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The Influence of Supply Network on Dairy Technology Adoption: Empirical Evidence from Urban and Peri-urban Dairy Farming Systems of Ethiopia

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Abstract

This paper aims at investigating how the supply network structure in which dairy farms are embedded influences their technology adoption. In order to consider the effects of network structure embeddedness on technology adoption, farm-level data were collected from 169 randomly selected dairy farms. Social network analysis was used to develop the structural characteristics and Poisson regression model was used to evaluate the influence of the network on technology adoption. The results indicate that the supply network interconnectedness increases farm's adoption of dairy technology while the supply network density decreases the likelihood of the adoption of dairy technology. Furthermore, the study shows the absorptive capacity positively moderates the effect of supply network accessibility on the likelihood of adoption of dairy technology in dairy farms. This study provides useful insights into the potential role of supply network structural characteristics and the moderating role of absorptive capacity on dairy technology adoption. Thus, in light of these findings, considerations should be given to policies that create an ecosystem of interactions through training, promoting fairs and innovation events to promote rapid dairy technology adoption by dairy farms.

Keywords: Supply network, innovation adoption, adaptive capacity, dairy farm, technology, Poisson model

Introduction

In Ethiopia, dairy production is generally a subsistence smallholder-based industry with relatively few small and medium commercial dairy farms. About 98.24% of the total cattle in the country are local breeds. The remaining 1.76% are hybrid and exotic breeds that accounted for about 1.54 and 0.22%, respectively. In 2019, close to 6.7 million dairy cows produced an estimated 3.6 billion liters of milk nationally, with most of it (over 95%) from local breeds (CSA 2019).

In an effort to improve the dairy sector, huge efforts have been made to disseminate dairy technologies through the support of governmental and non-governmental organizations in different parts of the country. However; the adoption of dairy technologies by farm households varies widely across different agro-ecologies and within the same agro-ecology based on various technical and non-technical determinant factors (Dehinenet *et.al*, 2014).

Previous studies on agricultural technology adoption have focused on the role farm-level characteristics have on technology adoption (Amare *et al.,* 2012; Asfaw *et al.*, 2011; Feder *et al.,* 1985; Sunding *et al.,* 1999). However, the agricultural innovation and technology adoption process involves several human and institutional actors rather than just technological and farm level characteristics (Weyori *et al*., 2018).

Given our current comprehension of factors affecting dairy technology adoption, the goal of this research is to examine how the network structure in which dairy farms are embedded influences technology adoption. In order to consider the effects of network structure embeddedness, we empirically address two interrelated research questions: First, what is the relationship between the structure of a farm's supply network and its technology adoption? Explicitly, we look at three important structural characteristics of supply networks. Second, what moderating role does a firm's absorptive capacity play in the association between the structural characteristics of a dairy farm's supply network and technology adoption? To test the hypothesized relationships empirically, we collected farm-level data from randomly selected dairy farms and used social network analysis to develop the structural characteristics.

The remainder of this paper is organized as follows. Section II provides the theoretical development of the research questions and the hypotheses. Section III describes the data collection, variables, and measures and presents statistical methods employed to test the hypotheses. We present results in Section IV, while Section V provides a discussion of the results, theoretical implications, and limitations of the study, as well as future research directions. Finally, the paper concludes with Section VI.

Theoretical Development and Hypotheses

Supply network

The dyadic perspective of buyer-seller relationship has primarily focused on linear or dyadic structure to capture the benefits of relationships between two parties. Hence, it fails to comprehensively capture a supply chain's dynamic, complex, and increasingly interdependent nature (Basole *et al*., 2018). However, a network approach provides a richer view by considering the various interactions taking place among firms in the supply network (Bellamy *et al*., 2014). A supply network is described by a directed network where each node represents an entity and each directed link denotes the material flow between two entities (from supplier to customer). A connecting rule then means a way that an entity selects its suppliers and customers in the supply network (Xuan *et al.*, 2011). The different firms in the supply network are generally referred to as supply network partners of a given focal firm in the network (Bellamy *et al.*, 2014).

The social network theory helps understand the benefits accrued due to the structural position of a given firm in a number of ways. Primarily, network theory focuses on explaining how patterns of social ties produce better economic outcomes and why inter-organizational networks are formed, collapse, succeed, or fail (Echols and Tsai 2005). In the supply network context, the "social" aspect refers to the interconnected network of suppliers, producers, service providers, and customers that engage in activities related to the procurement, use and transformation of raw materials in order to produce and deliver goods and services (Kouvelis *et al.,* 2006; Lamming *et al.,* 2000).

Supply network and technology adoption

The role of social networks and the behavior of other farmers in the process of technology diffusion are well established in adoption studies (Kassie *et al*., 2012; Bandiera and Rasul, 2006; Conley and Udry, 2010). In Ethiopia, the role of social networks on agricultural technology adoption has been revealed by adoption studies (Wossena et al., 2013; Amlaku *et al.*, 2012; Mekonnen et al., 2016).

Previous studies has shown that firms with broader social networks and greater social capital are more likely to become innovators or adopters of innovation (Jara-Rojas et al., 2012; Maertens and Barrett, 2012; Ramirez 2013; Runyan *et al*., 2006; Sligo and Massey, 2007; Wilson, 2000).

Structural characteristics of supply networks

According to Basole *et al.,* (2018), the structural characteristics of the supply network describe the topological nature of the network, including types and patterns of inter-firm relationships, the strength and nature of these relationships, the different tiers of relationships resulting from the tiered supply and delivery processes, the power, leadership, and influence in the supply network derived from these relationships. Bellamy *et al*., (2014) employed supply network accessibility and supply network interconnectedness to measure structural characteristics of supply network. These measures are important enablers of the flow of information and knowledge in the network. Thus, in this study we employ these two estimates to measure the supply network structural characteristics.

According to Bellamy *et al.,* (2014), supply network accessibility means how effectively a firm is able to access the different sources of information and knowledge assets in the network and supply network interconnectedness means how these sources of information and knowledge are structurally inter-linked together in the network.

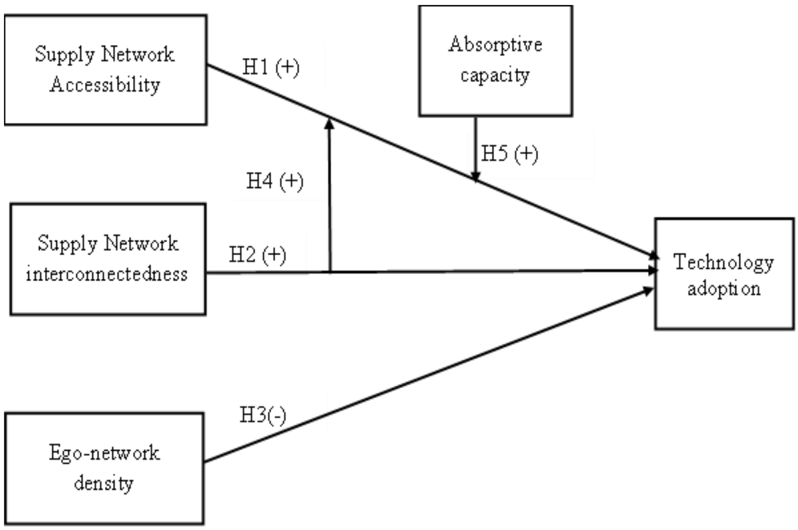

Figure 1: Conceptual model with proposed hypotheses (Own conceptualization)

We conceptually link the structural supply network characteristics of a focal firm (supply network accessibility, supply network interconnectedness, density and the interaction between supply network accessibility and absorptive capacity, and supply network density and network interconnectedness) with its technology adoption (Figure 1) above.

Supply network accessibility

Supply network accessibility refers to the effectiveness with which a firm can access information and knowledge from other members in its supply network, including indirect access to members with whom they do not share a direct relationship with (Bellamy *et al*., 2014). It also reflects the speed of information access. The position of a firm in the supply network can influence the way in which the firm innovates (Ahuja, 2000; and Schilling and Phelps, 2007). The level of accessibility in a dairy farm's supply network is positively associated with its technology adoption (Hypothesis 1).

Supply network interconnectedness

It can be defined as the degree to which supply network partners of a focal firm are connected to each other, and thus share direct links amongst themselves. Supply networks are considered to be densely interconnected when there are a large number of shared linkages that exist between the supply network partners of a focal firm (Bellamy *et al.*, 2014). Supply network interconnectedness based on multiple knowledge connections brings knowledge exchange for a focal firm and ultimately enhances the flow of information and knowledge among its members (Inkpen and Tsang, 2005). Zaheer and Bell (2005) provided evidence that high interconnectedness positively influences improvements in the efficiency and performance of a buying firm. Therefore, Supply network interconnectedness positively influences dairy farm's technology adoption (Hypothesis 2).

Density in Supply Networks

A supply network density can be defined as the degree to which all actors within a supply network are connected to each other (Ahuja, 2000). It indicates the potential for collaboration among members in a focal dairy farm's supply network (Choi *et al*., 2001). Previous studies showed the effect of network density on knowledge creation (McFadyen *et al.*, 2009) and on innovation (Carnovale and Yeniyurt 2015). On the other hand, Burt (1992) emphasizes the diversity of information available in a low-density network structure that can create opportunities for innovation. Given these controversies, some scholars suggested a contingency approach for the relationship between density and firm innovation. In which the context of the phenomenon under scrutiny is what dictates whether density's role is positive or negative (Adler and Kwon, 2002).

It is expected that the association between density and firm performance is much more pronounced in high-velocity industries such as the electronics industry and semiconductor industry (Bourgeois and Eisenhardt, 1988). Nevertheless, the dairy industry in Ethiopia is a low dynamic and more stable industry characterized by low rate of changes in technology and market conditions. Thus, long dairy technology life cycles and low-level new dairy technology generation are prevalent in such industries. Therefore, we posit that higher levels of density in dairy farm's supply network decreases dairy farm technology adoption (Hypothesis 3).

Interaction between supply network accessibility and interconnectedness

While both supply network accessibility and interconnectedness are individually important to drive the adoption of appropriate technology, the interaction between them can further influence technology adoption. We argue a positive effect of the interaction of supply network interconnectedness and supply network accessibility on firm technology adoption (Hypothesis 4).

Interaction between supply network accessibility and absorptive capacity

Cohen and Levinthal (1990) introduced the concept of absorptive capacity in the management literature and it is the key factor for enhancing the firm's ability to utilize and benefit from externally acquired knowledge. It is represented by the firm's ability to recognize, assimilate, and leverage knowledge. It may unveil greater adoption and exploitability of a given technology than those firms with less absorptive capacity (Micheels and Nolan 2016). Though network provides accessibility to knowledge and new information, the accessibility of such information or knowledge from network structures and their innovation performance implications are contingent up on both the focal firm's and alters absorptive capacity or capability (Zaheer and Bell 2005).

Previous studies have shown that both absorptive capacity and accessibility of information in the supply network are important for a focal firm to develop its innovation capabilities from external knowledge (Ernst and Kim, 2002; Bellamy et al., 2014). Research in agriculture has also shown that absorptive capacity is positively related to firm-level adoption of new agricultural technologies and practices in the Dutch pork industry (Tepic et al., 2012).

Finally, it should be noted that a dairy farm can still benefit from having access to knowledge in its supply network in the absence of high absorptive capacity, but its ability to influence this information to improve its innovation performance will be very limited. Thus, we propose the following hypothesis. Absorptive capacity of a dairy farm in the supply network positively moderates the influence of supply network accessibility on dairy technology adoption (Hypothesis 5).

Materials and Methods

Description the study area

This study was conducted in Addis Ababa, Bishoftu, Sebeta, and Mekele cities of Ethiopia. These areas were selected based on the Ethiopian control Bovine Tuberculosis Strategies project's (ETHICOBOT) baseline survey result in order to look at dairy farms supply network patterns across geographic locations. The ETHICOBOTS project was a 5-year research project awarded to a consortium of researchers in Ethiopia and the UK, consisting of epidemiologists, geneticists, immunologists, and social scientists. ETHICOBOTS set out to tackle the high burden of bovine TB in the Ethiopian dairy farm sector and to investigate the consequences of the on-going centrifugal trade of potentially infected dairy cattle to low prevalence regions and farming systems on transmission. The map of the study area is shown in Figure 2 below.

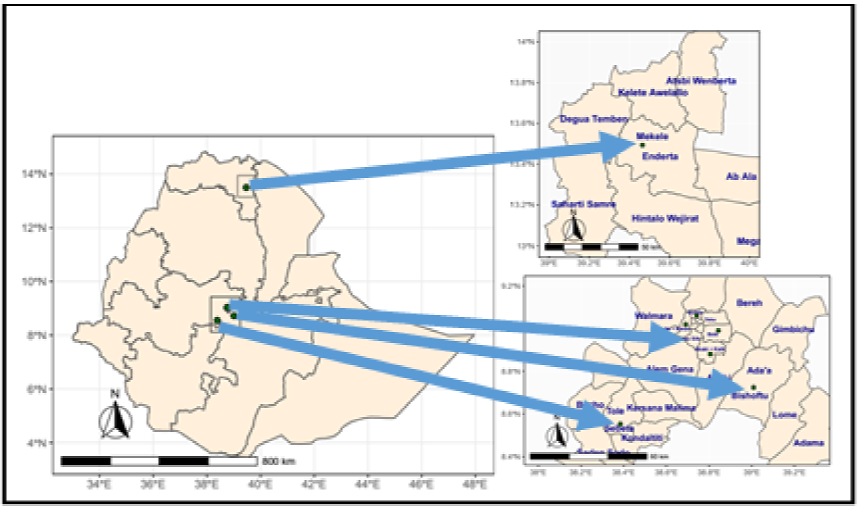

Figure 2: Map of the study area

Data types and sources

A survey methodology was employed to set up the quantitative part of our empirical research and to collect data to test the research hypotheses. Both qualitative and quantitative data types were used for cattle supply network analysis. In order to generate these data, secondary and primary data were collected for the study. Primary data were collected from sampled dairy farms in the study areas who are involved in dairy farm business.

Sampling procedure

The study followed a multi-stage sampling procedure to select the dairy farms in the study area. First, we stratified the study area into three strata based on the availability of market infrastructures or proximity to markets, i.e., near, middle and away from the markets. Then, we selected one sub-city/town from each stratum. Then, from each selected area, we selected one kebele or woreda from each selected sub-cities/town based on the dairy production. Finally, we randomly selected 169 dairy farms from the selected areas.

Data collection

The data collection was conducted using two survey instruments to achieve the objective of the study. One is using a structured questionnaire; each sampled dairy farm has been interviewed. The aim was to collect data related to dairy farm level characteristics. The second is related to the ego-network of the dairy farms in order to collect network data from the randomly selected dairy farms. For this, we administered the structured questionnaire developed by the EgoNet software based on the authors' information fed in to the program, which is important for the network data collection. Based on their links with suppliers and buyers in terms of goods exchange for the survey period, network data related to ego-alter and alter-alter relationships and attributes of alters were collected from the sampled dairy farms.

Variables and Measures

Dependent variable: dairy technology adoption

The study operationalizes dairy technology adoption as the number of different dairy technology components adopted. In livestock technology/adoption, there are a number of technology components that are often considered a technology package. These are the adoption of pure (exotic) breeds, improved crossbreds, the improved feeds and management, improved animal health management, and improved breeding or Artificial inseminations (AI services). Henceforth, we use the count of these dairy technology components adopted by the sampled dairy farms for the survey period as dependent with the value range of zero to five where zero stands for not adopting any of the stated technology components and five for a farm adopting all the five components.

Structural characteristics of supply networks

The study operationalizes three network structural characteristics:

Information centrality: used to measure supply network accessibility to represent the speed and extent of opportunities a firm has to access information and knowledge from other members in the supply network (Stephenson and Zelen, 1989). Information centrality is measured by the harmonic mean length of paths ending at a node i, with this length being smaller if i has many short paths connecting it to other nodes in the network:

$$IC_i = \frac{n}{nc_{ii} + \sum_{j=1}^{n} c_{jj} - 2\sum_{j=1}^{n} c_{ij}} = \left[C_{ii} + \left(\sum_{j=1}^{n} Cjj - 2\sum_{j=1}^{n} C_{ij}\right)/n\right]^{-1} \quad (1)$$

Where $B = D(r) - A + J, \quad C = (C_{ij}) = B^{-1}$

First, the matrix B is constructed by taking the diagonal matrix D(r) of the number of direct ties firm i has, subtracting it from the adjacency matrix A of the supply network, and adding the matrix J with all elements at unity. Next, information centrality scores are calculated using element entries of C, the inverted matrix of B, and the number of firms in the network n. The index has a minimum value of 0, but no maximum value. This measure of information centrality focuses on a firm's opportunities to access information and knowledge contained in all paths that originate (and end) at a particular node in a network. This measure is rooted in the theory of statistical estimation, where a path connecting two nodes is considered as a signal and the noise in the transmission of the signal is measured by the variance of this signal. The measure of information available through each transmission would then be the reciprocal of the variance (Stephenson and Zelen, 1989).

Network efficiency is used to measure the interconnectedness of a firm's direct partner supply network (Burt, 2001). The notion of network efficiency suggests that, if a focal node has at least one pair of direct sources who are also directly connected to each other, then its network is considered to be inefficiently connected. Thus, a network is considered to be inefficiently connected in a sense that there is at least one tie in the network that indirectly connects the focal node to the same source of knowledge, resource, or information. This tie would be considered as a redundant tie. We capture supply network interconnectedness by assessing the number of shared relationships that exist between the supply network partners of a focal firm. As mentioned earlier, we are also interested in capturing the extent to which a firm's supply network partners are densely (sparsely) connected. Assessing shared relationships helps provide insights into how closely knit a focal firm's partners are with each other and into possible redundant ties that are built into the supply network. More formally, network efficiency accounts for the level of supply network interconnectedness by adapting the efficiency equation from (Burt, 1992):

$$Interc_i = 1 - Effic_i = 1 - \left[\sum_j \quad \left[1 - \sum_q \quad p_{iq} m_{jq}\right]\right] / \, n_i \qquad (2)$$

Where piq is the proportion of focal firm i's ties invested in the relationship with q, mjq is the marginal strength of the tie between members j and q (that are both directly connected to i) and ni is the total number of direct partners of focal firm i. Since our supply network representations are binary, the values of mjq are set to 1 if a tie is present between members j and q and 0 otherwise.

Ego network density: it is the third component of supply network structure employed in the study. The ego network density is operationalized as the summation of all ties that a particular firm has within its ego network, over the total possible number of pairs within the ego network (Carnovale and Yeniyurt 2015). Thus, the ego network density for our supply network is computed using the following algebraic formula (Borgatti, 1997) as follows:

$$Ego\ network\ density_i = \left[\frac{\left(\sum_j \quad \sum_q \quad x_{jq}\right)}{\left(\frac{\{N(N-1)\}}{2}\right)}\right] \times 100, \ j \neq q \qquad (3)$$

Where Xjq represents the relative strength of the tie between alter j and alter q, and N represents the number of alters to which ego i is connected. Because we treated supply network as either present or absent (i.e., they do not vary in terms of strength), all values of Xjq were set to 1 if a relationship existed and 0 otherwise. The term [N(N-1)] was divided by 2 to reflect that supply networks are undirected ties.

Control variables

Farm scale: it is a dummy variable. It is measured whether a given farm is small, medium or large farms. The small farms are defined as farms that have less than or equal to five cattle, medium farms are those farms that have more than five cattle and the large farms are state or private (commercial farms with official license of operation).

Farm age: The study also used firm age to control its effect. Since older firms are expected to influence more of their existing technological competencies while younger firms are expected to experiment more with new technologies (Sorensen and Stuart 2000). Farm age was calculated as the number of years from the date of the farm's founding to the survey year.

Farm size**:** influences a firm's level of innovation output and performance, as larger firms have more financial means and greater resources to invest in innovation-related activities than smaller firms (Bellamy *et al.*, 2014). Teece (1992) obtained that firm size can both positively or negatively influence its innovation output. In this study, farm size is operationalized as the quantity of cattle a given farm has sold during the survey year. It is a continuous variable and measured by counting the number of the cattle sold by the farm.

Sex of dairy farm owner or manager**:** In order to control the gender effect in the investigation, the study employed sex of farm owner or manager in the model. Lu *et al.* (2009) in their study used the dummy variable gender to control its effect in the estimation of the role of network relationship on buyer-seller relationship and performance.

Education level**:** It is a continuous variable and measured in the number of years in schooling of dairy farm owner or manager. The education level of owners or managers affects innovation and financial performances.

Location**:** It is a dummy variable and employed to measure the geographical location of the dairy farm. This variable has a role in order to measure the proximity of the dairy farms to research institutions and market, in general to control the effects that come from geographical differences.

Econometric Model specification

The study operationalizes technology adoption as the number of different dairy technologies adopted by cattle farms as the dependent variable. A count variable that takes on only non-negative integer values makes a linear regression model inappropriate as it assumes the distribution of residuals to be homoscedastic, normally distributed. This could lead to coefficient estimates that are both biased and inconsistent. Hence, Poisson and negative binomial regression are more appropriate models for count data (Greene, 2003).

The Poisson regression model specifies that yi given xi is Poisson distributed with density is given by:

$$f(X_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \quad y_i = 0,1,2,.... \qquad (4)$$

and mean parameter is given by:

$$E[y_i|X_i] = \mu_i = exp(X_i'\beta) \qquad (5)$$

The model comprising (4) and (5) is usually referred to as the Poisson regression model. Given independent observations, the log-likelihood function is given by (Cameron and Trivedi, 2013)

$$lnL(\beta) = \sum_{i=1}^{n} \{y_i X_i'\beta - exp(X_i'\beta) - lny_i!\} \qquad (6)$$

In the presence of overdispersion, the assumption of Poisson regression that the mean and variance are equal does not hold. However, the negative binomial model accounts for overdispersion and helps avoid spuriously high levels of significance due to coefficients whose standard errors are underestimated (Cameron and Trivedi, 1986).

Hence, the study employed the negative binomial model to check for the presence of overdispersion.

The negative binomial model has the following form (Hilbe, 2011):

$$l = \sum_{i=1}^{n} \left\{y_i ln\left(\frac{\alpha exp(x_i'\beta)}{1+\alpha exp(x_i'\beta)}\right) - \frac{1}{\alpha} ln\big(1+\alpha exp(x_i'\beta)\big) + ln\Gamma\left(y_i + \frac{1}{\alpha}\right) - ln\Gamma(y_i + 1) - ln\Gamma\left(\frac{1}{\alpha}\right)\right\} \qquad (7)$$

The above equations for the model are expressed as log-likelihood functions, as is typical for a count model.

Results and Discussion

Descriptive statistics

The descriptive statistics results are presented in Table 1. Results show that out of the total sample respondents, 37% of the dairy farms are owned by female owners and 63% by male owners. The mean value of owners' educational level attained was 8th grade, dairy farm age was 12 years and hired employees in farms was about 1. Furthermore, about 39% of the dairy farms are members of dairy producers' cooperatives. For the year 2018/19, the sample farms on average obtained a revenue of 111,676 birr with minimum and maximum value of 4,600 and 448,370 birr, respectively. The sample farms composition in terms of study area was 15% from Sebeta, 30% from Mekelle, 31% from Addis Ababa and the rest 16% from Bishoftu. In a similar fashion, 36 of the farms were small-scale farms, 47% medium-scale farms and the rest 27% were large-scale farms. With regard to dairy farms contact with support institutions (namely, research, agriculture offices, higher learning institutions), 49% of the farms contacted these institutes to seek support. At the same time farms have a long-established contact with their supply partners for exchanging goods, on average about 4 years old relationship.

Table 1: Descriptive statistics of farm level characteristics

Variable	Mean	Std.Dev.	Min	Max
Sex of Owner/ manager	0.63	0.48	0	1
Farm age	11.5	10	1	48
Education level	7.69	4.68	0	16
Hired employees	1.36	1.58	0	10
Cooperative membership	0.39	0.49	0	1
Farm sales	111,676.6	74,365	4,600	448,370
Sebeta	0.16	0.36	0	1
Mekele	0.36	0.46	0	1
Addis Ababa	0.31	0.47	0	1
Bishoftu	0.17	0.37	0	1
Small farm	0.36	0.48	0	1
Medium farm	0.47	0.5	0	1
Support services	0.49	1.13	0	6
Ties duration	4.04	4.83	0	36

Adoption of dairy technology adoption

The percentages of sampled dairy farms adopting each of the dairy technology components is depicted in Figure 3. According to the results, the crossbreed dairy technology component was the most frequently adopted dairy technology component with an adoption rate of about 90%. Next, veterinary services were the relatively frequently used dairy technology components, being adopted at a rate of approximately 85%. The third frequently adopted group of dairy technology components was AI services and adopted at a rate of 74%. It was also found that improved animal health care and feed practices were relatively the frequently used dairy technologies and adopted at rates of 60 and 51%, respectively. Dairy technology components with relatively low adoption rates included improved forage crops and pure breeds dairy cows at adoption rates of 25 and 14%, respectively. Among the total sample farms, 10% of the farms adopted neither of the dairy technology components.

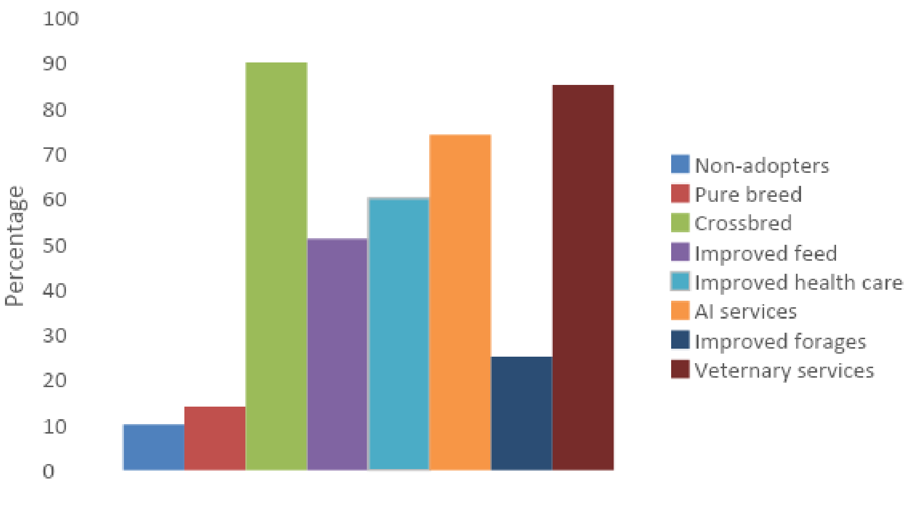

Figure 3: Dairy technology adoption

Diffusion of dairy technology components

Ryan and Gross (1943) in their study of the diffusion of hybrid seed corn in two Iowa communities have shown that the adoption of an innovation follows a normal, bell-shaped curve when plotted over time on a frequency basis. If the cumulative number of adopters is plotted against time, the result is an s-shaped curve. Figure 4 shows the plotted cumulative number of adopters for each dairy technology component's approaches to the ‘S’ curve. Diffusion of dairy technology for the dairy farm mainly started around 24 years ago in 1985. From 1985 to 1995, the diffusion of dairy technology components was so slow that there is no as such differences in the diffusion of the dairy technology components this could be attributed to the prolonged civil war from 1974 to 1991.Starting from 2000, a sudden rise of diffusion occurred and the gap among these technology components started to widen. Thus far, the crossbred dairy cows are the most widely diffused one, followed by diffusion of veterinary and AI services. Pure breeds are the least diffused dairy technology components in the sampled dairy farms over the diffusion period.

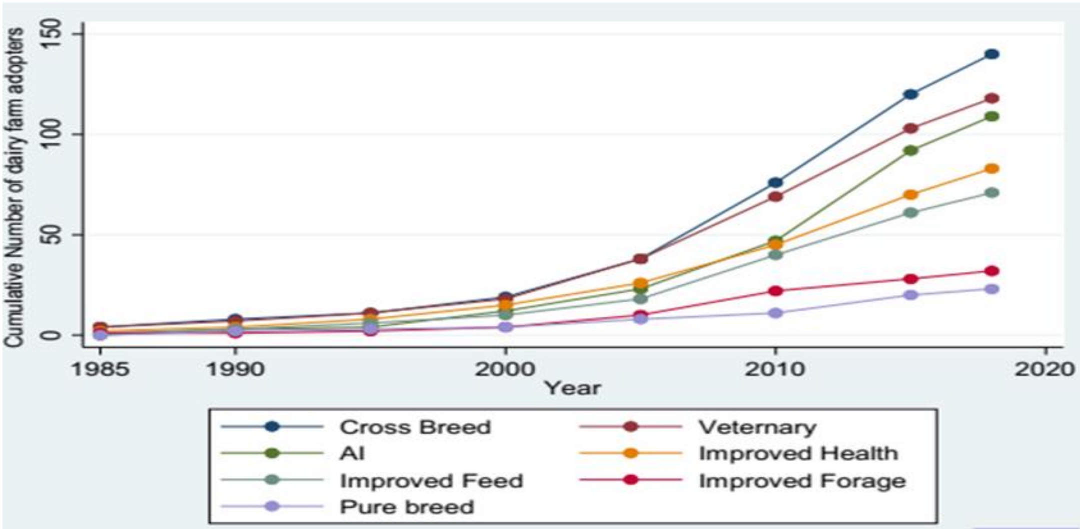

Figure 4: Dairy technology diffusion

Determinants of adoption of dairy technology

Empirical Model

Test for overdispersion

In order to check the presence of overdispersion problem in the count data, first we employed the negative binomial regression model and tested the dispersion parameter (alpha). Table 2 lists parameter estimates for empirical analysis of the negative binomial (NB) regression and Poisson regression (PR) models. The NB estimate of the overdispersion parameter is 0. This shows as there is no overdispersion problem and according to the LR test of H0: $\alpha=0$, the NB specification fails to reject the null hypothesis. This implies overdispersion and variance heterogeneity was not a problem in the count data. This test is also supported by the likelihood ratio (LR) test carried out to investigate whether or not the NB count data model reduces to the PR count data model. Test results demonstrate that the LR test statistic computed as LR = -2[LLNB - LLPR)] is not significant, where LL stands for log-likelihood values, and distributed as Chi-square with one degree of freedom. Hence, we employed the Poisson regression model under the robust standard error estimation specification.

Table 2: Poisson and Negative binomial regression model estimation results

VARIABLES	**Poisson**		**Negative Binomial .**	
	Coeff.	**St.Err.**	**Coeff.**	**St.Err.**
1. CONTROL VARIABLES				
1.1 Demography and socioeconomic variables				
Sex of Owner/ manager	0.102	0.066	0.102	0.066
Farm age	-0.001	0.003	-0.001	0.003
Education level	0.012	0.008	0.012	0.008
Hired employees	0.017	0.024	0.017	0.024
Cooperative membership	0.104	0.070	0.104	0.070
Firm sales	0.000***	0.000	0.000***	0.000
1.2 Location variables				
Sebeta	-0.133	0.101	-0.133	0.101
Mekele	0.138	0.090	0.138	0.090
Addis Ababa	0.000	.	0.000	.
1.3 Farm Scale				
Small firm	-0.251**	0.115	-0.251**	0.115
Medium firm	-0.293***	0.099	-0.293***	0.099
1.4 Institutional links				
Research link	0.050**	0.025	0.050**	0.025
AI Services	0.013**	0.007	0.013**	0.007
0. MAIN VARIABLES				
SN density	-1.331***	0.347	-1.331***	0.347
SN accessibility	-0.112	0.072	-0.112	0.072
SN interconnectedness	1.826***	0.483	1.826***	0.483
0. INTERACTIONS				
Veterinary*SN accessibility	0.00003**	0.000	0.000**	0.000
SN accessibility SN interconnectedness	0.180	0.204	0.180	0.204
Constant	1.103***	0.220	1.103***	0.220
(alpha)			0	
Pseudo r-squared	0.067		0.067	
Chi-square	108.857***		108.857***	
Akaike crit. (AIC)	523.550		523.550	
Bayesian crit. (BIC)	575.576		575.576	
Log likelihood	-243.775		-243.775	
N	148		148	

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

Model estimates

The results of the Poisson regression are presented in Table 3. In order to confirm model stability and to make sure that any significant effect is robust to the introduction of other effects, we estimated three different Poisson regression models by inclusion of variables sequentially.

Each model performance was tested based on the likelihood ratio test. The likelihood ratio tests indicate that the two models have more explanatory power than model 1. Model 1 entails only the control variables. Some of the control variables are significant. Specifically, membership to cooperatives, farm sales and support services institutions are shown to positively and significantly affect the adoption of dairy technology. On the contrary, location variables (Sebeta) and farm scale have a negative significant influence on dairy technology adoption. This suggests that dairy farms in Sebeta area compared to dairy farms in Bishoftu (reference group) tend to adopt dairy technology less likely compared to the reference group and that small and medium scale dairy farms have a lesser dairy technology adoption compared to large-scale dairy farm (the reference group is large-scale dairy farms). This suggests that farm scale is positively associated with dairy technology adoption.

Model 2 introduces the main effects of supply network density, supply network accessibility and supply network interconnectedness. Results suggest that the level of dairy technology adoption increased with a decrease in supply network density ($p < 0.001$), thus providing support for hypothesis 3. The finding of the significant negative association of supply network density on dairy technology adoption suggests that in the context of the dairy industry, dense networks are not conducive in the adoption of dairy technology. This finding complies with the argument of Granovetter (1973). According to Granovetter (1973), actors of dense networks tend to interact frequently, a high share of the information circulating in this social system is redundant. He posits that new information is mainly obtained through relationships to actors who are not members of the closely connected part of the network, the ‘weak ties’, rather than through close relationships (strong ties). Granovetter mainly discusses the effect of social structures on issues such as new technologies and information about job offerings (Granovetter, 1973, 1985).

Model 2 also displays a positive significant ($p < 0.001$) relationship between supply network interconnectedness and adoption of dairy technology, showing support for hypothesis 2. The result of the positive significant effect of supply network interconnectedness on dairy technology adoption illustrates that interconnectedness enhances collaborative initiatives that provide access to knowledge, resources, and information from other partners in the supply network. This finding supports our hypothesis 2. This result is in agreement with the findings of Inkpen (1996) and Inkpen and Tsang (2005).

However, the model 2 result yields an insignificant relationship between supply network accessibility and dairy technology adoption providing no empirical evidence supporting hypothesis 1. Our prior expectation was based on the previous literature that focal firms with high network accessibility acquire more information in terms of volume and diversity from their network partners in the supply network in which they work (Schilling and Phelps, 2007). This result suggests that supply network accessibility, in isolation, may not be a significant driver in dairy technology adoption.

Finally, model 3 entails the interaction related to hypotheses 4 and 5, and represents the full model.

According to model 3 in Table 3, the negative association between supply network density and adoption of dairy technology (Hypothesis 3) remains throughout the full model except a few changes in the coefficient at a significant level of $p<0.001$. Furthermore, the positive effect of the supply network interconnectedness on adoption of dairy technology (hypothesis 2) remains the same in the full model. This effect is also significant at $p < 0.05$.

With regard to the interaction variables in model 3, the results suggest that the positive association between supply network accessibility and dairy technology adoption is positively moderated by a firm’s absorptive capacity ($p<0.1$), thus providing support for hypothesis 5. This result provides empirical evidence that while structural characteristics in a supply network can enable information and knowledge flows to enhance dairy technology adoption, this association can be moderated by dairy farms’ veterinary expenditures used as proxy for farms’ absorptive capacity. The results show that investing more in veterinary services as a proxy for Research and Development (R&D) and manifestation of absorptive capacity, can be used to positively moderate the effects of supply network accessibility on dairy technology adoption. In their study on the influence of supply network structures on firm innovation output, Bellamy *et al.* (2014) showed that R & D moderates positively the effects of supply network accessibility on firm innovation output.

However, we obtained non-significant association between the moderation of supply network interconnectedness on supply network accessibility on dairy technology adoption, which did not support hypothesis 4. Our prior expectation was that dairy farms that maintain high supply network interconnectedness with having higher levels of supply network accessibility in supply network experience much knowledge and information access and sharing that ultimately fosters technology adoption. In general the non-significant factors found in the study may warrant further study in the future by including other important variables.

Table 3: Poisson regression model estimation results

VARIABLES	Model 1		Model 2		Model 3	
	Coeff.	**St.Err.**	**Coeff.**	**St.Err.**	**Coeff.**	**St.Err.**
1. CONTROL VARIABLES						
1.1 Demography and socioeconomic variables						
Sex of Owner/ manager	0.068	0.065	0.083	0.066	0.102	0.066
Firm age	-0.002	0.004	-0.002	0.003	-0.001	0.003
Education level	0.009	0.008	0.009	0.008	0.012	0.008
Hired employees	0.027	0.023	0.022	0.022	0.017	0.024
Cooperative membership	0.196**	0.076	0.111	0.070	0.104	0.070
Firm sales	0.000**	0.000	0.000**	0.000	0.000***	0.000
1.2 Location variables						
Sebeta	-0.123	0.084	-0.158	0.100	-0.133	0.101
Mekele	0.157*	0.088	0.102	0.079	0.138	0.090
Addis Ababa	0.000	.	0.000	.	0.000	.
1.3 Farm Scale						
Small firm	-0.211*	0.127	-0.164	0.135	-0.251**	0.115
Medium firm	-0.192*	0.104	-0.199	0.125	-0.293***	0.099
1.4 Institutional links						
Research link	0.068***	0.018	0.058**	0.025	0.050**	0.025
AI Services	0.011	0.008	0.012*	0.007	0.013**	0.007
0. MAIN VARIABLES						
SN density			-1.325***	0.347	-1.331***	0.347
SN accessibility			-0.061	0.070	-0.112	0.072
SN interconnectedness			1.718***	0.478	1.826***	0.483
0. INTERACTIONS						
Veterinary*SN accessibility					0.00003**	0.000
SN accessibility SN interconnectedness					0.180	0.204
Constant	0.969***	0.222	1.093***	0.207	1.103***	0.220
Pseudo r-squared	0.030		0.060		0.067	
Chi-square	42.458***		77.664***		108.857***	
Akaike crit. (AIC)	593.856		523.247		523.550	
Bayesian crit. (BIC)	632.820		569.492		575.576	
Log likelihood	-283.928		- 245.623		-243.775	
N	148		148		148	

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

Interaction/ Moderation effect

Further investigation of the interaction effects using the interaction plot tool provides additional information to help comprehend the interaction effects. We plot the predicted dairy technology adoption with changes in each corresponding variable, using high and low values of the variable values as one standard deviation above and below the mean, respectively.

The plots in Figure 5 show the interaction between a firm's supply network accessibility and its veterinary expenditures in two-way plots. The "low, mean and high veterinary expenditure" lines in Figure portray the moderating effect of veterinary expenditures, and explain the slopes of the effects of supply network accessibility on adoption of dairy technology when the values of veterinary expenditures are set to one standard deviation either below or above its mean value, and at the mean value. The graph shows that high veterinary expenditures positively moderate the effect of supply network accessibility on the likelihood of adoption of dairy technology in dairy farms.

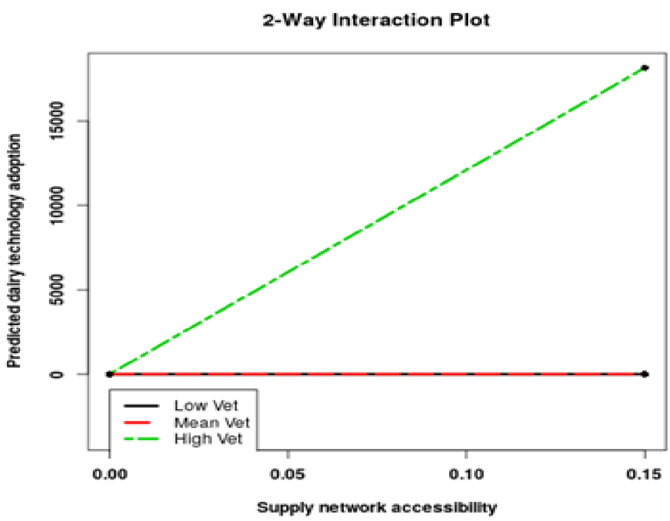

Figure 5: Interaction plot

Robust Estimation

Endogeneity

The study has also undertaken an endogeneity test. Because we are conducting experiments to predict the adoption of dairy technology network parameters (SN accessibility, density and interconnectedness), there could be an issue of endogeneity problem. Particularly, adoption might predict the network parameters and network parameters might predict adoption.

In order to address this potential endogeneity issue, the most and widely used methodological approaches in literature suggest running a two-stage least-squares regression with instrumental variables and employing the Hausman test (Greene, 2003). However, our model is a non-linear model; we opted for a non-linear instrumental variable estimation approach using the General Method of

Moments (GMM) estimator. The generic solution to this problem is a nonlinear instrumental variable approach as outlined in Mullahy (1997) and in Windmeijer and Silva (1997).

Next, we reviewed the literature to find appropriate instruments for supply network density, accessibility and interconnectedness. Bellamy *et al*., (2014) in his study selected instrumental variables from the count model considered as exogenous but found non-significant for the endogenous variables supply network accessibility and interconnectedness. Similarly, we employed this approach and identified the non-significant exogenous variables and potential instrumental variables form our Poisson regression model, namely sex of the owner, owner education level, farm age, and ties duration. Additionally, based on the studies conducted to address endogeneity by (Basole *et al*., 2017; Bellamy *et al*., 2014), we included network measure degree centrality. Centrality measures the involvement in the network (Knoke and Burt, 1983): the extent to which an actor is deeply involved in network relations (Burt, 1980; Wasserman and Faust, 1994). Ultimately, we totally chose sex of the owner, owner education level, farm age, and ties duration and degree centrality as instruments for potentially endogenous variables supply network density, supply network accessibility and supply network interconnectedness. Table 4 shows the result of the non-linear instrumental regression model estimated using the General Methods of Moments (GMM).

We conducted a test to test the validity of over-identification in our model since our endogenous model is an over-identified (more instrumental variables than endogenous variables). According to Hansen's test, we failed to reject the null hypothesis. Suggesting that all the instrumental variables employed in the model are valid. Then we look at the output of the endogenous model to investigate endogeneity. According to the result of the model, the estimated coefficients of the endogenous variables (supply network density, accessibility and interconnectedness) are not significantly different from zero suggesting that supply network density, accessibility and interconnectedness are exogenous variables. Hence, the parameter estimates for these network variables in our original count model do not appear to be affected by the endogeneity problem.

Table 4: The GMM estimate test for endogeneity

VARIABLES	Coeff.	Std.Err.
SN density	-3.113	(8.772)
SN accessibility	-0.595	(2.800)
SN interconnectedness	5.587	(18.27)
Cooperative membership	0.0854	(0.114)
Firm sales	-2.90e-07	(2.83e-07)
Sebeta	-0.149	(0.141)
Mekelle	-0.0715	(0.280)
Addis Ababa	-	
Small firm	-0.254	(0.169)
Medium firm	-0.257	(0.199)
Support services	0.0180	(0.145)
Constant	1.466***	(0.310)
N	148	

Theoretical implications

This study contributes to the growing literature of adopting a network analytic view of supply networks in the agriculture technology adoption. This has been realized by investigating how a dairy farm can accrue knowledge and information flow benefits about dairy technology from its supply network to enhance its technology adoption. The results of this study show that the benefit of low network density and high supply network interconnectedness along with the moderating effect of farm’s absorptive capacity on accessibility in a supply network yields a higher likelihood of adoption of dairy technology. Furthermore, the study contributes to the literature the importance of the strength of weak ties (Granovetter 1973) and structural holes (Burt, 2001) in agricultural innovation and technology adoption in the context of the dairy industry.

Limitations and directions for future research

While this study focused on three network structural characteristics namely on network density, supply network accessibility, and interconnectedness, future research should further include other important network structural characteristics that may influence farm’s technology adoption.

To add more, this study is based on first tier supply network partners of the ego network dataset. Hence for more information and investigate the role of supply networks on technology adoption, future study may conduct their investigation by incorporating second tier supply network partners.

Further, while we include a farm's veterinary expenditure as a reflection of a farm’s absorptive capacity, there may be other important factors capturing the farm’s amount of experience and potential ability to absorb incoming external knowledge. Future research should investigate further into other aspects that may affect a farm’s ability to absorb knowledge residing in the supply network.

Conclusion

This study examined the association between supply network structure and dairy farm technology adoption. Particularly, we focused on three structural characteristics: supply network accessibility, interconnectedness and density. We also estimate the interaction effects of absorptive capacity and supply network accessibility, and the interaction effect of supply network accessibility and interconnectedness. The study employed the farm level and ego-network dataset of sampled dairy farms in the dairy industry.

Our findings suggest that high network density negatively influences farm technology adoption, which implies that weak ties are important in dairy technology adoption in the context of the dairy industry. The plausible explanation is embeddedness in strong ties may also lead to lock-in (Grabher, 1993) and can well have negative effects on farm technology adoption. Such effects were likely to occur in our study given the low dynamics of technology generation in the dairy industry.

The results also indicate that interconnected supply networks help in the adoption of dairy technology. Additionally, the results show that the influence of the supply network accessibility on farm dairy technology adoption can be enhanced by a farm's absorptive capacity. In sum, the study contributes to the body of literature on both supply chain management and technology adoption in the context of the dairy industry by highlighting the role of the structural characteristics of supply networks, along with knowledge variables, in facilitating knowledge creation and thereby improving upon a farm's technology adoption.

Thus, in light of these findings, considerations should be given to policies that create an ecosystem of interactions through training, promoting fairs and innovation events to promote rapid dairy technology adoption by dairy farms.

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References

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. Admin. Sci. Quart., 45(3), p. 425–455.

Amare M., S. Asfaw and B. Shiferaw. 2012. Welfare impacts of maize-pigeonpea intensification in Tanzania. Agricultural Economics 43(1): 27–43.

Amlaku A., J. Sölkner, R. Puskur and M. Wurzinger. 2012. The impact of social networks on dairy technology adoption: evidence from Northwest Ethiopia. International Journal of AgriScience 2(11): 1062–1083.

Asfaw S., B. Shiferaw, F. Simtowe and M. Hagos. 2011. Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. Journal of Development and Agricultural Economics 3(9): 436–447.

Bandiera O., and I. Rasul. 2006. Social networks and technology adoption in northern Mozambique. Econ J., Volume 116, p. 869–902.

Basole R.C., S. Ghosh, and M.S. Hora. 2017. Supply Network Structure and Firm Performance: Evidence from the Electronics Industry. Ieee Transactions on Engineering Management, pp. 1-15.

Basole R.C., S. Ghosh, and M.S. Hora. 2018. Supply Network Structure and Firm Performance: Evidence from the Electronics Industry. IEEE Transactions on Engineering Management 65(1): 141–154.

Bellamy M., A. S. Ghosh, and M. Hora. 2014. The influence of supply network structure on firm innovation. Journal of Operations Management, Volume 32, 357–373.

Borgatti S.P. 1997. Structural holes: Unpacking Burt's redundancy measures. Connections, 20(1), p. 35–38.

Bourgeois L. J., and K. M. Eisenhardt. 1988. Strategic decision processes in high velocity environments: Four cases in the microcomputer industry. Manage. Sci., 34(7), p. 816–835.

Burt, R. S. 2001. Structural Holes versus Network Closure as Social Capital Social Capital, NY, pp. In: A. d. Gruyter, ed. Theory and Research. New York: s.n., pp. 31-56.

Cameron A. C., and P. K. Trivedi. 2013. Regression Analysis of Count Data. Second ed. New York: Cambridge University Press.

Carnovale S., and S. Yeniyurt. 2015. The role of ego network structure in facilitating ego network innovations. Journal of Supply Chain Management 51(2): 22–46.

Choi T.Y., K.J. Dooley, and M. Rungtusanatham. 2001. Supply networks and complex adaptive systems: Control versus emergence. Journal of Operations Management 19(3): 351–366.

Cohen W.M. and D.A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation Wesley. Administrative Science Quarterly 40 A (1): 128–152.

Conley T. G., and C. R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. American Economic Review, 100(1), pp. 35-69.

CSA (2019), Agricultural sample survey 2018/2019 on livestock and livestock characteristics. Central Statistics Authority. Addis Ababa, Ethiopia

Dehinenet G., Mekonnen H., Kidoido M., Ashenafi M. and Guerne Bleich E. 2014. Factors influencing adoption of dairy technology on small holder dairy farmers in selected zones of Amhara and Oromia National Regional States, Ethiopia. Discourse Journal of Agriculture and Food Sciences www.resjournals.org/JAFS ISSN: 2346-7002 Vol. 2(5): 126-135

Echols A., and W. Tsai. 2005. Niche and performance: The moderating role of network embeddedness. Strategic Management Journal 26(3): 219–238.

Ernst D., and L. Kim. 2002. Global production networks, knowledge diffusion, and local capability formation. Res. policy, 31(8), p. 1417–1429.

Feder G., R.E. Just, and D. Zilberman. 1985. Adoption of agricultural innovations in developing countries: a survey. Economic Development & Cultural Change 33(2): 255–298.

Grabher G. 1993. The weakness of strong ties: the lock-in of regional development in the Ruhr area. London, NewYork, Routledge, pp. 255-277.

Granovetter M. 1985. Economic Action and Social Structure: The Problem of Embeddedness'. American Journal of Sociology 91(3): 481–510.

Granovetter M.S. 1973. The strength of weak Ties. American Journal of Sociology 78(6): 1360–1380.

Greene W. H. 2003. Econometric Analysis. Noida, India: Pearson Education.

Gulati R., N. Nohria, and A. Zaheer. 2000. Strategic Networks. Strategic Management Journal, 21(3), pp. 203-215.

Inkpen A. 1996. Creating knowledge through collaboration. Calif. Manage. Rev., 39 (1), p. 123–140.

Inkpen A., and E. Tsang. 2005. Social capital, networks, and knowledge transfer. Acad. Manage. Rev., 30 (1), p. 146–165.

Jara-Rojas R., B. Bravo-Ureta, and J. Díaz. 2012. Adoption of water conservation practices: A socioeconomic analysis of small-scale farmers in Central Chile. Agric. Syst., Volume 110, p. 54–62.

Kassie M., M. Jaleta, B. Shiferaw, F. Mmbando, and M. Mekuria. 2012. Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania. Techno. Forecast Soc. Change, Volume 80, p. 525–540.

Kim Y., T.Y. Choi, T. Yan, and K. Dooley. 2011. Structural investigation of supply networks: A social network analysis approach. Journal of Operations Management, 29(3), p. 194–211.

Kouvelis P., C. Chambers, and H. Wang. 2006. Supply chain management research and production and operations management: Review, trends, and opportunities. Prod. Operation Manage., 15(3), p. 449–469.

Lamming R., T. Johnsen, J. Zheng, and C. Harland. 2000. An initial classification of supply networks. Int. J. Oper. Prod. Manage., 20(6), p. 675–691.

Lu H., J. H. Trienekens, S.W. F. Omta, and S. Feng. 2009. The Role of Guanxi Networks in Vegetable Supply Chains: Empirical Evidence from P.R. China. Journal of International Food and Agribusiness Marketing, 17 April, 21(2-3), pp. 98-115.

Maertens A., and C. Barrett. 2012. Measuring Social Networks Effects on Agricultural Technology Adoption. Am. J. Agric. Econ, 95(2), p. 353–359.

McFadyen M.A., M. Semadeni, and J.A. Cannella. 2009. Value of strong ties to disconnected others: Examining knowledge creation in biomedicine. Organization Science, 20 (3), p. 552–564.

Mekonnen D.A., N. Gerber, J.A. Matz, D.A. Mekonnen, N. Gerber, and J.A. Matz. 2016. Social networks, agricultural innovations, and farm productivity in Ethiopia.

Micheels E.T., and J.F, Nolan. 2016. Examining the effects of absorptive capacity and social capital on the adoption of agricultural innovations: A Canadian Prairie case study. Agricultural Systems. Elsevier B.V. 145: 127–138. Available at: http://dx.doi.org/10.1016/j.agsy.2016.03.010.

Mullahy J. 1997. Instrumental-variable estimation of count data models: Applications to models of cigarette smoking behavior. Review of Economics and Statistics 79(4): 586–593.

Ramirez A. 2013. The Influence of Social Networks on Agricultural Technology Adoption. Procedia - Social and Behavioral Sciences. Elsevier B.V. 79: 101–116. Available at: http://dx.doi.org/10.1016/j.sbspro.2013.05.059.

Runyan R., P. Huddleston, and J. Swinney. 2006. Entrepreneurial orientation and social capital as small firm strategies: A study of gender differences from a resource-based view. Int. Entrep. Manag. J., 2(4), p. 455–477.

Ryan B., and N.C. Gross. 1943. The Diffusion of Hybrid Seed Corn in Two Iowa Communities. Rural Sociology, Volume 8, p. 15–24.

Schilling M.A., and C.C. Phelps. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. Management Science 53(7): 1113–1126.

Sligo F., and C. Massey. 2007. Risk, trust and knowledge networks in farmers' learning. J. Rural. Stud., 23(2), p. 170–182.

Stephenson K., and M. Zelen. 1989. Rethinking centrality: Methods and examples. Social Networks 11(1): 1–37.

Sunding D., D. Zilberman, and G. Hall. 1999. The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector in a Changing Agricultural Sector. Handbook of Agricultural Economics, 47.

Tepic M., J.H. Trienekens, R. Hoste and S.W.F. Omtad. 2012. The influence of networking and absorptive capacity on the innovativeness of farmers in the Dutch pork sector? International Food and Agribusiness Management Review 15(3): 1–34.

Weyori A.E., M. Amare, H., Garming and H. Waibel. 2018. Agricultural innovation systems and farm technology adoption: findings from a study of the Ghanaian plantain sector. Journal of Agricultural Education and Extension. Taylor & Francis 24(1): 65–87.

Wilson P. 2000. Social Capital, Trust, and the Agribusiness of Economics. Agribusiness, 25(1), p. 1–13.

Windmeijer F.A.G., and J.M.C Santos Silva. (1997) Endogeneity in count data models: An application to demand for health care. Journal of Applied Econometrics 12(3): 281–294.

Wossena T., T. Bergera, T. Mequaninteb, and B. Alamirew. 2013. Social network effects on the adoption of sustainable natural resource management practices in Ethiopia. International Journal of Sustainable Development & World Ecology, 20(6), p. 477–483.

Xuan Q., D. Fang, L. Yanjun and W. Tie-Jun. 2011. A Framework to Model the Topological Structure of Supply Networks. Ieee Transactions on Automation Science and Engineering, April.8(2).

Yli-Renko H., E. Autio, and H. Sapienza. 2001. Social capital, knowledge acquisition, and knowledge exploitation in young technology-based firms. Strat. Manage. J., 22(6-7), p. 587–613.

Zaheer A., and G.G. Bell. 2005. Benefiting from network position: Firm capabilities, structural holes, and performance. Strategic Management Journal 26(9): 809–825.