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The role of network characteristics of the innovation spreaders in agriculture

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Abstract. The diffusion of innovations is largely influenced by the characteristics of the network of initial adopters (or innovation spreader). We investigate how these characteristics tend to influence the adoption rate and the speed of the diffusion process of a technological innovation in agriculture. The diffusion process is simulated through an Agent Based Model that replicates real-world data. We found that the closeness and the clusterization of the networks are the variables that tend to affect the most the capability of spreading innovations among members. Our findings have direct policy implications: since innovations help advancing the economic development of the agricultural sector, promoting the emergence of networks that have desirable characteristics would enhance growth. Our analysis provides specific insights on how to plan networks with desirable characteristics for the innovation spreaders.

Keywords: Diffusion of innovations, Agent Based Model, Social network analysis.
JEL Codes: C63, O33, Q18, Q55.

1. INTRODUCTION

Improving the diffusion of innovations is a key strategy to promote the economic development. The agricultural sector, more and more oriented toward a bio-based sector (Moro et al., 2019), is very much interested by innovations (Scoppola, 2015; Viaggi, 2015), and in a constant need of them as a way to face major challenges such ensuring food security, coping with climate change, and lowering the pressure on the environment. (Li et al., 2022; Ray et al., 2022) Investigating the network characteristics underlying the adoption and diffusion of innovations among farmers is very relevant, since the benefits that would be derived from a wide use and a fast adoption of promising innovations are undoubted (e.g. Hendricks, 2018; Chavas and Nauges ,2020). The success of innovations is tightly connected to the critical mass of their potential users and to their relationships: the successful innovations are generally associated with well performing networks of adopters capable of influencing both adoption and diffusion of innovations. The literature has pointed out clearly that the characteristics of the networks matter

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for the success of innovations – i.e. a fast diffusion with a high adoption rate – (Tey and Brindal, 2012; Banerjee et al., 2013; Barbuto et al., 2019). On the contrary, relatively little emphasis, with remarkable exceptions (Esposti, 2012; Vollaro et al., 2019; De Maria and Zezza, 2020), has been devoted to the agricultural sector.

Within the diffusion process, how social networks operate is key (Valente, 1995): the set and pattern of support, the friendship, and the communication relations are important in defining the evolution and the success of innovations (Morone and Lopolito, 2010): spreading them is "a special type of communication, in that the messages are concerned with new ideas" (Rogers, 2003:5). The innovations may be novel techniques or new strategies, on which the entrepreneurs have a scarce knowledge, and little experience: knowledge, familiarity, experience, and social learning are valuable catalysts for adoption (Santeramo, 2018, 2019). In fact, sharing information and reaching a mutual understanding on the innovation tend to favour its first adoption and diffusion (Rogers, 2003).

If the importance of networks is clear, the reason behind such a relevant role is still unclear. So simply, why networks are so crucial for the diffusion of innovations?

The ssocial networks act through several channels: first, they favour the circulation of *information,* by reducing the uncertainty and facilitating a better assessment of benefits and costs for the adopters; second, the redundancy of the information that can be derived through *social reinforcement,* also named as "indirect experience" (*cfr.* Santeramo 2019), helps overcoming uncertainty; third, the *homophily* among potential adopters, strengthened by the similarity of characteristics (e.g.level of education, socioeconomic status, individual preferences), favours common meanings, the sharing of beliefs and a mutual understanding (Rogers, 2003). In agriculture the third channel is an important catalyst for consumptions habits (Santeramo et al., 2018). This work focuses on the first and the second channels. In this regard, an actor's ability to circulate information to other actors depends on its position in the network, while its ability to be a source of social reinforcement depends on its level of clusterisation, also referred to as the density of neighborhoods, or, put differently, on how many of contacts are linked with oter members of the network (Namtirtha et al., 2021; Centola, 2010). The social network analysis (SNA), a technique devoted to study and investigate networks, uses indexes to quantify the network characteristics.

In this paper we investigate how the network characteristics (i.e. the SNA indexes to measure the position and the clusterisation level) of the initial adopter influence the diffusion of innovations in agriculture. We aim is to show which characteristics may predict the best spreaders. This outcome is informative for policy makers, innovators and practitioners interested in planning effective spreading campaigns. This study focuses on a technological innovation (mulching films), and relies on a case study derived from specialist horticultural farmers located in the Apulia region. The diffusion process for the innovative mulching films is replicated through an Agent Based Model (ABM), a powerful simulation modeling technique capable of capturing emergent phenomena with systemic characteristics stemming from the interplay of the individuals and which cannot be reduced to the system's parts (Bonabeau, 2002). The major ABM distinctive feature is its ability to describe the system from the perspective of its constituent units (Bonabeau, 2002).

The adoption of novelties is a complex process typically involving a large body of interacting actors. Although several computational models have been developed (Bass, 1969; Kumar and Kumar, 1992; Sharma et al., 1993; Tanner, 1978), the empirical investigations on micro-level decisions are limited and challenging (Janssen, 2020). One of the problems with these models is that they can explain the observed success in the diffusion processes, but cannot predict alternative emerging paths. The ABM approach helps overcoming this limitation. Proven its ability to describe the complex dynamics of the system by some simple rules acting at micro-level, it provides enough flexibility to capture the emergent phenomena (Bonabeau, 2002). In the specific case of innovation diffusion, the ABM modeling allows us to test various hypotheses on the characteristics of the agents, which represent the autonomous decision-making entities, i.e. in our analysis we refer to the farmers. We focus on their position in the networks and on their social connections. Differently from other approaches, the ABM can be aplpied in ex-ante analyses to predict whether a certain configuration is likely to succeed or to fail.

We have calibrated the model on real-world data, acquired through a survey and by collecting secondary data. A further novelty of our analysis is the use of information that can directly replicate an existing social network. In short, we use a mixed approach which combines a case study, the SNA and a simulation, to feed the empirical model and estimate the effects of the social relations on the diffusion of the innovation.

The next section describes our integrated approach. The section 3 presents the findings of the analysis. We conclude with a discussion and reflections on policy implications to emphasize the relevance of study of this kind.

2. BACKGROUND

A major issue in the process of diffusion of innovation is represented by the interpersonal communication channels, which play a crucial role in influencing the choice of the single agents to adopt or reject the innovation (Rogers 2003). These channels provide means for communication between people, including the information transfer needed to make agents aware of the novelty (Banerjee et al., 2013), and consists of the social relations connecting them (Chavas and Nauges, 2020; Genius et al., 2014). The most suitable social relations to play the role of communication channels are represented by friendship, kinship and professional relationships (Barbuto et al., 2017; Cheboi and Mberia, 2014; Wang et al., 2020).

This paper focus on the role of the network characteristics of the initial adopter in the diffusion of an innovation in a group of farmers. To analyze this process we model a network formed by nodes, each representing a farmer (i.e. agent), and links, each representing the social relations among farmers. The spread of the innovation is assessed by analyzing three outcomes: 1) the adoption rate – i.e. the fraction of farmers adopting the innovation within a time period; 2) the diffusion speed, which depend on the time required by the diffusion process to reach its maximum number of adopters; 3) the magnitude of the diffusion, that is a combination of the two previous outcomes (see table 3 below for details on their definitions and measurement). These outcomes are influenced by the nature of the network, and more precisely by i) the position of the innovation spreaders (Kitsak et al., 2010; Zhang et al., 2016), ii) by the structure of the network, proven that diffusion can reach more people and spread more quickly in clustered networks than in random networks, since the diffusion process is improved by reinforcing signals coming from clustered links (Centola, 2010); and iii) by the socio-demographic characteristics of the farmers forming the network (Banerjee et al., 2013).

As for the agents' characteristics, previous studies have shown that factors such as age, education level, mass-media exposure, experience in the sector, size of the farm are among the most important for the adoption of innovations (Reimers and Klasen, 2013; Wang et al., 2020). Moreover, agents involved in innovation adoption process typically exhibit an intrinsic "propensity to adopt", an individual preference towards the innovation which stimulate the farmers to the adoption when the perceived quality of the innovation is sufficiently high (Delre et al. 2007, van Eck et al. 2011). In other terms, each potential adopter has a resistance to innovate, and this reluctance can be modeled as as a farmer-specific adoption threshold: the first adopters have a very low threshold for adoption whereas the later adopters have higher thresholds (i.e. a stronger resistance to the innovation) that tend to be exceeded only when many other members of the network have adopted the innovation and have reported on its goodness (Macy 1991).

We hypothesize that the spreaders who have higher chances of reaching a vast majority of farmers in the network, by mean of one- (direct) or two- or more-step (indirect) relations, are expected to achieve a large spread; conversely, the spreaders who are closest to the vast majority of farmers are expected to allow a rapid spread and to reach the maximum number of adopters. Figure 1 depicts this process by representing a simple diffusion model. It illustrates the impact that the network characteristics of the spreader have on the number of adopters and on the time required to spread the innovation.

The time unit is conceived as the period needed for the information to pass from one agent to another, that is the time for the communication to occurs. The timing of the diffusion process is broken down in three periods: at t_0 one agent is picked from the network to become the first adopter of the innovation(i.e. the spreader); at t_1 the spreader informs on the existence of the innovation its neighbors (agents connected to the spreader), which become in turn aware of this novelty; at t_2 a second-order information-passing occurs, at t_2 when the spreader's neighbors transfer the information to their neighbors in turn. In both diagrams the agents are distinguished according to the time at which they adopt the innovation. There are four types of agents, represented by different gradations of grey on a black-to-white scale, assuming that the probability that informed agents adopt the innovation is 1: i) the black circle represents the spreader who adopts the innovation at time t_0; ii) the dark-gray circles represent the adopters at t_1 (also named early adopters); iii) the light-gray circles represent the adopters at t_2 (also named late adopters); iv) the white circles represent the non-adopters. Spreaders A and B are embedded in two to different networks exhibiting different network characteristics: spreader A has four direct links to other agents; spreader B has only two direct connections. As a result, the diffusion processes are very different: in diagram 1 we found four early adopters and one late adopter, while in diagram 2 the opposite is true. Put differently, the choice of spreader A leads to a fast diffusion, with four out of five potential adopters reached in the first period, while spreader B takes more periods to reach the vast majority of potential adopters but allows to spread the innovation to more adopters.

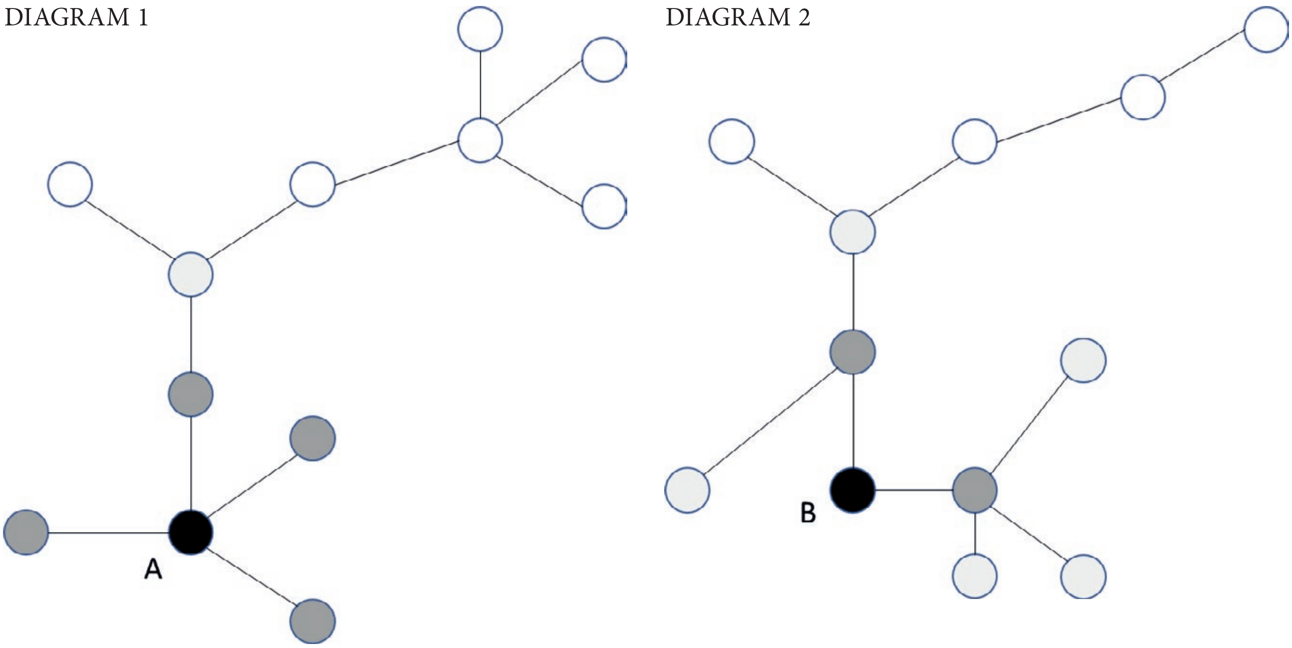

Figure 1. The impact of the network characteristics of the spreader on the size and time of diffusion. Source: own elaboration.

The most straightforward node indicator is represented by the *degree centrality* accounting for the number of connections the farmer has with other farmers (Wasserman and Faust, 1994). In our example (fig. 1), the degree of centrality of node A and B are respectively 5 and 3: the more the connection the farmer has, the higher its influence on closeby farmers, proven that a very central node can pass information to a large fraction of the network directly (with no mediators).

However, the degree of centrality is not the only source of influence. A great part of the influence that a node farmer has depends on its intermediary role in connecting other farmers. This happens when a node lies between two other nodes. The *betweenness centrality* concept has been developed to capture this characteristic: it is calculated as the sum of links connecting other nodes which pass through the original node (Borgatti et al., 2013) and is a measure of its bridge capacity.

Another measure of the centrality of a node is represented by the *closeness*. This index is expressed as the reciprocal of the farness of a given node. This latter index is the sum of the lengths of the shortest paths to every other node: the closer a node is to all the others, the higher its influence is likely to be. The index can be measured, as explained in the next section, as *average reciprocal distance* and through the *eigenvector*.

Finally, another relevant metrics related to the position of each single node is the *local clustering coefficient* which is the density (the total number of connections divided by the total number of possible connections) for the neighbourhood of the node (Borgatti et al. 2002; Newman, 2003): it measures the proportion of contacts which are linked together. A high level of local clustering generates reinforcing effects in the information passing which is an important issue in the adoption of a new behaviour or an innovation (Centola, 2010).

3. MATERIAL AND METHODS

We assess how the network characteristics of the spreaders influence the rate, the speed and the magnitude of the diffusion of the innovation in the farmers' network.

To this end we estimate the empirical model specified as follows:

$$Y_i = \beta_0 + \sum_{d=1}^{D} \beta_d X_{id} + \sum_{n=1}^{N} \beta_n X_{in} + \varepsilon_i \quad (1)$$

where Y_i represents the dependent variables capturing the diffusion process measured in terms of final fraction of adopters, speed of diffusion, and diffusion magnitude; X_{id} refers to the socio-demographics (D) of the spreaders, and X_{in} denotes their network structure (N). The variables of the model are described in Table 1.

To feed the model we adopted a mixed approach which combines case study analysis, SNA and simula-

Table 1. The variables of the model.

Name	Cod.	Kind	Description
Adoption rate	DIF	Dependent (Y_i)	The adoption rate is the proportion of farmers which adopted the innovation in consequence of the spreader operation
Speed	SPE	Dependent (Y_i)	The speed of diffusion is the complement to unity of the number of time steps employed by the spreader to reach its maximum adoption rate in relative terms respect to the slowest spreader (i.e. the one who employs the maximum steps in absolute terms)
Magnitude	MAG	Dependent (Y_i)	The magnitude of diffusion is the product of DIF and SPE
Education	EDU	Independent (X_{id})	education, it is a discrete variable varying in the range [1-5], according to the education level of the farmer (post-doc, degree, undergraduate = 1; high school =2; middle school = 3; elementary school = 4; no school = 5)
Mass-media	MAS	Independent (X_{id})	mass-media, which is a discrete variable ranging in the interval [0-3], according to the number of information channels used by the farmer among three kinds (firm web site, use of e-commerce, specialized journal subscription)
Experience	EXP	Independent (X_{id})	experience, that is a discrete assuming values in the range [1-4], according to the class of experience (< 5 years = 1; < 10 years = 2; < 20 years = 3; > 20 years = 4)
Age	AGE	Independent (X_{id})	age, it counts the age of the farmer
Size	SIZE	Independent (X_{id})	size counts the number of ectaras of the farm
Employees	EMP	Independent (X_{id})	employees represents the number of employees enrolled in the farm
Degree Centrality	DEG	Independent (X_{in})	The centrality degree of a given node is the number of nodes linked with it (Wasserman and Faust, 1994)
Betweenness	BET	Independent (X_{in})	This is a measure of the bridge capacity of a node and is expressed as the sum of links connecting other nodes which pass through the node analysed (Borgatti et al., 2013)
Closeness	CLO	Independent (X_{in})	This index is expressed as the reciprocal of the farness of a given node. This latter index is the sum of the lengths of the shortest paths to every other node. The normalized closeness, here used, is obtained dividing the closeness by the minimum possible closeness expressed as a percentage
Average Reciprocal Distance	ARD	Independent (X_{in})	This index represents a more accurate measure of closeness, including into the calculation not only the reciprocal of farness of the given node, but also the reciprocal of farness of the other nodes from the given node (Borgatti et al., 2013)
Eigenvector	EIG	Independent (X_{in})	It Is a centrality measure in which the other nodes connected to the node under analysis are weighted by how central they are. In other words, the centrality of each node is therefore determined by the centrality of the nodes it is connected to
Local Clustering Coefficient	LCC	Independent (X_{in})	The local clustering coefficient is the density (the total number of ties divided by the total number of possible ties) of the neighborhood of an actor (Borgatti et al. 2002; Newman, 2003)

tion. Figure 2 unfolds the procedure we have employed and explains how we have derived the input variables expressed in Eq. 1.

3.1 The case study

To define the boundaries of the network, we referred to the 107 specialist horticulture farmers surveyed in a previous study on the diffusion of mulching techniques (Scaringelli et al., 2016) in one of the largest horticultural areas in Italy (i.e. Province of Foggia). The sample analysed in that study covered the 2,8% of the population of farmers producing vegetables crops in that area and was representative of the local horticultural sector. The interviewed farmers were identified as potential adopters of a newer mulching technique based on biodegradable films derived from organic waste (Montoneri et al., 2011; Franzoso et al., 2015). This case study provided the socio-demographics represented by the X_{id} in the [Eq. 1] and described in Table 2.

The average level of education is 2.45: the farmers represented in the sample reached high or medium education. They use at least one information channel among web site, e-commerce, and specialized journal subscrip-

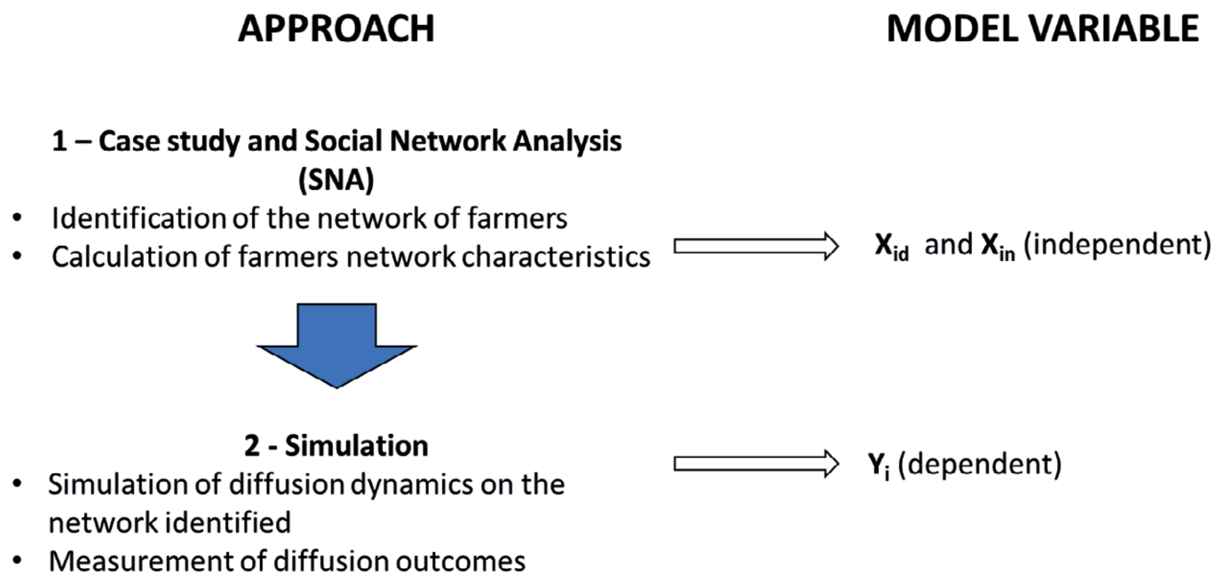

Figure 2. The integrated approach. Source: own elaboration.

tion. They have between 10 and 20 years of experience. They are, on average, 47 years old in mean, with the youngest and elder farmers being 24 and 75 years old respectively; 58% of farmers are in the 40-60 years old range (the standard deviation is 12 years). The variable with the greatest variability is the firm size: it varies between 4 and 1805 hectares, with 65% firms having less than 50 hectares. The average number of workers per firm is 13 with 80% of the sample with less than 20 employees.

Rather than having a probabilistic sample of horticulture sector, the rationale of choosing this case study was to obtain enough relational data to reproduce the complexity of a real farmer social network able to feed and calibrate the simulation model with a stylized representation of the interaction opportunities among farmers. These are based on the typical contact people have in a real-world network formed of group membership (representing, for example, co-workers), family and friend links, some connections to geographically close alters, and some ties to random alters in the population. Instead of using stochastically generated network by means of specialised software, which generates ideal network configurations (i.e. random networks or regular lattice), we adopted a participatory social network approach, a network survey technique directed at gathering data from actors well informed on the structure of network for their direct membership or for their expertise in the sector (Campbell et al., 2019; Delgadillo et al., 2020). We interviewed three experts, one agronomist with a long-time experience in local extension services and two expert farmers. These three interviewees know in depth the local context and the interactions among farmers. To ease the respondent's task and maximizing their recalling potential we employed the following investigation procedure: 1) we divided the geographical area of the case study into four quadrants and grouped the farmers belonging to each quadrant, obtaining four

Table 2. Statistics of the socio-demographics independent variables.

	Education (EDU)	Mass media (MAS)	Experience (EXP)	Age (AGE)	Firm size (SIZE)	Employees (EMP)
Mean	2.45	0.81	3.22	46.88	69.99	13.23
Min	0.00	0.00	1.00	24.00	4.00	1.00
Max	4.00	4.00	4.00	75.00	1805.00	112.00
Dev.st	0.79	1.05	1.06	11.50	176.76	15.68

Source: own elaboration on data from (Scaringelli et al., 2016).

groups; 2) for each group we asked the interviewees to recall the social links between farmers; 3) we repeated the procedure asking the interviewees to detect any intragroup links. Since the objective is to piece together the social network structure as accurately as possible, traced back friendship, kinship and professional relationships between the farmers. To this end we posed two driving questions: 1) *what are the farmers who are members of the same cooperative?*, 2) *what are the farmers who have known each other?*

In case the respondent acknowledged the existence of any relations between two farmers, each relation was further inquired by means of deeper analysis aimed at identifying also the kind of relation. For the relations acknowledged based on question 1, we asked the respondent to specify the if a professional relation existed between the two farmers connected asking the following sub-questions: i) *did they entered a professional agreement?*, ii) *do they share means or other resources?*, iii) *do they contract each other for any operation?*. For the relations acknowledged based on question 2 we also asked if the farmers connected were relatives of friends.

Of course, we did not expect that the three experts knew all the social interactions existing amongst the 107 members of the network, proven that this means to know information on 11.432 potential relations. Rather than mapping the entire web of relations, our goal was to obtain a realistic network configuration resembling the typical morphology of a real-world network. The use of the participatory social network approach allowed us to cover all the typical forms of actors' actual contact and not just random or regular ideal configurations.. Indeed, we obtained a network formed of 2152 total connections, 1595 of which are local intergroup links and 557 arelong intragroup links. To define the network characteristics of the farmer, we applied the principal social network indicators of centrality and position described in section two. These formed the second group of independent variables (X_{in}) in Eq.1.

3.2 *The simulation of diffusion process*

We simulated the diffusion outcomes within the network of farmers by means of an ABM. Although networks typically exhibit complex dynamics, we have intentionally focused on a simple model to trade-off the explanatory capacity and the clarity of interpretation of our results. It is formed of 107 agents interconnected which exactly reproduces the network described in the case study section. This web of social connections forming the network represents the interaction opportunity among agents which they use to exchange information about a technological innovation. The agents have specific attributes: (a) the preference toward the novelty; (b) the adoption threshold, as referred in the background section; (c) the level of education; (e) the spreader attribute, that is set *true* when the agent is used as spreader.

As descends from attribute (e), the model runs two types of agents: ordinary farmers and spreaders. The spreader does not have to take any decision about its behavior, proven that it is set as the first adopter at the model setup. Its unique role is to spread information on the innovation to its neighbors through the social relations interconnecting them. On the contrary, the ordinary farmers interact with the rest of the network, receiving and sending information and taking decision toward the adoption. In each time step, after having received information, each farmer recalculates its preference for the novelty on the base of its previous step preferences and the average of preferences of its neighbors weighted by a factor representing the level of homophily between the farmer and its neighbors. This average is then corrected multiplying it by a factor representing the years of education of the farmer. Then each farmer adopts (rejects) the novelty if its preference is greater or equal (lower) than its innovation threshold. This process is repeated until a specific time span is covered, and three diffusion outcomes of the spreader operation are obtained: i) the diffusion rate, that is the proportion of farmers which adopted the innovation; ii) the speed of diffusion, that is calculated as:

$$SPE_i = 1 - \frac{Steps_i^{max}}{max(Steps_i^{max})} \quad (2)$$

where SPE_i is the speed of spreader i, $Steps^{max}{}_i$ is the number of time steps employed by the spreader i to reach its maximum adoption rate; iii) the magnitude of diffusion, that is the product of the outcomes *sub* i) and ii). These outcomes represent the dependent variables (Y_i) in Eq.1 (see table 1).

The identification of the parameters of the model was based on the data available from the case study or according to the model internal logic. Specifically, at the model setup, (a) the preferences of the farmers toward the new technology was set at 0, assuming that nobody, excepting the spreader, knows the novelty; (b) the innovation threshold was calibrated using data from Scaringelli et al. (2016) which surveyed the attitude of the farmers towards the adoption of new kind of mulching films along a six-degree Likert scale (0 very adverse – 5 very favorable) (c) the level of education was set at the level of education of the respondents; (d) regarding the spreader attribute, we used each farmer as a spreader

Table 3. Statistics of the network independent variables.

	Degree Centrality (DEG)	Betweenness (BET)	Closeness (CLO)	Average Reciprocal Distance (ARD)	Eigenvector (EIG)	Local Clustering Coefficient (LCC)
Mean	20.11	62.26	0.08	45.34	0.73	54.70
Min	1.00	45.00	0.01	0.00	0.00	39.26
Max	98.00	101.67	0.26	1122.56	1.00	91.38
Dev.st	17.58	9.40	0.06	167.84	0.22	7.25

one at a time alternately across the 107 model runs. This was to find the network characteristics best predicting effective spreaders (i.e. those with high levels of outcomes). The analysis produced 107 specific combinations of spreader/farmers.

3. RESULTS

To guarantee the robustness of the simulations, each spreader/farmers combination has been replicated 100 times producing (107 x 100) 107,000 observations. Each simulation has been ran for 500 time periods, which is the time span that guarantees the convergence of the diffusion process for all spreaders and to reach a steady number of adopters. We computed the average adoption rate, speed, and magnitude of diffusion at each step. To provide an encompassing depiction of overall process, tables 3-4 report the statistics of the model variables.

Table 3 reports the statistics of the network characteristics. The value of the degree highlights that each farmer is connected to 20 other farmers in mean, intercepts the shortest path length among 62 other farmers (BET), and is rather close to others (closeness). These values are the effect of a rather connected network, where the chances for a farmer to know others and influence theme or receive influence is very high. This relational structure represents a good premise for the innovation to spread.

Table 4 contains the statistics of simulated diffusion variables. They represent preliminary findings, since can give some initial indications for on a diffusion strategy. The first result is that spreaders achieve a 25% adoption rate in means, that is, a random chosen spreader is expected to cause adoption in 25% of other farmers. We found that the slowest spreader employs 389-time steps to reach its maximum adoption rate. In mean, the spreaders employ the 50% of this time to reach their maximum, that is the 194-time steps. The magnitude considers both diffusion rates and speed of diffusion in a synthetic indicators of diffusion effectiveness. In mean, spreaders reach a level of 0.11. But there is a huge variation among these performances. Considers, for instance the adoption rates. Table 4 reports that the maximum obtainable adoption rate employing a single spreader is 41%. This means that there are some effective spreaders capable of obtain high rates (>35%). We found 10 spreaders reaching this threshold. On the other side there are 11 spreaders reaching a zero-diffusion rate. This calls for a careful analysis in designing a diffusion campaign. Indeed, while some spreaders can accomplish an effective campaign, choosing the wrong spreaders can result to a *cul de sac* dynamic, where the financial and human energies deployed would lead to a zero-result campaign.

The diagrams of the density functions of three diffusion variables back up these findings (Figure 3).

They show that the speed of adoption and the adoption rate are bimodal, with the former showing a higher peak for low speeds, and the latter showing a higher peak for higher levels of adoption rate. This means that, in this context there are several good spreaders in terms of effectiveness (high adoption rates) but most part of them employ long time to completely accomplish the diffusion. On the other hand, there are some ineffective spreaders, characterised by low adoption rate which are relatively fast in covering their spreading. The third diagram confirm the initial findings. The magnitude (the interaction of speed and adoption rate) has a bimodal distribution as well with higher peak for lower values. The underlying process is that the speed of adoption

Table 4. Statistics of the dependent variables.

	Adoption rate (DIF)	Speed (SPE)	Magnitude (MAG)
Mean	0.25	0.50	0.11
Min	0.00	0.00	0.00
Max	0.41	1.00	0.33
Dev.st	0.01	0.23	0.07

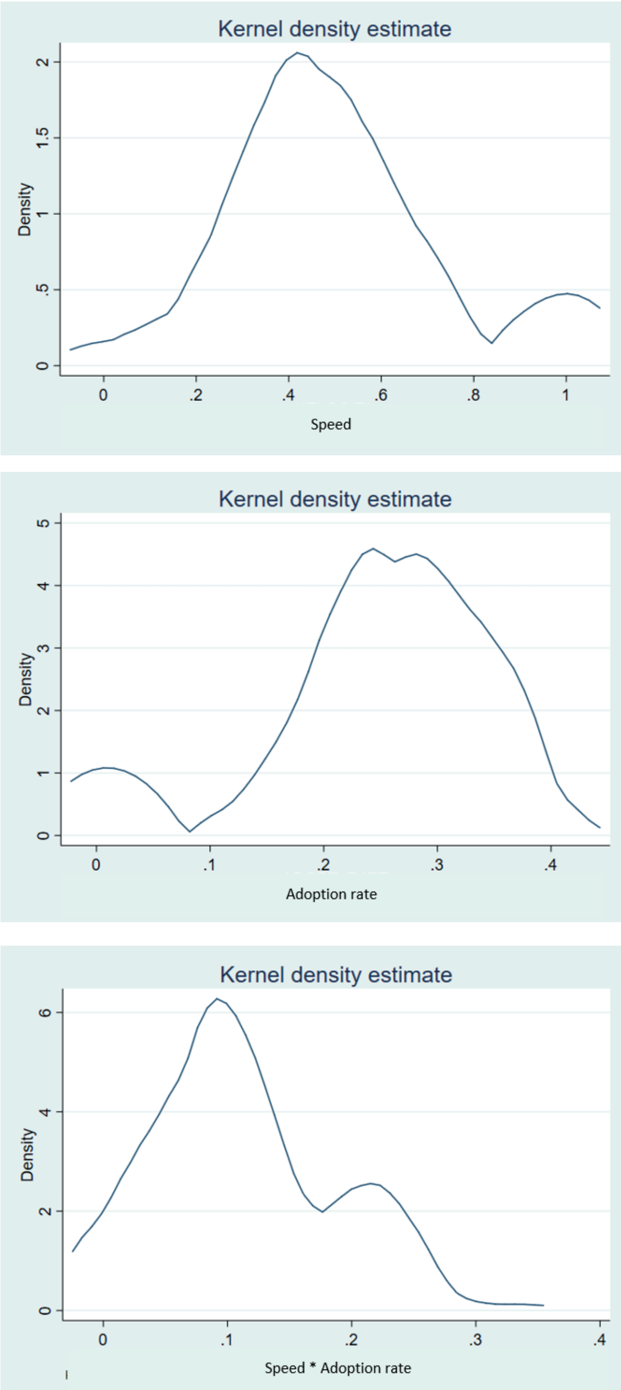

Figure 3.

dominates the adoption rate. Put differently, the share of spreaders capable of enhancing high and fast levels of adoption is rather limited (approximatively equal to one third of those that have average performance in terms of speed and rate of adoption).

We used the model in equation 1 to explain the three dependent variables, namely adoption rate, speed and magnitude. Table 5 reports the regression results.

The econometric analysis highlights the profile of the best spreader and, at the same time, provides deeper insights on the role of the network on the diffusion process. The model did not find any significant relation between the independent variables and the speed of diffusion. Moreover, none of the socio-demographics is able of influencing the performances in terms of rate of adoption and magnitude, possibly due to the fact that the spreaders have similar under socio-demographic characteristics so that these variables are unable to discern the best spreader. Likewise, four out of six network measures (i.e. DEG, BET, CLO and ARD) do not exhibit significant effects. This result is likely to depend on the use of macro characteristics of the network, which very dense and close, rather than of micro relational characteristics of the members.

On the contrary, EIG (i.e. eigenvector centrality) has a positive, significant and relatively high impact on the diffusion rates and on magnitude, while, surprisingly, LCC (i.e. local cluster coefficient) exhibits a negative, even though small, impact on the diffusion process. The eigenvector is a measure of how central the actors connected to the spreader are: it resulted the best predictor of an effective spreader. LCC measures the density of a local neighborhood and is high when the actor connected to the spreader are in turns themselves connected. The fact that this variable has a negative impact is due to the redundancy it produces at local level. In other words, since the acquaintances of the spreader are also acquaintances among themselves, the information on the innovation continue to circulate within a confined clique producing redundancy and waste of social reinforcement. All in all, this analysis shows that, in an agricultural context as the one investigated, the best measure to select effective spreader and increase the success chance of a diffusion campaign, is represented by the eigenvector, which identifies the central spreader who knows very central actors in turn.

4. DISCUSSION AND CONCLUSIONS

The innovations are catalysts of growth and their diffusion has been, during the last decades, a major driver of the economic development of the primary sector (Esposti, 2012; Scoppola, 2015; Viaggi, 2015; Moro et al., 2019): favoring a fast and complete spread of innovations should be a main goal in the policy agenda.

The paper aimed at finding the network characteristics that identify the best innovation spreaders. We fol-

Table 5. The results of the regression model.

	Adoption rate (DIF)			Speed (SPE)			Magnitude (MAG)		
	coefficients	σ	p-value	coefficients	σ	p-value	coefficients	σ	p-value
const	0,339	0,372	0,364	0,611	1,102	0,581	0,276	0,243	0,259
EDU	0,017	0,012	0,165	-0,031	0,035	0,380	-0,006	0,008	0,479
MAS	-0,008	0,009	0,406	0,019	0,027	0,479	-0,005	0,006	0,436
EXP	-0,007	0,010	0,502	0,045	0,030	0,137	0,004	0,007	0,581
AGE	0,000	0,001	0,857	0,000	0,003	0,905	0,000	0,001	0,751
SIZE	0,000	0,000	0,944	0,000	0,000	0,620	0,000	0,000	0,943
EMP	0,000	0,001	0,611	0,002	0,002	0,424	0,001	0,001	0,127
DEG	-0,005	0,008	0,528	0,021	0,025	0,403	0,001	0,005	0,846
BET	0,000	0,000	0,593	-0,001	0,001	0,187	0,000	0,000	0,447
CLO	-0,022	0,022	0,313	0,083	0,065	0,203	0,007	0,014	0,628
ARD	0,018	0,026	0,475	-0,082	0,076	0,282	-0,010	0,017	0,546
EIG	1,698	0,698	0,017**	0,248	2,069	0,905	1,504	0,456	0,001***
LCC	-0,100	0,047	0,034**	0,003	0,138	0,980	-0,079	0,030	0,011**
R-quadro	0,450			0,106			0,553		

lowed an integrated approach by using an ABM model to simulate the diffusion performances of alternative potential spreaders.

We found that the ARD, a measure of how much each node is close to the whole network, and the clustering coefficients, which are related to the density of the neighborhood of a given node, are the main important factors to forecast the successfulness of an innovation spreader. These findings indicate that the diffusion of innovations in agriculture is fostered by spreaders relatively close and well connected to the rest of the web. Furthermore, to enhance the diffusion of innovations in agricultural networks, the innovation spreaders should be highly clustered, so as to provide the needed information reinforcement required for the adoption to occur. We have also observed a low share of agents with a high level of adoption rate, a further proof that designing sets of spreaders capable of influencing the network areas is much in need to promote technologies adoption.

These findings have direct implications for the policy agenda. For instance, they may be included in the design of policy measures and, in particular, within the context of the admissibility and the selection criteria in rural development plans:in order to enhance the spread of innovations, exploiting the relationships linking farmers in rural areas, the future policies may promote the creation of social interactions among farmers (i.e. promoting public and private social events to interconnect farmers); second, the policies for rural development may prioritize the requests of funds coming that are solicited by the most performing innovation spreaders, in order to exploit the multiplier effect that they will produce; third, the innovations should be promoted in areas where the existing networks are likely to be more receptive, a feature that can be easily proxied by the measures discussed in our paper. All these suggestions can be easily translated in admission and selection criteria in rural development plans: our analysis has direct implications for a better implementation of the future interventions.

Few words of caution. The present paper focuses on a case study with specific characteristics in terms of density of the network and clusterization of farmers, therefore the conclusions on the effects that the individual characteristics have on the rate of adoption would be externally valid only for those cases that are reasonably similar to our case study. Thus, in order to further increase the external validity of our conclusions it would be recommendable the analysis of different network structures (e.g. high vs. low density, regular vs. randomized structure, high vs. low average degree, or so). To the extent that promoting innovations in agriculture is a priority for stakeholders in public and private sectors, similar studies should be encouraged.

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