AAAE Conference Proceedings (2007) 225-237

Organic Rural Innovation Systems and Networks: Findings From a Study of Ethiopian Smallholders

Spielman D.J., Davis K.E., Negash M. and Gezahegn Ayele

IFPRI, P.O. Box 5689 Addis Ababa, Ethiopia

Abstract

Agriculture in Ethiopia is changing. New players, relationships, and policies are influencing the ways in which information and knowledge are used by smallholders. While this growing complexity suggests opportunities for Ethiopian smallholders, too little is known about how these opportunities can be effectively leveraged to promote pro-poor processes of rural innovation. This paper examines Ethiopia's smallholder agricultural sector from an innovation systems perspective to understand the changing roles, responsibilities, and interactions of diverse actors in relation to smallholder livelihoods. The paper uses a combination of qualitative and quantitative research tools to paint a picture of the innovation landscape at both the system and local levels. Findings suggest that public sector extension, administration, and related service providers form a closely-knit network in rural Ethiopia with the ability to influence smallholder access to knowledge and information. Given the Government of Ethiopia's priorities of improving rural welfare by increasing market access among smallholders, these findings suggest the need for policies and programs designed to strengthen innovative capabilities among rural service providers from the public sector, and to create more space for private and civil society actors to participate in smallholder innovation networks.

Keywords: Ethiopia, Agricultural development, innovation, technology, Social networks, Social learning

A transformation in Ethiopian agriculture?

The development objectives set forth by the Government of Ethiopia (GoE) revolve around a long-term plan for agriculture development-led industrialization (ADLI). This plan incorporates policies and strategies designed to promote a market-led transformation of smallholder agriculture; decentralize political, economic, and administrative powers and functions; drastically improve the rural infrastructure network; and disseminate new crops and crop technologies. Implicit in this set of objectives, policies, and strategies is the need for greater innovativeness in the agricultural sector to enhance productivity, increase output, and reduce poverty (MoFED 2005, 2002).

The GoE's approach draws heavily on the resources and capacities of those public sector agencies that are conventionally viewed as pillars of the country's formal innovation system: public sector research, extension, and education services (EEA/EEPRI 2006; Kassa 2005). However, the approach also calls for the development and engagement of other potential sources of innovation: private and civil society sectors; cooperatives and cooperative unions; domestic and foreign firms; rural investors and entrepreneurs; and non-governmental and community-based organizations.

Given the complexity posed by this approach, a "systems-based" perspective might help us understand how agricultural innovation systems and processes are changing in Ethiopia. Thus, this paper draws on the "innovation systems" approach, an increasingly popular way of studying how society generates, exchanges, and uses information and knowledge, and how systems can be strengthened to promote innovation and distribute the benefits of innovation more equitably (Lundvall 1985, 1988; Freeman 1987, 1988; Nelson 1988; Dosi et al. 1988; Edquist 1997). The framework represents a significant change from the conventional, linear perspectives on agricultural research and development by emphasizing the importance of studying an *innovation system* as a single unit: the agents involved in the innovation process, their actions and interactions, and the formal and informal rules that regulate their practices and behaviors. In effect, an innovation system embeds technological change within a larger, more complex system of networks comprising heterogeneous actors, socioeconomic institutions, and organizational cultures.

Thus, while there is emerging evidence to suggest that formal structures in Ethiopia's innovation system are changing in response to the GoE's approach, there is limited study of the extent to which these changes are strengthening the innovative capabilities of both organizations and individuals in the agricultural sector. This paper attempts to shed more light on the changing nature of Ethiopia's agricultural innovation system with a combination of both system- and local-level analyses.

Note that this study abstracts from the question of how to make smallholders more innovative, for example, by promoting basic and technical education, improving access to rural credit, or by developing more appropriate technologies. Recommendations along these lines are important, and should be the subject of continuous empirical investigation. However, the intent of this study is not to provide insights and recommendations on how to make a better farmer, but how to support farmers with better networks, and therefore greater opportunity to innovate.

Methods, Data and Data Sources

The system-wide analysis provides a situational diagnosis of the changing trends in Ethiopia's agricultural innovation system with an emphasis on the role of key innovation actors in the system; changes in shared beliefs and cultures that influence the practices and behaviors of key innovation actors; and an assessment of innovation performance. Data and information are drawn primarily from semi-structured interviews conducted with 77 key informants representing 35 different organizations in the public, private and civil society sectors conducted in the latter half of 2006. As will be shown below, this method provides a rich overview of Ethiopia's changing agricultural innovation system.

The local-level analysis draws on two distinct methods. First, a sub-sample of households from the 2005 Ethiopian Smallholders Commercialization Survey (ESCS) were re-surveyed in mid 2006 to shed light on local innovation networks among smallholders. The re-surveying process entailed (a) a series of focus group interviews conducted in 10 separate *kebeles* (peasant associations) with two groups of five smallholders at each *kebele* and (b) key informant interviews with other innovation system actors in the same locality as these sites. The data and information drawn from this process were used to conduct the social network analyses discussed below (Annex A). Second, a wider sub-sample of smallholders covered by ESCS was used to estimate adoption decisions with respect to modern apiculture technologies (Annex B). As will be demonstrated below, the combination of these two methods sheds light on the role and importance of smallholder innovation network in rural Ethiopia.

Findings and Results

System-level analysis

Ethiopia's agricultural innovation system includes a vast and ever-changing landscape of organizations and institutions, both formal and informal. Key elements of this system include the public sector's agricultural extension services; a national and sub-national public research system; farmers' cooperatives and cooperative unions; a small but growing private sector in the agro-industrial sector; a pro-investment business climate and regulatory system; and diverse traditional systems for the management of indigenous knowledge resources (Spielman et al. 2006).

Yet Ethiopia's innovation system—in all its diversity—faces several obvious challenges. One challenge is strengthening linkages among innovating actors in a way that gives rise to new and diverse opportunities to promote innovation. This includes increasing cooperation and coordination between different public organizations at different levels (specifically, at the federal and regional levels) and between public organizations and newer players in the system (that is, between public education, research and extension, on the one hand, and private companies and civil society organizations, on the other).

Findings from the system-level analysis suggest that while the public sector remains the single most important source of information and technology for smallholders, private companies and civil society organizations are potentially important, though often untapped, contributors to rural innovation. The few successful examples of collaboration and networking among these actors—in areas such as non-traditional high-value crops in the horticulture and apiculture sectors—demonstrate the importance of partnership in improving smallholder livelihoods.

However, these findings also suggest that successes have been limited in size, number, and impact for several reasons. First, public service providers, private industry, and civil society organizations are often resistant to pursuing collaborative efforts—to forming innovation networks that integrate heterogeneous actors—at the federal, regional, and local levels. This is partly due to a weak innovation climate: despite some forward-looking policies on science and technology, education, and private investment, there are few incentives to stimulate closer collaboration between government, industry, and other players. It is also partly due to limited capacity at all levels of the system—federal, regional, and local—to make collaboration efforts viable.

The weak innovation climate and lacking capacity emanate partly from organizational cultures, particularly among public sector providers of rural services that remain hierarchical, averse to change, and persistently focused on linear science.

This is evident in a shared belief driving public sector programs and activities that

(a) food security and food self-sufficiency are largely synonymous,

(b) the development and dissemination of new technologies to smallholders will generate the yield and output increases that are critical to achieving food security and reducing poverty, and

(c) the innovation system's primary function is to develop and disseminate these new technologies.

The approach eschews a more nuanced understanding of innovation systems and processes—of the need for integration among heterogeneous actors to promote innovation. It also fails to recognize the need for new, more creative approaches to strengthening individual capabilities in the research, education, and extension systems; transforming organizational cultures into shared beliefs and practices that are more responsive to the changing need of the agricultural sector; and forging linkages between smallholders, extension agents, and actors in private industry and civil society.

The ultimate outcome of this weak innovation system is, by most measures, a stagnant agricultural sector. Per capita agricultural GDP grew at just 0.48 percent between 1996 and 2005 and displayed significant volatility year on year. Per capita grain production grew at just 1.38 percent, while cereal yields have stagnated around 1.2 metric tons per hectare. The use of inorganic fertilizer is limited to just 37 percent of farmers, while their application rates remain at about 14 kg/ha. Rural incomes and livelihoods remain largely unchanged throughout the country, even despite recent upswings due to several successive years of favorable rainfalls.

These findings are not necessarily new: several prior studies have similarly argued that Ethiopia's innovation system is inadequate relative to the development challenges facing the country. Consider, for example, findings from a World Bank study on the role of knowledge in economic growth in developing countries (Chen and Dahlman 2005). The study develops a knowledge economy index (KEI) to measure investments in education, innovation, information and communication technologies, and economic incentives, arguing that where such investments promote creation and use of knowledge in economic production, they consequently encourage sustained economic growth. KEI scores for Ethiopia fall short of regional comparators in every category, thus suggesting that Ethiopia's wider innovation system is stifling its growth potential (Table 1) (KAM 2006).

Table 1. Knowledge Economy Index scores, Ethiopia, c. 2004

Indicator[a]	Ethiopia	Africa	India	China
Economic incentive regime	1.37	2.57	3.11	4.10
Innovation	0.61	3.03	3.64	4.78
Education	0.81	1.39	2.11	3.93
Information and communication technology	0.10	2.51	2.00	4.24

[a] Scores are based on Knowledge Economy Indicators that are based on a broad set of underlying indicators and scaled from 1 (lowest) to 10 (highest).
Source: KAM 2006.

While it might be argued that knowledge economy measures are too limited in their ability to capture innovativeness potential in a largely smallholder economy, (For example, the KEI uses measures such as patent applications or scientific and technical journal articles which, under a limited set of circumstances, are adequate measures of innovativeness in the agricultural sector.) other studies reach the same conclusion with the use of broader measures. For example, IKED (2006) argues that university-industry-government relations in Ethiopia—the critical nexus that often defines innovative capacity within a system—require significant strengthening. They recommend more autonomy and room for specialization in universities to improve conditions for entrepreneurship, financial and other incentives to encourage networks that bring together different actors and capabilities, and continued long-term investment and improvement in the educational and infrastructural foundations of an innovation system.

But few of these studies combine their analysis of system-level innovativeness with local-level analysis, instead relying solely on macro-level social and economic data that fails to capture the underlying importance of building innovative capabilities among diverse individual and organizations, strengthening institutions that capitalize on these capabilities to promote innovation, and implementing policies that accelerate innovation processes among smallholders and their networks. These issues are examined in the next section.

Local -level analysis

Findings at the local level based on social network analyses (Annex A) indicate that rural innovation networks combine a range of public, private, and civil society organizations, the hypothetical extent of which is illustrated in Figure 1. While these findings are based on case studies that should not be interpreted as nationally representative, they do offer some interesting insights for further consideration.

Specifically, findings also show that public service providers play what might be termed as *the* central role in smallholder innovation processes. Bureaus of agriculture and rural development, development agents (DAs or extension agents), *kebele* administrations, credit and savings institutions, and cooperatives—all public, quasi-public, or state-supported rural service providers—are closely linked with smallholders, with each other, and with the process of promoting and financing the use of information and technology. While this finding is not surprising in itself, it is the magnitude and consistency with which these service providers are linked into smallholder networks that draws attention to their role. Simply stated, extension and related public services are a compelling force in rural Ethiopia.

Finding also suggest that while these actors are key providers of information, inputs, and credit related to improving smallholder output and productivity, their role is far less evident with respect to developing marketing linkages or transmitting price information to smallholders. Efforts to promote smallholder commercialization through public service providers seems to be somewhat impeded by the public sector's limited experience and capabilities with markets.

Related findings also suggest that private sector actors—market traders, brokers, moneylenders, and private companies—are often peripheral to smallholder innovation networks. In the case study sites where market agents did operate, their ties to smallholders, public sector service providers, and civil society organizations were typically weak or non-existent.

Conversely, in the case study sites where civil society organizations operated, their ties to these same actors were relatively stronger. This finding applies to a variety of organizations, including local and international NGOs, NGOs more closely associated with the GoE, and community-based organizations established under the auspices of NGO activities. Moreover, these NGOs were often tied not only to local public sector service providers, but also to a range of other actors beyond the immediate locality such as research institutes and universities.

Consider, for example, the case of Wemberma *woreda* (district), a highland area in Amhara region with good market access and surplus production of both maize and wheat. Findings from Wemberma illustrate how innovation processes in the *woreda* are a combination of *technological* changes (adoption of improved seed-fertilizer packages for maize and wheat, and diversification into new crops/technologies such as onions and apiculture); concurrent *organizational* changes (close strategic coordination among public service providers of input and credit); and *institutional* changes (individual marketing of crop surpluses local market agents and collective marketing through cooperatives). Yet findings also illustrate that smallholders in Wemberma depend on a small number of key nodes for production inputs, credit, and information—namely, their local Bureau of Agriculture and Rural Development (BoARD), their local cooperative, and the Amhara Credit and Savings Institution (ACSI) (Figure 3). These three institutions, along with the local *kebele* administration, operate as a closely-tied network for the smallholder: access to inputs from the BoARD requires access to credit from the cooperative or ACSI, which in turn depends on a referral from the *kebele* administration. At the same time, smallholders in Wemberma depend on an even smaller number of key nodes for market information and linkages—nodes that are almost entirely unlinked from the production-related network.

Another finding from Wemberma is that networks vary within communities. Close examination of networks associated with the two separate focus groups interviews in Wemberma reveals important differences (Figures 2a and 2b). First, smallholders in the first group (selected a priori based on evidence that they had adopted new crops, crop technologies, and/or cultivation practices) were found to be members of a larger network than the second group (selected based on evidence of minimal or adoption of these same factors). These findings suggest, without implying causality in any direction, that innovators are associated with better access to sources of production knowledge/information, inputs/materials, credit/finance, and market linkages/price information, and thus a potentially greater number of livelihood options and opportunities.

Results from an econometric analysis of apiculture technology adoption by smallholders shed additional light on these findings by modeling technology adoption and network membership as a Baysian updating process of the forwarding-looking smallholder who learns about a new production technology (Annex B). Findings (presented in Table 2) suggest the following.

First, smallholders learn from their peers. Peer network effects have a significant effect on apiculture adoption. Given the manner in which peer network is defined and the marketable nature of the crop, these findings are model consistent: larger peer networks that provide information on one's economic (that is, market) activities will generate a stronger influence on the adoption decision for technology that relates to a marketable crop output.

Second, smallholders learn from sources other than their peers. Non-peer (extension) network effects show a significant, and considerably larger in magnitude, effect on apiculture adoption. Given the manner in which non-peer network effects are measured—effectively, whether the household has received extension advice from any source on beehiving—and the supply-driven nature in which modern beekeeping technologies have been introduced in the study area, the non-peer network effects are consistent. However, market networks effects are insignificant, reinforcing the finding that innovation is supply-driven by extension rather than market-driven by product demand articulated by traders. Similarly, community network effects are insignificant, suggesting that community-based organizations (including cooperatives) are not immediately relevant to technology adoption decisions in this particular case.

Third, a household's wealth has a significant effect on apiculture adoption. Where household wealth effectively proxies for household poverty status, these findings suggest that adoption is significantly driven by the household's asset stock (land, livestock, production, housing, and other household assets).

Finally, apiculture adoption is not significantly influenced by other common determinants. Credit access, for example, is insignificantly related to adoption. This is consistent with observations that the operative technology—a modern beehive—is neither a capital-intensive technology for most households, nor costly when supplied by extension services. Similarly, neither education nor experience is significantly related to the probability of adoption, suggesting that the operative technology is not knowledge-intensive.

In sum, smallholder innovation is driven by different types of networks. Extension services—primarily those provided by DAs and the BoARD—are significant drivers of innovation in the case of apiculture. Peer networks are similarly significant, but are of a much smaller magnitude.

Table 2. Apiculture estimation results

Dependent variable = 1 if household adopts modern beehive, 0 otherwise

Probit regression estimates with robust standard errors reported in parentheses

	Model 1 (Baseline)		Model 2 (Probit)		Model 3 (Probit FX)	
Peer network	0.0012 (0.0006)	**	0.0009 (0.0005)	*	0.0012 (0.0005)	***
Non-peer network (extension)	0.2293 (0.0952)	***	0.1970 (0.0885)	***	0.3415 (0.1244)	***
Non-peer network (community)	0.0021 (0.0053)		-.0048 (0. 0049)		-0.0008 (0.0051)	
Non-peer network (traders)	0.0003 (0.0002)		0.0002 (0.0002)		0.0002 (0.0002)	
Age			-0.0006 (0.0021)		-0.0008 (0.0019)	
Age^2			0.0010 (0.0121)		0.0012 (0.0018)	
Literacy			0.0046 (0.0127)		0.0014 (0.0106)	
Dependency ratio			-0.0001 (0.0001)		-0.0001 (0.0001)	
Female-headed household			-0.0169 (0.0130)		-0.0125 (0.0102)	
Land owned			0.0072 (0.0033)	**	0.0081 (0.0041)	**
Assets (ln)			0.0190 (0.0063)	***	0.0209 (0.0063)	***
Credit (ln)			0.0013 (0.0020)		0.0022 (0.0017)	
Mean LGP			9.86e-07 (0.0001)			
Market access			0.0018 (0.0128)			
Log pseudo-likelihood	-221.92		-208.04		-196.42	
Kebele fixed effects	No		No		Yes	
Instrumental variable	No		No		No	
Observations	1140		1140		1140	
Pseudo R^2	0.0441		0.1039		0.1539	

Note: *** denotes significance at 99 percent confidence level; ** at 95 percent; and * at 90 percent

Conclusions and Recommendations

This paper presents evidence based on system- and local-level analyses of Ethiopia's innovation system; how its history and character influences smallholder innovation processes; how integrated networks of heterogeneous actors can potentially strengthen the country's innovation system; and, ultimately, how such networks can enhance efforts to increase agricultural productivity and commercialization among smallholders.

Findings suggest that this potential is not yet being fully realized. While the dynamics of innovation in Ethiopia are changing, innovation tends to follow a linear path of supply-driven technology dissemination through the public sector. Public providers of extension, administration and financing services are the dominant source of information and resources in smallholder innovation networks, particularly when compared to other, non-state sources of information in financing in these networks. This suggests that the potential contributions of other innovation systems actors—private industry, entrepreneurs, civil society, and so on—often remain untapped.

To illustrate this argument, this paper examines the role of different types of networks that affect smallholder innovation and adoption decisions. Conventional networks that revolve around extension and other public services are common with respect to a range of localities, crops, and technologies. Peer networks—family, friends and neighbors who serve as sources of economic advice—are also common, but of far less importance when it comes to putting smallholders into contact with alternative sources of information and resources. Bridging links—ties that bring smallholders into contact with other actors in private industry or civil society—are similarly common, although their appearance and importance tends to vary between the localities covered by this study. Other types of non-peer networks—traders, community organizations, and traditional institutions—exist, but are of varying relevance to innovation and adoption, again, depending on the site, crop, or technology.

Stronger integration of these various networks could potentially provide smallholders with the means to improve their responses to new technological or market opportunities. Stronger, more diversified, collaborations between and among the public sector, private industry, and civil society—coupled with further improvements in the policy environment and organizational cultures that influence the formation and application of collective and individual innovative capabilities—could strengthen innovation processes in the country's agricultural sector.

Given the GoE's priorities for agriculture and rural development discussed earlier, these findings suggest several points for further consideration. First, efforts to boost on-farm productivity and the commercialization of farm surpluses among smallholders might require stronger and more diverse roles for *both* market and non-market actors to facilitate innovation—technological innovation in how agricultural commodities are produced, *organizational* innovations in how they are sold, and *institutional* innovations in how knowledge and information to do so is produced, exchanged, and used.

Second, further consideration might be given to the conventional role assigned to public sector service providers. For instance, the public sector might be better suited to a bridging or facilitative role between smallholders and market agents, rather than a role that can potential crowd other innovation system actors out of the market. Given the GoE's strategic emphasis and sizable investment in increasing the productivity and commercialization of smallholder agriculture, findings also suggest the need for policies, programs, and practices to (a) encourage the entry of new actors in the agricultural sector, particularly private industry, as a means of introducing new sources of knowledge and technology to smallholders; (b) strengthen the willingness and ability of public sector service providers to interact with new actors and networks in support of smallholder innovation; and (c) develop new [incentive] mechanisms to incentivize greater heterogeneity of actors in the agricultural sector, closer integration of heterogeneous actors, and greater investment in technical *and* organizational innovation. Efforts to this end include investment in programs that actively link private industry, cooperatives, and civil society organizations with public research, education, and extension services to scale up commodity-specific value chains, local innovation clusters, and local area development initiatives.

This is not to say that the public provision of information, input, credit, and administration is unnecessary: rather, it will remain a critical components of an innovation network where rural market failures—poor access to markets, weak purchasing power among smallholders, and information asymmetries between buyers and sellers of crop surpluses—are common. However, the absence of both heterogeneity *and* integration within networks can also constrain innovation in so far as innovation occurs within bridging links, i.e., new knowledge is generated not through repeated interactions between agents well known to each other, but through more exploratory interactions with agents who are relatively new to a network and are responding to new market or technological opportunities. Highly dense networks that revolve around a few central agents—public sector service providers, in the case of rural Ethiopia—offer fewer bridging links and thus less unique information and resources with which to innovate.

In sum, further development of Ethiopia's rural innovation systems at the national, regional, and local levels is critical to the creation of a more commercialized agricultural sector where dynamic and responsive networks are effective in responding to rapidly-changing market and technological conditions. This suggests the need for policies and programs designed to strengthen innovative capabilities among rural service providers from the public sector, and create more space for both public sector service providers and other actors to participate in smallholder innovation networks.

References

Bandeira, O. and I. Rasul. 2006. Social networks and technology adoption in Northern Mozambique. *The Economic Journal* 116: 869-902.

Bardhan, P. and C. Udry. 1999. *Development microeconomics*. Oxford: Oxford University Press.

Borgatti, S. 1998. *Social network analysis instructional web site.* <http://www.analytictech.com/networks/>, accessed March 1, 2006.

Chen, D. H. C. and C. J. Dahlman. 2005. *The knowledge economy, the KAM methodology and World Bank operations.* Washington, D.C.: World Bank.

Dosi, G., C. Freeman, R. Nelson, G. Silverberg, and L. Soete (eds.). 1988. *Technical change and economic theory.* London: Pinter.

Edquist, C. (ed.). 1997. *Systems of innovation approaches: Technologies, institutions and organizations.* London: Pinter.

EEA/EEPRI (Ethiopian Economic Association/Ethiopian Economic Policy Research Institute). 2006. *Evaluation of the Ethiopian agricultural extension with particular emphasis on the participatory demonstration and training extension system (PADETES).* Addis Ababa: EEA/EEPRI.

Freeman, C. 1987. *Technology policy and economic performance: Lessons from Japan*. London: Pinter.

_______. 1988. Japan: A new national system of innovation. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, and L. Soete (eds.), *Technical change and economic theory.* London: Pinter.

Hanneman, R. A. and M. Riddle. 2005. *Introduction to social network methods*. Riverside, CA: University of California, Riverside. < http://faculty.ucr.edu/~hanneman/ >, accessed May 14, 2006.

IKED (International Organisation for Knowledge Economy and Enterprise Development). 2006. Ethiopia: Innovation and growth in international comparison. Paper prepared for the Triple Helix Conference on Transforming University-Industry-Government Relations in Ethiopia, May 29-31, Addis Ababa.

KAM (Knowledge Assessment Methodology). 2006. The World Bank Knowledge for Development (K4D) website: Knowledge Assessment Methodology. <http://web.worldbank.org/WBSITE/EXTERNAL/WBI/WBIPROGRAMS/KFDLP/EXTUNIKAM/0,,menuPK:1414738~pagePK:64168427~piPK:64168435~theSitePK:1414721,00.html>, accessed December 15, 1006.

Kassa, H. 2005. *Historical development and current challenges of agricultural extension with particular emphasis on Ethiopia.* Ethiopian Economic Association (EEA)/Ethiopian Economic Policy Research Institute (EEPRI) Working Paper No. 2/05. Addis Ababa: EEA/EEPRI.

Lundvall, B. 1985. *Product innovation and user-producer interaction.* Äalborg, Denmark: Äalborg University Press.

———. 1988. Japan: A new national system of innovation. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, and L. Soete (eds.), *Technical change and economic theory.* London: Pinter.

MoFED (Ministry of Finance and Economic Development), Federal Democratic Republic of Ethiopia. 2002. *Ethiopia: Sustainable development and poverty reduction program.* Addis Ababa: MoFED.

_________. 2005. *Ethiopia: Building on progress: A plan for accelerated and sustained development to end poverty*. Addis Ababa: MoFED.

Nelson, R. R. 1988. National systems of innovation: Institutions supporting technical change in the United States. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, and L. Soete (eds.), *Technical change and economic theory,* pp. 309–329. London: Pinter

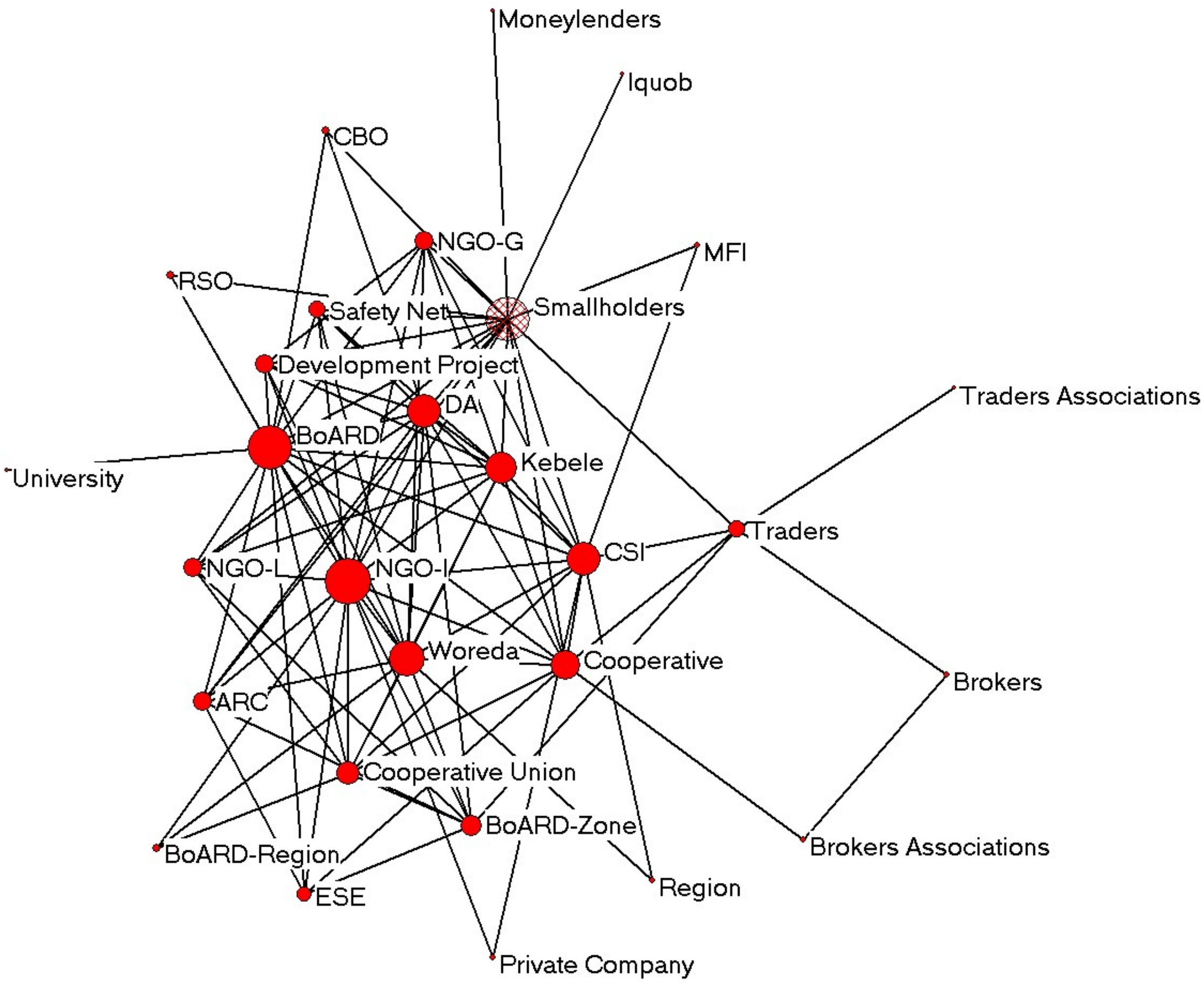
Scott, J. 2000. *Social network analysis: A handbook*. 2nd Ed. London: Sage Publications.

_________. 2004. *Four Ethiopias: A regional characterization assessing Ethiopia's growth potential and development obstacles.* Washington, D.C.: World Bank.

Spielman, D.J., M. Negash, K. Davis, and G. Ayele. 2006. The smallholder farmer in a changing world: The role of research, extension and education in Ethiopian agriculture. Paper presented at the "Ethiopia Strategy Support Program (ESSP) Policy Conference 2006, Bridging, Balancing, and Scaling up: Advancing the Rural Growth Agenda in Ethiopia," Addis Ababa, Ethiopia, June 6-8, 2006.

World Bank. 2004. Four Ethiopias: A regional characterization assessing Ethiopia's growth potential and development obstacles. Washington, D.C.: World Bank.

Annex



Note: ARC: Agricultural Research Center; BoARD: Bureau of Agriculture and Rural Development; CBO: community-based organization; CSI: credit and savings institution; DA: development agent; MFI: microfinance institution; NGO-G: government-associated NGO; NGO-I: international NGO; Kebele: kebele administration; NGO-L: Local NGO; RSO: Religious or social organization.

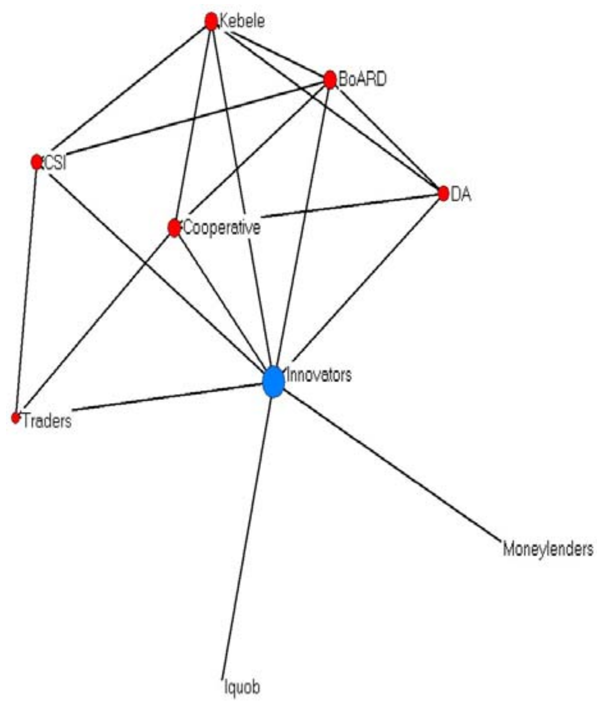


Figure 2a. Social networks of focus group 1, Wemberma

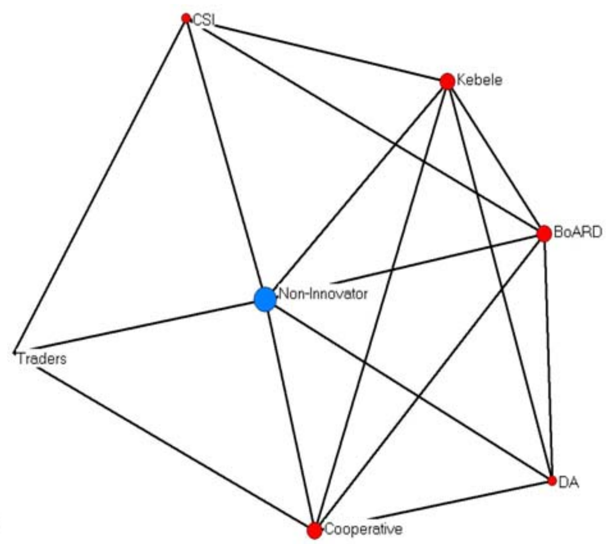


Figure 4b. Social networks of focus group 2, Wemberma

Note: Ties indicate relationships between nodes. Node size is calculated based on degree centrality.

Annex A: Social Network Analysis

This study explores the use of social network analysis to test the hypothesis that local-level social networks are associated with identified innovation processes. To do so, households initially surveyed by the ESCS were purposively selected based on evidence contained in the data that identified them as engaging in some innovative practice. The selected innovations were associated with the adoption of the following crops/technologies: oilseed (linseed, sesame, sunflower, canola, Niger seed); apiculture (primarily modern beehives); non-traditional beans (mainly fasiola and haricot beans); potatoes (improved varieties); and onions, garlic, and leeks.

Ten sites for further study were chosen from the enumeration areas (EAs, roughly mapping to *kebeles*) previously sampled under the ESCS in an effort to capture (a) different agro-climatic or agro-potential regions; (b) multiple crops/technologies being used in a given site; (c) different administrative regions; and (d) physical accessibility of the site (Table A1). While these criteria do not generate a nationally-representative sample of crops, technologies, or sites, they do provide a basis for informative case studies with potential significance to national and regional policy.

Households in each site were selected according to a rough index generated with ESCS data on specific crop/technology adoption, cultivation practices (e.g., innovative water management techniques or use of improved seed); ownership of modern production assets (hand- or foot-operated mechanical water pumps, and motorized (diesel) water pumps); and contact with agricultural extension services. Representatives of approximately five households with the highest scores and five households with the lowest scores were selected for separate focus group interviews, and were denoted (for convenience only) as "innovators" and "non-innovators" respectively (Table A2). These focus groups were conducted by the research team in mid 2006 at each of the 10 sites using participatory rural appraisal (PRA) tools that focused on sources of information and knowledge, production inputs, credit, and market linkages.

Table A1. Selected sites for in-depth study

Woreda (region)	Crop/technology	AEZ	Growth/Development Potential[b]
Wemberma (Amhara)	apiculture/onion	M1, M2	Medium Potential –Low Risk
Janamora (Amhara)	oilseed/apiculture/potato	M2	Medium Potential –Low Risk
Hawzen (Tigray)	apiculture/oilseed	SM2	Low Potential – High Risk
Hintalo (Tigray)	apiculture/onions	SM2	Low Potential – High Risk
Ambo (Oromia)	oilseed/potato	M2	Medium Potential –Low Risk
Becho (Oromia)	beans/oilseed	M2	Medium Potential - Low Risk
Tikur Inchini (Oromia)	oilseed	SH2, M2, H2	High Potential–Low Risk
Kedida Gamela (SNNP)[c]	beans/potato	SH2	Low Potential – Low Risk
Badawacho (SNNP)	beans	SH1	Low Potential - Low Risk
Soro (SNNP)	oilseed/potato	SH2	Low Potential – Low Risk

[a] M1 is hot to warm moist lowlands; M2 is tepid to cool moist mid-highlands; SM2 is tepid to cool sub-moist highlands; SH1 is hot to warm sub-humid lowlands; SH2 is tepid to cool sub-humid mid highlands and H2 is tepid to cool humid mid highlands. *Source:* EIAR (pers. comm.).

[b] Source: World Bank 2004.

[c] Southern Nations, Nationalities, & Peoples (SNNP) regional state.

Table A2. Social network analysis: descriptive statistics for focus group participants

Characteristics	Innovators	Non-innovators
Number of observations	49	48
Mean group size	5	5
Female PRA participants (%)	12	28
Mean age (years) (sd.)[a]	45 (12.8)	46 (16.9)
Mean education (no. of years) (sd.)	3 (3.0)	1.8 (3.0)
Mean land size (ha) (sd.)	1.84 (1.6)	1.23 (0.9)
Land size range (ha)	0.3–8.7	0.1–5.3
PRA participants who are household heads (%)	92	90
PRA participants from women-headed households (%)	10	25

[a] sd denotes standard deviations given in parentheses

Table A3. Social network analysis elements

Element	Definition
Node	Any discrete individual, actor, corporate or collective unit
Ego	Node of interest or analysis
Alter	Nodes that are connected to the ego
Dyad	A pair of nodes and the (possible) tie(s) between them
Network	Graphical representation of relationships that displays points to represent nodes and lines to represent ties
Network boundary	Natural delineations between actors and relationships or artificial limits set by the researcher
Network size	The total number of nodes in the network
Network centralization	Degree to which network revolves around single node
Degree	Number of ties to a specific node
Network density	Proportion of nodes that are actually tied out of all the potential ties
Centrality	Measure of position of power in the network; can be measured as degree; closeness; between-ness; or eigenvector centrality
Cliques	Maximum number of actors who have all possible ties present among themselves
Core	Cohesive sub-group where the actors are connected in some maximal sense
Periphery	Nodes that are only loosely connected to the core and have minimal or no linkages among themselves
Coreness	The degree of closeness to the network core of each actor
Structural hole	Areas in network with limited links; if removed, network would break
Effective size	The network size of an ego minus the average degree of alters
Redundancy	The average degree of ego's alters (not counting their tie to ego)

Following the PRAs conducted at each site, additional semi-structured interviews were conducted with key actors identified by the PRA participants. These interviews were used to further validate information provided by the PRA participants, and included key informants in the immediate locality of the site (for example, development agents, cooperative managers, *kebele* officers, and leaders of community-based organizations); and in the *woreda,* zonal, or regional headquarters (for example, development agents, cooperative managers, bureau of agriculture officers, managers of credit and savings institutions, traders, brokers, NGO representatives, and others). Interviews were guided by questions similar to those posed to PRA participants.

Using data gathered from the PRA, the study then conducted social network analyses of each site. Because SNA is a little-known tool in this type of research, we describe it here in some detail (Table A3) (For further details on the methodology, see Hanneman and Riddle (2005); Scott (2000); and Borgatti (1998).

In SNA, each actor in a network—whether an individual, organization, or some other entity of interest—is termed a "node."

The actor of interest is known as the "ego." Links between nodes or "ties" denote some form of interaction between nodes. Where a tie links an ego to another node, that node is referred to as an "alter."

Ties can be analyzed with respect to their strength, frequency, distance, or other such measures depending on the focus of inquiry. These ties also reflect the key unit of analysis in SNA—the dyad, or a pair of nodes. Dyadic attributes can include the nature of social or economic relationships captured by the dyad, the characteristics of interactions in the dyad, or the ways in which information or resources flow in the dyad. Each network has a size—determined by the total number of nodes—and a boundary—natural delineations between actors and relationships or artificial limits set by the researcher.

Relational data obtained for SNA are usually put into a square actor-by actor matrix, with some value equal to or greater than one in the cell where there is a relationship (or a relationship of some characteristic or magnitude if the value includes some set of numbers including but not limited to one), and a zero where there is no tie. These data are then used to calculate the various measures set forth in Table A3.

Annex B: Econometric Analysis

This study introduces econometric analysis as a means of adding further robustness to the hypothesis that local-level social networks contribute significantly to smallholder innovation processes. The smallholder innovation process can be described as his or her decision-making process over the adoption of a new technology. This process can be modeled as a Baysian updating process of a forward-looking smallholder who learns about the parameters of a new technology for a known production function (Bardhan and Udry 1999). The approach discussed here closely follows Bandiera and Rasul (2006) in which a smallholder's use of information about a given crop of crop technology is used as the basis to examine the effects that individual and social learning have on a smallholder's decision to adopt a new technology.

The target input model

Suppose smallholder i in period t produces some output in quantity q_{it} which declines in the square of the distance between the actual inputs used (k_{it}) and some uncertain target input level ψ_{it} , or

$$q_{it} = 1 - (k_{it} - \psi_{it})^2$$

Assume that the target input level (ψ_{it}) is not known by smallholder i at the time the input is applied. After the inputs are applied and the output is realized, the smallholder updates his beliefs about the target input level. The realization of output may be a period shorter than an entire growing season, e.g., the time lapse between application of some input and the germination of improved seed.

Let ψ^* denote the average optimal target input level. To maximize output, the smallholder attempts to gather information that improves his estimate of this optimal target input level. The smallholder's target input level fluctuates around ψ^* such that

$$\psi_{it} = \psi^* + \varsigma_{it}$$

where ς_{it} denotes transitory shocks to the optimal target input and is normally distributed with a mean of zero and known variance $\left(\varsigma_{it} \sim i.i.d.\, N\left[0, \sigma_\psi^2\right]\right)$, implying that expectations of the stochastic term equals zero, or $E_t(\varsigma_{it}) = 0$.

In period *t,* smallholder *i* has beliefs about ψ^*. We assume that his beliefs are normally distributed $\left(N\left[\psi^*, \sigma^2_{\psi it}\right]\right)$ and that fluctuations around ψ^* are reflections of individual-specific and/or time-specific factors.

We make a simplifying assumption that the input is costless, such that the i^{th} smallholder's profits is his output (q_{it}) multiplied by some constant price *(p)* which is normalized to 1. The i^{th} smallholder's expected output is thus

$$E_t(q_{it}) = 1 - E_t\left[\psi_{it} - E_t(\psi_{it})\right]^2 = 1 - \sigma^2_{\psi it} - \sigma^2_{\varsigma}$$

In other words, smallholder *i*'s expectations of his output (a) increase with the certainty of his expectations about applying inputs at the optimal target level; and (b) decrease with increases in the variance of transitory shocks to the optimal target input level.

The social learning model

An important question remains to be addressed in the model set forth above: how do smallholders form their expectations? Here, we demonstrate how individual and social learning processes affect technology adoption.

Proposition 1. Smallholders learn by doing. Suppose that smallholder *i* learns about the optimal level of input use by inferring from his observations of output. In period t-1, the variance of smallholder *i*'s prior belief about ψ^* is $\sigma^2_{\psi i,t-1}$. Once the smallholder has observed ψ_{it} in time period *t,* he updates his beliefs about the variance of ψ^* such that

$$\sigma^2_{kit} = \frac{1}{\dfrac{1}{\sigma^2_{\psi i,t-1}} + \dfrac{1}{\sigma^2_{\varsigma}}}$$

based on the application of Bayes's rule (Bayes's Rule demonstrates how an initial belief about hypothesis A can be updated in the light of new evidence B. Specifically, a posterior belief about the probability of hypothesis A conditional to hypothesis B [P(A|B)] is calculated by multiplying our prior belief P(A) by the likelihood P(B|A) that B will occur if A is true, or $P(A|B) = \dfrac{P(B|A)P(A)}{P(B)}$). By defining $\rho_0 = 1/\sigma^2_{\varsigma}$ as the precision of the information generated by the i^{th} smallholder's own trial, and $\rho_{i0} = 1/\sigma^2_{\psi i0}$ as the precision of the i^{th} smallholder's initial beliefs about the true value of ψ^*, then

$$\sigma^2_{kit} = \frac{1}{\rho_{i0} + I_{t-1}\rho_0}$$

where I_{t-1} is the number of trials *I* has with the new technology on his own farm between periods 0 and *t – 1.* Further substitution yields

$$E_t(q_{it}) = 1 - \frac{1}{\rho_{i0} + I_{t-1}\rho_0} - \sigma^2_{\varsigma}$$

From this equation, we find that the smallholder's expected output is an increasing function of the number of trials he has with the new technology, i.e., learning by doing, or

$$\frac{\partial E_t(q_{it})}{\partial I_{t-1}} = \frac{\rho_0}{\left(\rho_{i0} + I_{t-1}\rho_0\right)^2} > 0$$

We hold off on further differentiations until we are able to construct a more complete model of the smallholder's social learning process.

Proposition 2. Smallholders learn from others. Suppose that smallholder *i* is a member of a social network *n(i),* the members of which share information with *i* at no cost to either *i* or any other member. With this supposition, the farmer now incorporates inferences he makes about trials undertaken by members of his network *in addition to* his inferences about his own trials. Thus, Equation (5) becomes

$$\sigma^2_{kit} = \frac{1}{\rho_{i0} + I_{t-1}\rho_0 + n(i)_{t-1}\rho_0}$$

This implies that smallholder *i*'s expected output is dependent on inferences from his trials *and* his inferences from the trials of his network members, or

$$E_t(q_{it}) = 1 - \frac{1}{\rho_{i0} + I_{t-1}\rho_0 + n(i)_{t-1}\rho_0} - \sigma^2_{\varsigma}$$

Proposition 3: Learning affects expected output. Partial differentiations of Equation (9) obtain the following results:

The i^{th} smallholder's expectations of his output are increasing in the use of the new technology by a member of his social network, implying that social networks generate a positive learning externalities, or

$$\frac{\partial E_t\left(q_{it}, n(i)_{t-1}\right)}{\partial n(i)_{t-1}} = \frac{\rho_0}{\left(\rho_{i0} + I_{t-1}\rho_0 + n(i)_{t-1}\rho_0\right)^2} > 0$$

The i^{th} smallholder's expectations of his output are increasing in the precision of his own initial information relative to the information obtained from his social network

$$\frac{\partial^2 E_t\left(q_{it}, n(i)_{t-1}\right)}{\partial \rho_{i0}\partial n(i)_{t-1}} < 0$$

The i^{th} smallholder's expectations of his output are increasing in the precision of initial information obtained from his social network, implying that the learning externalities vary across networks.

$$\text{(1)} \qquad \frac{\partial^2 E_t\left(q_{it}, n(i)_{t-1}\right)}{\partial \rho_0 \partial n(i)_{t-1}} < 0$$

Information acquired from learning by doing and learning from others are substitutes for on another.

$$\frac{\partial^2 E_t\left(q_{it}, n(i)_{t-1}\right)}{\partial I_{t-1}\partial n(i)_{t-1}} < 0$$

The adoption decision model

Next, we examine the smallholder's technology adoption decision. We denote smallholder *i*'s decision to adopt the technology in time period t as $a_{it} = 1$, and $a_{it} = 0$ otherwise. Smallholder *i* does so with full knowledge of the riskless return $\left(\bar{q}\right)$ to his existing technology. The smallholder's decision to adopt depends on his assessment of the future stream of profits $\left(V_t\right)$ from period *t* to *T,* or

$$\text{(2)} \qquad V_t\left[I_{t-1}, n(i)_{t-1}\right] = \max_{a_{is}\in\{1,0\}} E_t \sum_{s=t}^{T} \delta^{s-t}\left\{(1-a_{is})\bar{q} + a_{is}q_s\left[I_{s-1}, n(i)_{s-1}\right]\right\}$$

where $I_{s-1} = \sum_{t=0}^{s} a_{is}$ denotes the total number of trials conducted by *i* through period s; $n(i)_{s-1}$ denotes the total number of trials conducted by *i*'s social network in the same period; and δ is the discount rate.

Smallholder *i*'s future stream of profits can thus be represented as

$$\text{(3)} \qquad V_t\left[I_{t-1}, n(i)_{t-1}\right] = \max_{a_{it}\in\{1,0\}}(1-a_{it})\bar{q} + a_{it}E_t q_t\left[I_{t-1}, n(i)_{t-1}\right] + \delta V_{t+1}\left[I_t, n(i)_t\right]$$

The smallholder adopts the technology in period 0 if the expected profit stream of the new technology exceeds the expected profit of the existing technology, or

$$\text{(4)} \qquad E_o q_o\left[0, n(i)_0\right] + \delta V_1\left[1, n(i)_0\right] \geq \bar{q} + \delta V_1\left[0, n(i)_0\right]$$

Two further assumptions should be noted here. First, the new technology is considered to be an absorbing state: once the smallholder adopts the technology, he does not switch back. Second, the adoption of the new technology may occur even when the existing technology is more profitable.

The opposing network effects

The derivative of the net gains from adopting in period 0 with respect to the total number of trials undertaken by smallholder *i*'s social network is

$$\text{(5)} \qquad \frac{\partial E_0 q_0\left(0, n(i)_0\right)}{\partial n(i)_0} + \delta\frac{\partial\left\{V_1\left[1, n(i)_0\right] - V_1\left[0, n(i)_0\right]\right\}}{\partial n(i)_0}$$
$$= \frac{\rho_0}{\left(\rho_{i0} + n(i)_{t-1}\rho_0\right)^2} + \delta\sum_{s=1}^{T}\delta^s\left\{\frac{\rho_0}{\left(\rho_{i0} + s\rho_0 + n(i)_0\rho_0\right)^2} - \frac{\rho_0}{\left(\rho_{i0} + (s-1)\rho_0 + n(i)_0\rho_0\right)^2}\right\}$$

As expected, this implies that smallholder *i*'s decision to adopt is positively related to the number of trials undertaken by his social network (the learning externality effect). However, this also implies that smallholder *i*'s decision is negatively related to the number trials undertaken by his social network because the value of information from his own adoption is lower as more network members adopt. In other words, as more network members adopt, it makes more sense for the smallholder to learn from the network rather than undertake his own trials, i.e., a strategic delay effect.

Let a_{iv}^{*} denote the present value of the net gains to smallholder *i* in *kebele v* from adopting some crop or technology, a value that is inherently unobservable to all but smallholder *i*.(We use the term *kebele* here to denote Enumeration Area for convenience only. Although the two terms generally map to the same geographical areas, there is some variation in the administrative boundaries of a *kebele* and the Enumeration Area boundaries used by the CSA.

) We can define the present value of the net gains to smallholder *i* in period 0 as

$$a_{iv}^{*} = a\left[n(i), \underline{X}_v, \underline{Z}_v, u_{iv}\right] = f\left[n(i)\right] + \alpha \underline{X}_i^0 + \beta \underline{Z}_v + u_{iv}$$

where $n(i)$ measures the information available to smallholder *i* about the new technology from his social network; $\underline{X}_v$ a vector of individual characteristics describing smallholder *i;* Z_v a vector describing common observable characteristics across area *v;* and u_{iv} a term capturing unobservable determinants of the present value to smallholder *i* in area *v.* We can specify the smallholder's adoption decision as a discrete choice,

$$a_{iv} = 1 \quad if\ a_{iv}^{*} > 0$$
$$a_{iv} = 0 \quad otherwise$$

The probability *(P)* that the i^{th} smallholder adopts the technology is thus given by

$$P\left(a_{iv} = 1\right) = P\left(u_{iv} > -\left\{f\left[n(i)\right] + \alpha \underline{X}_i^0 + \beta \underline{Z}_v\right\}\right) \quad (6)$$

We estimate Equation (6) using household-level data on apiculture, a relatively new technology based on the introduction of modern beehives. The commodity in question, honey, holds considerable value in local markets for domestic consumption purposes.

The data are described as follows, with summary statistics given in Table A1. *Adoption* is measured as a dichotomous (binary) variable: 1 if the household owns and uses modern beehives for honey production, 0 otherwise. Insufficient heterogeneity and indivisibility in the number of modern beehives owned and used by households in the sample rules out possibility of an alternative Tobit estimation based on adoption intensity.

Age of the household head proxies for experience, and is assumed to increase the probability of adoption but at a decreasing rate, such that the estimated parameter is predicted as positive and an age-squared term as negative. *Educational status of the household head* provides a dummy measure of whether the household head is literate or not to account for the extent to which the technology is knowledge-intensive, that is requiring some degree of literacy to adopt and use effectively.

Household dependency ratio measures the number of household members who are economically dependent on those who are economically active, and is considered to be more accurate than a dependency ratio calculated solely based on the age of household member, wherein members beyond a given age range (both above and below) are considered dependent on members within the same age range. The measure is used to predict the effect of the household's budget constraint on its ability to experiment with and adopt new technologies, such that a higher dependency ratio reduces the probability of adoption. This effect is assumed to be greater than the opposing effect that a large number of household members might have on the household labor constraint. Thus, the parameter is predicted as negative. *Female-headed household* enters as a dummy to control for unique disadvantages relating to the adoption of new technologies without the social capital afforded by a male head of household, and is predicted as negative.

Land asset ownership denotes the households total land holdings (measured in hectares), and enters both as a measure of the household's stock of productive assets that can support adoption of the technology, and a proxy for the household's asset-based wealth. While both effects are predicted as positive, note that certain technologies such as apiculture are not land-intensive, suggesting a weak relationship with the dependent variable. *Other asset ownership* denotes the total value (measured as the natural log of the total assets' birr value) of livestock, production, household, and housing assets owned by the household, and similarly enters as a measure of the household's stock of productive assets that can support adoption of the technology, and a proxy for the household's asset-based wealth. Where survey respondents were unable to provide an assessment of a given asset's current value, the value was imputed using *woreda*-level averages for the value of those same assets. Both the land and other asset ownership variables are predicted as positive. *Credit* measures the total amount of loans the household received in the last one year (also in log values) and indicates the household's access to a financial capital from all possible sources including friends, relatives, money lenders, private traders, government, and NGOs. Estimated coefficients for land assets, other assets, and credit are predicted as positive.

Peer network measures the number of persons that are not associated with the BoARD or an NGO to whom household members (above 15 years of age) can go to for advice about their economic activities. We assume a positive peer network effect, but deviate from Bandeira and Rasul (2006) by omitting estimation of the decreasing returns to network size, which argues that as more network members adopt a given crop or technology, the value of information that the smallholder gains from his or her own adoption process exceeds the value of information gained from the network (thus implying a negative coefficient on the square of the peer network effect).

A set of variables defining distinct non-peer networks in which the household participates described as follows. *Extension network* is a dummy variable that reflects whether the household has received a visit on beehiving in the last two years from an extension agent (a DA, a representative from the BoARD, or an NGO) in the last two seasons. *Community network* is the number of formal and informal community groups in which the household is a member, including women's association, youth association, elders association, water users' group, church/mosque group, cooperatives and credit and saving institutions. *Market network* is a number of traders that the household has contact with, both inside and outside the *kebele.* The estimated coefficients on all non-peer networks are predicted as positive.

The inclusion of these networks variables necessarily raises the possibility of endogeneity arising from self-selection (where modern beehive adopters participate in networks as a result of their adoption decision) and simultaneity (where the mean behavior of the networks influences the adopter, who in turn influences the network). We assume that the extension network variable is correctly specified given the consistently supply-driven nature of the technology's dissemination. However, these problems still remain with respect to the peer network variable. Thus, in the absence of an adequate set of instrumental variables, estimation of the model provides insight into correlation at best, rather than causality.

The mean length of growing season enters as a variable to account for agroclimatic risk of the *kebele*. *Market access* enters as a dummy variable to measure whether the kebele is characterized by high or low accessibility to a market center. This measure is a proxy for actual walking distance from a given household to market, a measure that is not consistently available from the ESCS data. *Kebele* fixed effects are used in lieu of these two *kebele*-specific variables in alternative estimations of the model to control for unobservables at the *kebele* level that may affect adoption.

We estimate Equation 0, substituting a_{iv} for a^*_{iv}, with a probit regression in which adoption is specified as a function of these variables in the form

$$a_{iv} = \beta_0 + \beta_1(Age) + \beta_2(Age^2) + \beta_3(Literacy) + \beta_4(Female) + \beta_5(Land) + \beta_6(\ln Assets)$$
$$+ \beta_7(Credit) + \beta_8(Peer) + \beta_9(Non\ peer) + \beta_{10}\left(\overline{Lgp}\right) + \beta_{11}(Market) + u_{iv}$$

Estimation of Equation (21) generates parameters that are reported as the marginal effects of the given variable on the probability of adoption. Additional estimations for robustness are reported below.

Results of probit estimations of apiculture adoption based on Equation (21) above are presented earlier in Table 2. Model 1 presents a baseline estimation of adoption using the two variables of interest: peer network and non-peer network. A larger peer network size significantly increases the smallholders' probability of adoption, although the magnitude of the reported marginal effects suggests that existence of a non-peer network (effectively, contact with extension) is significantly more influential on the probability of adoption.

Model 2 presents a more complete estimation of Equation (21). Both peer and non-peer networks remain significant and positive with similar magnitudes as in the baseline model. In addition, measures of household land and non-land asset ownership are found to significantly increase the smallholders' probability of adoption.

Model 3 presents an estimation of Model 2 with *kebele* fixed effects, substituting for agroclimatic and market access control variables introduced in the previous models. Again, both peer and non-peer networks remain significant and positive, with similar magnitudes as in previous estimation models.

Results suggest the following. First, smallholders learn from their peers. Peer network effects have a significant effect on apiculture adoption. Given the manner in which peer network is defined and the marketable nature of the crop, these findings are model consistent: larger peer networks that provide information on one's economic (that is, market) activities will generate a stronger influence on the adoption decision for technology that relates to a marketable crop output.

Second, smallholders learn from sources other than their peers. Non-peer (extension) network effects show a significant, and considerably larger in magnitude, effect on apiculture adoption. Given the manner in which non-peer network effects are measured—effectively, whether the household has received extension advice from any source on beehiving—and the supply-driven nature in which modern beekeeping technologies have been introduced in the study area, the non-peer network effects are consistent.

However, market networks effects are insignificant, reinforcing the finding that innovation is supply-driven by extension rather than market-driven by product demand articulated by traders. Similarly, community network effects are insignificant, suggesting that community-based organizations (including cooperatives) are not immediately relevant to technology adoption decisions in this particular case.

Third, a household's wealth has a significant effect on apiculture adoption. Where household wealth effectively proxies for household poverty status, these findings suggest that adoption is significantly driven by the household's asset stock (land, livestock, production, housing, and other household assets).

Finally, apiculture adoption is not significantly influenced by other common determinants. Credit access, for example, is insignificantly related to adoption. This is consistent with observations that the operative technology—a modern beehive—is neither a capital-intensive technology for most households, nor costly when supplied by extension services.

Similarly, neither education nor experience is significantly related to the probability of adoption, suggesting that the operative technology is not knowledge-intensive. In sum, smallholder innovation is driven by different types of networks. Extension services—primarily those provided by DAs and the BoARD—are significant drivers of innovation in the case of apiculture. Peer networks are similarly significant, but are of a much smaller magnitude.

Table A1. Descriptive statistics for apiculture adoption (standard deviations in parenthesis)

Explanatory variable	Non-adopters (n=1081)	Adopters (n=59)	Total sample (n=1140)
Age (years)	45.02 (15.01)	46.85 (15.00)	45.12 (15.01)
$Age^2 \times 10^{-2}$	22.52 (14.93)	24.16 (15.49)	22.61 (14.95)
Peer network (no.)	3.97 (7.09)	6.92 (15.78)	4.12 (7.79)
Extension network (no.)[a]	0.02 (0.12)	0.12 (0.33)	0.02 (0.14)
Community association network (no.)	1.28 (1.14)	1.49 (1.12)	1.29 (1.14)
Market network (no.)	8.67 (16.41)	12.53 (22.15)	8.87 (16.77)
Literacy (1/0)	0.37 (0.48)	0.44 (0.50)	0.37 (0.48)
Dependency ratio	53.25 (56.44)	49.49 (45.16)	53.05 (55.90)
Female-headed household (1/0)	0.21 (0.41)	0.10 (0.30)	0.20 (0.40)
Land owned (ha)	1.34 (1.27)	2.09 (2.00)	1.38 (1.33)
Assets (ln)	7.81 (1.30)	8.55 (0.94)	7.85 (1.29)
Credit (ln)	2.30 (2.83)	2.90 (3.21)	2.33 (2.85)
Mean LGP (days)	207.67 (70.62)	206.51 (68.74)	207.61 (70.49)
Market access (1/0)	0.32 (0.47)	0.32 (0.47)	0.32 (0.47)

[a] Note that in the case of apiculture, only one household responded that it had received visits from both a DA and another source (in this case, an NGO), and is thus assigned a value of 1. Figures in parentheses are average values.