network only and not for the other networks. This means that farmers can become more productive by increasing their number of trading partners in order to reduce transaction costs and search costs. On the other hand, close friendships with business partners (i.e. the social network of the farm) have no significant effect on the productivity. This confirms the *weak ties* hypothesis (Granovetter, 1973; Montgomery, 1992), as we find that weak ties (e.g. with trading partners) are more important than strong ties (e.g. close friendships).

The literature provides contradictory results regarding the effect of the density of the firm's network, Our empirical study clearly supports the *closure argument* (Granovetter,

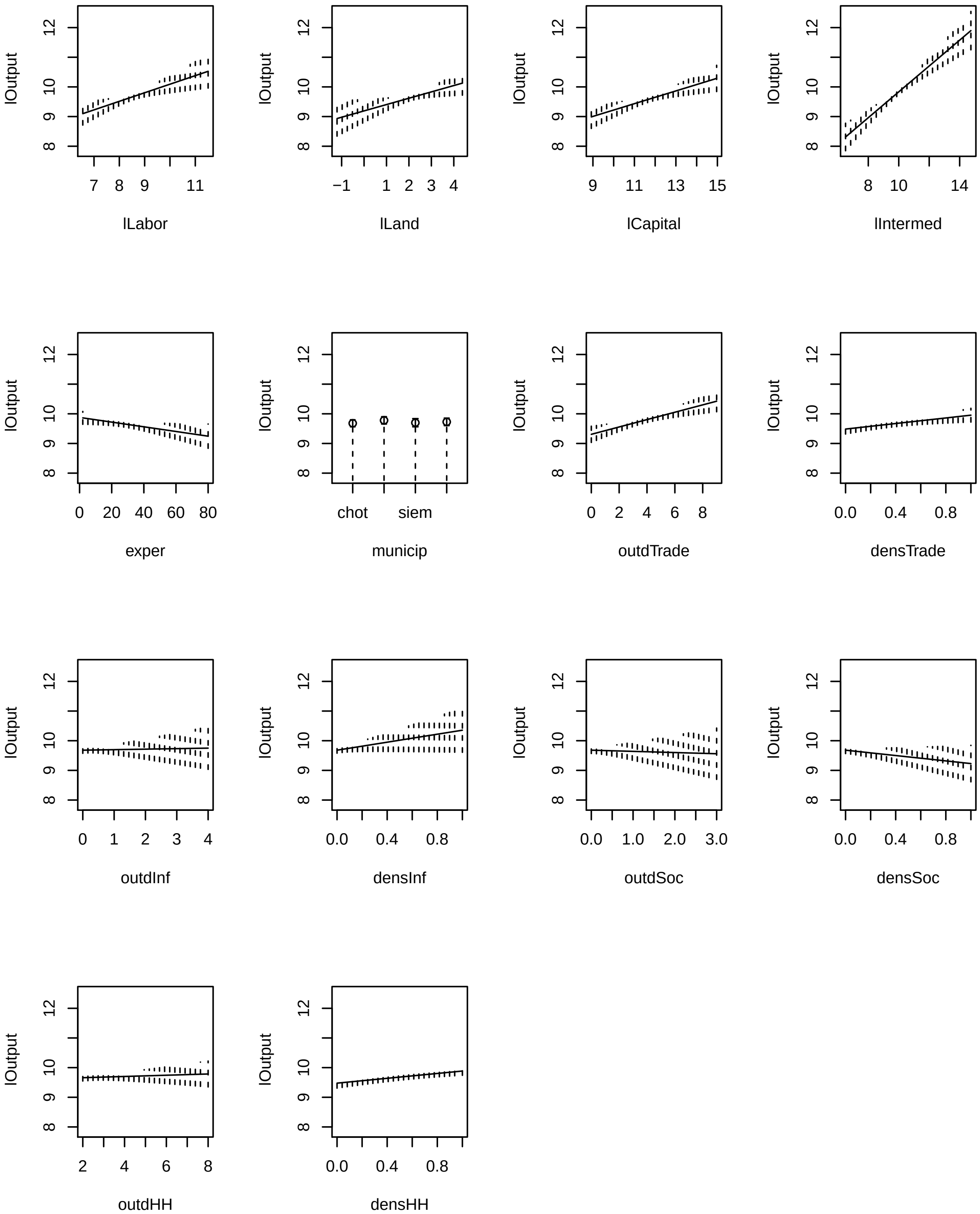

Figure 1: Graphical illustration of the estimation results

1985; Coleman, 1990), as we find that the densities of three out of four networks positively influence productivity. Our analysis does not support the *gossip argument* (Coleman, 1990; Burt, 2001), because the estimated marginal effects of the densities are positive even when the density is already very high.

6 Conclusion

As most data sets do not allow a distinction to be made between inputs used for production and resources dedicated to gather information and to trade goods, the variables that are typically used for estimating production functions generally include technical and institutional transaction costs. We showed that this results in estimating an "augmented" production function that also includes the trading of goods and activities to improve the production technology. A vast literature shows that networks can promote the gathering of reliable information in an economical way. Our empirical study generally supports these results. Large and dense trading networks and dense information networks and household networks have a positive impact on a farm's productivity. Our results support the *weak ties* hypothesis (Granovetter, 1973; Montgomery, 1992) and *closure argument* (Granovetter, 1985; Coleman, 1990), but they do not support the *gossip argument* (Coleman, 1990; Burt, 2001).

Still, further research should be conducted in this field, especially further empirical studies are needed to obtain more reliable information about the coherency between networks and the specific types of transaction costs. Since the farming sector has some very special characteristics (e.g. close connection between household and farm, mainly located in rural areas which include special norms and a special culture due to small and closed communities), the representativeness of our results is generally limited. In this context, it would be interesting to also study other sectors to see whether the effects of networks differ between sectors. Furthermore, future research should include more advanced network parameters and additional types of networks, not just ego-centred. Finally, future work should focus on the separation of technical transaction costs and the different forms of institutional transaction costs. However, the last two suggestions require data that are difficult and costly to collect.

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