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How Change Agents and Social Capital Influence the Adoption of Innovations among Small Farmers

Evidence from Social Networks in Rural Bolivia

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ABSTRACT

This paper presents results from a study that identified patterns of social interaction among small farmers in three agricultural subsectors in Bolivia—fish culture, peanut production, and quinoa production—and analyzed how social interaction influences farmers' behavior toward the adoption of pro-poor innovations. Twelve microregions were identified, four in each subsector, setting the terrain for an analysis of parts of social networks that deal with the diffusion of specific sets of innovations. Three hundred sixty farmers involved in theses networks as well as 60 change agents and other actors promoting directly or indirectly the diffusion of innovations were interviewed about the interactions they maintain with other agents in the network and the sociodemographic characteristics that influence their adoption behavior.

The information derived from this data collection was used to test a wide range of hypotheses on the impact that the embeddedness of farmers in social networks has on the intensity with which they adopt innovations. Evidence provided by the study suggests that persuasion, social influence, and competition are significant influences in the decisions of farmers in poor rural regions in Bolivia to adopt innovations. The results of this study are meant to attract the attention of policymakers and practitioners who are interested in the design and implementation of projects and programs fostering agricultural innovation and who may want to take into account the effects of social interaction and social capital. Meanwhile, scholars of the diffusion of innovations may find evidence to further embrace the complexity and interdependence of social interactions in their models and approaches.

Key words: social networks, agricultural innovation, change agent, social capital, Bolivia

1. INTRODUCTION

For a long time, scholars in sociology have emphasized that people's behavior is determined in part by their embeddedness in social networks. This knowledge is becoming increasingly used in the study of how farmers adopt innovations, complementing studies that have shown how innovation has diffused in rural communities based on a gradual process of diffusion dependent on resource endowments (land, credit, and farm inputs), economic incentives, and demographic and agro-ecological characteristics. The farmers' position in social networks determines how they can access information on the use of knowledge and technology and complementary resources such as credit, land, and subsidized inputs that are important in innovation processes. Embeddedness in social networks also enables farmers to learn the best ways of applying new and improved knowledge and technology and to judge their usefulness and effects.

Few empirical studies show (1) how resource-poor farmers in developing countries, based on their embeddedness in social networks, interact, exchange information, and—jointly with change agents promoting their use—learn how best to apply innovations and (2) how that interaction influences the level of adoption of new knowledge and technology. This paper expands on conceptual and methodological work in the study of innovation processes among farmers by providing empirical evidence from the analysis of social interaction among smallholders in impoverished areas in rural Bolivia, responding to the question of how interactions between farmers and promoters of innovation influence technology adoption.

This paper reports on one of two complementary studies on adoption of technological innovation packages by smallholders involved in fish culture or the production of peanuts or quinoa in three Bolivian regions: the humid tropics, the valleys, and the altiplano. The study described here was an in-depth analysis of the effects of change agents (e.g., input sellers, buyers, extension agents, project staff, etc.) and social capital on the individual adoption decisions of farmers embedded in social networks. The second study (Hartwich et al., forthcoming) focuses on the incorporation of a range of networking parameters in various econometric models that explain the adoption of innovations of individual farmers on the basis of diverse variables depicting sociodemographic, economic, and agro-ecological conditions. Both studies were conducted by the International Food Policy Research Institute (IFPRI) in collaboration with the Bolivian Agricultural Technology System (SIBTA), the Trópico Húmedo and the Valles Foundations for Agricultural Development, and the PROINPA Foundation.

The two studies draw from information gathered from interviews with 360 farmers and 60 change agents and other actors involved in innovation networks in 12 microregions in Bolivia. In each region, a set of innovations related to one of the three sectors of fish culture, peanut production, or quinoa production has been advanced by a particular promoter of innovations, usually a nongovernmental organization (NGO) or project consultant agency. The data were analyzed with tools of social network analysis as well as correlation and multivariate regression analysis, testing a set of hypotheses on the effects of social influence, cohesion, brokerage, and equivalence on the farmers' adoption of innovations both on the regional (network) level and individual (farmer) level.

The paper is organized into six sections. Section 2 presents an extensive literature review of sociological and economic approaches to the study of innovation. Section 3 derives the hypotheses to be tested and describes research methods, data processing, and data analysis. Section 4 reveals the general features of interactions among agents found in the social networks underlying the innovation cases studied. Section 5 presents the results of testing the hypotheses. The paper concludes by pinpointing the overall findings and the policy implications that follow from them and presenting some reflections on challenges to the study of rural innovation and future topics of research.

2. THEORETICAL BACKGROUND

All innovation is social innovation. Innovation does not happen "out there" in the world of objects. . . . Innovation can properly be understood only by studying the social basis of innovation. (Tuomi 2002, 5–6).

One key observation highlighted in many studies is the role of social links and community structure in the diffusion process. Communications and information relating to new knowledge were shown to be embedded within the more general fabric of social interactions among individuals. The pattern of information flows received and transmitted by individuals is thus related to their social environment, the network of their contacts, and their status within that network. (Feder and Savastano 2006, 1287)

When using the term *innovation*, scholars from different fields of thought (e.g., Mahajan and Peterson 1985; Rogers 2003; Damanpour and Schneider 2006) refer to different concepts—such as ideas, practices, products, services, processes, technologies, policies, structures, and administrative systems—that the adopting unit perceives as new. Perhaps most conveniently and broadly, an innovation is best understood as anything new successfully incorporated into social or economic processes.

The spread of innovations across social groups over time is referred to as the diffusion of innovations (Brown 1981; Stoneman 2002). It is one of the most-studied and best-documented social phenomena in academic disciplines ranging from geography and sociology to economics, education, and marketing (Mahajan and Peterson 1985). The classic definition by Rogers (2003) considers diffusion as the process by which an innovation is communicated through certain channels over time among members of a social system. Diffusion can also be regarded as the cumulative pattern of individual adoption decisions in time—that is, the timing of individuals' decisions about adopting, rejecting, or discontinuing an innovation within a social group. Adoption is commonly understood as the decision to make full use of an innovation, which encompasses the mental process that an individual undergoes from first hearing about to finally adopting an innovation (Feder et al. 1985; Rogers 2003).

2.1. Diffusion of Agricultural Innovations: Early Approaches

The study of the diffusion of innovations emerged as a prominent research field after the publication of a seminal work by Ryan and Gross (1943), two rural sociologists who analyzed the switch to hybrid corn seeds among farmers in two communities in Iowa, highlighting the importance of communication processes.

In the light of this seminal study, early diffusion researchers were motivated to improve extension services and the marketing of new seeds and technology in the rural United States, given the lengthy periods then required for spreading even the most valuable innovations. Consequently, those scholars concentrated on identifying the key factors that constrained adoption decisions. According to Ruttan (2003), the practical insights obtained by early diffusion researchers (e.g., the recommendation to concentrate extension efforts on opinion leaders during the early stages of diffusion) led to the explosive expansion of this type of study by rural sociologists in the 1950s and 1960s. Several generalizations on the diffusion process—including the S-shaped pattern of cumulative adoption, the distinctions among various adopter categories according to their innovativeness (speed of adoption), and the phases that a farmer goes through before deciding to adopt—resulted from the evidence accumulated from those studies (cf., Beal et al. 1957; Copp 1958; Rogers 1958, 1962, 1976; Rogers and Shoemaker 1971). Those generalizations, in turn, gave rise to what is known as the classical diffusion model (Rogers 2003), which characterizes diffusion as a phenomenon of contagion or information spread among potential users; according to this model, all what was required for the occurrence of diffusion, in an almost automatic fashion, was that users could have access to information on innovations.

Early diffusion studies by rural sociologists put some emphasis on the sociopsychological factors determining individual adoption. Authors such as Ryan (1948), Gross (1949), Wilkening (1950a, 1950b, 1952, 1954), Pedersen (1951), Gross and Taves (1952), Lionberger (1952, 1953), Marsh and Coleman (1955, 1956), and Hildebrand and Partenheimer (1958) stressed the significant role of differences in personality, education, and economic status on adoption behavior; others, like Fliegel and Kivlin (1962, 1966a, 1966b), highlighted the effects of farmers' perceptions about the attributes of innovations on adoption.

Most of those early authors also emphasized the significant influence of structural factors, such as belonging to distinct neighborhoods or local or ethnic groups, on adoption decisions, given the social influence exerted by group values and norms (cf., Lionberger 1954; Marsh and Coleman 1954; Young and Coleman 1959; Van den Ban 1960; Coughenour 1964; Flinn 1970). Insights from these studies converged in the late 1960s with advances in diffusion studies conducted by (1) communication scholars, who recognized the limitations of the mass media in advancing diffusion and who stressed the role of human interaction in shaping the process, and (2) medical sociology researchers, who recognized social cohesion as a key determinant of the diffusion of new prescription drugs among physicians (Menzel and Katz 1955; Coleman et al. 1957, 1966; Katz et al. 1963; Ruttan 2001). As a result, studies on diffusion of innovations advanced toward a relational perspective that emphasizes the effects of sociostructural factors, explaining diffusion not only on the basis of individual attributes but also according to the relationships among the various actors involved in the process (see Lionberger and Copus 1972).

2.2. Agricultural Innovation in Developing Countries

The study of the diffusion of agricultural innovations in developing countries has been profoundly influenced by the works of Griliches (1957, 1960a, 1960b, 1962). In his reassessment of the diffusion of hybrid corn in the United States using econometric modeling, Griliches stated that the observed patterns of adoption timing were largely explained by the profitability of innovation to the individual farmer, generating heated controversies concerning the previous explanations purported by rural sociologists (cf., Brandner and Strauss 1959; Havens and Rogers 1961; Babcock 1962; Rogers and Havens 1962).

Griliches's perspective was soon taken up and furthered by analysts interested in boosting technological innovation in developing countries. The theoretical and empirical works that proliferated assumed that farmers behave as profit maximizers and considered the heterogeneity of attributes and resource endowments among individuals as the key determinant of diffusion patterns because of its effect on the utility of adoption for individuals. The likely effects of numerous factors on individual adoption were tested, deriving insights and policy recommendations that were basic for the design of most technological change efforts implemented as part of the Green Revolution and subsequent agricultural development programs (cf., Falcon 1970; Bell 1972; Perrin and Winkelmann 1976; Ruttan 1977; Feder et al. 1985; Feder and Umali 1993; Sunding and Zilberman 2001; Smale 2005).

However, after 1970, the more relational approaches applied to the analysis of agricultural innovation processes were put aside by economists as well as rural sociologists. The latter concentrated their attention on issues such as the socioeconomic consequences of adoption or the adoption of conservation and organic practices (Rogers and Svenning 1969; Gotsch 1972; Havens and Flinn 1975; Röling et al. 1976; Pampel and Van Es 1977; Goss 1979; Shingi et al. 1981; Ashby 1982; Freeman et al. 1982; Nowak 1987; Ruttan 1996, 2003; Fliegel and Korsching 2001).

The dominance of individualistic and profit-maximizing approaches to agricultural innovation has not gone without critique and amendment. Rogers (1979, 2003), for example, criticized the "psychological bias" in diffusion research, citing its excessive focus on individuals as the unit of analysis and researchers' tendency to hold individuals responsible for their own situations and problems. Smale, discussing the adoption of low external input agriculture, states that "the critical role of such factors as adaptation processes, information sources, social capital, externalities, and the slow payoff time from adoption, which characterize low external input technologies, are not easily addressed by such models" (2005, 1335). In fact, development practice has at times evidenced the occurrence of slow and partial adoption irrespective of the profitability of the innovations at stake. This observation has been supported by theories on conservative and imitative behavior as a rational choice when facing uncertain outcomes (cf., Alchian 1950; Arrow and Fisher 1974). As a result, researchers have included learning effects in adoption models (cf., Hiebert 1974; Lindner et al. 1979; Feder and O'Mara 1982) usually understanding learning as a Bayesian process of updating individual beliefs triggered by personal experience and the experiences of others.

A more explicit consideration of the relational perspective and the effects of social interactions in studies on the adoption of innovations in agriculture has been spurred in recent years as a consequence of paradigmatic shifts that have been under way since the 1970s both in economics and the study of innovation in business and in advanced economies. On the one hand, the scope of economics as a discipline has been widened by considering nonmarket interactions, their structure, and their externalities—a phenomenon largely derived from the emergence of noncooperative game theory, the consideration of household perspectives in labor economics, and the emergence of endogenous growth theory in macroeconomics (cf., Akerlof 1997; Akerlof and Kranton 2000 Barr 2000; Manski 2000; Brock and Durlauf 2001; Durlauf 2001, 2004; DeMarzo et al. 2003; Jackson 2007a, 2007b).

On the other hand, evolutionary approaches that understand innovation as a disequilibrium process which entails uncertainty -its advance cannot be predicted as it depends on the competition among diverse technological options (cf., Silverberg et al. 1988; Ruttan 1997; Sharif 2006)- have enriched the theory and empirical analysis of technical change and innovation by highlighting the role of institutional structures and settings (e.g., innovation systems) in supporting and shaping efforts to advance technology (Lundvall et al. 2002; Nelson and Nelson 2002). The innovation systems concept—that is, "the network of organizations, enterprises and individuals focused on bringing new products, new processes and new forms of organization into social and economic use, together with the institutions and policies that affect their behavior and performance" (World Bank 2007, xiv)—is a key concept in these evolutionary approaches and highlights the interactive, systemic, and dynamic nature of innovation; it has become a basic framework for understanding and promoting agricultural innovation (Hall et al. 2005; Spielman 2006).[1]

The impetus of this multipronged reconsideration of social interactions in economics and other fields has permeated into adoption studies in agriculture, where an increasing number of scholars are pursuing a deeper understanding of the social processes affecting adoption decisions. The major advances to date can be grouped into three main areas:

- Numerous authors have used learning models to test the effects of social interactions, continuously refining the specification of social learning effects (cf., Besley and Case 1994; Foster and Rosenzweig 1995; Pomp and Burger 1995; Fischer et al. 1996; Cameron 1999; Henrich 2001; Marra et al. 2003; Hinrichs et al. 2004; Abadi Ghadim et al. 2005; Munshi 2005; Alene and Manyong 2006). In some cases, these models build on Bayesian approaches but go beyond the assumption that farmers access freely the outcomes of their experimenting neighbors and that information quality is not lost in the process, considering learning in the framework of social networks (e.g., Conley and Udry 2001, 2004; Bandiera and Rasul 2006).
- Contagion models have frequently been used in the study of diffusion in economic geography and marketing, and some authors have used them to demonstrate the influence of physical proximity among actors on their adoption behavior (e.g., Abdulai and Huffman 2005), considering at times social network parameters (e.g., Nyblom et al. 2003).
- Diverse models consider various effects attributed to social interactions, such as the conformity pressures exerted on individuals' behavior by social contacts, reference groups,

[1] Jarrett (1985) and Biggs (1990) are early examples of how an innovation systems perspective had already been introduced in agricultural innovation studies.

and social structures; the role of opinion leaders; and the effect of social capital (e.g., Warriner and Moul 1992; Boahene et al. 1999; Narayan and Pritchett 1999; Isham 2002; Caviglia-Harris 2003; Jagger and Pender 2003; Nyangena 2004; Sapp and Korsching 2004; Feder and Savastano 2006; Hogset 2006; Katungi 2006; Moser and Barrett 2006; Moxley and Lang 2006; Van den Broeck and Dercon 2007).

Laudable as they are, these pioneering efforts have also been subjected to numerous criticisms derived from the challenge of combining very diverse traditions and analytical frameworks. Obstacles for an adequate formulation of a model include the abundance of subjectively formalized concepts in the sociological tradition (of which social capital is a good example); the endogeneity problem of the observed effects of interaction; and the simplistic specification of social interactions and peer effects in econometric models (Manski 2000; Jackson and Yariv 2005). To Manski, Social Network Analysis (SNA) is a very promising approach for sorting these obstacles, though its potential has not been realized.

2.3. Adoption of Innovations and Social Interactions

This section provides a review of the most fundamental concepts and perspectives regarding the effects of social interactions on the diffusion of innovations in agriculture and other fields. These perspectives represent diverse disciplinary origins (e.g., economics, sociology, organizational studies, and agricultural extension) and are related to distinct approaches within the literature of social learning, social capital, and social influence that are only partly known and applied in agricultural economics and sociology. Particular emphasis is placed here on structural parameters that can be derived at the level of individuals rather than groups or farming communities, thus being amenable for their inclusion in econometric models as attributes describing the position of individuals in the social structure. This review is instrumental in leading to the formulation of the hypotheses tested in the present study.

2.3.1. Economic Perspectives

Development economics often takes the standpoint that social interaction determines to a certain degree the adoption of innovations because it provides access to information, inputs, infrastructure, and institutions (e.g., risk-sharing and coordination mechanisms), all of which are considered important factors contributing to the implementation of innovative ideas (Chwe 2000; Kranton and Minehart 2001; Okten and Osili 2004; Hogset 2006; Fafchamps 2007; Van den Broeck and Dercon 2007).

The effects of interactions on information exchange and learning has always been the topic of preference among development economists (Young 2002, 2005). According to Zhao (2005), access to information about innovations is the key factor affecting the dynamics of adoption processes. Authors like Feder and Slade (1984), Feder et al. (1985), and Abadi Ghadim et al. (2005) have demonstrated that, for profitable innovations, the accumulation of experience and learning eventually induce farmers to adopt innovations as (1) initial beliefs about their characteristics are updated; (2) their utilization gets increasingly efficient, thus increasing the probabilities of deriving higher payoffs; and (3) the uncertainties about their performance decrease as knowledge improves.

Farmers can access information through various sources and mechanisms, such as visits from extension agents, participation in training activities, and exposure to mass media. Learning has been acknowledged as another key source of information for farmers, and one that is fundamental for promoting adoption under uncertain conditions because it helps to modify the perceived risk of innovations (cf., Foster and Rosenzweig 1995; Munshi 2005; Yamauchi 2007). Abadi Gadhim et al. (2005), for example, posit that farmers' perceptions of innovation risk and farmers' risk aversion are the most important of all variables influencing the level (intensity) of adoption. Feder et al. (1985), based on their summary of empirical studies considering the effects of risk and uncertainty on adoption, hypothesize that exposure to appropriate information through a range of communication channels reduces subjective uncertainty. The consequent reduced uncertainty should lead to increased adoption, assuming all other factors remain unchanged.

Indeed, abundant empirical evidence shows that farmers get involved in diverse learning processes, either by experimenting in their own plots before full adoption (learning by doing) or by actively or passively taking advantage of the experiences and performance of neighbors, friends, and relatives who have experimented with the innovation (learning from others, learning spillovers, or social learning). Empirical studies in agriculture,[2] as well as in other economic activities,[3] have consistently found that social learning processes predict localized conformity effects (i.e., contagion by physical proximity and direct interaction).

2.3.2. Organizational Science Perspectives

DiMaggio and Powell studied the phenomenon of isomorphic change in organizations, by which "rational actors make their organizations increasingly similar as they try to change them" (1983, 147). They propose the existence of three isomorphic processes: (1) coercive processes, which result from formal and informal external pressures applied through a diversity of mechanisms, such as group norms, expectations of compliance, invitations to collude, persuasive messages, and overt force; (2) mimetic processes, in which imitation of the more legitimate or successful examples in the field is utilized as a viable and inexpensive alternative to facing uncertainty, especially in the case of complex technological change or ambiguous problems, goals, and contexts; and (3) normative processes, which result from the impulse to standardize methods and procedures in the distinct occupational fields as a means of enhancing the exchange of information and increasing effectiveness. Building on those processes, DiMaggio and Powell suggest a set of predictors of isomorphic change that has been used in the analysis of the adoption of innovations. This analytical framework has been further developed by several scholars in organizational science to analyze the diffusion of organizational innovations, considering innovation as a social contagion process (Haveman 1993; Mizruchi and Fein 1999). For our analysis of agricultural innovation processes among smallholders, the relevant hypothesis that can be derived from this field is that one actor (organization) ends up imitating the behavior of those he or she depends on more strongly or perceives as successful.

2.3.3. Sociopsychological Perspectives

Scholars in the field of social psychology argue that interactions not only influence the acquisition of information but also enable individuals to learn about social norms and influence others' attitudes and behaviors (Kohler et al. 2007). Social psychologists argue that attitude formation is largely a process of comparison against similar others; because this process has little effect among strangers, it occurs largely within the boundaries of social communities and networks. Within a social network, the effects of interpersonal processes depend both on the characteristics of the relationships and on where those relationships fit into the structure of the network. Interpersonal processes vary with the kind of larger structural unit (network) within which individual ties are embedded (Erickson 1988).

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[2] See, for example, Feder et al. (1985), Besley and Case (1994), Foster and Rosenzweig (1995), Pomp and Burger (1995), Conley and Udry (2001), Marra et al. (2003), Abadi Ghadim et al. (2005), Munshi (2005), Bandiera and Rasul (2006), Doss (2006), and Yamauchi (2007).

[3] See, for example, Ellison (1993), Ellison and Fudenberg (1993, 1995), Kapur (1995), Bikhchandani et al. (1998), Bala and Goyal (1998), DeMarzo et al. (2003), Choi et al. (2005), and Young (2007). The social learning approach is closely related to the literature on bandwagons, information cascades, and herd behavior (e.g., Banerjee 1992; Banerjee and Fudenberg 2004; Bikhchandani et al. 1998; Ellison and Fudenberg 2001; Gale and Kariv 2003; and Neill 2005), which discusses how, in situations of incomplete information and uncertainty, mimetic behavior and herding may represent rational options.

2.3.4. Social Capital and Collective Action Perspectives

The opinions among scholars on the meaning, content, and economic consequences of social capital are very diverse.[4] One broad division can be traced between scholars who consider social capital an aggregate characteristic of social groups and those who believe it is an individual trait derived from social interactions (Borgatti et al. 1998). Here the emphasis is on studies related to the group-level notion of social capital. Studies centered on the individual perspective—also called social network capital (e.g., Fafchamps and Minten 2002; Mouw 2006; Chantarat and Barrett 2007)—pay more attention to the effects of network structure on behavioral and economic outcomes (cf., Sobel 2002; Granovetter 2005; Jackson 2006); they are discussed further in Section 2.3.5.

Many studies on social capital focus on the influence of trust on various organizational outcomes. A review of this literature by Dirks and Ferrin (2001) found that trust is significantly and positively associated with innovation in empirical works on topics such as the accuracy of information shared with superiors in vertical relations, the openness in intra- and inter-organizational communication, the performance of collaborative tasks, support for leaders, and the perceptions relative to the changes and innovations proposed by leaders.

Works on social capital and collective action by Flora and Flora (1993), Flora et al. (1997), Flora et al. (2004), and Emery and Flora (2006) assess the effects of collective action on change processes. To these authors, investing in more connections among organizations and groups ("bonding" social capital) and in more links to external organizations and technical support agencies ("bridging" social capital) is fundamental to promoting change and innovation in rural areas.

Various scholars have considered social capital as a determinant of the adoption of innovations. For example, Barr (2000) defines social capital in terms of network density and found that entrepreneurs within the manufacturing sector with larger and more diverse sets of contacts have more productive enterprises.[5] In agriculture, Narayan and Pritchett (1999) found greater use of modern agricultural inputs among households from villages with larger social capital indexes. These researchers found that social capital, measured as the quantity and quality of villagers' participation in farmers' organizations, facilitated the diffusion of innovations both directly, in response to more linkages among individuals, and indirectly, by reducing uncertainty about alters' compliance in adoption-related transactions. The latter effect was attributed to improved flows of information, tighter enforcement mechanisms, and the informal insurance role of social capital. Nyangena (2004) found evidence of increasing adoption of conservation practices in response to trust and increased group activity, both variables commonly used as indicators of social capital. Katungi (2006) and Katungi et al. (2006) found that social capital is a key factor in information exchange and that compared with women, men generally have better access to social capital and consequently to information on innovations.

The concepts of social capital and collective action are highly interrelated. Some authors argue that social capital refers to the structure of social relationships and that collective action refers to the flows of those interactions. Social capital (i.e., social cohesion, shared norms and values, and trust among members) facilitates collective action, and collective action helps building additional social capital (Meinzen-Dick et al. 2004). Numerous scholars,[6] under the CGIAR systemwide program on collective action and property rights (CAPRi), have dealt with the adoption of innovations as a form of collective action, which is very often the case for adoption of sustainable agriculture and natural resource management innovative practices. The analytical framework used by members of the CAPRi program differentiates innovations according to the degree of collective action and the degree of tenure security

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[4] See, for example, Coleman (1988), Flora (1998), Woolcock (1998), Falk and Kilpatrick (2000), Fafchamps and Minten (2002), Agnitsh et al. (2006), Fafchamps (2006), and the collaborative volumes edited by Serageldin and Dasgupta (2001) and Atria (2004).

[5] Additional authors in fields other than agriculture include Fountain (2000), Maskell (2000), Nahapiet and Ghoshal (2000), Patton and Kenney (2003), Frank et al. (2004), Ruuskanen (2004), and Upadhyayula and Kumar (2004).

[6] See, for example, Knox et al. (1998), Ravnborg et al. (2000), Swallow (2000), Pender and Scherr (2002), and Dévaux et al. (2007).

required for adoption, as well as according to the spatial and temporal scale required to reap the benefits of adoption (Knox et al. 1998).

Collective action, expressed as joint investment, building or maintenance of infrastructure and equipment, or regulations generated and enforced for the management and exploitation of common resources, or even more commonly as the simple sharing of information, may be an important factor directly limiting the degree of adoption of innovations. More often, however, collective action has an indirect effect on adoption through its interaction with other determining factors. For example, collective action can reinforce the negotiation power of otherwise marginalized groups and improve their access to information; it can even be employed to oppose or modify the characteristics of promoted innovations. The formation of networks and other forms of collective action can facilitate the coordination efforts required for adoption. Collective action—expressed, for example, through reciprocity norms—can also emerge as a risk-sharing and mutual help mechanism to cope with labor shortages as well as with the food insecurity, environmental, and price risks associated with innovations. In addition, collective action can facilitate the adoption of innovations requiring indivisible investments, thus reducing the restrictions on participation of the resource poor. Finally, nontraditional microfinancing institutions have facilitated access to credit to the poor through group loans or by requiring collective action as a form of collateral (Knox et al. 1998).

2.3.5. Social Network Perspectives

In 1981, Rogers and Kincaid asserted that "the essence of the diffusion of an innovation is the human interaction through which one individual communicates a new idea to one or more other individuals. . . . As these interpersonal communication flows become patterned over time, a communication structure emerges and is predictive of behavior" (229). To Rogers (2003), a turning point in diffusion studies came with a series of publications on the "epidemiology" of a new drug among physicians, which made use of sociometric data (Menzel and Katz 1955; Coleman et al. 1957, 1966); they found that the more connected doctors, along with fellow physicians at the center of their friendship networks, were the first to prescribe an innovative medical treatment.

Since those studies, many analyses of social networks have been conducted to describe the process of diffusion of information and innovations in numerous fields, including marketing, organizational studies, industrial development, and medical sociology.[7] In addition, applications of social network analysis to the analysis of other contagion (imitation) processes further inform the study of the diffusion of innovations.[8] However, direct applications of social network analysis to study the diffusion of innovations in agriculture have been more limited.

Understanding of the concept of social network analysis varies widely.[9] In a commonly accepted definition (Marsden and Lin 1982; Wasserman and Faust 1994), social network analysis is characterized as a "perspective" or "approach" that considers interactions among social actors and the regular patterns of those interactions (i.e., social structures), at the core of its inquire endeavors. Network analysis considers all human actors as participating in a social system composed of many actors who serve as

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[7] See, for example, Reingen and Kernan (1986) and Brown and Reingen (1987) for marketing; Tushman (1977), Rice and Aydin (1991), Burns and Wholey (1993), Westphal et al. (1997), Hansen (1999), Ahuja (2000), McGrath and Krackhardt (2003), Reagans and McEvily (2003), Gibbons (2004), Obstfeld (2005) and Zhou and Delios (2006), as well as the reviews by Borgatti and Foster (2003) and Brass et al. (2004), for organizational studies; Harkola and Greve (1995) and Sorenson et al. (2006), for industrial development; and Rogers (1979), Burt (1987), Strang and Tuma (1993), Rosero-Bixby and Casterline (1994), Valente (1995, 2005), Montgomery and Casterline (1996), Kohler (1997), Valente et al. (1997), Valente and Saba (1998), Kincaid (2000), Van den Bulte and Lillien (2001), and Kohler et al. (2007) for medical sociology.

[8] See, for example, Galaskiewicz and Wasserman (1989), Mizruchi (1990), Davis (1991), Galaskiewicz and Burt (1991), Haunschild and Miner (1997), Haunschild and Beckman (1998), Kraatz (1998), Hëdstrom et al. (2000), Still and Strang (2007).

[9] Concepts of social network analysis range from "analytic paradigm" (Leinhardt 1977), "intellectual tool" (Wellman and Berkowitz 1988), "methodological tool" (De Nooy et al. 2005), and "set of methods" (Dagenne and Forsé 1999) for the systematic study of social structure, to simply a "collection of quantifying tools to graph social structures in the economy" (Smith-Doerr 2006).

reference points for each other's decision making. The nature of the relationships in the network impinges on the focal actor's perceptions, beliefs, and actions (Borgatti and Foster 2003), the organization of those relationships reveals the social structure within which the focal actor is embedded, and analyzing that organization allows for detecting emerging social phenomena often unperceived at the individual actor level (Knoke and Kuklinski 1982).

According to Kohler et al. (2007) and Hogset (2005), social networks affect the diffusion of innovations through social learning, joint evaluation, social influence, and collective action processes. Through social learning, people learn about an innovation's existence and characteristics and take advantage of alters' experiences to lower uncertainties related to adoption. Joint evaluation allows network members to reinterpret and moderate risky innovations to make them more realistic and meaningful in the local context. Social influence accounts for the enforcement of social norms and the effects of prevailing opinions and attitudes on individuals' preferences and behavior.[10] Finally, networks act as devices for resolving externalities and coordination problems for collective action.

Most diffusion studies carried out by social network analysts have approached diffusion as a homogenizing communication process by which individual attitudes and behavior are influenced toward agreement by the social microstructure (Wejnert 2002). Network influences on behavior are categorized by Burt et al. (1994) into four broad classes of hypotheses:

- *Inequality hypotheses* explain why some actors obtain more rewards from their participation in a network. Exchange theory posits that interdependent interests and differential positions within a system make certain actors powerful. On the other hand, social network capital or structural holes theory asserts that missing connections in a network create competitive advantages for players positioned as brokers.
- *Embedding hypotheses* explain the occurrence of "unexpected results" (in the sense of economic considerations) in transactions embedded in social networks. Elements of resource dependence, social identity, and transaction costs theories are used to describe the creation and functioning of the institutions and identities required to manage those economically irrational relationships.
- *Contingency hypotheses* describe how similar processes can generate distinct outcomes as a result of an actor's position in the network structure. The actor's position is defined by the direct and indirect relationships the actor maintains with other types of actors in the network.
- *Contagion hypotheses* describe how network structures bring actors together, making the ideas and behaviors of some contagious to others who are either emotionally close (cohesion theories) or taken as referents in the surrounding context (equivalence theories).

Contagion hypotheses have dominated the study of the diffusion of innovations within the social networks perspective. Contagion is described as a phenomenon led by physical or social proximity factors; according to Valente (1995, 11-12), contagion is "the specific process of innovation diffusion" by which individuals monitor others and imitate their behavior to adopt (or not) innovations. It is also called the "diffusion effect" (Rogers 2003) or the "majority rule" effect (Valente 2005).

Contagion occurs through cohesion (direct ties, affective proximity), structural equivalence (comparitors, social proximity), popularity (opinion leaders, centrality), bridges to distant sources (weak ties or information brokers), or spatial proximity. Consequently, social network analysts have generated

[10] Dagenne and Forsé (1999), for example, indicate that in traditional rural communities, communications occur through a tight network of contacts that are affective (kin, friends, and neighbors) or normative (local institutions and hierarchies) in a context that gives preeminence to security, continuity, and tradition. Thus, innovation faces prejudice from the outset.

various models to predict the effects of network structure on attitude agreement among people tied by distinct relationships and occupying different structural locations:[11]

- *Cohesion*: Direct interactions between individuals—especially in cohesive subgroups—accounts for adoption of numerous innovations. Cliques, or densely knit subgroups, contain many of the preferred comparitors of focal actor and generate a sense of belonging in their members that imposes on them more pressure to conform to internally accepted attitudes and behavior. Because of both effects (comparison and conformity pressures), the greater the density (or reachability) within the subgroup, the stronger the influence and the greater the expected similarity among its members. Strong (homophilous) ties, which characterize cohesive relations, are key for the intranetwork diffusion (especially for diffusing tacit knowledge, which is characteristic of complex technological innovations) because of their relevant role in processes of social influence, comparison and learning process.[12] The most common variables predicting adoption are inversely related to network size and directly related to network density. Frequency of interactions among members is also often used.
- *Equivalence*: For authors like Burt (1987), competition among people of similar status (i.e., people with similar reference groups and structural position) is the driving force of contagion. People with ties to the same or similar types of people tend to behave similarly, even if they are not connected to each other. The greater the regular equivalence of two actors, the greater the expected similarity in their behavior (Borgatti and Everett 1992). According to Wejnert (2002), equivalence among individuals is determined by demographic factors (sex, age, race, marital attributes), social factors (education, occupation), and cultural factors (language, tradition, religion, values, norms). Bothner (2003) found that small firms are most affected by innovation decisions of their competitors, especially if they are diversified across market segments.
- *Bridges and brokers*: Weak heterophilous ties are fundamental in the early diffusion of new ideas and behaviors because they provide local bridges to otherwise disconnected parts of the whole network, as well as links to nonredundant external sources of information (Liu and Duff 1972; Granovetter 1973, 1982; Hansen 1999; Levin and Cross 2004). Burt (1992, 2005) revised Granovetter's hypothesis on the "strength of weak ties" and suggested that, rather than relying on the weakness of the tie, the strength relies on the bridging function of the actors. Those actors span the "structural holes" of the network by acting as brokers of information among distinct subgroups. Because of their distinct role in the network, such brokers can also become early adopters. The positional advantages these brokers enjoy constitute their social capital or social network capital.

- *Prestige*: Prominent and well-connected members (those with high centrality in the network—that is, those tied to many others, or to many events in affiliation networks), often called "opinion leaders" (Weiman, 1991) are usually early adopters of innovations that are consistent with group norms (cf. Borgatti and Everett 1997; Faust 1997, Borgatti 2005). Meanwhile, marginalized and disconnected network members are less affected by others' judgments on their attitudes and

[11] See, for example, Burt (1978, 1980, 1982, 1987, 2005); Friedkin (1984, 1998, 1999); Erickson (1988); Michaelson and Contractor (1992); Mizruchi (1993); Marsden and Friedkin (1994); Harkola and Greve (1995); Friedkin and Johanssen (1997); Valente (1996, 2005); Strang and Soule (1998); and Wejnert (2002).

[12] On homophily effects, authors like Brass et al. (2004) and McPherson et al. (2001) indicate that diffusion is boosted among actors with similar social, organizational, and strategic characteristics, because people perceive it is easier and more relevant to learn from those in similar conditions. Nevertheless, homophily can also operate to resist adoption; that is the reason why diffusion requires a certain level of heterophily (and weak links) for information to flow among subgroups (Gatignon and Robertson 1985; Dagenne and Forsé 1999). That is a relevant issue for assessing the role of opinion leaders (Feder and Savastano 2006).

behavior and thus are more likely to adopt innovations that are not consistent with group values and norms (Becker 1970; Rogers 2003). Prestige explanations account for contagion through unreciprocated relations: lower-ranking members might be motivated to adopt because they aspire to resemble powerful leaders; and adoption by central actors can shift locally accepted patterns, dragging the others with them into adoption.

- *Spatial proximity*: Contagion among spatially proximate actors is one of the most common findings in diffusion research. Geographic proximity facilitates various types of interaction and influence processes; aside from sociometric data, physical location data have good predictive power for adoption patterns. These models assume that network members are distributed in a social space in such a way that spatial closeness corresponds to closeness of relationship. The closer two people are, or the more strongly tied they are, the more likely they are to have similar sets of comparitors and thus similar attitudes. For some topics, attitude similarity declines rapidly with spatial distance; for other topics, social comparison includes weaker ties, and thus similarity declines more slowly with distance. Spatial proximity models are very restrictive because they imply no asymmetry and intransitivity or subgroups in network relations. Nyblom et al. (2003) and Udry and Conley (2005) present applications of spatial models to diffusion of agricultural innovations.

Beyond those general models, network effects on attitudes and behavior (adoption) can also be predicted considering various levels of structural analysis, with parameters at the node (individual) level as well as the dyad, triad,[13] subgroup, and network levels (cf., Buskens and Yamaguchi 1999; Monge and Contractor 2003; Contractor et al. 2006).

At the individual level, nodes with higher centrality measures are opinion leaders. They tend to be early adopters of culturally acceptable innovations and generally are opponents of culturally unacceptable ones (Becker 1970).

At the dyad level, attitude and behavior are affected by the following:

- *Frequency of interaction:* The more frequent the interaction, the more chances that both parties will learn to interpret each other's attitudes accurately.
- *Multiplexity of interaction*: The more kinds of positive relationships the members of a dyad share, the more widely they agree.
- *Strength of interaction*: Stronger ties (on a positive relation) lead to stronger agreement between dyad members compared with weakly tied and unconnected nodes. Conversely, a negative tie may prevent social comparison or induce disagreement.
- *Asymmetry of interaction:* In authority-based relations, it may prevent comparison or provoke disagreement; in esteem-based relations, subordinates may take superiors as reference or model (Erickson 1988; Sparrowe and Liden 1997, 2005).

At the triad level, structural balance and transitivity concepts (Wasserman and Faust 1994), based on early cognitive balance concepts (Heider 1946), have been used to predict similarity based on the mere stability of structures (for valued, directed graphs). These forces imply that, in a triad structure, a nonadopter tied to two adopters will end up adopting. Krackhardt (1998, 1999), Krackhardt and Kilduff (2002), and Dekker (2006) indicate that Simmelian-tied dyads (i.e., dyads embedded in three-person cliques) reach higher agreement relative to dyads in general. Extending these arguments, it can be hypothesized that someone tied to two intense adopters, or someone tied to two promoters of an

[13] A dyad is a set of two actors (nodes) and the interactions between them. A triad is a set of three actors (nodes) and the interactions between them.

innovation that are themselves strongly tied to each other, will end up adopting more intensively than predicted from a merely dyadic perspective.

Finally, at the network level, centralized structures (e.g. core–periphery structures characterized by high centralization parameters) are likely to accelerate the pace of diffusion as soon as the diffusing element—information, knowledge, or technological innovations—reaches the core actors in the network, such as opinion leaders (Rogers 2003). Social network analysis at this level provides objective measures and specific predictions on the effects of aggregate network structure, which is applicable to assessing regional differences in adoption diffusion.[14] The effects of location-specific networks can also be tested considering different innovations and activities. Isham (2002) indicates three characteristics of social structures that promote a more rapid diffusion: (1) *group homogeneity*, which is the degree of similarity in certain attributes and beliefs between interacting individuals; (2) *participatory norms*, which describe the degree to which local customs promote communication and interactive decision making; and (3) *leadership heterogeneity*, which is the degree to which leaders within the network differ in certain social and economic attributes or contacts across social subsystems.

2.3.6. Rural Communication and Extension Perspectives

Influence of other farmers. According to Feder and Slade (1985), the dynamics of diffusion processes depend mostly on horizontal communication among farmers. Adoption is strongly influenced by members of the same social group. New ideas are more easily adopted when they come from others who are similar in several respects. Outsiders are not entirely trusted, especially in conservative locations. Farmers then monitor and have a perception of other farmers' experiences and performance, and they learn from discussing their own experiences with friends and neighbors.

However, kin, friends, and neighbors generally have access to the same innovations as the focal farmer. Consequently, farmers often resort to more-vertical communications to gain access to innovations. Opinion leaders, who are also local farmers, are sufficiently heterophilous to be good sources of new information and advice. They usually enjoy considerable influence on the way other locals think and behave (Fliegel and Korsching 2001; Rogers 2003).

Opinion leadership is not a characteristic applicable under all conditions of rural innovation. Some farmers might be opinion leaders in a wider context, and others might have leadership roles restricted to specific issues. Opinion leaders for midsize farms under certain conditions can be useless for smaller operations or under other conditions, and social interaction among those groups can be limited. Separate communication networks might also exist for men and women, thus limiting the flows from opinion leaders from one sex to farmers of the other sex (Van den Ban and Hawkins 1996; Rogers 2003; Feder and Savastano 2006).

Information and advice are not the only aspects that flow through horizontal and vertical communications among farmers. Mayfield and Yapa (1974), for example, describe the existence of horizontal and vertical communication ties in rural India, indicating that the vertical flow was characteristic for the direction of influence and authority; this type of interaction was tempered by the social interaction induced by obligatory intercaste reciprocity and attendance at village gatherings, which produced a more homogeneous mix of information flow.

Information and influence are also communicated among farmers within organizational settings. Jagger and Pender (2003), for example, analyzed farmers' participation in different types of organizations as a determinant of the adoption of different kinds of innovations. The effects were generally positive but contingent on the type of organization and innovation considered.

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[14] Differences in adoption behavior among regions are seldom tested in econometric studies because the differences include not only agro-ecological variations but also differences in factors not related to agricultural potential, such as infrastructure, access to markets for inputs and outputs, and institutional and sociocultural factors (Doss 2006). Location effects are generally modeled as dummy variables, without specific hypotheses on their likely effects and lacking objective measures to account for such effects.

Influence of external change agents. Frambach (1993) asserts that despite recognizing the relevance of supply-side factors in explaining the adoption of innovations, diffusion theory and research have too often taken an adopter-side perspective, ignoring the influence of the supplier on diffusion. Even scholars specifically interested in social interactions as drivers of diffusion have generally omitted innovation suppliers (change agents) in their models, as if the only relevant interactions were those existing among farmers. Such omissions and simplifications can lead to misleading interpretations.[15]

This observation suggests the need for assessing the role played by all types of actors interacting in innovation diffusion processes, particularly change agents active at the local level. This is reminiscent of the central arguments posited by innovation system scholars who highlight the active role played by public and private providers of information and technical advice, input sellers, product buyers, and other external agents in the network of interactions within those systems. Those "external" actors are in frequent contact with each other and with "local" actors of the system, thus impinging on farmers' attitudes and behavior.

Rogers defines a change agent as "an individual who influences clients' innovation decision in a direction deemed desirable by a change agency" (2003, 473). According to this definition, change agents are external actors of an organizational origin. The classic diffusion literature in agriculture uses the term *change agent* as almost synonymous with *extension agent*. Nonetheless, *change agent* can be applied to the wider variety of actors approaching farmers to promote adoption of specific innovations (e.g., input sellers) and those providing farmers with or giving them access to information and inputs that are fundamental determinants of adoption (e.g., credit providers or product buyers who inform farmers on market requirements).

Farmers' interactions with change agents can be described as unbalanced: almost vertical in terms of the status and information endowments of the concurrent actors and almost unidirectional given its explicitly persuasive nature. The vertical and persuasive nature of this interaction is in part responsible for the impersonal treatment that has characterized the analysis of change agents' influence in diffusion processes.[16] Most early studies conducted by rural sociologists treated farmers' contacts with extension agents as equivalent to their contacts with the mass media, considering both indifferently as the effect of "external information sources." Only a few researchers characterized this relationship as falling between interpersonal communication and access to the mass media.[17] Subsequently, most diffusion studies in agriculture, both by sociologists[18] and economists,[19] have regularly included farmers' interactions with

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[15] An example of the consequences of omitting the supply side is provided by Van den Bulte and Lillien (2001) who reanalyzed the classical study of diffusion of a medical drug among physicians by Coleman et al. (1966), showing that most of the effects originally attributed to social interactions became insignificant once the marketing efforts of innovation suppliers were taken into account. In fact, marketing variables accounted for most of the observed adoption patterns.

[16] Vertical interactions have been addressed with an explicit consideration of the characteristics of the interacting actors in organizational studies by the leader–member exchange perspective and other related approaches (Liden and Graen 1980; Newell and Swan 1995; Sparrowe and Liden 1997, 2005), which consider the downward movement of information in organizations and its positive effects on innovation processes, as well as intra-organizational leader–subordinate dyads and the determinant effects of those vertical interactions on subordinates' performance (influence, career evolution, innovation involvement). However, those perspectives are only partially useful in understanding the change agent–farmer relationship because they apply to intra-organizational settings where members are subject to formal hierarchical ties. In those situations, especially if the organization is centralized and highly stratified, leaders can resort to coercive pressure (via explicit or implicit rewards or negative contingencies) to achieve conformity of practices, homogeneity of behavior, and increased adoption rates. In contrast, change agent–farmer interactions take place in a wider context, where farmers are not obliged to participate but rather are persuaded or induced to do so.

[17] Among those researchers, Menzel (1971) called the contact with change agents "quasi-mass communication," while Lin and Burt (1975) called it "local media communication."

[18] See, for example, Coleman (1951), Fliegel (1956), Wilkening (1956), Rogers and Beal (1958), Copp et al. (1958). Lindstrom (1958), Coughenour (1960), Photiadis (1962), Polgar et al. (1963), Kivlin and Fliegel (1967), Lin and Burt (1975), Opare (1977), Hooks et al. (1983), Thomas et al. (1990), Saltiel et al. (1994), Fliegel and Korsching (2001), Glendinning et al. (2001), Lasley et al. (2001), and Mitchell (2006).

[19] See, for example, Huffman (1978); Lockheed et al. (1980); Feder and Slade (1984, 1986a, 1986b); Feder et al. (1987); Harper et al. (1990); Longo (1990); Birkhaeuser et al. (1991); Strauss et al. (1991); Hussain et al. (1994); Wadsworth (1995);

extension agents among the set of explanatory variables for adoption but have considered only the existence or frequency of such interactions. In most cases, those studies have found that it is a significant factor positively affecting adoption timing and intensity.

However, interpersonal communication and influence processes are at play here as in every other human interaction. Rogers' theoretical contribution in this area (2003) was exceptional, because he discussed how a series of individual traits of change agents were likely to affect their effectiveness and performance.[20] More recently, Moser and Barrett (2006) gathered empirical evidence of how social conformity pressures (i.e., the nonpecuniary incentives for farmers to conform their behavior to that of their neighbors or to the wishes of people in positions of influence and power) included the personal influence of extension agents and played a significant role in the adoption decisions and use patterns of innovations among Malagasy rice farmers.

Another factor that has limited a more detailed assessment of the specific effects of change agent–farmer interactions on diffusion is one of the basic generalizations derived from early diffusion studies, according to which external sources are basically relevant to spreading information about innovations at the earlier stages of diffusion. According to this argument, those interactions would be relevant mostly for persuading the minority of pioneers and early adopters, playing just a secondary role in the decisions of most farmers who rely on earlier adopters as sources of influence (Valente 1996; Rogers 2003; Smith-Doerr and Powell 2005).[21] However, this may be an oversimplified picture of the complex network of influences that various actors exert along the adoption–decision process. Table 1 shows how extension theory and practice have over time added more details to the picture. Regretfully, these insights have not been adequately considered in empirical adoption studies.

Table 1. Farmers' main sources of information in every phase of the adoption process

PHASE	1. Awareness	2. Interest	3. Evaluation	4. Trial	5. Adoption
CHARACTERISTICS	Farmer learns about innovation	Farmer becomes interested and gathers details	Farmer mentally examines whether innovation suited for use	Small-scale trial to minimize risk	Large-scale use, ongoing practice
MAIN INFORMATION SOURCES	1. Mass media 2. Government agencies 3. Salespeople 4. Other farmers	1. Mass media 2. Government agencies 3. Salespeople 4. Other farmers	1. Government agencies 2. Salespeople 3. Trusted farmers 4. Friends and neighbors	a. Salespeople b. How-to publications c. Friends and neighbors	1. Personal experience 2. Friends and neighbors

Source: Carey 1999

Current et al. (1995); Saín and Barreto (1996); Ramírez and Schultz (2000); Evenson (2001); Knight et al. (2003) ; Owens et al. (2003); Ransom et al. (2003); Marsh et al. (2000, 2004); Feder et al. (2004); Mercer (2004); Abdoulaye and Sanders (2005); Abdulai and Huffman (2005); Oladele (2005); Bravo-Ureta et al. (2006); and Dinar et al. (2007).

[20] Rogers (2003) states that change agents' success in securing adoption is positively related to (1) the outreach efforts of the agent; (2) their "client orientation" (as opposed to an "agency orientation"); (3) program compatibility with clients' needs; (4) their empathy with clients; (5) their degree of homophily with clients (the higher the social status, social participation, formal education and cosmopolitanism of the client, the better their interaction); (6) their credibility in the clients' eyes; (7) their utilization of opinion leaders; and (8) the development of clients' skills to evaluate innovations.

[21] This perception shaped the training-and-visit (T&V) system of extension promoted by the World Bank for the diffusion of Green Revolution technologies in the mid-1970s. The T&V system focused extension efforts (and incentive mechanisms) on innovators and early adopters (Röling et al. 1976). The rationale for the strategy came from the two-step model of communications (Katz and Lazarsfeld 1955, Katz 1957), according to which these "influentials" (Weimann 1994) or "innovation champions" (Howell and Higgins 1990), characterized as more educated and cosmopolitan, less risk averse, and more open than their peers to external information, could be more easily induced to adopt and would act as models to the other farmers. Once a certain threshold of adopters had been surpassed, the accumulated mass of contagious sources would suffice for the ulterior contagion via peer-to-peer communication, requiring no additional support.

Table 1 can be improved in at least two ways. First, change agents in the table are only represented by salespeople and government agencies. However, the diversity of change agents has become much larger in the last two decades in developing countries, with technical agents from NGOs and projects financed by a large diversity of agencies becoming central actors in substituting for a shrinking public sector.

Second, the table considers only the role of actors as sources of information. According to Van den Ban and Hawkins (1996), when restricted to informational and advisory services, extension agents have limited power to influence farmers, because that influence depends on farmers' willingness to trust the extension agents' intentions and on the agents' ability to help farmers achieve goals. However, when agents are also responsible for the distribution of incentives to adopt, they enjoy much more power and opportunities to persuade farmers to change in the promoted direction. In fact, the promotion of innovations among poor farmers in developing countries by extension agents is usually accompanied by a diversity of persuasive mechanisms and incentives that reduce risk and palliate farmers' limited investment and absorptive capabilities for adoption (e.g., subsidized or free provision of key inputs, infrastructure, and technical advice; and marketing support to ensure household earnings while "incubating" entrepreneurship). Deployment of such mechanisms has the effect of yielding steeper S-shaped diffusion curves that reach adoption ceilings in much shorter periods.[22] These inducing measures are applied even more intensively by NGOs and development projects, which are often urged to meet quantitative goals and show results in the limited time span allowed by sponsors and authorities. As a result, change agents are likely to have more influence on adoption timing and rates and to remain influential along the adoption process than is generally acknowledged in the literature.

The persuasive nature of extension practice paved the way for the creative design of multiple schemes and strategies for inducing adoption that are now found in developing settings. Many early extension programs were based on the common assumption that changes in knowledge (i.e., providing information) would be followed first by changes in attitude and then by changes in behavior. However, as relationships between those variables proved neither lineal nor evident, more parallel incentive mechanisms were introduced in extension practice (Leeuwis and Van den Ban 2004). In this context, Röling considered extension as "interventology"—that is, as "an instrument of premeditated, deliberative intervention to achieve the interventors' goals . . . only effective by inducing voluntary change and hence by satisfying client goals" (1988, 39).

Van den Ban and Hawkins (1996) provide a good summary of the diverse methods that extension agents resort to for influencing farmers' behavior. They include (1) compulsion or coercion (agents apply sanctions to enforce recommended practices, as in the case of dairy inspectors); (2) exchange (e.g., extension agents organizing farmers to obtain fairer trade negotiations with external merchants and then supervising farmers to comply with those agreements); (3) advice (trusted expertise gives extension agents the say on which solution to choose for a certain problem); (4) training to influence farmers' knowledge levels and attitudes (to increase the confidence, capacities, and commitment of capable and cooperative farmers); (5) manipulation (influencing farmers' knowledge and attitudes without farmers' awareness); (6) providing means (such as soft credits for purchasing land or inputs) with positive distributional effects (generally used as a temporary measure to stimulate initial adoption up to a threshold); (7) providing a service as temporary relief in performing a time-consuming task (e.g., completing forms or registering information; if sustained, this could generate dependence or create a need for a service market); (8) changing farmers' social or economic structure (by prioritizing participation of the worse-off in the services or by forming self-help groups; usually opposed by those individuals or groups losing power or income as a result of the introduced changes).

Besides extension agents, local authorities and formal leaders can also play the role of change agents: they exercise power by virtue of their positions and can have considerable political and social

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[22] Many authors question the sustainability of those innovations: once external funds and incentive mechanisms are dropped, abandonment rates are usually very high (cf., Current et al. 1995; Fischer and Vasseur 2002; Alavalapati et al. 2004).

influence given the command they exert over local resources and the prestige and prominent position they occupy in the local network. They may also wield considerable power over collective decisions and can play a legitimizing role over the activities of other external change agents.

For technological innovations, such as agrochemicals or crop varieties, the role of the private sector (product developers, input sellers, product buyers) has grown extensively in developing countries through marketing strategies such as providing free samples, partial financing, technical support, a secured market, and additional services used when implementing initial trials as well as during the period of increasing replacement of previous technologies. Using the strategies has given these actors an increasing role in determining the decisions of farmers to innovate (Berdegué and Escobar 2002; Berdegué 2005).

3. METHODOLOGY

This study combined elements of econometrics and social network analysis to assess diffusion processes of agricultural innovation in various regions and agricultural sectors in Bolivia.

3.1. Research Question and Hypotheses Tested

The main research question of this study was how interactions between farmers and other change agents and actors in the farmers' communication networks influence their behavior toward the adoption of agricultural innovations. A set of variables describing the likely effects of interactions on the adoption of innovations by farmers were tested with regard to both the influence of the aggregate structure of interactions in every study region and the specific interaction between individual farmers and the main promoter of innovations. Those descriptors of social interaction showing a more significant association with adoption behavior were further combined in simple econometric models to test their combined effects and the robustness of those results.

Combining the insights and predictions postulated by the various perspectives reviewed in Section 2 led to the derivation of the set of hypotheses shown in Table 2 on the expected outcomes of the key analyzed interactions.

3.2. Operationalization of Adoption

Many innovation studies use dichotomous variables to account for adoption (Doss 2006). That approach is valid for indivisible technologies and management practices that cannot be partially implemented. However, to assess the adoption of innovations that can be partially implemented, such as new inputs or cultural practices, continuous measures are preferable. That is especially true for externally induced innovations, because most farmers end up adopting, at least in small proportions, while incentives last. Moreover, continuous dependent variables are also preferable when conducting cross-sectional studies in developing countries, because the actual (observable) intensity of innovation use is a more reliable figure than farmers' recall on the time of initial adoption. Nonetheless the utilization of a continuous dependent variable carries the problem of identifying the appropriate time for measuring adoption intensity when employing cross-sectional survey data.

Table 2. Set of hypotheses tested

Level of Analysis	Hypothesis	Operationalization
Microregional (network)	1. A region with more social interaction has a more intense average adoption.	The average degree of adoption is greater: a. the greater the network density; and b. the shorter the average distance to market.
	2. A region where interaction is more concentrated around a few central actors has a more intense average adoption.	The greater the network centralization, the greater the average degree of adoption.
	3. A region where the promoter of innovation is better reputed has a more intense average adoption rate.	The greater the degree centrality of the promoter in the network of interactions among change agents in a region, the greater the average degree of adoption.

Table 2. Continued

Level of Analysis	Hypothesis	Operationalization
Individual	4. A farmer with more frequent participation in more organizations adopts more intensively.	Adoption is more intense: a. the greater the number of organizations the farmer is affiliated with; and b. the more frequently the farmer participates in organizational meetings.
	5. A farmer with more intense interactions adopts more intensively.	Adoption is more intense: a. the greater the frequency of conversations on technological issues between the farmer and other actors; b. the greater the frequency of conversations on market issues between the farmer and other actors; and c. the more alters a farmer has a frequent or very frequent interaction with (i.e., the greater the farmer's degree centrality in a network that considers only frequent and very frequent interactions to define the existence of ties).
	6. A farmer exposed to more and better-quality persuasion adopts more intensively.	Adoption is more intense: a. the greater the frequency of interaction between the farmer and the main promoter of innovation; b. the greater the frequency of interaction between the farmer and other technical agents; c. the greater the frequency of interaction between the farmer and market agents (input sellers, product buyers, and transporters); d. the lower the frequency of interaction between the farmer and other farmers; e. the greater the frequency of interaction between the farmer and other agents who interact frequently with the main promoter of innovation; f. the higher the farmer's trust on externally-provided technical information; and g. the higher the farmer's trust on externally provided market information.
Mixed	7. A farmer with stronger ties to local peers behaves like the local average adopter	The higher the frequency of interactions between the farmer and other farmers, the closer to the network average is the farmer's adoption rate.
	8. A farmer's adoption behavior is determined by that of local comparitors (referents).	The higher the structural equivalence between two farmers, the more similar their adoption intensity rates.

Another argument for using a continuous variable to depict adoption behavior is that adoption is a dynamic process through which individual farmers pass from becoming familiar with an innovation, to forming an attitude about it, to making a decision on its possible adoption or rejection, to implementing the innovation on a trial basis, and finally confirming or discontinuing the decision (Rogers 2003). Even after adoption has been confirmed, the degree or intensity of adoption (e.g., the share of the total operation using the adopted innovation) is highly variable from season to season.[23] On the other hand,

[23] Among other factors, innovations can be gradually adopted or abandoned as (1) the factors that determined their initial

cross-sectional studies are static by definition, being unsuited for studying before and after situations,[24] learning effects, or the welfare impacts and distributional outcomes of adoption (Feder and Umali 1993).

According to Cameron (1999), cross-sectional data captured early in the diffusion process—when the innovation has not diffused widely and thus social learning is ongoing—yield estimates that are not seriously biased by the omission of a learning component. Results from Feder and Umali (1993) and Dong and Saha (1998), who found that many of the key constraints of early adoption (such as farm size, tenure, education, extension, and credit) lose significance as diffusion proceeds,[25] and from Feder and Slade (1984), who found that over time most farmers adopt and their levels of use converge to a ceiling, also suggest focusing on early adoption and its determinants, when policy initiatives to encourage adoption may be effective.

Thus, for externally induced diffusion processes, adoption studies relying on cross-sectional data are likely to perform better when capturing data on adoption intensities a few years after efforts for promoting those innovations were initiated.

In the cases analyzed for this study, the innovations consisted of sets[26] of five to eight individual components (including, in the case of peanut production, the introduction of improved varieties, plant protection measures, introduction of enhanced agronomic procedures, and support in marketing) that had been promoted during the preceding two to three years. The actual composition of the sets varied according to subsector and region.[27] Given the preceding observations, the main dependent variable used was adoption intensity of those innovation sets at the end of the third year following initiation of the project interventions that promoted their use. An estimate of adoption intensity was calculated for every farmer according to the following procedure: The intensity of utilization of each component was estimated by the surveyor, relative to the expected condition under complete adoption (e.g., the percentage of total area planted to quinoa using the recommended practice, or the percentage of total peanut harvest processed with the recommended procedure). Once individually estimated for every component (on a percentage basis), a single average of adoption intensities was calculated for each farmer across all the locally promoted components.

With this type of data, the focus of the study was not to analyze processes of innovation over time but to find out, in various adoption scenarios, what factors influence farmers' decisions to adopt innovations, particularly in terms of the interactions and communications they maintain in their surrounding social networks.

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adoption differ from those that affect intensity of use; (2) they are further adapted and redesigned by adopters to respond to local conditions; (3) their initial outcomes persist or even improve as farmers learn by doing, exchange additional information and experiences with their peers and advisors, and sequentially adopt additional components of a larger package; and (4) their performance is compared with competing alternatives and its potential is affected by emerging complementary innovations (Feder 1982; Byerlee and de Polanco 1986; Leathers and Smale 1991; Smale et al. 1994; Gebremedhin and Swinton 2003).

[24] Retrospective data can be collected from farmers, but recall and selection biases can be present (Deseran and Black 1981; Bernard et al. 1984; Freeman et al. 1987; Doss 2006)

[25] According to Feder and Umali (1993), in time, it is the location-specific agroclimatic and environmental variables that become the main determinants of differences in adoption rates.

[26] This paper uses the term *set* instead of *package* because the latter is normally associated in Latin America with a linear model of communication that conceptualizes innovations as ready-to-use products designed by the experts and transferred by extension agents to passive farmers whose only role is to accept or reject the offer. *Package* also implies a sense of unity, so that complete acceptance of the whole group of recommendations is preferable over sequential adoption because of the expected synergies among components. In the present case, the analyzed sets included both related and independent components.

[27] A companion study (Hartwich and Monge, forthcoming) undertakes the analysis of adoption of those specific innovations individually, per crop. The present study was interested in testing whether the effects of social interactions on adoption could be detected at a broader level of analysis (i.e., across technologies or crops).

3.3. Data Collection

The innovations analyzed in this study were sets of technological recommendations promoted among small-scale producers involved in either fish culture (in the region of the humid tropics), cultivation of peanuts (in the region of the valleys), or quinoa production (in the altiplano region). Thus, the cases studied present a sample across very distinct subsectors and regions. In each of these three subsectors, four microregions were selected where different sets of technological recommendations were transferred by different technical assistance agencies. In each microregion, diffusion of the focal innovations had been in place during the preceding two and a half to three years.

Data were collected in the field from September to December 2005 by three teams, each consisting of two students and one supervising researcher. A total of 360 farmers were interviewed (120 from each of the three economic activities) using a stratified sampling procedure. In each of the 12 microregions, 25 producers were randomly selected among all adopters, and 5 more were randomly selected from the nonadopters stratum. In most microregions, the 25 producers constituted more than 50 percent of the whole population, and in few cases, they constituted 100 percent of the population. It is worth noting that this type of sampling procedure is not optimal for a more in-depth analysis of social interactions. An extensive literature discusses the inconveniences of normal sampling methods for studying networks given the boundary specification problem and, even worse, because the actual picture of the structure of interactions that can be obtained from the opinions of a few respondents can be incomplete and misleading (Marsden 2005).

Farmers were interviewed regarding three aspects of their interactions (i.e., their communication with other actors regarding technological issues):

- Frequency (valued according to a Likert scale ranging from 5 = very high to 1 = very low)
- Usefulness (valued according to a Likert scale ranging from 5 = very useful to 1 = not useful)
- Effectiveness (at generating practical and timely solutions to field problems, measured as a binary variable with 1 = yes and 0 = no)

Data were gathered using a questionnaire that guided farmers to identify the specific names of the most relevant promoters of innovation they interact with frequently. The promoters were classified according to a taxonomy of “types of actors” applicable across microregions, which included the following categories: NGOs or projects, research institutions, public extension agencies, input sellers, product buyers, transporters, relatives, neighbors, farmers’ organizations, and local governments. To complete the set of independent variables, data were also collected regarding farmers’ sociodemographic attributes, their perceptions on the utility of adopting the promoted innovations, and their resource endowments.

Based on the data gathered from farmers, a list of key change agents was developed for each microregion, and arrangements were made to interview a representative of each change agent using a similar questionnaire to obtain relational data on farmers’ interactions with other change agents. Again, the same types of relations—that is, communications on technological innovation issues—were assessed using the same three indicators (frequency, usefulness, and effectiveness). This allowed for approximating the network of interactions in both directions (from farmers to change agents and from change agents to farmers) in each region.

3.4. Definition and Estimation of Relational Variables

The relational data obtained were based on perceptions of small farmers and change agents on their interactions regarding technological issues with other farmers and specific change agents operating in their microregion. Those data were aggregated into affiliation or bimodal networks, where farmers (actors) were qualified with regard to their affiliation to other farmers and change agents they interact with (events). Bimodal networks can be written in matrix form and allow the application of a wide range of social network analysis tools that provide estimators of relational variables required for testing the proposed hypotheses. The set of variables used is described in Table 3.

Table 3. Variables used

Variables	Description	Type
Dependent		
Intensity	Average degree of adoption across the diverse components of the set of innovations promoted in every microregion (in percentage terms)	Continuous (%)
Intensity_Reg	Average of all intensities reported in every microregion	Continuous (%)
Independent		
Relational		
Density	Network density in every microregion	Continuous (index)
Centralization	Degree of network centralization in every microregion	Continuous (index)
Prestige	In-degree centrality of the main promoter of innovation within the network of interactions among change agents in every microregion	Continuous (index)
Centrality	Degree centrality of every farmer in the farmer–agent affiliation networks	Continuous (index)
Promoter	Frequency of farmer's interaction with the main promoter of innovations in every microregion	Ordinal
Other_Tech	Frequency of farmer's interaction with other technical change agents (researchers, extension agents from the government, NGOs, projects)	Ordinal
Other_Mkt	Frequency of farmer's interaction with other market change agents (input sellers, product buyers, transporters)	Ordinal
Other_Farm	Frequency of farmer's interaction with other farmers (neighbors, relatives)	Ordinal
Simmel	Degree of cohesion of farmer's ties to other change agents strongly tied to the main promoter of innovations	Continuous (index)
Struct_Equiv	Degree of structural equivalence between pairs of actors	Dummy
Membership	Number of organizations farmer affiliated with	Continuous
Meetings	Frequency of farmer's participation in organizational meetings	Ordinal
Conversa_Tech	Frequency of farmer's conversation with other actors on technological issues	Ordinal
Conversa_Mkt	Frequency of farmer's conversation with other actors on market issues	Ordinal
Trust_Tech	Degree of farmer's confidence in externally provided technical information	Ordinal
Trust_Mkt	Degree of farmer's confidence in externally provided market information	Ordinal
Other		
Distance	Farmer's distance to the main market for his or her product	Continuous (km)
Distan_Reg	Average distance to markets in every microregion	Continuous (km)
Consumption	Output share destined for household consumption	Continuous (%)
Education	Education level of household head	Ordinal
Age	Age of household head	Continuous
Farm_Size	Size of farm	Continuous (ha)
Experiment	Farmer's self-declared propensity to experiment	Ordinal
Output	Expected output increases as a result of adoption	Ordinal

The following paragraphs provide brief descriptions of the methods used to compute the most important of the variables listed in Table 3. Intensity was already described in Section 3.2.

Density is a simple cohesion measure that, on the individual node or network level, indicates the proportion between actual ties and possible ties. Calculating network density required using the data on the frequency of interaction between individual farmers (as actors) and other farmers and change agents (as events) and following common procedures of processing affiliation networks with UCINET (Borgatti et al. 2002). First, based on the bimodal networks, the sociomatrix of the bipartite graph was generated for each microregion. Then the data was dichotomized by setting the cutoff point greater than 3, thus considering as present only the ties characterized by a frequent or very frequent interaction. Density estimates were obtained after those transformations.

Centralization is an indicator of how much a network presents a core-periphery structure. It is regularly computed with Freeman's formula, $\sum [c_* - c_i] / \max \sum [c_* - c_i]$, which implies adding the differences in centrality between the most central actor, c_*, and all other actors, c_i, normalized by the maximum centralization possible over all connected graphs, $\max \sum [c_* - c_i]$, which is regularly the star graph. In this study, it was calculated using Everett and Borgatti's recommendations for extending regular centralization to affiliation networks (2005). First, Centrality was computed; this variable is the degree centrality of every farmer in the affiliation network, which corresponds to a count of ties between actors and events normalized by the maximum number of events each farmer could have been affiliated with. It was also necessary to compute the degree centrality of every event, which was the count of ties between events and actors normalized by the maximum number of actors every event could have hosted. With those data, it was possible to identify c_*, the actor with the highest degree centrality (either an actor or an event), to use in estimating centralization. Finally a particular normalization term was computed based on the formula $(n_o n_i - n_i - n_o + 1)(n_i + n_o) / (n_i n_o)$, where n_o is the size of the node set that contains the actor with the highest centrality score (this value could be either n or m), and n_i is the size of any other node. It represents the maximum degree centrality possible in affiliation networks.

Prestige is an in-degree centrality index representing the number of times the main promoter of the set of innovations in every microregion was nominated by other change agents as the object of frequent or very frequent interactions, normalized by the maximum possible number of nominations. This measure was taken from the square matrix of interactions among the distinct change agents present in every microregion.

For Promoter, farmers determined their frequency of interaction with the specific organization acting as the main promoter of the set of innovations in every microregion, based on a Likert scale with the following options: 5 = very frequent, 4 = frequent, 3 = intermediate, 2 = infrequent, and 1 = very infrequent. In the case of Other_Tech, Other_Mkt, and Other_Farm, their values were determined by taking averages across the values assigned by each farmer, based on the same Likert scale, to the various change agents and actors belonging to each of the following categories (i.e., all research and extension agencies plus NGOs and projects but excepting the promoter for Other_Tech; input sellers, product buyers, and transporters for Other_Mkt; and neighbors, relatives, and farmers' organizations for Other_Farm).

To compute Simmel—an index of Simmelian or embedded ties—first, out of the original bimodal network in every microregion, a new affiliation network was generated by simply deleting the column corresponding to Promoter. The new matrix thus generated was then multiplied by another one consisting of a single column that contained the values of the frequency of interaction of all other change agents with the main promoter. This procedure generated a single column of indices of the embeddedness of farmers' ties to other change agents (excluding Promoter) as affected precisely by those agents' interactions with Promoter. Simmel does not deal with triads but rather with Simmelian or cohesive dyads, as described by Krackhardt and Kilduff (2002) and Reagans and McEvily (2003).

Estimating Struct_Equiv, or the degree of structural equivalence between each pair of nodes, required the following procedure: First, the bimodal network of each microregion was dichotomized, leaving as present only the ties indicating a frequent or very frequent interaction. Then the bimodal networks thus obtained were transformed into one-mode affiliation matrices—that is, matrices that show the number of events that every pair of farmers coincides with. Put another way, cells in these matrices indicate the number of social influence agents to which both farmers in a dyad are structurally equivalent—that is are coincidentally tied by frequent or very frequent interactions. Finally, the degree of similarity among every pair of actors was calculated using the Jaccard coefficient.[28]

Meetings, Conversa_Tech, and Conversa_Mkt were assigned values directly by farmers based on a Likert scale containing the following options: 5 = at least once a week, 4 = every other week, 3 = once a month, 2 = every other month, and 1 = practically never. Finally, the variables Education, Experimentation, and Output were also directly evaluated by farmers, based on the Likert scales with the following ranges: from 5 = very advanced to 1 = very basic for Education; from 5 = likes it a lot to 1 = completely dislikes it for Experimentation; and : from 5 = very high to 1 = insignificant for Output.

It is important to clarify that, strictly speaking, this study did not analyze how social networks determine farmers' adoption processes. It did not reconstruct the complete specific reference group surrounding each interviewed farmer and therefore could not discriminate between learning and mimicking processes. Instead, social network analysis tools were used to process relational data and generate a diversity of structural attributes that can be easily incorporated into econometric models as determinants of adoption at the individual level, arguably as descriptors of individual social capital.

3.5. Data Processing and Analysis

Basic input into the data analysis comprised the perceptions of individual farmers on their interactions with a diversity of change agents in a microregion, aggregated into affiliation matrices. Moving from a site-specific level of analysis to a more aggregate level, as a means of comparing interactions among subsectors or even obtaining a general picture across all subsectors, required fitting raw relational data to the fixed number of categories of change agents specified earlier (our taxonomy of 10 types of change agents).[29] Diverse graphs were generated as a result, which allowed visualizing diverse structural features of those interactions.

All graphs shown in the results section were generated using the NetDraw software included as part of the Ucinet for Windows software (Borgatti et al. 2002). NetDraw generates network graphics on the basis of a spring-embedding algorithm that allows a better visualization of the relative distances and positions of actors and events in the network. NetDraw locates nodes in a two-dimensional space according to the criteria of (1) observability (avoiding overlap), (2) the number of ties reported by each actor (actors with higher degree centrality are closer to the center of the network), and (3) maintaining the same length for all ties. In addition, in bimodal networks, the more events in which two nodes coincide, the closer those nodes are located to each other.

Social network analysis tools in the Ucinet software were used to undertake the diverse procedures required to compute the various relational variables described in Section 3.4. The diverse variables found as key determinants of adoption at the regional level were then combined in regression analysis using standard OLS procedures. The results from the OLS estimation as well as bivariate correlation analysis (Pearson's coefficient and Kendall's tau-b [τ]) were then tested with Ucinet software, which is instrumental for running diverse statistical testing procedures by simulation (randomization), running permutation-based significance tests, and using quadratic assignment procedures (QAP) (Baker and Hubert 1981; Krackhardt 1987, 1988; Snijders and Borgatti 1999; Hanneman and Riddle 2005).

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[28] In low-density networks, the "matches," "correlation," and "distance" measures of similarity are inconvenient because they show low variation among actors. The Jaccard coefficient is a good option because it calculates the number of times that both actors in a dyad report a tie to the same event as a percentage of the total number of ties reported, thus ignoring cases where none is tied to that event (Hanneman and Riddle 2005).

[29] Despite generating composed data (e.g., averaging ordinal data and aggregating data into "average" nonexisting relations), this procedure was deemed very helpful for generating aggregate-level graphs that permitted to visualize the general trends found.

The rationale for the application of permutation testing procedures is as follows: Because relational data are, by definition, not independent, their statistical analyses should not be undertaken using standard statistical procedures. The standard formulas for computing standard errors and inferential tests on attributes in correlations and regressions generally assume independent observations. Applying them when the observations are not independent can be misleading. In general, the standard inferential formulas for computing sampling variability (i.e., standard errors) give unrealistically small values for network data. Using a standard inferential formula results in the worst kind of inferential error—the false positive, which means rejecting the null when one should not. To avoid these problems, permutation approaches can be used to calculate sampling distributions of statistics directly from the observed networks by using random assignment across hundreds or thousands of trials under the assumption that the null hypothesis is true.

Finally, a set of regression analyses using a Tobit model were applied to understand multivariate effects on the individual level of adoption of innovation. Various models were run, including or excluding certain explanatory variables testing their combined effect and the robustness of the results. Tobit models are censored normal regression models perfectly fit to the type of dependent variable used in the present study (ranging from zero to 100 percent and censored to the left as the sample population consists of both adopters and nonadopters) and have been frequently used in studies of adoption of agricultural innovations (cf., Adesina and Baidu-Forson 1995; Pender and Kerr 1998; Feder and Savastano 2006; Moser and Barrett 2006).

The innovation adoption decision by farmers is assumed to be motivated by utility maximization considerations and taken on the basis of their individual capacities and endowments with resources; the socioeconomic and agro-ecological framework conditions; and the way farmers are embedded in the social reference network for the innovation, determining access to knowledge and learning. If the perceived utility of adopting is larger than a certain threshold (e.g., if it is larger than the utility perceived based on the traditional technology), the innovation is expected to be adopted while a second decision, regarding the intensity of adoption, takes place (Akinola and Young 1985).

The nonobservable underlying utility function that ranks the preference of the *i*th farmer is given by $U\,(C_i, S_i, N_{ij})$, where C_i is a vector of individual capacities and characteristics determining smallholder attitudes toward innovation, S_i is a vector describing common socioeconomic and agro-ecological characteristics, and N_{ij} is a vector describing farmers' embeddedness in (and connection to) social networks. Although the utility function is unobserved, the relation between the utility derivable from a *k*th technology is postulated to be a function of those vectors and a disturbance term having a zero mean:

$$U_{ik} = \alpha_k F_i(C_i, S_i, N_{ij}) + u_{ik}, \; i = 1, \ldots n; \; k = 1,2 \tag{1}$$

where $k = 1$ for the proposed innovation package, and $k = 2$ for the old technology. Equation (1) does not require the function F_j to be linear. Because the utilities U_{ik} are random, the *i*th farmer will select the alternative $k = 1$ if $U_{1i} > U_{2i}$ or if the nonobservable (latent) random variable $y^* = U_{1i} - U_{2i} > 0$. The probability that Y_i equals one (i.e., that the farmer adopts any of the components of the proposed packages) is a function of the independent variables:

$$\begin{aligned} P_i &= Pr(Y_i = 1) = Pr(U_{1i} > U_{2i}) \\ &= Pr[\alpha_1 F_i\,(C_i, S_i, N_{ij}) + e_{1i} > \alpha_2 F_i(C_i, S_i, N_{ij}) + e_{2i}] \\ &= Pr[(e_{1i} - e_{2i}) > F_i\,(C_i, S_i, N_{ij})\,(\alpha_2 - \alpha_1)] \\ &= Pr[\mu_i > - F_i\,(C_i, S_i, N_{ij})ß] \\ &= F_i(X_i ß) \end{aligned} \tag{2}$$

where X_i is the $n \times m$ matrix of the explanatory variables, ß is an $m \times 1$ vector of parameters to be estimated, $Pr(\,)$ is a probability function, μ_i is a random error term, and $F_i(X_i ß)$ is the cumulative distribution function for μ_i evaluated at $X_i ß$. The probability that a farmer will adopt any of the components of the proposed packages is then a function of the vector of explanatory variables and of the unknown parameters and error term. For all practical purposes, equation (2) cannot be estimated directly without knowing the form of F. It is the distribution of μ_i that determines the distribution of F. If μ_i is normal, F will have a cumulative normal distribution. Following equation (2), the functional form of F is specified with a Tobit model, where μ_i is an independently, normally distributed error term with zero mean and constant variance σ^2:

$$\begin{aligned} Y_i &= X_i\beta \text{ if } i^* = X_i\beta + \mu_i > T \text{ (adoption)} \\ &= 0 \text{ if } i^* = X_i\beta + \mu_i \leq T \text{ (nonadoption)} \end{aligned} \tag{3}$$

where Yi is the probability of adopting (and the intensity of use of) the proposed innovations; i* is a nonobservable latent variable, and T is a nonobserved threshold level. The Tobit model therefore measures not only the probability that a farmer will adopt any of the proposed innovations but also the intensity of use of those innovations once adopted. Thus, equation (3) is a simultaneous and stochastic decision model (Langyintuo and Mekuria 2005).

4. STRUCTURAL PATTERNS OF INTERACTION

Before moving toward the testing of hypotheses, a descriptive analysis of the relational data was performed to visualize the structural patterns of interactions farmers maintain with a range of agents who explicitly (by technology transfer, technical advice, and joint learning) or implicitly (by providing opinions and information) influence farmers' decisions to adopt innovation.

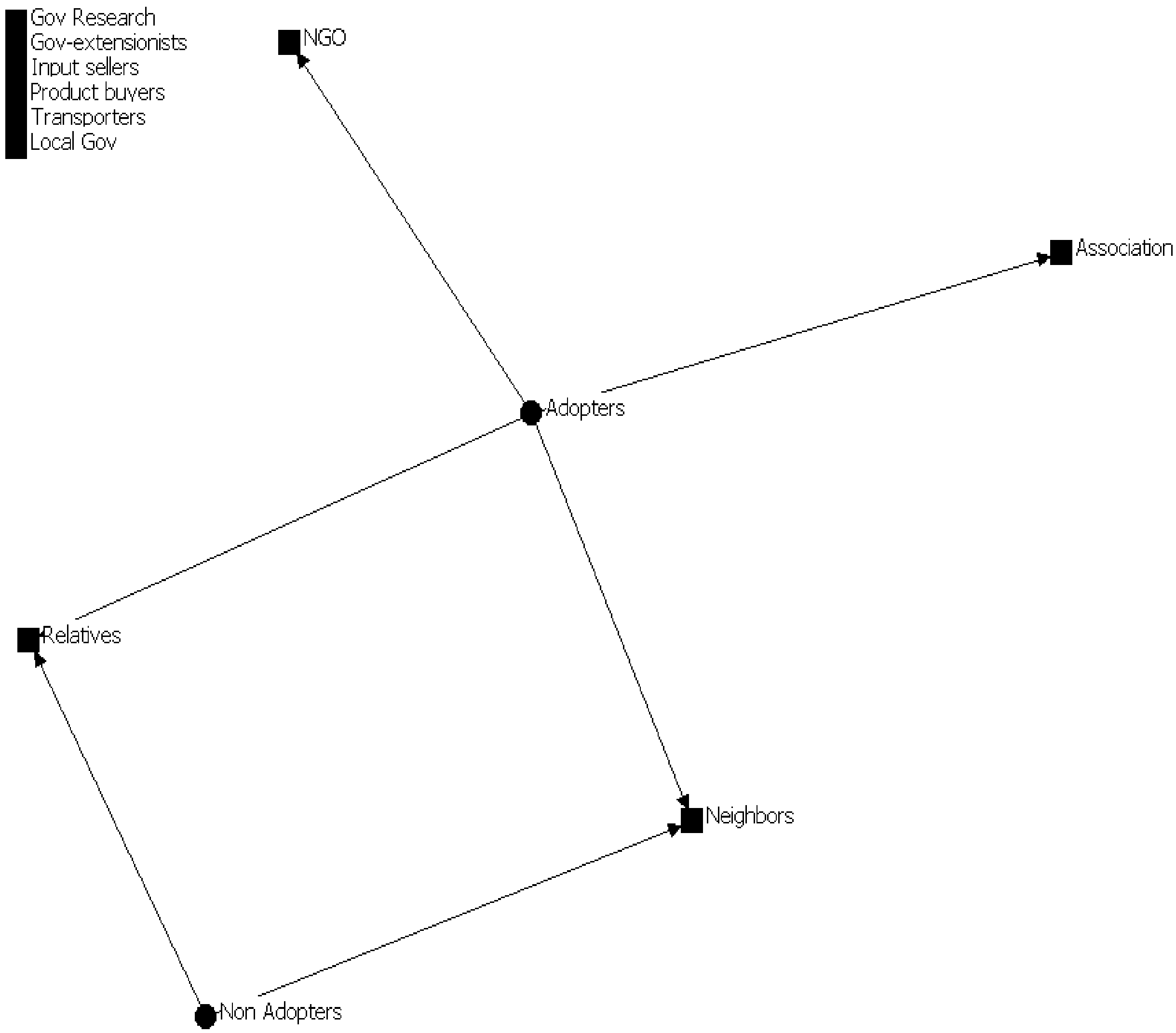
4.1. Effective Interactions of Adopters and Nonadopters

By treating data at the most aggregate level (i.e., averaging across all subsectors and regions by adopter and nonadopter categories), and by setting 0.7 to be the cutoff point for deciding whether an effective tie exists between the average adopter (nonadopter) and any of the 10 defined categories of agents,[30] a simple graph was obtained showing the categories of agents with whom adopting and nonadopting farmers maintain interactions that they consider effective for finding solutions to technical problems (Figure 1). Agents to whom no effective links were mentioned by either farmer category are listed in the upper-left corner of Figure 1.

Apparently at this level of aggregation, the major difference between adopters and nonadopters is that the former consider their interactions with NGOs and farmers' associations effective, whereas the latter do not. Farmers' interactions with the public sector and market agents were not included at this aggregated level: they were considered ineffective by more than 70 percent of the farmers. On the other hand, farmers' interactions with neighbors and family members were, on average, effective for both adopters and nonadopters. Remarkably, NGOs and projects were the only external agents with which farmers maintained effective links; this is consistent with farmers' specifying NGOs as having—in the context of particular or public development projects—actively pursued the introduction of innovations among farmers. NGOs can thus be considered the main external promoters of agricultural innovations in the analyzed cases.

[30] Because the "effectiveness" of the interaction was specified as a dichotomous variable, a 0.7 average value for the interaction with a certain type of agent would indicate that 70 percent of the respondents in the group (either adopters or nonadopters) considered effective their interactions with that type of agent.

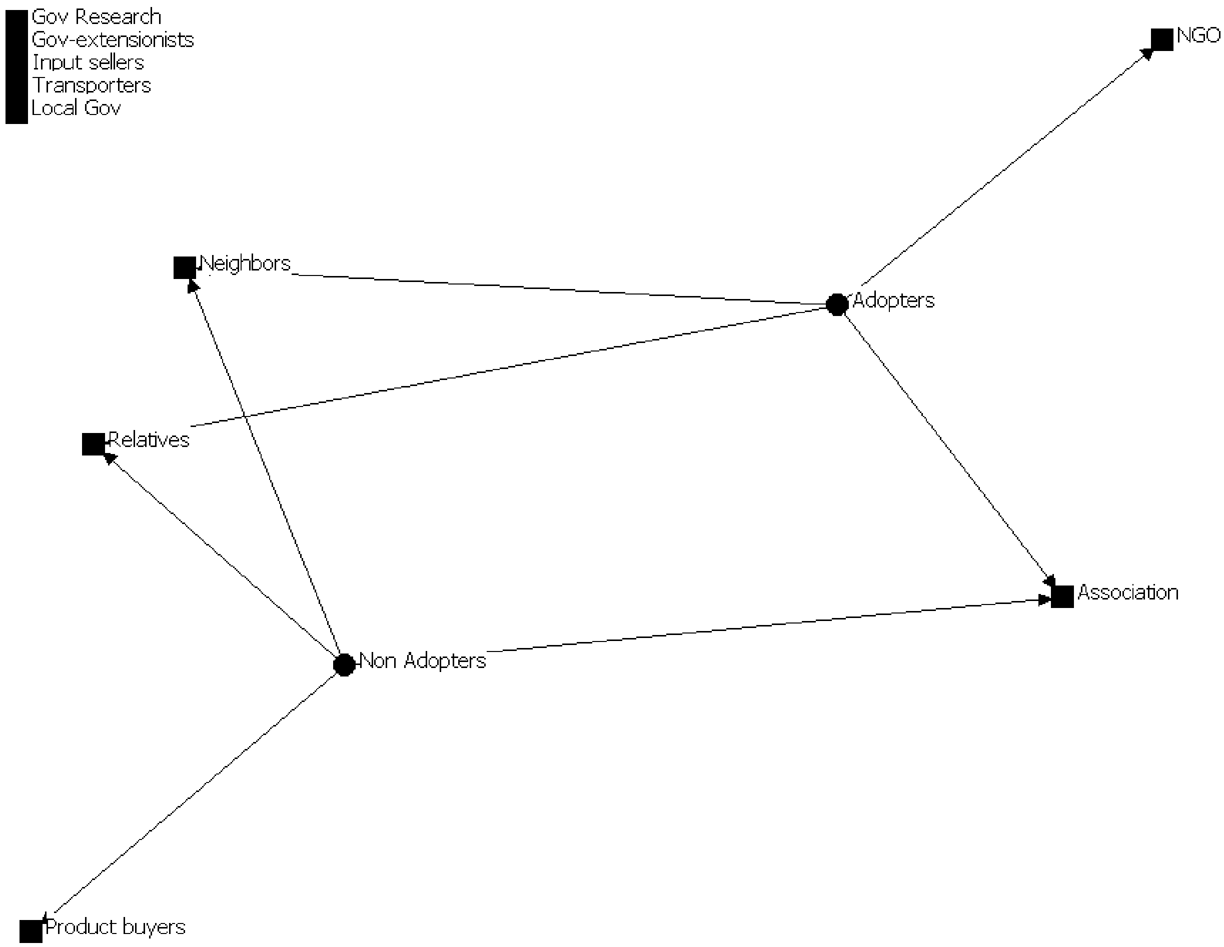
Figure 1. Agents with whom the average adopter and nonadopter maintain effective interactions



Note: Circles = average innovation adopter and non-adopter; squares = change agents.

Figures 2a–c disaggregate by subsector the effective interactions maintained by farmers with other agents regarding the solution of technological problems. The patterns are similar to those depicted in Figure 1, with certain distinctions: In fish culture (Figure 2a), nonadopters also maintained effective links with product buyers. This can be explained by buyers of fish culture products often discussing matters of product quality with producers and providing them with information on how to improve production toward that end.

Figure 2a. Agents with whom the average adopter and nonadopter in fish culture production maintain effective interactions

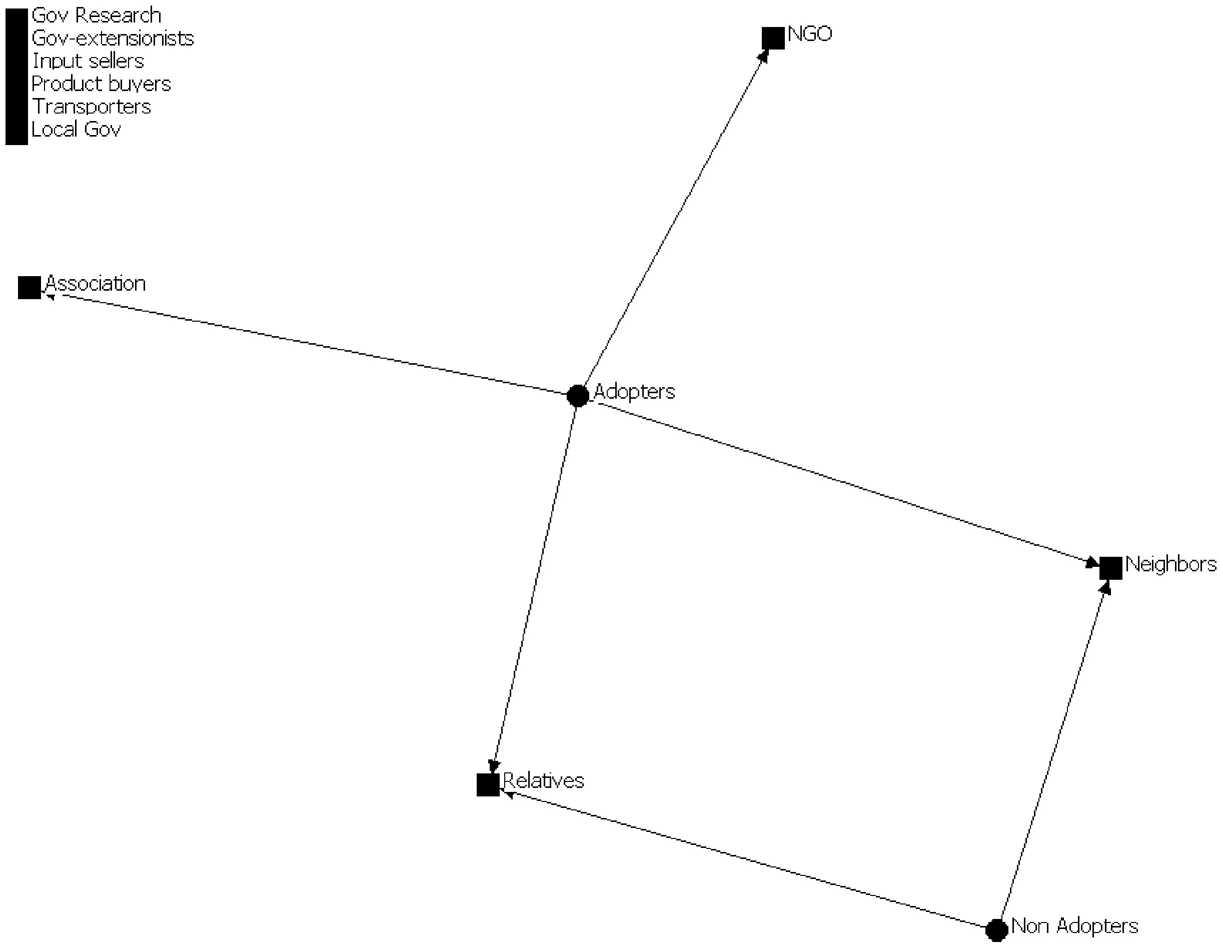


Note: Circles = average innovation adopter and non-adopter; squares = change agents.

In quinoa production (Figure 2b), the situation depicted is the same as that shown in Figure 1, with nonadopters finding their effective links restricted to individual peers and adopters indicating effective links with farmers' associations and NGOs. This reflects the high degree of association found among quinoa-producing farmers in the altiplano region. The study revealed that few farmers in that region maintain individual relations with change agents or make independent choices. Rather, decisions on farming seem to be made collectively under the guidance of farmers' associations in which almost all farmers have membership.

In peanut production (Figure 2c), adopters maintained effective interactions not only with NGOs and farmers' associations but also with market agents, such as product buyers and input suppliers. This reflects a strong market orientation in peanut production; in fact, 93 percent of peanut producers sell parts or all of their produce (Hartwich et al. 2006), and they can link up with a range of product buyers and input suppliers. Besides, some NGO projects that promote new forms of peanut production and marketing maintain and facilitate close affiliations with buyers and input suppliers.

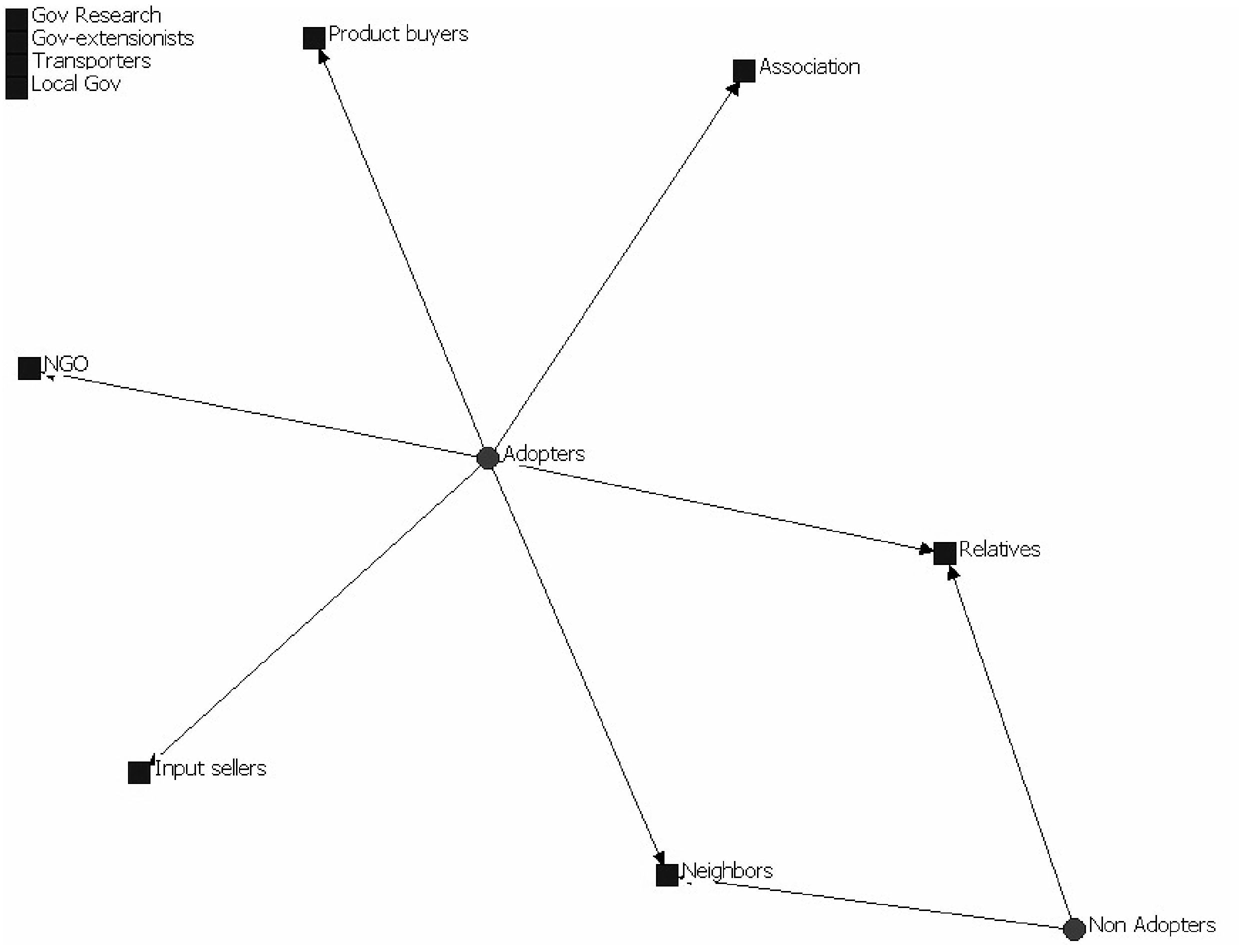
Figure 2b. Agents with whom the average adopter and nonadopter in quinoa production maintain effective interactions



Note: Circles = average innovation adopter and nonadopter; squares = change agents.

Deeper insight into the structure of interactions in which farmers are embedded was obtained by plotting the ties of all individual farmers to the types of agents with whom they felt they had effective interactions. Figure 3 depicts the totality of such relations, clearly showing farmers' neighbors, relatives, and associations, as well as NGOs, in central positions in the graph, indicating that more farmers reported having effective ties to those agents. Most interviewees said those agents were the most effective sources of information among the network of agents they interact with to solve technological problems. To the other extreme, governmental research and extension agents occupy a rather peripheral position in the perception of farmers. This certainly reflects governmental services practically ceasing operations long ago. In fact, it is only lately that research and extension activities have been promoted again by SIBTA, but mainly through third-party agents such as NGOs, producers' associations, and independent consultants.

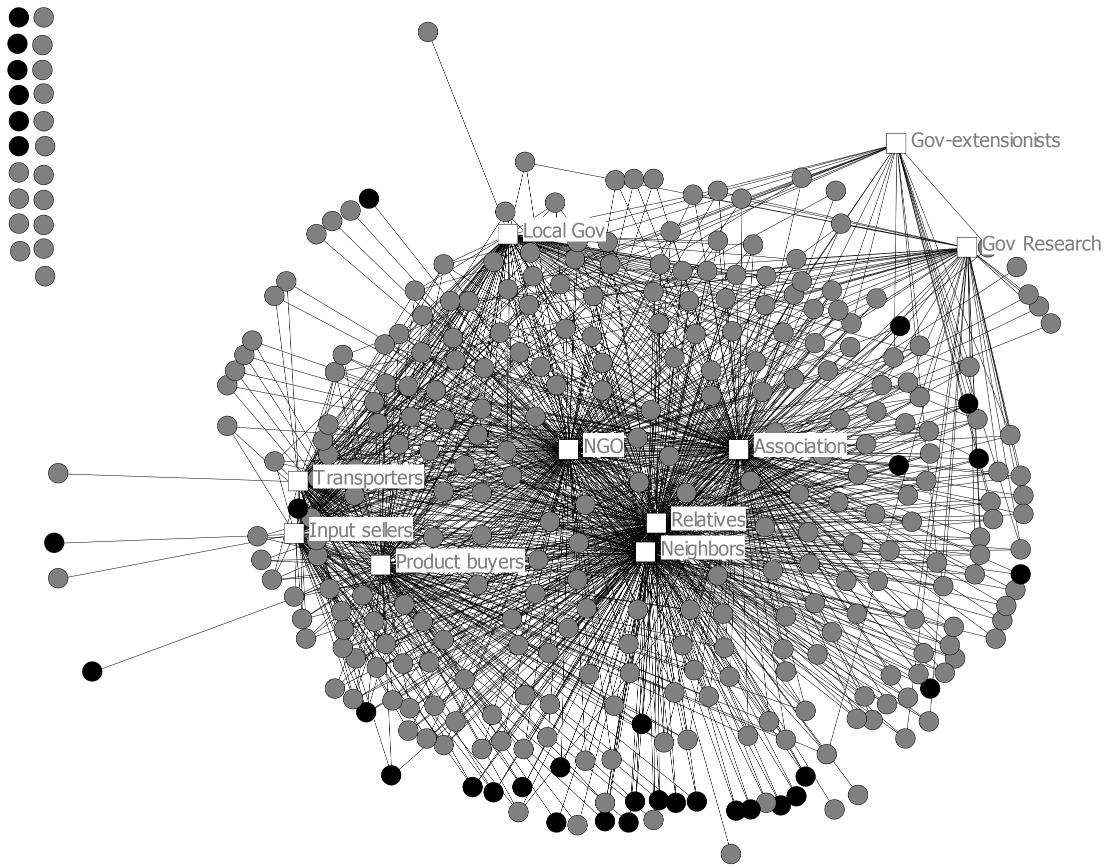
Figure 2c. Agents with whom the average adopter and nonadopter in peanut production maintain effective interactions



Note: Circles = average innovation adopter and nonadopter; squares = change agents.

Among nonadopters, a considerable proportion (10 percent) reported no effective interactions with any agents (as depicted in Figure 3 by the isolated black nodes on the left), whereas only 5 percent of the adopters reported no effective interactions with any agents (gray isolates to the left). Nonadopters reporting any interactions are shown concentrated in the lower portion of the figure, because their effective ties were basically restricted to other farmers (neighbors and relatives) and market agents (product buyers and input sellers). Meanwhile, adopters are more evenly distributed in the figure, reflecting the multiple interactions they maintained with the diverse set of agents, especially with other farmers, NGOs, and farmers' associations and to a lesser extent with market agents and local governments, which are almost at an equal distance to the core of the graph.

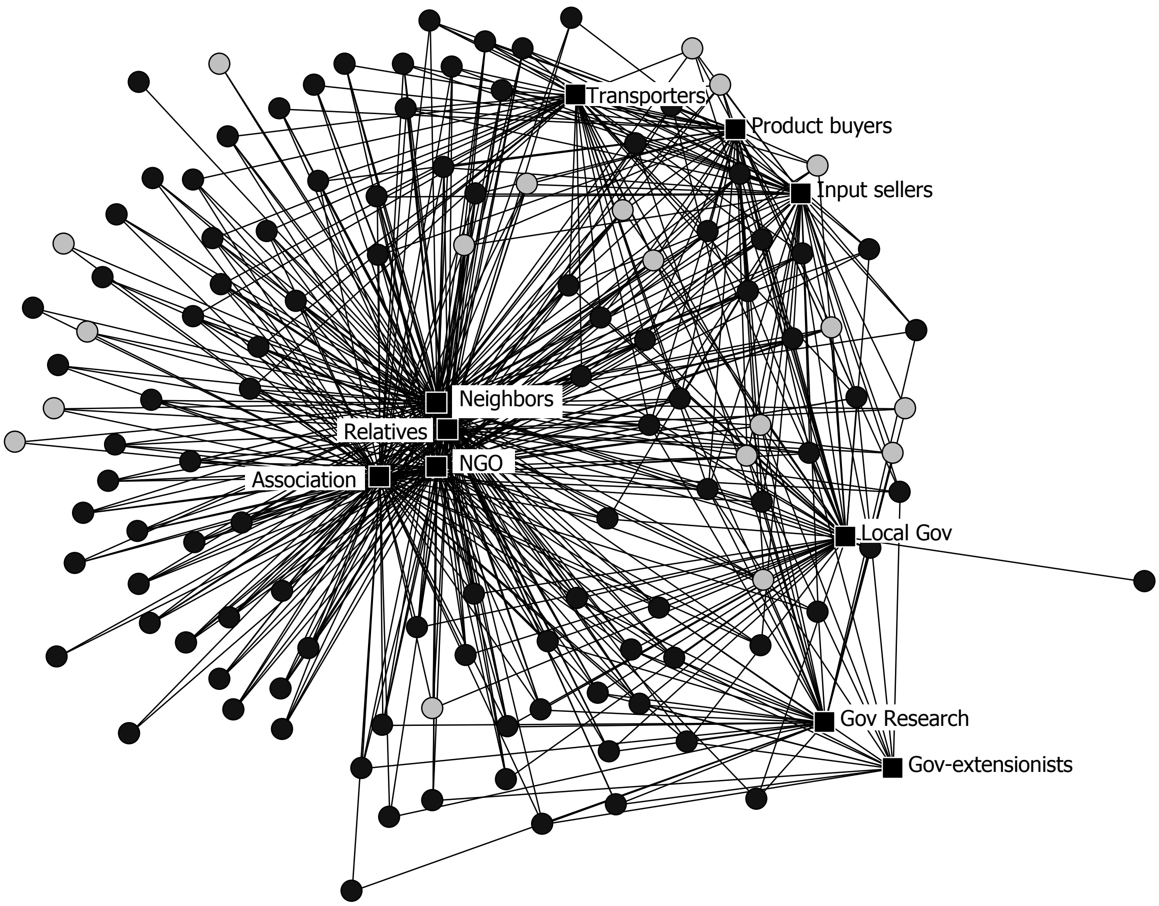
Figure 3. Agents with whom all producers indicated having effective interaction



Note: White squares = agents; grey circles = innovation adopters; black circles = nonadopters; isolates are located at the left margin.

When disaggregated per subsector (see Figures 4a–c), plotting of individual farmer interactions renders similar patterns, with the following particularities: NGOs had a highly central position in fish culture, an intermediate one in quinoa production, and a more marginal one in peanut production. On the one hand, this reflects the doubts of quinoa producers regarding their interactions with NGOs (and their closer affinity to their associations). On the other hand, in peanut production, it reflects innovation promotion by both NGOs and farmers' associations (at times through publicly funded projects).

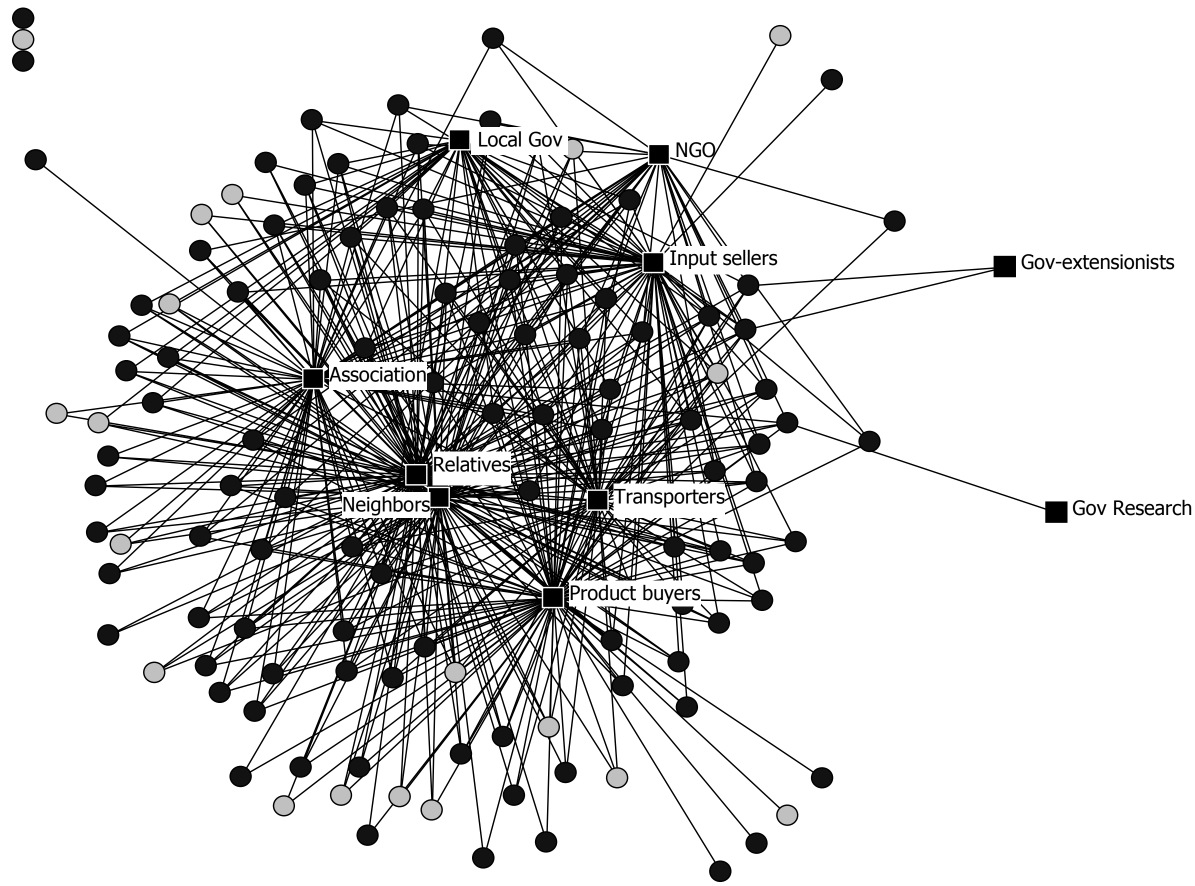
Figure 4a. Affiliation of fish culture producers to diverse types of agents



Notes: Black circles = innovation adopters; gray circles = nonadopters; squares = change agents

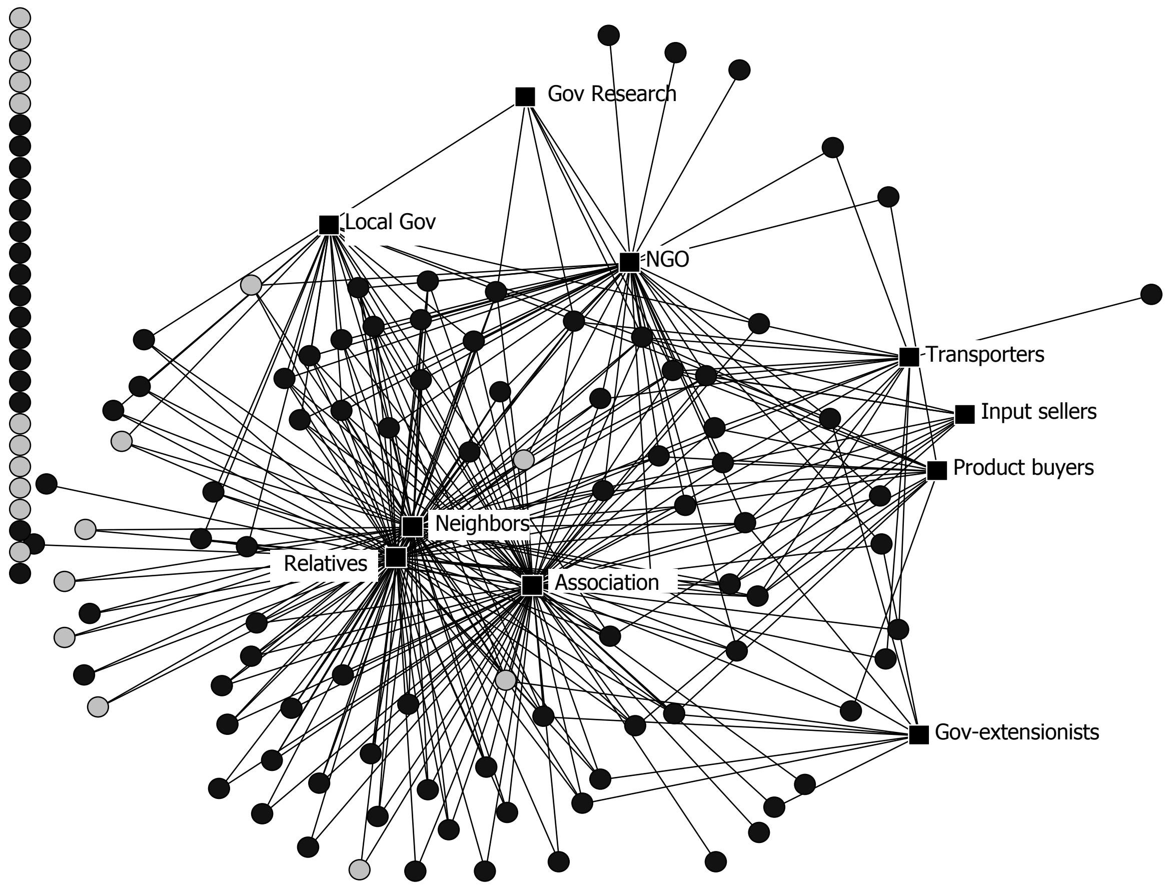
As shown in Figures 2a–c, peanut farmers seem to have a much more effective interaction with market agents than their counterparts in fish culture and quinoa production. In quinoa production, a much larger share of farmers were negative about the effectiveness of their interactions with other innovation agents, reflecting a broader cultural phenomenon in the altiplano region where indigenous farmers are often skeptical about new patterns of production brought to them from external agents (Muñoz Elsner et al. 2004).

Figure 4b. Affiliation of peanut producers to diverse types of agents



Notes: Black circles = innovation adopters; gray circles = nonadopters; squares = change agents

Figure 4c. Affiliation of quinoa producers to diverse types of agents

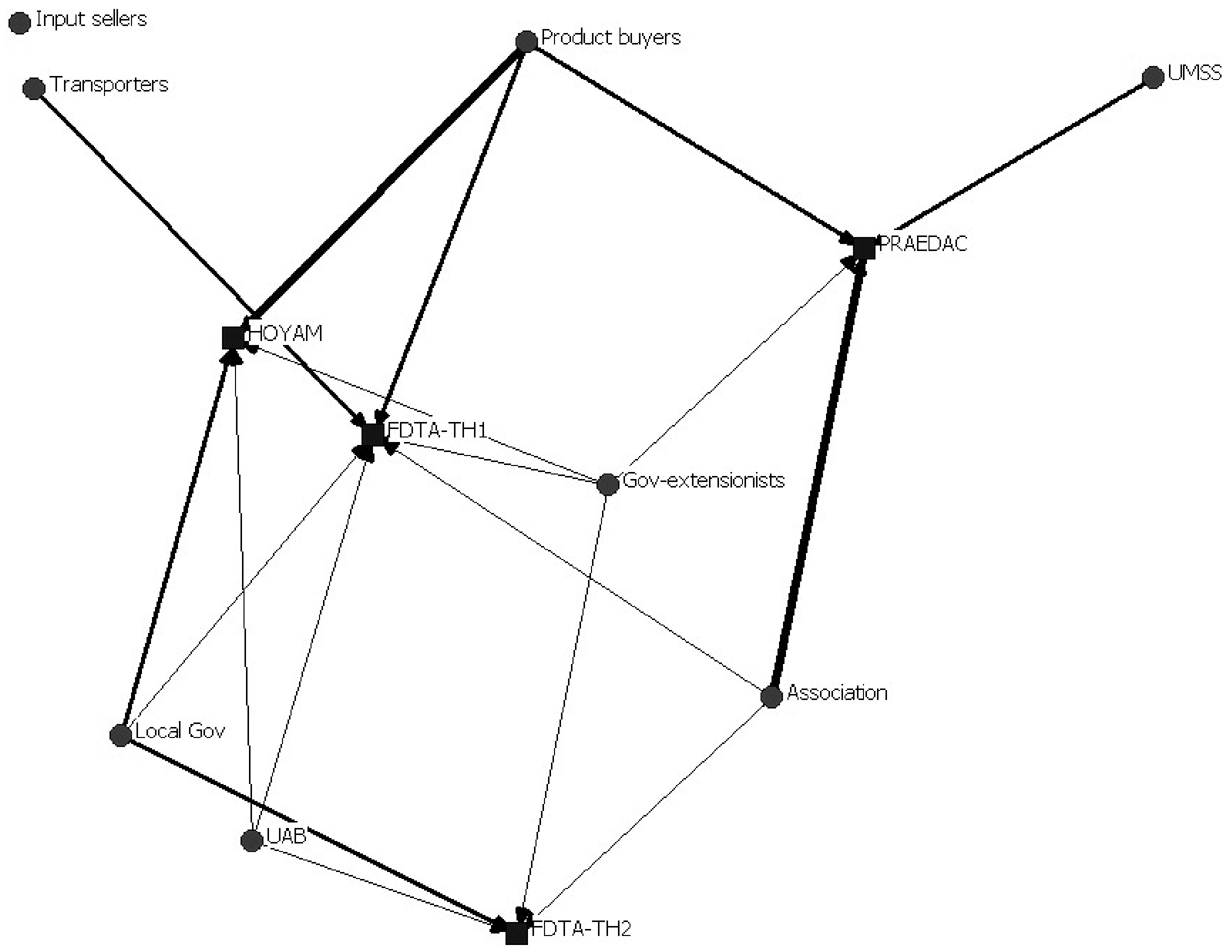


Notes: Black circles = innovation adopters; gray circles = nonadopters; squares = change agents

4.2. Networks of Interactions among Agents that Influence Farmers' Decisions

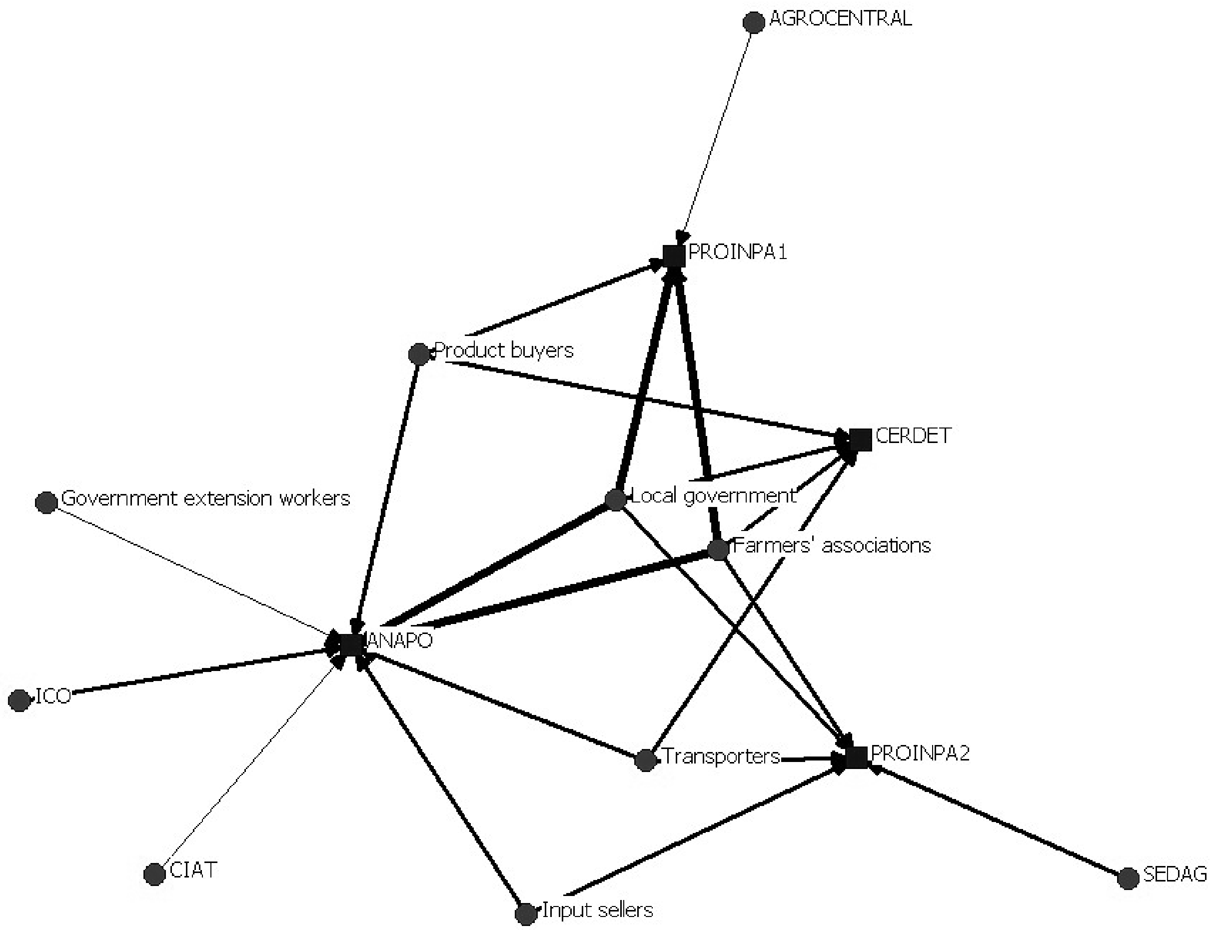
To complete this section, Figures 5a–c depict the patterns of interactions among the four main promoters of innovation mentioned by farmers in every subsector (one per microregion, shown in the figures as squares) and other innovation agents or types of agents (depicted as circles). Line width represents the frequency of interactions among them (only very frequent, frequent, and intermediate levels are shown).

Figure 5a. Main promoters of innovations in quinoa production and their more frequent counterparts



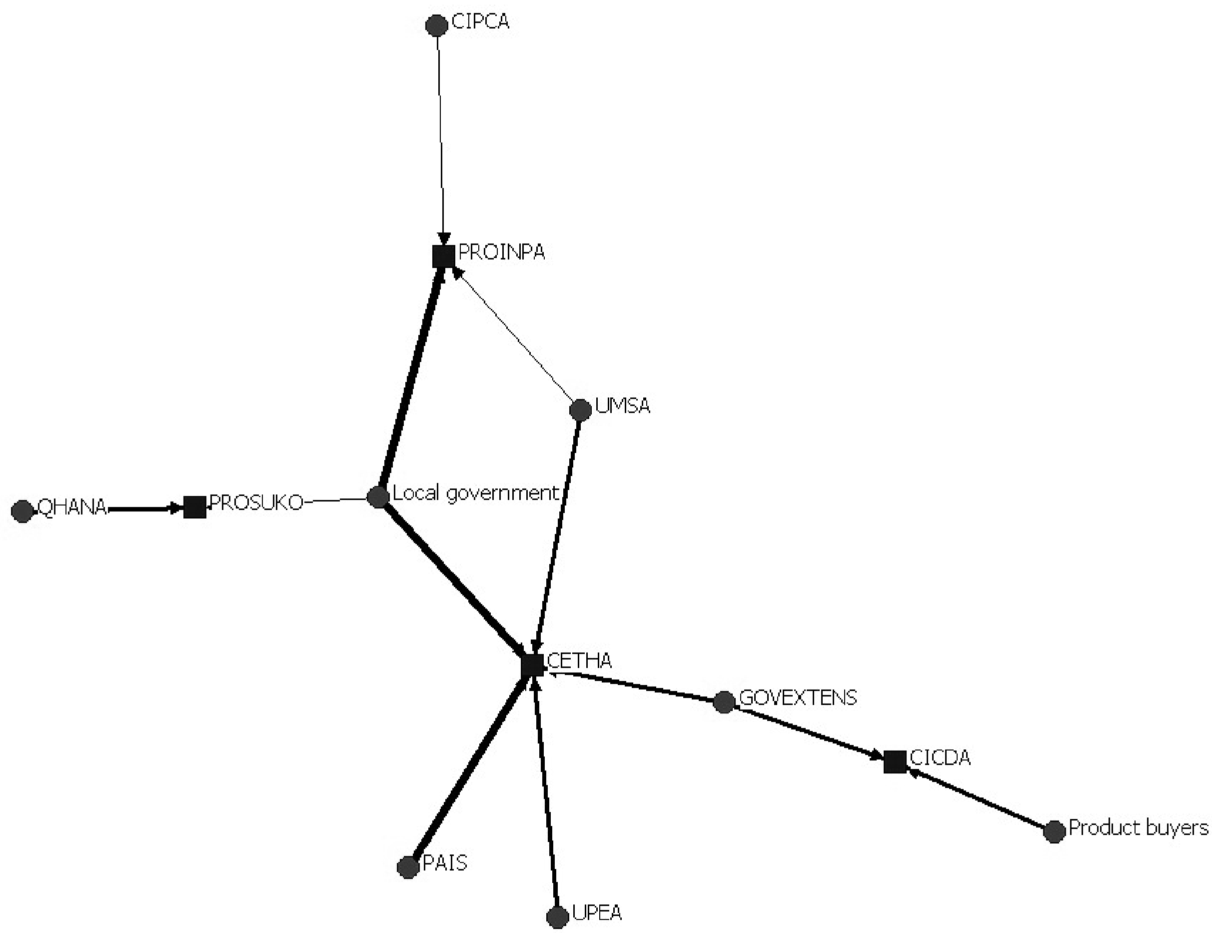
Note: Squares = Main innovation promoters; circles = other change agents

Figure 5b. Main promoters of innovations in peanut production and their more frequent counterparts



Note: Squares = Main innovation promoters; circles = other change agents

Figure 5c. Main promoters of innovations in quinoa production and their more frequent counterparts



Note: Squares = Main innovation promoters; circles = other change agents

Apparently, every main promoter of innovation was involved in a different set of relationships. For example, while the Fundación FDTA-TH1(Fundación de Desarrollo y Transferencia Agrícola - Trópico Húmedo) in Trinidad (fish culture) and ANAPO (Asociación de Productores de Oleaginosas y Trigo) in Mairana (peanut production) maintained frequent contact with six or more other types of agents, the NGOs CICDA (Centro Internacional de Cooperación para el Desarrollo Agrícola) and PROSUKO (Programa Suka Kollos) in southern altiplano and Pucarani (quinoa production), respectively, scarcely maintained contacts with two alters. In general, the networks of interaction among innovation agents were richer in peanut production, intermediate in fish culture, and sparser in quinoa.

5. HOW RELATIONAL PARAMETERS INFLUENCE THE ADOPTION OF INNOVATION

This section describes the results from testing the hypotheses formulated on the effects of social interactions on the intensity of adoption of innovations at the regional and individual farmer levels.

5.1. Influence of Relational Parameters on Adoption at the Network Level

Table 4 summarizes relational and demographic information for each of the variables required for testing hypotheses 1 through 3 related to the influence of the structure of interactions at the regional (network) level on the average adoption level at each of the studied regions.

Table 4. Network parameters—average values per microregion

Activity	Microregion	Intensity_Reg (%)	Density (%)	Distan_Reg (km)	Centralization (%)	Prestige (in-degree centrality index)
Fish culture	1	55.83	39.7	37.9	50.15	16.000
	2	61.9	43.7	42.8	53.26	22.727
	3	55.0	37.0	30.7	72.41	19.048
	4	72.5	39.3	20.0	69.73	26.316
Peanut production	1	50.12	29.4	12.9	70.1	45.833
	2	52.73	42.3	16.7	54.79	28.571
	3	49.49	35.9	6.3	48.97	38.095
	4	64.86	44.2	22.5	38.46	38.889
Quinoa production	1	53.16	23.9	7.5	52.04	17.647
	2	27.41	11.8	74.8	76.44	20.000
	3	41.73	33.0	9.0	39.26	15.789
	4	57.51	24.2	36.7	71.07	5.882
Average		**53.52**	**33.7**	**26.5**	**58.06**	**24.566**

Adoption intensities (Intensity_Reg) for the sets of innovations promoted in every region ranged from 27.4 percent to 72.5 percent, with a general average of 53.5 percent. The average network density—that is, the ratio of possible to present ties at the regional level—was 33.7 percent, ranging from 11.8 percent to 44.2 percent among the regions. The average distance to market for farmers participating in the study was 26.5 km, while regional averages ranged from 6.3 to 74.8 km. It is interesting to note that the region with longest average distance to markets also had the lowest density of interactions (as common sense would suggest). However, the opposite was not true: the shortest average distances to market did not coincide with denser networks. The degree to which affiliations between farmers and innovation agents were centralized around one agent ranged from 38.5 percent to 76.4 percent in the various regions, with a general average of 58.1 percent. Finally, in the networks of interaction among the agents that influence farmers' adoption decisions, the prestige of the main promoter of the package of innovations—measured as their in-degree centrality—ranged from 5.9 to 45.8 percent among regions, with a global average of 24.6 percent.

Table 5. Averages, standard deviations and Pearson correlation coefficients of regional network variables

Variable	Average	Standard deviation	Variable 1	2	3	4
1. Intensity_Reg	53.52	11.41	—			
2. Density	33.70	9.78	.711***	—		
3. Distance	26.50	19.69	–.353	–.406	—	
4. Centralization	58.06	11.41	–.146	–.519	.489	—
5. Prestige	24.57	11.53	.120	.320	–.379	–.156

Note: *** p ‹ .01

The standard bivariate correlation coefficients between the variables required for testing the effects of social interactions on adoption intensity at the regional level are shown in Table 5. Even for the small number of regions (networks) available for comparison in this section of our analysis ($n = 12$), evidence was obtained of a positive and highly significant association between network density and the average intensity of adoption in the region, supporting the prediction proposed in hypothesis 1. The other relational variables were not significantly associated with average adoption intensities; thus, our evidence did not provide support for hypotheses 2 and 3, even though the sign of the correlation coefficients were in the predicted direction (except for centralization).

Table 5 also shows high correlation levels (though not significant) between some of the relational variables tested. In particular, network density was negatively associated with centralization and distance, and centralization was positively associated with distance. In all cases, the sign of the association is the one expected based on theoretical considerations.

In bimodal networks, a high centralization level means that most actors are primarily attached to a single event (agent). The rationale for hypothesis 2 was that if most of the interactions related to technical innovations in a region were centered on the main promoter, less noise would be evident in those interactions and adoption levels would be higher. In the analyzed cases, it was rather the richness and multiplicity of contacts with a diversity of agents (events) influencing farmers' decisions—that is, the density of interactions in the network of farmers and agents—that spurred adoption levels upward.

To conclude, the simultaneous effects of the diverse variables used were tested by combining them into a very simple regression model for predicting average intensities of adoption at the network level. Table 6 reports the results for two specifications: model 1 includes only the four relational variables tested, and model 2 includes one additional nonrelational variable, Consumption_Reg, which reflects the average share of product output destined for home consumption by all farmers in a region (average = 30.12 percent, standard deviation = 32.92). This variable was significantly correlated with adoption intensity ($r = -.713$, $p < .01$).

Table 6. Results from standard OLS regression and permutation-based significance tests for average adoption intensity at the regional (network) level

Variable	Model 1 (Intensity_Reg1)	Model 2 (Intensity_Reg2)
Intercept	7.608	47.273
	(1.000)	*(1.000)*
Density	1.024 **	.490
	(.038)	*(.277)*
Distan_Reg	– .159.	– .159
	(.738)	*(.726)*
Centralization	.353	.083
	(.199)	*(.468)*
Prestige	–.199	–.244
	(.707)	*(.690)*
Consumption_Reg	—	–.162
		(.776)
$R.^2$	.636	.685
R^2 adjusted	.429	.415

Note: Simulation-based *p* values in parenthesis (** *p* ‹ .05)

As Table 6 shows, model fit was high in both instances. However, aside from the Intercept, Density was the only variable with a significant coefficient in model 1, while none of the coefficients in model 2 was statistically significant. It would seem that by introducing the nonrelational variable into model 2, the strong association between density and intensity of adoption in model 1 was unmasked as largely spurious. Before making those conclusions, however, it is necessary to recall that our sample of networks was very small (*n* = 12).

5.2. Influence of Relational Parameters on Adoption at the Individual (Farmer's) Level

Another test included in the study focused on the degree of association between diverse relational characteristics of individual farmers and their particular intensity of adoption as formulated in hypotheses 4 through 6. Table 7 presents the averages and standard deviations for all variables considered in this section and shows the degree of association among them. Correlation tests were conducted following two approaches: Pearson correlation coefficients (*r*) were used whenever both variables were of continuous or interval nature, and Kendall's tau-b (τ) were used for the cases in which at least one of the variables was ordinal. Permutation-based significance tests were conducted and their results are indicated as usual.

Almost two-thirds of the variables included in the calculations to reflect some aspect of farmers' interactions (X1 to X13) yielded significant correlations with adoption intensity, providing good support for hypotheses 4 and 5, as well as partial support for hypothesis 6. According to this preliminary evidence, the intensity of adoption of innovations by Bolivian farmers in three very different economic subsectors and across 12 different agro-ecological and sociocultural regions seems positively influenced by (1) a more frequent and more intense participation of the farmer in organizations, (2) a more frequent individual interaction with other social-influence actors (mostly with peer farmers and technical change agents), and (3) exposure to a more intense and better-quality persuasion by the promoters of innovation (and their close partners).

Table 7. Correlations between variables of social interactions and adoption intensity at the individual level

Variables	Average	Standard deviation	Y	X1	X2	X3	X4	X5	X6	X7	X8
Y. Intensity	*53.28*	*24.93*	—								
X1. Centrality	*.34*	*.21*	.33**	—							
X2. Promoter	*3.69*	*1.10*	.27**	.35**	—						
X3. Other_Tech	*2.34*	*1.07*	.05	.20**	–.06	—					
X4. Other_-Mkt	*2.58*	*.88*	.04	.30**	–.01	.12*	—				
X5. Other_Farm	*3.53*	*.77*	.19**	.53**	.34**	–.01	.10*	—			
X6. Simmel	*37.26*	*19.32*	.21**	.47**	.04	.31**	.45**	.06	—		
X7. Membership	*1.35*	*.84*	.32**	.14**	.11*	.20**	–.11*	.10*	–.08	—	
X8. Meetings	*2.81*	*1.24*	.12**	.10*	.15**	.26**	–.07	.06	–.08*	.27**	—
X9. Conversa_Tech	*2.77*	*1.29*	.15**	.17**	–.09	.24**	.16**	.08	.06	.19**	–.33**
X10. Conversa_Mkt	*2.69*	*1.33*	.14**	.15**	–.04	.24**	.25**	.07	.04	.19**	–.21**
X11. Trust_Tech	*3.29*	*1.07*	.03	.13**	–.07	–.02	.17**	.05	.15**	.03	.03
X12. Trust_Mkt	*2.83*	*1.21*	.00	.05	–.02	–.14**	–.01	–.01	–.04	.02	.12**
X13. Distance	*26.25*	*38.66*	–.10	–.05	–.09	–.19**	–.02	–.11*	10	–.19**	.03
X14. Consumption	*32.91*	*37.37*	–.31**	–.24**	.06	.10	–.23**	–.12**	–.30**	.13	–.18**
X15. Education	*2.96*	*1.03*	.09*	–.01	–.20**	.15**	.08	–.09	–.01	.10*	–.07
X16. Age	*44.66*	*12.73*	–.17**	–.16**	–.04	.03	.00	–.08*	–.03	–.14**	–.01
X17. Age^2	*2156*	*1216*	–.18**	–.17**	–.04	.03	.00	–.08*	–.06	–.13*	–.01
X18. Farm_Size	*14645*	*35485*	.06	–.02	–.13**	.11*	.07	–.04	–.11*	.30**	–.04
X19. Experiment	*3.84*	*1.06*	.13**	.15**	–.04	.23**	.15**	.03	.07	.14**	–.18**
X20. Output	*3.74*	*.92*	.11*	.18**	.12*	.09	.06	.08	.13**	–.07	–.17**
Variables	*X9*	*X10*	*X11*	*X12*	*X13*	*X14*	*X15*	*X16*	*X17*	*X18*	*X19*
X10. Conversa_Mkt	–.58**	—									
X11. Trust_Tech	–.12**	–.11*	—								
X12. Trust_Mkt	–.01	–.03	–.32**	—							
X13. Distance	–.01	.15**	–.03	–.04	—						
X14. Consumption	.19**	.18**	.14**	.06	.02	—					
X15. Education	–.20**	–.15**	.06	–.10*	–.04	.01	—				
X16. Age	.01	.04	.07	.06	.06	.10	–.12**	—			
X17. Age^2	.01	.04	.07	.06	.05	.12*	–.12**	.99**	—		
X18. Farm_Size	–.12**	–.18**	.04	.09*	–.06	–.16**	.19**	–.01	–.01	—	
X19. Experiment	–.25**	–.20**	–.14**	.01	–.01	–.08	.30**	–.04	–.04	.09*	—
X20. Output	–.25**	–.20**	–.18**	–.16**	.00	–.15**	.01	.03	.03	–.06	.15**

Note*:* ***p* ‹ .01; **p* ‹ .05

The following subsections present a brief discussion of the implications of these results in terms of supporting the postulated hypotheses, before testing the combined effect of these relational variables, together with other nonrelational traits included in Table 7 (X13[31] to X20) on adoption intensity, using regression analysis.

5.2.1. Bonding Social Capital: Farmers' Organizations and Intensity of Adoption (Hypothesis 4)

In our sample, farmers had membership in from 0 to 5 organizations, with an average membership of 1.35 organizations per household, which seems a normal number by Bolivian standards.[32] On average, the interviewed farmers participated in organization meetings almost once a month. The positive and significant correlation of both variables (i.e., the number of organizations that farmers are affiliated with [X7] and the intensity of farmers' participation in those organizations [X8], both commonly treated in the literature as indicators of bonding social capital) with the intensity of adoption provide good support for hypothesis 4, highlighting the positive effects of farmers' involvement in peer organizations on innovation. Grootaert and Narayan (2004), Muñoz Elsner et al. (2004) and SOS FAIM (2004) have similarly found that farmers' participation in organizations plays a notable role in increasing household welfare and innovation in Bolivia.

5.2.2. Connectedness and Intensity of Adoption (Hypothesis 5)

The role of farmers' social connectedness as a factor in inducing higher adoption (hypothesis 5) obtained good support on the basis of the positive and significant association found between the three indicators used to describe the intensity of interactions and adoption levels. Either measured as the frequency of conversations on technological or market issues with other actors (X9 and X10) or as the degree centrality of the farmer in the network of farmer affiliations to innovation agents through frequent interactions (X1), higher connectedness, in quantitative terms, was consistently associated with greater adoption levels. It appears that farmers get relevant information out of these relationships, which support them in their decisions to adopt innovations.

5.2.3. Persuasion and Influence: The Effects of Specific Agents, Cohesive Triads, and Trust on Adoption Intensity (Hypothesis 6)

Although the significant association between connectedness and adoption intensity suggests that more connections predict more adoption, correlation tests also show that connection is both a quantitative and qualitative issue: whom farmers are connected to also matters significantly. Their interactions first with external information agents and second with peer farmers were the most strongly associated with the farmers' adoption intensity.

The positive and significant correlation found between the frequency of interaction with the main promoter of innovations (X2) and adoption intensity supported the first component of hypothesis 6. It can be interpreted as evidence of the effectiveness of the persuasive efforts implemented by promoters of innovation. These results also highlight the importance that promoters of innovation should give to the quality and frequency of interaction they maintain with potential adopters.

On the other hand, the positive and significant association found between the frequency of interactions with other farmers (X5) and adoption intensity is contrary to expectations according to part (d) of hypothesis 6. Formulation of this component was based on the assumption that communities in the studied regions would be rather conservative, so that social norms would run against innovation and

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[31] At the regional level, the average distance to markets was considered a good proxy for the level of interactions within the region. However, at the individual level, distance to markets (X13) was not used as a relational variable because farmers could be located far away from the market but close to each other or, even more importantly, close to other innovation agents.

[32] In a study covering 1,000 households in the four main ecological regions of the country, Grootaert and Narayan (2004) found that the average household belonged to 1.4 groups and associations.

farmers with a greater interaction with their peers would be more constrained by those norms.[33] On the contrary, those interactions seem to spur greater adoption, rendering an image of rather innovation-prone farmers. These results could reflect, in part, the fact that most innovation promoters rely heavily on group communication techniques for servicing and training farmers (as also evidenced by the high correlation observed between the frequency of interaction with promoters and with other farmers [X2 and X5]).

The frequency of interaction of farmers with other technical agents (aside from the main promoter)—that is, X3 and X4—had only a weak (insignificant) association with adoption intensity. Interestingly, however, the frequency of interaction with those who were strongly tied to the main promoter (X6), was in effect significantly associated with more adoption, thus providing support to part (e) of hypothesis 6. The fact that both variables (X2 and X6) were not correlated indicates that those two influences are different. Additional influence on farmers' behavior would thus derive—in the direction suggested by the main promoter—from interacting with other agents closely related to the main promoter. This constitutes evidence of the existence of indirect influences or network effects that are not observable if the analysis remains concentrated at the still simplistic world of dyads.

These findings allowed for characterizing the persuasive efforts of innovation promoters as having a two-fold impact on farmers' attitudes and behavioral responses. On the one hand, there is a direct or "marketing" effect by which farmers adopt more intensively as a result of a more frequent direct interaction with the promoter. On the other hand, an indirect or "network" effect further influences farmers (and actually prompts them to adopt more intensively) when they interact frequently with other agents also strongly tied to the promoter: the pressures to conform with the expected behavioral response increase, and the social distance between promoter and farmers decrease as a result of a *tertius iungens* (Obstfeld 2005), a third party that joins and facilitates interaction (Figure 6).

[33] See for example Godoy, Franks, and Alvarado. (1998) and Godoy, Morduch, and Bravo (1998).

Figure 6. Simple model of the effects of strong ties among members of a triad

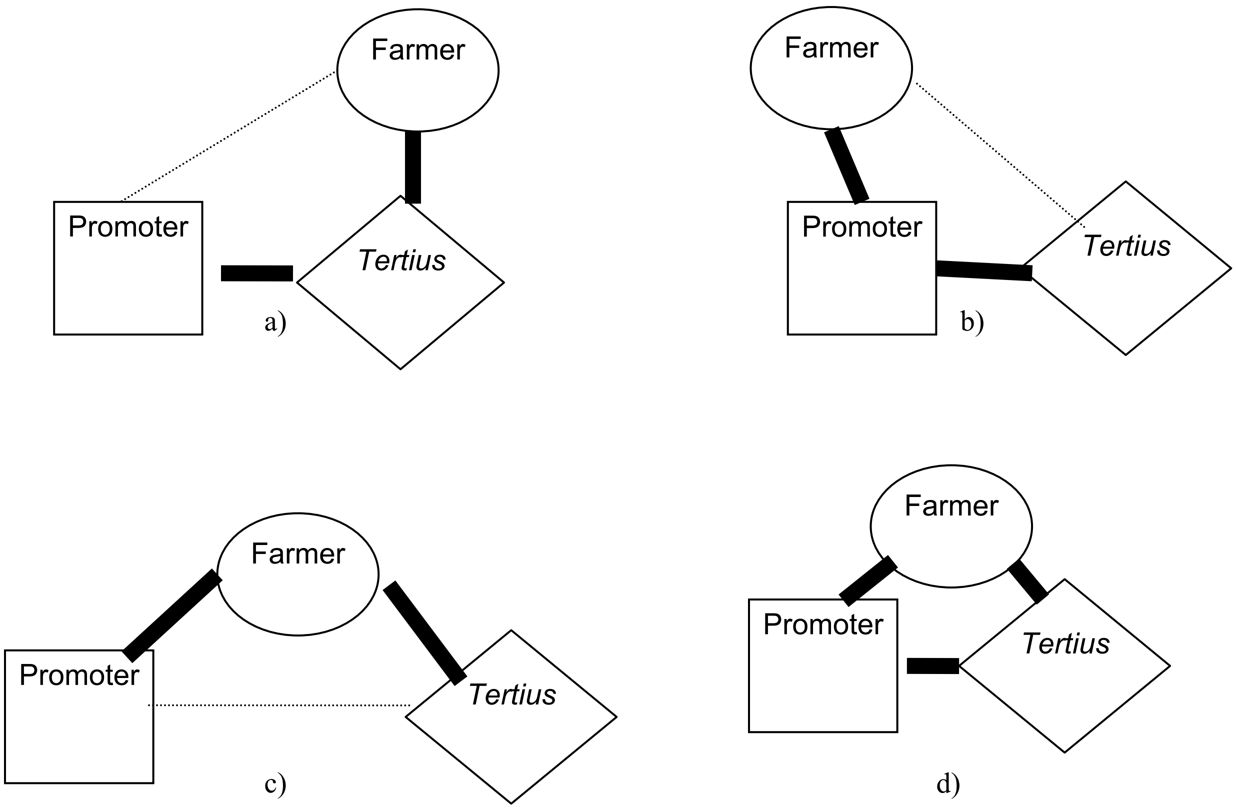

Figure 6 shows a simple model of the farmers' interaction with change agents in a triadic form, while considering the strength of ties linking pairs of actors. Strong ties (which, for the purposes of this study, are synonymous with frequent interactions and are depicted in the figure as thick lines) shorten the social distance between interacting actors. Only when all members of a triad are strongly tied to each other, as in part (d) of the figure, does an embedded or Simmelian tie occur, implying a further constraint on individual behavior (more pressure to comply with expectations) as well as a reduction in the social distance among all actors in the triad. In this study, that corresponds to a reduction in the differences between expected and actual behavior among the interacting actors. From the promoter's perspective, that means increased acceptance by farmers of the focal innovation.

To complete our discussion of hypothesis 6, it appears that the variables related to trust on information provided by outsiders (X11 and X12) are not significantly correlated with adoption intensity. Both coefficients have the expected sign, but the association was not significant in either case. This seems a contradictory result, because trust is a basic prerequisite for accepting innovations promoted by outsiders. Nonetheless, these variables are not specifically referred to the interaction with the main promoter of innovations but rather are applicable to any type of agent. In summary, they reflect the general predisposition toward technical and market information provided by external agents, a perception not necessarily reflecting farmers' trust in the main promoter.

5.2.4. Correlations among Explanatory (Relational) Variables

Table 7 shows high correlation levels among numerous relational variables. This is not surprising given that some of them were specifically included to reflect diverse aspects of the same phenomena.[34] In fact, the set of hypotheses address various aspects of one main phenomenon related to the farmers' interactions with other agents influencing their attitudes toward innovation. The variables then are logically interrelated, and thus a large degree of correlation among them was expected. Based on these results, the most relevant factors were selected for inclusion in the ulterior regression exercise. The data shown in Table 7 allowed for verifying whether distinct titles were used for variables that captured essentially the same process.

The highest correlation obtained (0.58) was among X9 and X10, which raises the issue of farmers not being overstrained to differentiate among the usefulness of technical and market aspects they discussed in their conversations with other change agents. The next highest correlation (0.53) appeared between farmers' degree centrality (X1) and the frequency of interactions with other farmers (X5). X1 was also strongly correlated with the remaining variables describing the frequency of interactions with other agents (X2, X4, and X6). Finally, the index of embedded ties (X6) was also highly correlated with the frequency of interactions with market agents (X4), who together with X3 are the main agents likely to have strong interactions with the main promoter of innovations. In summary, the largest correlations among relational variables were obtained for reasonable and easily explainable instances.

5.2.5. Regression Analysis with "Relational" Individual Attributes

A final step in the analysis of possible explicators of adoption intensity at the individual level was to include the variables used for testing hypotheses 4 through 6 as individual attributes in a regular regression model (Table 8). From the list of relational variables, only those of major interest were selected,[35] and two Tobit models with relational variables were specified. The first (model 2 in the table) includes X1 (farmer degree centrality) and X7 (number of organizations the farmer is affiliated with); the second (model 3 in the table) excludes the centrality measure and instead includes X2 (the frequency of interaction with the main promoter), X5 (the frequency of interaction with other farmers), and X6 (the index of Simmelian ties).

The left part of the Table 8 compares the regression results of the two models just described with model 1, which includes only nonrelational variables regularly included as determinants of the intensity of adoption by small farmers in econometric studies. The right part of the table compares the same three models expanded to include dummy variables for 11 of the 12 studied regions (for readability, the coefficients of those 11 variables were dropped from the table).

A quick comparison of the groups of models to the left and right of Table 8 allows for the realization that the inclusion of relational variables to the base model of each group (i.e., models 1 and 4, respectively) causes a slight reduction in the standard error of the estimate (i.e., the value of sigma or an ancillary parameter), as well as a moderate improvement in model fit measures.

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[34] Also, and especially in the case of bimodal networks, the methods used to estimate some of the relational parameters artificially reduced variability (e.g., dichotomization of valued graphs), thus approximating some of the measures in terms of their levels of association with the behavioral variable.

[35] Selection of the variables used in the various models was based on the following criteria: (1) ease of data collection and/or observability (avoiding the use of elaborated indices and giving preference to data that did not require a great deal of recall and estimation by farmers), (2) ease of estimation (when using individual relational parameters), (3) high correlation levels with a dependent variable, and (4) low correlation levels with other independent variables included (to avoid multicollinearity problems).

Table 8. Tobit regression coefficients for the diverse models of adoption intensity specified (*n* = 276)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sigma (intercept)	18.518***	18.410***	17.600***	16.037***	15.993***	15.322***
	(.746)	*(.742)*	*(.779)*	*(.717)*	*(.713)*	*(.765)*
X1. Centrality	—	9.113*	—	—	1.462	—
		(5.328)			*(5.259)*	
X2. Promoter	—	—	5.140***	—	—	.853
			(1.281)			(1.190)
X5. Other_Farm	—	—	1.786	—	—	1.015
			(1.708)			*(1.797)*
X6. Simmel	—	—	–.005	—	—	.233**
			(.072)			*(.099)*
X7. Membership	—	1.155	.232	—	2.551	1.338
		(1.641)	*(1.670)*		*(2.005)*	*(2.081)*
X13. Distance	–.066**	–.059**	–.042	.002	.004	-.001
	(.027)	*(.028)*	*(.028)*	*(.029)*	*(.029)*	*(.031)*
X14. Consumption	–.156***	–.149***	–.153***	–.084	–.082	–.082
	(.030)	*(.031)*	*(.037)*	*(.068)*	*(.068)*	*(.074)*
X15. Education	1.136	1.403	2.501**	3.455***	3.591***	3.526***
	(1.147)	*(1.161)*	*(1.253)*	*(1.188)*	*(1.178)*	*(1.177)*
X16. Age	–0.118	–.086	–.073	-.035	–.026	–.025
	(.097)	*(.095)*	*(.097)*	*(.082)*	*(.082)*	*(.085)*
X18. Farm_Size	.000	.000	.000	-.000	-.000	-.000
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
X19. Experiment	1.189	.787	1.237	3.211***	3.199***	3.606***
	(1.253)	*(1.314)*	*(1.251)*	*(1.200)*	*(1.228)*	*(1.190)*
X20. Output	3.258**	2.952**	3.232**	3.111**	3.014**	3.279**
	(1.318)	*(1.368)*	*(1.412)*	*(1.260)*	*(1.274)*	*(1.289)*
X21. Gender	-.194	-.606	.342	.198	-.173	-.204
	(2.457)	*(2.432)*	*(2.552)*	*(2.288)*	*(2.337)*	*(2.389)*
Fit measures:						
Log pseudo-likelihood	–1188.596	–1186.945	–1067.575	–1149.237	–1148.454	–1033.089
$R^{2\dagger)}$	.152	.162	.228	.354	.367	.415

Note: Robust standard errors in parentheses; ***$p < .01$; ** $p < .05$; * $p < .10$.

† The pseudo-R^2 normally presented as part of the output of STATA is McFadden's pseudo-R^2, which may not be the best measure of fit. This study calculated the R^2 between the predicted and the observed values, which is closer and can be interpreted similarly to the R^2 obtained from an OLS regression (see, http://www.ats.ucla.edu/stat/stata/dae/tobit.htm).

Analysis of models 1 through 3 reveals that, when included, one of the relational variables appears as the one with the largest effect on the dependent variable. In model 1, the most determinant variable is an indicator of farmer-expected output resulting from innovation. In model 2, centrality appears as the key variable for determining adoption intensity, while in model 3 the frequency of interaction with the main promoter of innovations is the variable with the largest effect on adoption intensity. In both models 2 and 3, the expected output occupies the second position. Model 3 allows visualizing that, among the diverse ties that form degree centrality measures; it was the degree of interaction with innovation promoters what mattered the most in the studied cases.

The inclusion of location effects (i.e., models 4 through 6) caused an important improvement in terms of fit measures compared with those obtained with the first three models. Even though models including relational variables show better fit measures than the base model for this group (model 4), only one of the relational variables (X6) appears now as making a significant contribution to adoption intensity. Besides, consideration of location or contextual effects raised other variables as significant determinants of adoption (e.g., X15 and X19) and questioned the power of others (e.g., X13 and X14). However, the problem of including location dummies in a model is that they capture too many effects at once; therefore, one has no idea what one is accounting for. In fact, it is very likely that location dummies obscure the explanatory power of all relational variables used in this study, because the agents that farmers interact with are location specific.

A more detailed discussion of the theoretical model used as the basis for the present specifications, as well as a review of the econometric concerns surrounding the modeling of peer effects and a comparison of alternative approaches to proceed, will be the subject of a companion paper (Hartwich and Monge, forthcoming). The present paper focuses on demonstrating a simple way of including a diversity of relational variables into normal econometric models. Moreover, the high significance of the effects of some of the relational variables tested as additional components in a set of standard explanators of adoption intensity should suffice to highlight the potential gains of their consideration and inclusion in adoption studies.

5.3. Effects on Adoption from Mixed Levels

5.3.1. Social Influence by Peers and Adoption Intensity

Hypothesis 7 posits that those farmers with stronger (i.e., more frequent) ties to their local peers (relatives, neighbors, and farmers' organizations) are characterized by a closer-to-average adoption behavior (in terms of the speed and intensity of adoption) compared with farmers reporting less frequent interactions with other farmers.

This is a complementary idea to that discussed for part (d) of hypothesis 6. The rationale behind this hypothesis comes from diverse arguments related to the innovativeness of farmers who are well connected to their local peers (a trait often used as a proxy for identifying opinion leaders). Some authors argue that this type of farmer tends to be innovative in modern societies but behaves conservatively in traditional settings, because multiple links make the farmer more constrained by the locally accepted norms (i.e., the farmer faces higher conformity pressures; Godoy, Franks, and Alvarado 1998; Godoy, Morduch, and Bravo 1998; Rogers 2003). A very similar prediction, though based on a very different argumentation, has been reproduced in network models of social contagion by physicists like Watts (2003, 2004). Watts argues that highly connected actors are more vulnerable to contagion and are more instrumental in the propagation of information in poorly connected networks, although they tend to be stable (conservative) in highly connected networks. For this study, the microregions were assumed to be rather traditional, with strong interactions among locals who are not strongly integrated to the market and have infrequent interactions with external agents.

Results from the test for hypothesis 6 already provided sufficient evidence against these arguments, pointing to a positive correlation between adoption intensity and the frequency of interaction with other farmers. Congruently, the tests applied in this study did not provide for the hypothesis: the correlation coefficient between the frequency of interaction with other farmers and the difference between the regional average and individual adoption levels was rather low and not statistically significant ($r = .051$).

According to Watts' arguments (2003, 2004), this might be a result of the local networks being not so highly connected, something confirmed by the low density levels obtained in the analyzed regions. On more sociological or anthropological grounds, the picture that emerges from these results is that the analyzed networks are not so poorly integrated to the market nor so conservative, allowing highly connected actors (opinion leaders) to behave rather innovatively.

5.3.2. Social Comparison (Competition) and Adoption Intensity

Testing hypothesis 8 required conducting a QAP[36] correlation test between the matrix of Jaccard similarities among actors with regard to their ties to alters and a matrix showing the absolute value of the difference in adoption levels between all pairs of actors. The Pearson coefficient for this test of correlation between the two matrices was –0.073. The level of association was low but significant, indicating that the higher the similarity between two farmers (in terms of the number of agents that both have frequent interactions with), the smaller the difference in their levels of adoption. To confirm these results, the same test was conducted for every region. The Pearson coefficient was negative and significant in 8 of 12 regions, negative but not significant in 3 regions, and positive but not significant in 1 region. Thus, this study was able to verify the existence of this weak but significant association between structural equivalence and adoption intensity, which is equivalent to showing the existence of a weak tendency, among sampled farmers, to compete with and imitate the behavior of others in their comparison group.

[36] QAP correlation calculates measures of nominal, ordinal, and interval association between two matrices and uses quadratic assignment procedures to develop standard error tests for the significance of association (Krackhardt 1987, 1988; Hanneman and Riddle 2005).

6. CONCLUSIONS AND POLICY IMPLICATIONS

This paper presents results from a study that used the methods and tools of social network analysis to analyze the effects of relational parameters on innovation processes that involve farmers and change agents in the diffusion of new agricultural knowledge and practices. As shown through an extensive literature review, the focus on relational parameters and effects of networking can contribute substantially to the understanding of innovation processes and have been intensively used for this purpose in fields such as sociology, marketing, and industry development. However, in the field of agricultural innovation in developed countries, a domain still dominated by economic models that explain adoption of innovations solely on the basis of resource endowment and sociodemographic parameters, effects of networking have only recently been introduced and often only in models that include a simplistic network variable.

The analysis conducted in this study is not intended to elaborate a comprehensive econometric model for explaining adoption behavior of farmers—that is left to other studies and publications—but to explore a wide range of hypotheses related to the effects of social influence, cohesion, brokerage, and equivalence on farmers' adoption of innovations and to identify measures that contribute to a better understanding of innovation processes. Thus, we encourage practioners in development to focus on the effects of social interaction when they promote agricultural innovation, and econometricians might discover reasons to take into account the complexity and interdependence with which social interactions influence agricultural innovation processes and go beyond the inclusion of a randomly chosen network variable in standard models on the adoption of innovation.

In our approach, we have distinguished between innovating producers and those who influence farmers' behavior toward adoption of innovation either purposefully (as do projects and extension agents, and eventually buyers and input providers) or unpurposefully by serving as peers and providing references (as do other farmers, neighbors, leading producers, and village authorities). The interactions between innovators and innovation promoters—a relation of particular importance in development settings where diverse external agents try to influence farmers—have rarely been analyzed in detail. However, if information were collected only on the basis of a bimodal farmer–peer network, the analysis would be cut short in terms of the relations among the farmers as well as among the peers; both of these relations, however, are important to understanding the way communication and interaction influence the behavior of farmers. Meanwhile, the tools of social network analysis—for example, the measures of centrality, brokerage, and closure and the identification of subgroups—cannot be fully deployed when only bimodal network data are available:

In fact, the relational and interaction measures derived from our analysis must be carefully interpreted because we were not dealing with a regular "social network" of peer-to-peer contacts within a closed community but rather with patterned interactions describing the affiliation of individual farmers with different types of agents within a region. Even when other farmers were included as one of the categories with which farmers could be affiliated, the individual interactions among peer farmers could not be ascertained in detail. In this sense, the density measures estimated for each region gave us only a rough approximation to the real cohesion measure that could have been obtained by considering farmers' ties to the set of peers with which they interacted, including other farmers. It might be argued that, estimated this way, the contributions of change agents are overestimated in the cohesion measures. In reply, we might argue that this way of dealing with relational data is also useful for accounting for the qualitative difference existing between these "vertical" linkages and the more "horizontal" ties that link farmers to their peers.

Our analysis generated comfortable evidence with regard to the importance of four main effects of farmers' interactions on their decisions to adopt innovations brought to them from the outside:

- *The persuasiveness of change agents*. Change agents, including NGOs, projects, and other agencies fostering adoption of innovation by means of technical assistance and technology transfer, can trigger the adoption of innovations among farmers by being more persuasive in performing activities intended to improve the quality and quantity of the services they provide. In our study, we detected persuasion processes on the basis of the strong effects of the frequency of interactions with the main promoter of innovations on observed adoption intensity.

- *The density of the network of social interactions and the intensity of social capital*. On the network level, comparing 12 microregions, our results indicate that the denser the network of interactions between farmers and other agents involved in innovation processes, the higher the expected adoption intensity. Further, at the individual level, the intensity of adoption of innovations by producers in three agricultural subsectors and across 12 agro-ecologic and sociocultural microregions is positively influenced by a more frequent and more intense participation of farmers in producers' organizations and more frequent interactions with other agents—mostly, with peer farmers and with key promoters of innovation. These findings suggest that farmers' interactions with other farmers as well as change agents and peers substantially influence farmers' decisions to adopt innovations. The embeddedness of producers in farmers' social networks as well as their actual social capital and the social capital they are able to develop explain the way they can interact with other agents.

- *The social influence that other agents in the network impose on producers.* Pressure to comply with socially accepted norms and standards is another factor of importance in a farmer's decision to adopt an innovation. In the study, social influence was evidenced by the effects of cohesion on adoption at the network and individual levels. The more intensely farmers participate in the network, the less likely they are to behave differently from their peers. In regions showing receptiveness to promoted innovations, as were all the microregions analyzed in this study, compliance pressures induce adoption.[37]

- *Competition with social referents.* The greater the equivalence of two actors—for example, in terms of their ties to change agents and other actors—the greater the expected similarity in their behaviors. Producers would be moved toward adoption once those with similar patterns of social interactions adopt the innovation, regardless of the existence of direct ties among them. This phenomenon was evidenced by the corroboration of the effects of equivalence on a similar behavioral response (adoption intensities). The producers interviewed have a tendency to compete with and imitate the behavior of others in their comparison group.

These findings have a number of implications for anyone involved in and making decisions on the design and implementation of projects and programs fostering agricultural innovation in poor rural communities:

- The study results call for a more nuanced understanding of how the embeddedness of farmers in social networks influences their decision to adopt innovations brought to them by various change agents. The exposure to new knowledge and technologies as well as the provision of subsidies to encourage adoption may not be enough if the social interactions are not appropriate.

- It is important to consider how the knowledge and technologies are transferred. Holding single training events and randomly visiting farmers and showcasing innovation practices may not be enough. Rather, it is the intensity of interactions with the main agent promoting the innovation as well as the opportunities given to the farmers to transfer codified knowledge into tacit knowledge for practical application that defines the efficiency of

[37] This is, of course, a dynamic aspect of diffusion: the earlier in the process, the fewer adopters and the higher the reluctance to try risky alternatives; compliance pressures then favor the status quo.

extension and innovation promotion programs. Also it matters to which farmers in the network the information is transferred, because some farmers, through their more central position, may be more capable to transmit the information.

- Those who promote innovations should also interact intensively with other agents who implicitly or explicitly contribute to the diffusion of innovation and influence farmers. In fact, the cumulative information that a producer gathers from all those interactions that allows him or her to consider risks and make the most rational decision on the adoption of an innovation.

The study also points to several interesting topics for future research. One is to further explore the effects of social interactions on adoption focusing on the full set of interactions occurring within rural communities, including all interactions of farmers and other agents. This would allow a more detailed exploration of the diverse roles played by every farmer and by specific change agents and the application of the full range of tools offered by social network analysis.

Farmers are linked to their neighbors through a diversity of interactions that span well beyond the sharing of information, such as risk sharing and credit, exchange of products and gifts, kin and friendship ties, and so on, all of which are likely to exert some influence on innovation processes. It would therefore be interesting to further explore the multiplex nature of the ties farmers become involved in and how those cumulatively influence the adoption of innovations. Additionally, it would be interesting to see how social networks as composed by dynamic multiplex ties evolve over time.

Another challenge constitutes applying more-creative methods for sampling by using, for example, a combination of the classic snowballing and other more ego-centered approaches, or by concentrating the analysis on smaller populations defined through narrower boundaries where a full enumeration of the relevant network can be obtained.

With regard to the inclusion of social network parameters in econometric studies of adoption of innovation, the challenge may be to find solutions to the independence condition that variables need to fulfill and that network parameters, by definition, cannot fulfill. Even more challenging may be to start experimenting with approaches that would integrate more intimately and evenly the contributions of social network analysis and econometrics to the study of innovation. This might entail formulating socioeconomic models that include not only vectors of attributes depicting the relational characteristics of the network but also matrices of interaction to consider more intimately the complex effects of interactions on the dependent variable.

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