Alma Mater Studiorum - Università di Bologna

DOTTORATO DI RICERCA IN

SCIENZE E TECNOLOGIE AGRARIE, AMBIENTALI E ALIMENTARI

Ciclo 33

Settore Concorsuale: 07/A1 - ECONOMIA AGRARIA ED ESTIMO

Settore Scientifico Disciplinare: AGR/01 - ECONOMIA ED ESTIMO RURALE

ESSAYS ON SOCIAL NETWORKS, ALTRUISM AND INFORMATION DIFFUSION

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Esame finale anno 2021

Abstract

Innovations are vital for economic growth and improving the livelihood of society. In developing countries, where the overwhelming majority of the population is agrarian, adopting environmentally friendly technologies and combating climate change are more important than ever. However, the adoption rate of such technologies in developing countries is still low. Understanding both determinants of technology adoption and how new information about such issues diffuses within a community plays a significant role to effectively and equitably improve technology adoption rate in particular and welfare in general. This dissertation consists of three standalone articles that contribute to this cause and speaks to the economics literature concerning technology adoption and information diffusion in one way or another.

Technological innovations can be broadly classified as either brand new (radical) or upgraded (incremental). Having a clear understanding of the two groups of innovations' determinants plays a vital role in increasing their adoption rates. The first empirical paper focuses on this theme. We collect primary data from experts in the energy field and apply factor analysis and ordered logit regression to identify the drivers of the introduction and diffusion of bioenergy innovations in Ethiopia. The results reveal that the respondents' intentions to adopt brand new technologies are related to specific external conditions (i.e., factors supporting and hindering the behavioral performance) and the expected environmental benefits (i.e., a favorable attitude toward the consequences of the choice). Differently, the motivations to adopt an upgraded technology are negatively affected by a lack of knowledge of the innovation's public benefits (i.e., weak attitude), but positively associated with the social referents' judgments (subjective norms). The results highlight the importance of targeting different instruments to increase the adoption rate of the two types of innovations.

Lack of adequate knowledge/information is one of the serious impediments to increase the technology adoption rate and introduce new ideas. One common approach to diffuse new information to a broader society is contacting central (popular) individuals and rely on them to spread it via their social networks. The second and the third empirical paper of this thesis shed light on how we should select informants to effectively and equitably disseminate new information, mainly concerning environmental issues.

There are different standard centrality measures (SCMs) to select central individuals. The SCMs are based on network position and fail to incorporate central individuals' intrinsic motivation to spread information. In this study, we introduce an augmented centrality measure (ACM), which is a modifying eigenvector centrality measure, where the adjacency matrix is weighted by the altruism level of connected nodes.

To demonstrate the relative advantage of ACM, we collect primary data containing friendship networks, altruism, socio-economic characteristics, and prior climate change knowledge of 3693 Ethiopian high school students studying in 68 classrooms. One student was selected from each classroom, received training on climate change issues, and encouraged sharing the information with his/her classmates. Then, we reevaluate the climate change knowledge of all students in the post-training period. Our second paper's main result shows that selecting informants based on ACM achieves a better outcome than selecting informants based on SCMs to diffuse the information.

In the third paper, we further investigated the implications of centrality measures used to target informants from a gender perspective using the same experiment and data. In conservative societies like the one in Ethiopia, friendships tend to be gender-biased due to several reasons. Therefore, selecting informants based on SCMs could have an unintended consequence while diffusing information. Our analysis shows that as the informants' SCMs increase, the information inequality between their male and female classmates increases. Specifically, the informants' SCMs are negatively associated with their female classmates' knowledge of climate change compared to male classmates. In contrast, the informants' ACM is positively correlated with both male and female classmates' knowledge scores. It implies that selecting informants based on their altruism and network position (ACM) can reduce the information inequality between males and females.

The results from the two papers suggest that targeting informants based on network position and behavioral attributes ensures more effective and equitable transmission of information in social networks than selecting informants on network centrality measures alone. Notably, when the information is concerned with environmental issues.

ACKNOWLEDGEMENTS

First and foremost, praise and thanks to God for his blessings throughout my study to complete the thesis successfully.

I would like to express my sincere gratitude to the University of Bologna and the Institute of Advanced Studies for their unfailing support and assistance throughout my study. I am also grateful to the Erasmus Mobility Program for financially supporting my travel and data collection related costs in Ethiopia.

I am extremely grateful to my supervisor Prof. Marco Setti. He provided me all-rounded support to achieve my full potential over the past three years. He helped me set my research agenda, secure a grant for data collection, suggest courses and literature, and give me very interesting feedback during our frequent discussions. Moreover, he helped me to set my career goal and prepare for my next research endeavor. I am looking forward to keeping working with him. Professor was a great source of encouragement whenever I lose track and get frustrated with my research work. Apart from academics, he was my go-to person whenever I faced difficulty with my day to day life as an international student in Italy. He is one of the most positive person I ever know in my life. I am very thankful for everything you have done for me.

My sincere thanks go to Prof. Luca Merlino for hosting me at the University of Antwerp and for his invaluable guidance and support in developing the experimental design and data collection. And special thanks to Prof. Guilhem Cassan, Prof. Andrea Galeotti, Prof. Zenebe Gebreegziabher, Dr. Karoly Takacs and Dr. Simone Piras for their insightful comments and for the hard questions that helped me to see the research from various and broad perspectives.

I would like to express my gratitude to the high school students in Bahir Dar, Ethiopia, the school principals, the teachers (facilitators), supervisors and the data encoders who helped me during the data collection process, without whom I would have no content for my thesis. My gratitude also goes to the Amhara Region's Bureau of Education for granting me permission to undertake the survey, and Bahir Dar University's economics department, especially Mr. Taddesse Emiru, for allowing me to use their computer labs for data encoding purposes.

I am extremely grateful to my parents and my siblings for their unconditional love, prayers, and support throughout my life; thank you for giving me your best. Many thanks to my brothers

Wendimagegn Ghidey and Dawit Ghidey for always being there for me. My deepest gratitude goes to my husband Natnael Simachew for his support and encouragement, without which the three-year journey would have been difficult; you have been amazing, and you kept me going!

Last but not least, my gratitude is to my extended family members, friends, and colleagues for their encouragement and support.

Atsede

April, 2021

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Chapter 1

Introduction

Innovations are vital for economic growth and improving the livelihood of a society. They are even more crucial in developing countries where the imbalance between demand and supply increases over time. Although the rise in demand due to population growth explains the major share of the growing imbalance, inefficient utilization of resources also plays a significant role in aggravating the problem. Innovations could be the main solution to this imbalance through increasing productivity and reducing inefficient utilization of resources. However, the adoption rate of technology in developing countries is low (Udry, 2010; Duflo et al., 2011).

Several factors contribute to the low adoption rates (Croppenstedt et al., 2003; Udry, 2010). Among others, the availability of perfect information/knowledge related to innovation is crucial in the adoption decision. Several studies also show that social learning plays a significant role in individuals' decision processes (Bandiera and Rasul, 2006; Conley and Udry, 2001; Foster and Rosenzweig, 1995). Individuals learn from their peers, friends, and acquaintances about the existence of innovation, its profitability, its use, and other related information (Krishnan and Patnam, 2014; Magnan et al., 2015; Miller and Mobarak, 2015; Oster and Thornton, 2009; Cai et al., 2015). Therefore, social networks have a crucial implication for information diffusion. They are even more crucial in developing countries where formal institutions are missing to spread such vital information. Moreover, some researchers argue that beyond the information effect, social networks could affect the adoption rate via endorsement effects (Jackson and Yariv, 2011). [1]

Understanding the characteristics of social networks is vital for designing an effective intervention to spread information and diffuse technologies. Among other network characteristics, individuals' positions in the network have significant implications for information diffusion (Banerjee et al., 2013; Beaman et al., 2018; Jackson and López-Pintado, 2013). In particular, information can be effectively diffused by targeting central individuals who are highly connected in the network. This approach has several advantages. For example, since only a few individuals who serve as informants to their network receive the information to spread it to their village/local area, targeting central individuals is cost-effective and easy to apply. Central individuals also have more knowledge about their community and society (Alatas et al., 2016); they know who needs the information most and can spread it to those individuals efficiently.

One approach to selecting central individuals is to rely on their network positions. There are different standard network centrality measures (SCMs) that are widely used to select central individuals in the network. Degree centrality, betweenness centrality, closeness centrality, Bonacich centrality, and eigenvector centrality measures are some of the well-recognized SCMs in the network literature (Jackson, 2010). Although all of these measures show the central position of the individuals in the network topology, their implications vary across applications (Bloch et al. 2019). Empirical evidences also show that the effectiveness of the diffusion process through networks depends on which centrality measure is adopted to select the central individuals (Banerjee et al. 2012; Beaman and Dillon 2018).

The SCMs are constructed based on objective criteria. One way or another, they are directly related to the number of connections one has in narrowly or broadly defined terms. Such exclusive reliance on network position implies that SCMs miss some relevant factors; notably, they fail to incorporate central individuals' behavioral attributes to spread information effectively.

[1] However, empirical evidence shows that the endorsement effect is negligible, and the effect of social networks on individuals' decisions occurs through the information effect (Banerjee et al., 2013).

Moreover, individuals may strongly prefer to be connected and engaged in social interactions with others like themselves, which is referred to as "*homophily*" in the psychology literature. In a network with strong homophily, information diffusion through targeting central individuals (via SCMs) could have unintended consequences in the diffusion process, such as increasing inequality across social groups (Beaman and Dillon, 2018). In extreme cases, where the network is completely segregated, the information may be diffused only in the sub-groups where the first informant is located (Jackson et al., 2017). Hence, considering targeting tools beyond SCMs could be vital. One possible option is combining network position and individual behavioral attributes such as altruism. Since altruistic individuals care about others' well-being, selecting informants using the altruism augmented centrality measure (ACM) could effectively spread the information and also minimize inequality among social groups.

Several studies examine the role of the SCMs on the diffusion process in general and on information diffusion in particular (Banerjee et al., 2013; Beaman and Dillon, 2018; Cai et al., 2015). Quite a few studies have also tried to examine the relationship between network position and behavioral attributes (Brañas Garza et al., 2006; Kovářík et al., 2012; Caria and Fafchamps, 2019). However, to the best of our knowledge, there is no empirical evidence that shows the importance of combining network position and altruism in selecting informants to diffuse information.

This study has three main objectives. The first aim is to identify the main behavioral factors that determine the diffusion of a brand new (radical) or upgraded (incremental) innovation. According to the theory of diffusion of innovations, which is popularized by Everett Rogers in 1960s, at an early stage of the diffusion process, only a few agents decide to adopt while the majority of potential adopters take time to decide. This indicates that individuals may have different preferences in adopting brand new and upgraded innovations. Therefore, understanding the main behavioral attributes that determine individuals' decisions to adopt the two types of innovations separately could have crucial implications for policy interventions to increase the innovation adoption rates.

The second objective is to show the importance of augmenting the SCMs by incorporating informants' altruism to diffuse information, especially when the information is related to environmental issues. In particular, we introduce an augmented centrality measure (ACM), which is a modified eigenvector centrality, where the strength of links is weighted by altruism levels. Since altruistic individuals care about the well-being of others, they are more willing to contribute to the environmental good than others. This study looks at the effectiveness of selecting informants solely based on their network positions compared to selecting informants based on combining their network positions and their altruism levels in disseminating information.

The third objective of the thesis compares information inequality across gender groups when informants are selected based on SCMs and ACM. When information is diffused through central individuals, the presence of homophily and network segregation, less-connected groups, including minorities and females, may not receive the information, exacerbating information inequality. Thus, this study examines whether the ACM could play a vital role in reducing the adverse consequences of network segregation on information diffusion, particularly from a gender perspective.

The thesis consists of six chapters, including the three empirical studies that address the above objectives using primary data collected from Ethiopia.

Chapter 2 provides a summary of some influential diffusion models used to explain the spread of innovations and information from the marketing, epidemiology and network literature. Both diffusion models with and without network structures are discussed. This chapter is concluded by providing overviews of empirical studies that show the effects of network characteristics on information diffusion.

Chapter 3 presents our first empirical study, which identifies the main behavioral factors affecting the adoption of brand new and upgraded bioenergy innovations in Ethiopia. Using primary data collected from Ethiopian experts in the energy field, the study provides behavioral insights (including social norms/influences) into diffusing the two types of bioenergy innovation in Ethiopia. Therefore, this study gives useful and general information about the implicit role of social networks in the diffusion process by showing the effect of social norms on intentions to adopt the innovations.

In chapter 4, an ACM is introduced through combining the social network analysis with behavioral economics, and its implications to diffuse information related to climate change are shown. The empirical study is based on experimental evidence. The experiment was conducted by providing a training about climate change to a randomly selected student from each classroom who served as an informant to their classmates. Using the variation of trained students' network centrality and altruism, the study shows that selecting informants based on ACM outperforms selecting informants based on SCMs to diffuse information.

In chapter 5, our third empirical study is presented. This study uses the same experimental design and data as the previous study presented in chapter 4. Using the classroom network structure, it starts by showing the network segregation between male and female classmates. Then, using informants' social networks and their altruism, this study shows the role of selecting informants based on ACM to ensure equity by reducing the consequences of network segregation on information diffusion.

Chapter 2

Information diffusion process in social networks

Innovations, ideas, and information are easily diffused through social interaction (Kim et al., 2015; Cai et al., 2015; Beaman et al., 2018; Banerjee et al., 2019; Akbarpour et al., 2020). The diffusion of innovation not only depends on its features (benefit and cost) but also on the density of societal connections (Lamberson, 2016). Individuals' decisions are influenced by their neighbors/friends. To predict the causal association of social interaction and the diffusion process, it is important to understand and to model how individuals' interaction patterns affect their decision and diffusion process (Jackson, 2014). There are different models that explain the influence of social networks on the diffusion process. Some of these models implicitly show the implications of social interaction on the diffusion process, while others explicitly include the network structure in the model. In this chapter, some of the influential diffusion models developed in marketing, epidemiology, and the network literature are presented. We conclude by providing an overview of empirical studies that have investigated the role of social networks on the diffusion process, particularly within the domain of information diffusion.

2.1 Diffusion models

2.1.1 Bass Model

Bass (1969) model is one of the earliest models, and it is widely used in marketing analysis to show how a new product/technology is diffused in the market. The Bass model is a macro model, as it shows the aggregate innovation of the diffusion process in a society (Jackson and Yariv, 2011). It shows that the proportion of potential adopters that will adopt an innovation in a given period is a linear function of the proportion of current adopters (Bass, 1969). The model assumes that there are initial adopters who make their own decisions to adopt the innovation. These individuals could have connections and interactions with others; however, their decision to adopt the innovation is not influenced by others. They are called innovators. There are also other potential adopters who decide to adopt the innovation by following the innovators. These individuals are influenced by social interaction; they are called imitators. Thus, the adoption rate of an innovation at a given time is a function of two parameters: the rate at which innovators adopt the innovation and the rate at which imitators are influenced by previous adopters (Jackson, 2010).

To express the Bass model mathematically, assume a discrete time where $F(t)$ is the fraction of individuals who adopt the innovation at time t. Let say p represents the rate of innovators who adopt the innovation and q refers to the rate of imitation. Then, the model is represented by the difference equations:

$$F(t) = F(t-1) + p(1 - F(t-1)) + q(1 - F(t-1))F(t-1) \tag{2.1}$$

where $F(t-1)$ is the fraction of previous adopters, and $1-F(t-1)$ is the fraction of potential adopters who have not adopted but might adopt at time t. $p(1 - F(t-1))$ is the fraction of innovators who may independently decide to adopt without the influence of previous adopters. $q(1 - F(t-1))F(t-1)$ are fraction of potential adopters who adopt the innovation through imitating others. Assuming at time t adoption is not yet made, the general form of the model for a continuous period can be transformed to:

$$f(t) = (p + qF(t))(1 - F(t)) \tag{2.2}$$

where f(t) is the rate of change of adoption over time, and F(0) is equal to zero.

As equation 2.2 shows, the diffusion process of the innovation is determined by the two parameters (p and q) and the proportion of imitators that is a function of the previous adopters ($F(t)$). Graphically the diffusion curve depends on the relative size of p and q. As our simulation shows, when the rate of innovators is higher than that of imitators $p > q$, the diffusion process can be represented as figure 2.1, and when $q > p$ the diffusion curve would have an S-shape as represented on figure 2.2. Both the Bass model and the empirical findings describe that diffusion curve as S-shaped. [1] The intuition of the S-shape curve can be interpreted through classifying the entire diffusion process in three stages (Leskovec et al., 2007). At the initial stage, since the diffusion process depends entirely on the rate of innovators, only a few individuals adopt the innovation. When there are enough innovators to be imitated, the diffusion rate increases exponentially due to social influence. Gradually, as the size of potential adopters who have not adopted yet is low, the rate of diffusion declines, and the diffusion curve flattens at the end.

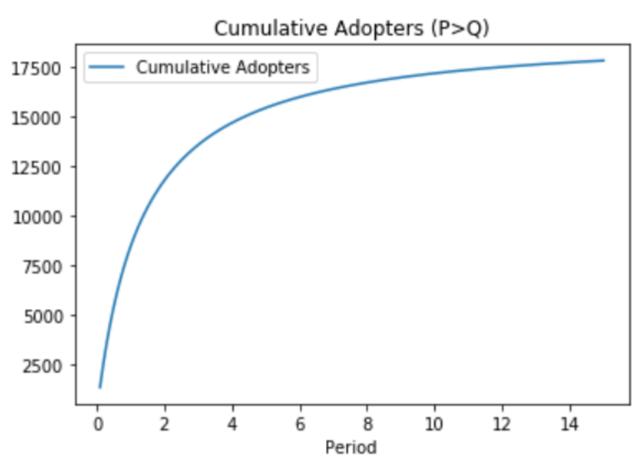

Fig. 2.1: When P = 0.75 and Q=0.03

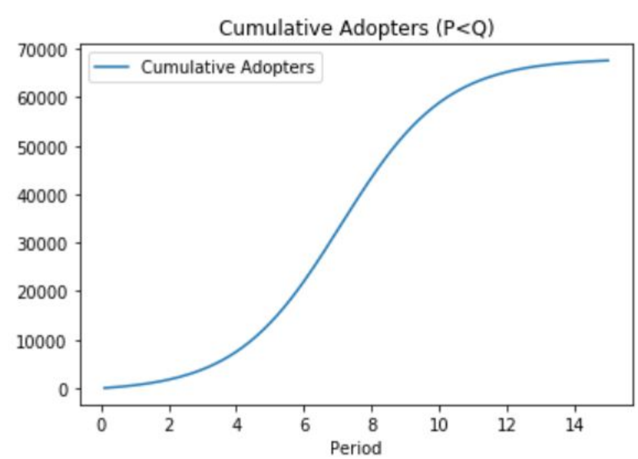

Fig. 2.2: When P=0.03 and Q=0.38

Although the model gives useful insight into the influence of social networks on the diffusion of innovations by showing the effect of imitation, it assumes an exogenous completed network, and

[1] For example, see (Nelson and Winter, 1977; Pizer and Popp, 2008; Allan et al., 2014; Rogers, 2010; Hötte, 2020).

the interaction between innovators and imitators is considered mechanical (Jackson and Yariv, 2011). Thus, the model fails to show the effect of network characteristics on the diffusion process.

2.1.2 Contagion Models

Since contagious diseases spread through contact (mechanically from an individual to others), the spreading process of disease is an intuitive way to describe the diffusion process that does not involve individuals' strategic interactions such as the spreading of ideas and information (Jackson and Yariv, 2011; Akbarpour et al., 2020). In this section, using the contagion model, the information diffusion process without explicitly including the network structure is presented.

The susceptible-infected (SI), susceptible-infected-recovered (SIR), and susceptible-infected-susceptible (SIS) are among the widely applied diffusion models in the epidemiology literature (Lamberson, 2016; Newman, 2010). Given that these models are similar except for some slight assumption differences, in this section, the SIR model is discussed. [2] The SIR model identifies the main factors and conditions that determine the diffusion process (information in our context). In general, the model is based on the assumption that the total population in a network is categorized by two states: individuals who have not heard the information yet (the uninformed), and those who have heard (the informed). The model further assumes that an informed person mechanically shares the information to uninformed individuals through contacts (Lamberson, 2016; Newman, 2010). It implies that the probability of spreading the information depends on the type and extent of interaction of the individual. Moreover, after some time, informed individuals become reluctant to pass along the information since the information is no longer new to them. The diffusion of the information declines over time.[3]

To describe the full model, assume there are N individuals, and some are uninformed and others

[2] For other contagion models (e.g., see (Newman, 2010)).

[3] the original model uses infected and susceptible instead of informed and uninformed. The wordings are changed for convenience as it suits our analysis. Moreover, the original model includes recovery rate, which we present as "oldness of the information". It is possible to assume that people tend to forget information as times goes by, and gradually refrain from talking about it.

are informed regarding the innovation, denoted by S, and I, respectively. Moreover, D represents the average number of contacts an individual has from the population at a given period of time. Suppose the information spreads randomly between informed and uninformed individuals. Then, SD is the average number of uniformed individuals that one contacts, and I/N is the probability of an individual contacting an informed person. Thus, the number of new informed individuals over time is equal to SDI/N. Moreover, all types of information may not spread with the same probability. Some types of information are passed along in every contact between informed and unformed individuals, while other types of information are not. Suppose θ is the probability that information sharing is successful in a given contact between informed and uninformed individuals. Then, the probability of the uninformed individual's hearing the information at a given time can be calculated as θSDI/N. The model also assumes that after some period of time, the informed individuals perceive the information as old and stop sharing it with others. Let us η denote the probability that an individual perceives the information as old. Then, the average number of informed individuals who actively spread the information per unit of time is equal to (1-η)I. Therefore, over time, the information is spread if the average number of newly informed individuals is greater than the expected number of informed who stop sharing it.

$$\theta SDI/N > \eta I \tag{2.3}$$

At the early stage of the information diffusion process, many individuals are not informed, implying that N is nearly equal to S. Hence, the condition of the information diffusion can be reduced to:

$$\theta d > \eta \tag{2.4}$$

Equation 2.4 shows that the diffusion process is determined by three parameters: the probability of successful information dissemination, the probability of perceived oldness of the information, and the average contacts of the individuals. The model gives useful insights into the importance of a network on information diffusion by including the individuals' average contacts in the model. Specifically, information spreads as the average number of contacts grows.

2.1.3 Contagion Models with Network Structures

Individuals' behaviors are highly determined by social interactions. For example, an individual who has many criminal friends and acquaintances is more likely to commit crimes (Calvó-Armengol and Zenou, 2004; Patacchini and Zenou, 2012b). Similarly, the decision whether to adopt an innovation or join a program is determined by the adoption decisions of friends and acquaintances (Banerjee et al., 2013; BenYishay and Mobarak, 2019; Miller and Mobarak, 2015). Moreover, the effect of a network on individuals' behaviors or decisions is not determined only by their direct contacts; rather, it is also affected by other aggregate network characteristics (Patacchini and Zenou, 2012a). Therefore, it is important to investigate the effects of the network structure's characteristics on diffusion by explicitly including it in diffusion models.

The SIR model presented above is based on the assumption that uninformed individuals make contact with informed individuals randomly, and their contact is sufficient to diffuse the information. However, in reality, people have a specific network (friends or acquaintances) whom they contact frequently, and the probability of meeting a random person is close to zero. The probability that an individual gets informed is affected by a set of her potential contacts (her network structures), and other the rest of the individuals are seldom important in this regard (Lamberson, 2016; Newman, 2010). The model with the network structure explains the spread of information in a similar way as that presented above; however, in the network version, an individual has contacts with her potential networks instead of the entirety of the population. As the result, the spread of the information is affected by the network's characteristics.

To describe the model with the network version, let us say there are N individuals in a given network; at initial period ($t = 0$), a single individual is informed, while others are uninformed. For simplicity, let us assume every informed individual perceives that the information is old after a specific period of time and stops spreading it to others. In the next period ($t = 1$), with a given probability (θ), an informed individual passes along the information to the uninformed neighbors successfully. Similarly, at $t = 2$, individuals informed in period $t + 1$ pass the information to their uninformed neighbors with the same probability. The diffusion of the information continues until all potential uninformed individuals in the network receive the information.

In general, it is possible to say that the necessary condition of diffusion stated in equation 2.4 is affected by the network characteristics. Therefore, at a constant (θ), the information diffusion process could vary from place to place due to the network structure differences. Therefore, it is important to identify and incorporate the network characteristics to determine the diffusion process.

2.2 Network Characteristics and Diffusion Process

This section discusses how social interaction affects the diffusion process. According to Jackson et al. (2017), the network characteristics could be categorized as aggregated (macro) and individual (micro) based on their effects on the diffusion process. The classification helps to explain under which types of network structures information/technology can rapidly spread, and the micro-network characteristics address the question such as who is the vital person in the society to rapidly and effectively diffuse it (Jackson, 2014; Jackson et al., 2017).

2.2.1 Macro Network Characteristics

Although there are many aggregated network characteristics, for practicality, only a few, such as degree distribution and segregation pattern among individuals, are discussed below.

2.2.1.1 Degree Distribution

An individual's number of connections with others is called an individual's degree (Jackson et al., 2017). The degree distributions provide useful information about the aggregate connectivity of a society and individual variation in terms of connectivity. In particular, the average degree of a network measures the average number of links (friends, neighbors, or others) an individual has in a given society. It shows the density of links presented in the network. A denser social network implies a higher average degree and stronger connectivity, which facilitates a higher rate of diffusion or contagion within a society (Jackson, 2014). Using the network density information of a given society, it is possible to predict whether an information/disease can be widespread. Moreover, the connectivity difference within the network that is captured by the degree variance also has a significant implication on the diffusion process. Given a similar average degree of two networks, the one with the higher variance could perform better in spreading information, as individuals with high connectivity could serve as a bridge or an information hub for their networks (Jackson et al., 2017). Highly connected individuals are more likely to be the first to learn new information from their many connections, and they serve as informants to many others through social interactions. In general, assuming all other things remain constant, as the degree of distribution of the network increases, the diffusion rate of the information/technology increases (Alatas et al., 2016; Jackson et al., 2017).

2.2.1.2 Homophily and Network segregation

Most friendships or social connections are highly determined by the individual's attributes such as gender, ethnicity, age, income, and so on. Individuals have strong preferences to connect with others similar to themselves, which is called *homophily* (McPherson et al., 2001). In strong homophily, only similar individuals connect with each other and form a larger network component, and the remaining individuals form another network graph (subgraph) with a relatively small network size.[4] Homophily and network segregation exist either due to individuals' preferences or by a force that limits their opportunity to interact with others (Bramoullé et al., 2012). The implication of the existence of homophily in a network has significant consequences in the diffusion of technology/information or contagion of diseases. For example, in a network with strong homophily, information may not spread to all groups of the society; it may only diffuse in a network where the first informed person exists. Moreover, this is reflected in current political debates as well, where people only interact and share information with like-minded contacts, which leads to political polarization (Halberstam and Knight, 2016).

[4] A component is a subset of connected nodes that creates a subgraph in a network (Newman, 2010; Jackson, 2010)

2.2.1.3 Average Distance and Network Diameters

In a network, the distance between two individuals is measured as the number of links that exist to connect them in the shortest path (Jackson, 2010). [5] As the distance between two individuals increases, there are many links in between to connect them. A network's average distance has crucial implications for the diffusion process. In particular, it determines the accessibility, the speed of diffusion, and the efficiency and accuracy of the information. For instance, in a network with a higher average distance, the network is sparser, and the information has to travel a longer distance to reach from one individual to another. As a result, it may take a long time, may not reach all individuals, and may decline in accuracy. The longest distance between a pair of connected individuals in a network is the network diameter. In general, the diameter of a network reveals whether a network is sparse or dense. Moreover, the diameters of a network provide useful information for setting a boundary for the diffusion process that can spread through the shortest paths (Jackson et al., 2017). Therefore, the combination of both the average distance and the diameter of a network provides useful information about the distribution of the distance between nodes in a network.

2.2.2 Micro-Network Characteristics

In this subsection, the main micro-network characteristics and their implications for the diffusion process are discussed. In particular, centrality measures in the network and the strength of links between nodes are discussed below.

2.2.2.1 Centrality Measures

A node's position in the network and to what extent the position is central is called centrality (Jackson et al., 2017). It is one of the intuitive and widely applicable network characteristics. Since network centrality shows the network position of a specific individual, it provides useful information to select injection points, for example, for targeting important individuals for vaccination against contagion, or to make behavioral changes through influencing others (Banerjee

[5] shortest path length is, among the alternatives, the minimum number of links to reach from one node to the other.

et al., 2019; Banerjee et al., 2013; BenYishay and Mobarak, 2019; Miller and Mobarak, 2015). In the network literature, there are different well-recognized SCM, including degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality. All these centrality measures show the central position of individuals in the network topology; however, their implications and concepts vary (Bloch et al., 2019). Some of the centrality measures are presented below.

Degree Centrality: Degree centrality simply counts the number of links (connections) a node has. For example, in a friendship network, the degree centrality of an individual equals the number of friends she has. It can be considered a measure of popularity of individuals in the network (Bloch et al., 2019). Since it captures the number of an individual's immediate contacts, it can be useful for understanding the role of nodes on their direct contacts in the diffusion process. In particular, it gives direct and useful insights into identifying a person who plays a significant role in contagion by spreading a disease to his neighbors in the network. An individual with a high degree centrality has the potential to spread disease/information to many of his network neighbors through social contacts. The degree centrality measure is very simple, but it does not give the full information about how well a node is connected in a network. For example, a node with a low degree of centrality may have an important network position by being connected with other central nodes or by having a closer contact with many nodes in the network (Jackson, 2010).

Closeness Centrality: Closeness centrality measures the distance of a node from other nodes in the network. In other words, it indicates, on average, how close a node is to other nodes in the network and how a node reaches others easily and quickly (Jackson et al., 2017). A node's closeness centrality can be calculated using the inverse of the average distance of a node from others (Bloch et al., 2019). If $\sum_{j \neq j} l_{ij}$ is the distance of node i from all others nodes j in the network, then the node's closeness centrality Cl_i can be calculated using a functional form of:

$$Cl_i = \frac{n-1}{\sum_{i \neq j} l_{i_j}} \tag{2.5}$$

Equation 2.5 implies that as a node's distance from others increases, its closeness centrality decreases. In other words, a node with higher closeness centrality is closer and can easily and quickly reach other nodes in the network. Thus, closeness centrality does not only consider a node's direct friends, but it also provides information about her proximity to her indirect links with others' nodes.

Katz-Bonacich Centrality: Bonacich centrality is one of the most intuitive measures. It captures the importance or influence of a node in the network and measures the importance of a node as a function of her neighbors' (her friends') importance in the network (Jackson, 2010). It does not only considers the connectivity or closeness of a node with others in the network but also incorporates how many important nodes have close contacts with the node. It is an applicable measure for identifying the influential person in the network to diffuse information or/and to select a person who has bargaining power in the network for negotiation.

To present the functional form of Bonacich centrality, let us assume that G is a matrix of node friendship (the adjacency matrix), such that G_{ij} is equal to one if i and j are connected (friend), and 0 otherwise. Let us say δ is the discount factor with a value between 0 and 1 that is used to discount the length of the walk from node i to others in the network exponentially. Closer-distance nodes (with a shorter walk-length) are given a higher value than others. In general, the centrality of node i can be expressed by:

$$Bonacich_i(G, \delta) = \sum_l \delta^l \sum_j G^l_{i_j} \tag{2.6}$$

The magnitude of δ determines the importance of distant links to the centrality measures. As the δ value approaches zero, distant nodes are less valuable for determining centrality, and the centrality is closer to degree centrality. In contrast, when δ is large, distant nodes are important and centrality is influenced by the entire network structure (Jackson, 2010).

Eigenvector Centrality: Eigenvector centrality is a special form of the Katz-Bonacich centrality measure. In particular, the centrality of a person is a function of the centrality of his neighbors in the network. The centrality of a person i is the sum of the centrality of her neighbors (Bonacich, 1987). Thus, using this measure, individuals are considered central if they have many links with other central individuals in the network. It is very intuitive and useful for identifying the influential and powerful individuals within a network. As an individual's eigenvector centrality increases, the person is more influential in the network.

$$Eigenvector_i = \sum_{i \neq j} G_{ij} * Eigenvector_j(g) \tag{2.7}$$

Where G_{ij} and g are the adjacency matrix and vector of centrality.

There is also empirical evidence that shows that individuals with a high eigenvector are influential in politics, in monitoring others, and in diffusing information to others in their network (Banerjee et al., 2012; Breza and Chandrasekhar, 2019; Cruz et al., 2017).

2.2.2.2 The Strength of Connections

In most cases, a network graph (connections) is represented in a matrix using binary values (Newman, 2010; Jackson, 2010). The binary values show the presence of links between two nodes, and it takes a value of 1, otherwise zero. However, a network graph with binary values could miss important information such as the strength of links between nodes (Jackson et al., 2017). For example, an individual may receive opinions or advice from her different contacts. However, she may not give the same weight to opinions from different sources. She could give more weight to opinions coming from some contacts than from others. In such a context, the representation of a network graph using binary values could lead to biased conclusions by missing important information about the heterogeneity of ties.

One of the simple ways to include the strength of ties in the network is by categorizing links as weak and strong. Empirically, individuals' links can be classified as strong or weak by adding additional information about the links, such as how much time the connected individuals spend together and how frequently they meet in a given period of time. The other approach to including the heterogeneity of links in the network is to encode a matrix where each element represents the weight (intensity, frequency, or other links' attributes) of the relationship from one node to the others (Newman, 2010). This approach provides the flexibility to weight links between two nodes at different values (Jackson et al., 2017). For example, in some cases, an individual could give more weight to the opinion of her friend, but her friend may not reciprocate in the same manner. Hence, adopting node-specific weighting measures could be important.

2.3 Empirical Reviews: Social Networks and Information Diffusion

In this section, some relevant studies that show how individuals' network centrality and strength of links affect information diffusion are reviewed. From the aggregated network characteristics, studies that show the impact of homophily in information diffusion are also included.

Several studies show that individuals with a high degree of centrality disproportionately benefit from obtaining information about an innovation, a job, a promotion, or a program (Beaman et al., 2018; Bramoullé and Huremović, 2017; Yang et al., 2019). However, the impact of informants' degree centrality on information diffusion is inconclusive. On the one hand, empirical evidence shows that highly connected individuals are good injection points to diffuse information. For example, Banerjee et al. (2012), finds that highly connected individuals spread information about the opportunity to earn money by participating in laboratory games in rural villages in India. On the other hand, there are studies that find no significant correlation between degree centrality and information diffusion (Beaman and Dillon, 2018). [6] Similarly, using an experimental approach, Beaman and Dillon (2018) examines the effectiveness of informants' SCM (degree centrality, betweenness centrality) on information diffusion in Mali. Their results show that individuals selected with both degree and between centrality measures are not significantly different than randomly selected informants in terms of information diffusion.

As noted in section 2.2.2, the major drawback of degree centrality measures is that they capture only the connectivity of an individual himself and do not consider his connections' network positions. However, the diffusion process is highly influenced by the network pattern (who is a

[6] Beaman and Dillon (2018) and use different SCM, including degree centrality, comparing its effect on the diffusion process

friend of whom) and the centrality position of both direct and indirect friends. Hence, empirical studies examine the importance of an individual's and his friends' network centrality on the diffusion process using Bonacich and eigenvector centrality measures. For example, Banerjee et al. (2012), using the network position of randomly selected first-informed individuals to their villages, examine the effect of informants' eigenvector centrality on micro-finance participation in rural villages of India. They find that the villages' average micro-finance participation increases as their informants' eigenvector centrality increases.

There is also evidence that individuals with high eigenvector centrality are influential in their network, and they affect others' behavior/commitments through spreading information about others' commitments. For example, Breza and Chandrasekhar (2019) examines individuals' commitment to saving money when they are monitored by individuals with high eigenvector centrality. They find that when the monitor's centrality increases, since savers hear gossip about themselves through back channels, they become more committed and increase their savings. Moreover, high eigenvector central individuals have more information about others in their communities, and they can be useful for policy intervention by easily identifying individuals who are in need of support (Alatas et al., 2016). In general, empirical evidence suggests that the effectiveness of central individuals on information diffusion depends on the types of centrality measure applied to identify them. In particular, the information is diffused effectively if informants are selected not only for their direct but also their indirect connectivity.

Moreover, the effectiveness of information diffusion and knowledge aggregation is also influenced by the strength of ties between nodes (Bakshy et al., 2012; Hahn et al., 2020; Yang et al., 2019). For instance, Bakshy et al. (2012), using 253 million Facebook users, show that weak ties play a more significant role in propagating novel information than strong ties.

As individuals also prefer to connect with others like themselves, social interaction is highly determined by other individual characteristics. Homophily commonly exists in social network data; for example, Currarini et al. (2009) shows that friendships among US high school students are highly influenced by ethnicity and race, implying that students of the same race are more likely to be friends than students of different races. The existence of homophily in networks could have significant consequences for the welfare distribution between groups (Beaman et al., 2018; Patacchini and Zenou, 2012a; Smith, 2000). This may indicate individuals are biased; they are more likely to pass along useful information to others like themselves. For instance, Beaman et al. (2018) documented that males are less likely to refer females for a job, even though they are qualified for the position. Similarly, Patacchini and Zenou (2012a) used the UK Labor Force Survey and found that individuals are more likely to pass along job information to others within their ethnic groups. Moreover, when there is strong homophily, the probability of information/technology diffusion is limited to a specific group (Beaman and Dillon, 2018). In some extreme cases, it may not spread to other groups, and the information/technology may not be diffused within the entire population, which could cause welfare inequality between groups. Beaman and Dillon (2018) show isolated groups in the society such as females are less likely to hear the information when the informants are selected based on SCM in Mali.

In some extreme cases, an intervention through central individuals could have unintended consequences through widening the inequality between social groups. These adverse effects could be because most of the SCM are based on objective measures that fail to incorporate behavioral incentives of the informants. There are also empirical studies that show the association between individuals' network position and their behavioral attributes. For instance, Leider et al. (2009) studied the social networks of U.S. college students and showed that donors (dictators) gave more to direct friends (friends with a social distance equal to 1). Similarly, Goeree et al. (2010) using students' social networks and dictator games, showed that donors' offers were inversely correlated with the recipients' social distance. In contrast, Brañas Garza et al. (2005) finds that when dictators do not know the identity of their recipients, they offer their friends the same as strangers.

Moreover, few studies show the effect of network position on altruism using lab experiments (Branas-Garza et al., 2010; Caria and Fafchamps, 2019). For example, Branas-Garza et al. (2010) use the dictator game and find that, on average, central individuals are altruistic and they are more willing to give to others. In contrast, isolated individuals are less altruistic and behave more selfishly. On the other hand, using the public-good game, Caria and Fafchamps (2019) show that central individuals are as altruistic as other average individuals in the network. Moreover, they find that central individuals are more concerned about others' expectations, and they become more altruistic when they are informed about their group's expectations. This could indicate central individuals behave altruistically with the motivation to gain more social recognition, rather than to improve others' well-being.

In general, few studies examine the behavioral attributes (altruism) level of central individuals. To our knowledge, there is no empirical evidence on the importance of augmenting the SCM by combining both informants' altruism levels and their network positions to diffuse information. Altruistic individuals could play a vital role in spreading information, in particular, and in welfare distribution in general (Foster and Rosenzweig, 2001; Chen et al., 2014; Obrenovic et al., 2020). Therefore, it could be important to adopt an ACM and examine its effectiveness on information diffusion and its implication in reducing the effect of network segregation on economic outcomes.

Chapter 3

Behavioral Precursors in the Innovation-decision Process: The Case of Bioenergy in Ethiopia

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Abstract

Despite ample potential energy sources, most developing countries depend highly on fuelwood to meet their energy needs, with repercussions on the environment and human health. Bioenergy innovation is one way to combat this issue, the adoption rate of which remains low in many of them. Using primary data collected from Ethiopian experts in the energy field, this study combines factor analysis with ordered logit regression to identify the drivers of the introduction and diffusion of bioenergy innovations. Moreover, this study detects and analyzes the behavioral precursors of the respondents' intention to adopt brand new or upgraded bioenergy innovations. The results reveal differences between their decision-making processes and suggest targeted research and policy strategies to boost the adoption rate of bioenergy innovation.

Keywords: Theory of Planned Behavior, Adoption, Bioenergy, Orderd Logit Model, Ethiopia

[1]This chapter is largely drawn from Alemayehu, A. G., Gebreeyesus, A., Palladino, G., Setti, M. (2020). Behavioral precursors in the innovation-decision process: The case of bioenergy in Ethiopia. Energy Strategy Reviews, 30, 100499.

3.1 Introduction and Conceptual Background

Energy is a fundamental resource for any economic system and of strategic significance for developing countries whose economies are starting to take-off. Moreover, widespread access to clean and affordable energy improves environmental quality and individuals' well-being. However, despite ample potential for energy production, most developing countries depend highly on fuelwood to meet their energy needs. This dependence has severe repercussions for eco-systems, including deforestation, land degradation (Mekonnen, 1997), and biodiversity loss, as well as indoor air pollution and high rates of mortality and morbidity (Drabik et al., 2016). Thus, considering the negative effects on the quality of life and climate change, there is an urgent need for sustainable energy-related innovations [2] (Dincer, 2000; Omer, 2008; Akella et al., 2009). Addressing this need requires careful consideration of challenges and opportunities affecting the adoption of feasible solutions and the exploitation of local renewable sources. On the one hand, efforts should be made to improve the efficiency and sustainability of currently deployed technologies, e.g., by introducing eco-compatible biomass or ameliorated tools in the energy generation process. On the other hand, strategies should be designed to create an environment for entrepreneurs, investors, and other stakeholders that is conducive to the adoption of radical innovation and smart energy systems (Tessema et al., 2014; Lund et al., 2017). Accordingly, this study aims at identifying and analyzing the major factors affecting the adoption and diffusion of both these two types of bioenergy innovations in Ethiopia and refers to bioenergy as the energy generated from renewable and sustainable biological sources.

In the past two decades, the Ethiopian government has launched several energy generation projects to meet domestic demand. However, only 23% of the total population currently has access to electricity (Group et al., 2017). Moreover, there is a huge energy access divide between the country's urban and rural areas. Specifically, while 87% of the urban population has access to electricity, only 5% of the rural population is connected to an electrical grid (Group et al., 2017). Indeed, Ethiopia's energy sector is highly dependent on biomass (firewood, charcoal, crop

[2] For example, (Gebreegziabher et al., 2017) shows that the diffusion of improved cooking stoves has the potential to save around 1,400 ha per year from deforestation in Ethiopia.

residues, and animal dung) that accounts for 89% of the national total energy consumption in 2010 (MoWIE, 2012; EUEI, 2013). As such, millions of women and children in rural areas devote their time collecting fuelwood for domestic functions (e.g., food cooking and lighting) (Karekezi and Majoro, 2002), while the urban poor spend a sizable amount of their income on their daily energy needs (Kebede et al., 2002). Imported petroleum is an alternative power source in Ethiopia, accounting for 7% of total energy use, while an important and growing source is represented by the hydropower generation (Mondal et al., 2018).

Nevertheless, the rising demand for fossil fuel due to population and economic growth forces the country to allocate a large portion of its financial reserves to import oil, negatively affecting the trade balance and level of pollutant emission. Introducing sustainable bioenergy technology can be one of the prime solutions to the country's growing energy demand, providing widespread energy access for both urban and rural households. However, like other developing countries, the adoption rate of modern, clean, and sustainable energy technology in Ethiopia is low (Gebreegziabher et al., 2017; Beyene et al., 2015; Beyene et al., 2015). Thus, it is crucial to analyze the determinants that can hinder or boost the deployment and propagation of bioenergy innovation in rapidly evolving economies such as Ethiopia.

Several factors are influencing the choice to adopt sustainable (bioenergy) innovation (Rauschmayer et al., 2015). Among these, Kabir et al. (2013) find that socio-economic conditions, such as educational level, strongly influence the decision to adopt novel bioenergy technologies in Bangladesh; Pine et al. (2011) show that awareness of health conditions is the main factor that affects the adoption rate of modern improved biomass stoves in Mexico, and Sovacool (2013) identifies the effect of public-private partnership in diffusing renewable energy services. Together with contextual, technological, and economic determinants, studies confirm the importance of behavioral precursors affecting the decision-making process (Wilson and Dowlatabadi, 2007; Kaufmann et al., 2009; Knobloch and Mercure, 2016). These behavioral precursors are significant when the choices are repetitive and deal with vital resources as in the case of the energy-related decisions. For instance, agents might develop positive or negative preferences for new solutions as a result of their propensity for perceived challenges and opportunities (e.g., time and risk preferences), their knowledge and awareness of innovation-related outcomes,or social pressures (Cialdini et al., 1990; DellaVigna, 2009; Evans, 2012; Young, 2009; Mallett, 2007). Behavioral precursors represent an essential leverage for supporting innovation-oriented motivations and decisions. Accordingly, policy interventions aimed to increase the adoption rate of new energy solutions should take into due account of these factors. However, there is limited evidence on the behavioral precursors that drive the adoption of novel, environmentally friendly technologies (Steg and Vlek, 2009; Kollmuss and Agyeman, 2002; Steg et al., 2014). Since the individual and situational diversity implies an array of behavioral patterns (Ajzen, 1985; Ajzen, 1991; Sen, 1992), when addressing the choice to adopt a new energy solution (especially in developing societies), it is important to study the decision-making process by differentiating between categories of adopters and between types of innovations (Kaufmann et al., 2009). Indeed, agents may have specific preferences when coping with a brand new or an upgraded technology. This affects the aggregate rate of innovation adoption, thus of energy access, in a society. According to the innovation diffusion theory (Rogers, 2010), new technology dissemination depicts an S-shaped curve where only a few adopters in the early stage invest in the innovation, while other agents take time to choose. This raises the question of what factors influence individuals to adopt an upgraded (ameliorative) innovation instead of a newly available one.

Regarding the types of innovations, this study categorizes new bioenergy solutions in to brand new (i.e., radical) and upgraded (i.e., improved) innovation based on whether the innovation is yet to be introduced in the target community (e.g., waste-to-energy plants) or comes with a new feature enhancing the performances of already-implemented tools and systems (e.g., more efficient cook stoves). This enables distinguishing between adopters with a high propensity to deploy a brand new bioenergy technology (BNT) and adopters oriented toward an upgraded bioenergy technology (UBT) [3]. By detecting the behavioral precursors driving the adopters' innovation-decision processes for the two types of innovations, this study provides behavior-centered insights relevant to the introduction and diffusion of new bioenergy technologies in Ethiopia. These goals are achieved by analyzing cross-sectional primary data from a survey of 95 Ethiopian stakeholders, using both

[3] Throughout this study, the terms intention, motivation, and preference are considered synonymous, and so are the terms of behavioral precursor and behavioral antecedent.

factor analysis (FA) and ordered logit methodologies. The results reveal that the respondents' intentions to adopt a BNT are related with specific external conditions (i.e., factors supporting and hindering the behavioral performance) and with the expected environmental benefits (i.e., favorable attitude toward the consequences of the choice). Differently, the motivations to adopt an UBT are negatively affected by a lack of knowledge of the innovation's public benefits (i.e., weak attitude), but positively associated with the social referents' judgments (subjective norms). The remaining part of this study is structured as follows: section 2 describes the theoretical framework, focusing on the selected behavioral model. Section 3 provides insights on the methodological approach; section 4 presents the results; and, finally, section 5 provides discussion and concludes with some policy implications.

3.2 Theoretical Model and Research Objectives

Different economic and psychological models aim to explain human behavior when deciding to adopt innovation(Darnton, 2008; Chatterton, 2011). For instance, the subjective expected utility models assume that decision-makers are rational, selfish (thus focused on their payoff), and efficient users of fully available information sets. According to these models, when choosing an option the agents reliably identify, evaluate, and compare all attributes of feasible alternatives.However, theoretical constructs and empirical evidence show that agents' decisions often deviate from this standard scheme (Knobloch and Mercure, 2016). Since judgments are comparative, individuals contrast the real option with their personal expectation ("similarity judgments," (Tversky, 1977)), thus resorting to heuristics and incurring systematic biases (DellaVigna, 2009). In particular, evidence shows that when dealing with a choice inherently associated with uncertainty and framed as a gain (such as the bioenergy innovation-decision this study analyzes), people tend to display risk-averse behavior. This raises two questions. First, to what extent can the contextual conditions influence this aversion and explain the deviation of the agents' actual decision from the standard model? Second, which other behavioral precursors (e.g., attitudes and abilities) contribute to the low adoption rates of cost-effective technologies? To address these questions, recent studies have identified some behavioral factors, such as social influence and individuals' awareness of environmental benefits (Kabir et al., 2013; Kaufmann et al., 2009; Halder et al., 2016; Gao et al., 2017) that systematically affect agents' decision to adopt green technologies.

By referring to alternative behavioral models such as the Theory of Planned Behavior (TPB, Ajzen, 2015), this study analyzes behavioral precursors that account for different levels of propensity for bioenergy innovation (Figure 3.1). The TPB is a socio-psychological model that is largely adopted in different fields of behavioral analysis, such as environmental psychology (Thøgersen, 2014; Russell et al., 2017; Schlüter et al., 2017) and innovation diffusion (Kiesling et al., 2012). The TPB does not assume decision-makers' rationality, but describes the human behavior as the result of a structured process derived from a series of cognitive determinants (behavioral precursors). Unlike the standard model that infers the decision-making process from observed behavior, the TPB analyzes the process by directly assessing its constitutive elements. According to the TPB, an individual's decision is a function of the intention to engage in the behavior, i.e., the motivation is the immediate antecedent of the performable action and measures the interest in the option (Ajzen, 1985; Kaufmann et al., 2009). In turn, the individual's intentions are assumed to depend on specific precursors: attitudes, subjective norms, and perceived behavioral control; which are considered distant predictors of the behavior.

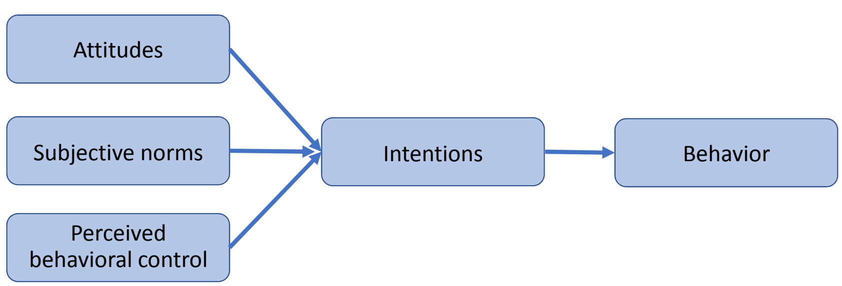

Fig. 3.1: The theory of Planned Behavior- TPB (Source: Ajzen, 2015)

Attitudes express beliefs and evaluations of positive or negative thoughts (i.e., knowledge) and feelings (i.e., awareness and moral norms) about the possible consequences of performing the behavior. In this study, attitudes are elicited by the knowledge and awareness of the expected outcomes of adopting a bioenergy innovation. Specifically, these outcomes include the assessed profitability of the innovation and the considered healthy and environmental benefits the technology can generate in terms of improved individual and community's quality of life and reduced level of pollutant emissions.

Subjective norms (the second behavioral precursor affecting the individual's intentions) are determined by the social customs and judgments on the considered behavior and its implications (descriptive and injunctive norms, i.e., what the social referents such as customers and citizens do or approve, respectively (Cialdini et al., 1990)). We derive the subjective norms from the respondents evaluation of what the others do (i.e., imitation) or think (i.e., social acknowledgment and collaboration with customers as measure of their opinion) about the bioenergy-oriented choice.

The third antecedent of the motivations is the perceived behavioral control that refers to the individual's evaluation of the opportunities and challenges affecting the performance of the behavior. In this study, the control factors concern both the decision-makers' skills and abilities to deploy and manage the new technology as well as the external conditions (e.g., availability of feasible technologies and relational resources) facilitating or interfering with the decision to adopt the innovation. Therefore, we measure the accessibility to public financing, the capacity to design relevant organizational strategies, the availability of solutions provided by the research, and the collaboration with foreign universities to study the relationship between the respondents' perceived behavioral control and their intention to adopt the bioenergy innovations.

This study derives a behavioral segmentation of Ethiopian experts based on their intention to introduce alternative bioenergy innovations with different risk levels, and, according to the TPB, directly measures the related behavioral precursors through surveyed evaluations of the main obstacles and drivers affecting the decision. The survey is designed to test whether there is an asymmetry between the adopters' decision-making processes as defined by the following research hypotheses:

- The intention to adopt a BNT is significantly affected by extrinsic (situational) conditions (i.e., the perceived behavioral control);
- The intention to adopt an UBT is significantly affected by intrinsic (individual) factors (i.e., their attitudes).

The first hypothesis is based on the assumption that adopters of a BNT are in general eager to try a new solution or more likely to be open-minded, and possess abilities and skills (Rogers, 2010) that enable them to exploit the possible economic, environmental, and social benefits that sustainable technologies can provide. Therefore, adopters' strong intention to use a brand new innovation is more likely affected by contextual factors such as collaboration with research centers and access to cutting-edge bioenergy technologies. By contrast, adopters of an UBT are assumed to react weakly to technological innovations; thus, their intention to adopt a new bioenergy solution is expected to be affected by an inadequate knowledge and awareness of the possible outcomes the performable behavior can produce.

3.3 Methodology

3.3.1 Sampling and Data Collection

Purposive sampling technique was used to select and recruit the respondents among the local experts active in the energy sector in Addis Ababa and Mekelle cities, Ethiopia. Addis Ababa is the capital of Ethiopia and by far the largest city, while Mekelle is a regional capital city with flourishing bioenergy sector. The two cities were chosen because they include various representative experts with direct and grounded experience in the energy domain. Moreover, the sample was aimed to include entrepreneurs who actively deal with innovation-centered decisions in the energy sector including entrepreneurs from agriculture, processing industries, and energy services as well as private and public operators (e.g., consultants and extension services), and policymakers. The experts were selected by local university partners, contacted at their local address by enumerators, and invited to the local universities (Addis Ababa University, and Mekelle University) to participate in the survey.

The primary data were collected using a pre-validated self-administered questionnaire in October, 2015, and in December, 2015, in Mekelle and Addis Ababa, respectively. Respondents participated as representative of their organizations, were briefly introduced by the enumerators about the questionnaire that even included questions specific to their organizations, and provided with clarifications whenever they raise concerns. The questionnaire includes four sections, and it aims to measure the respondents' evaluations about the different topics using an ordinal scale ranging from 1-9. In the first section,experts are required to assess their level of interest in adopting the two types of bioenergy innovations (i.e., BNT and UBT). The second and third sections focus on the respondents' opinion on the obstacles and drivers affecting the introduction of bioenergy innovation (19 obstacles and 14 drivers: Table A1 and A2, respectively), while the fourth section deals with the main factors motivating the diffusion of innovation (15 determinants: Table A3). These last sections are designed to elicit respondents' behavioral precursors associated with the adopters' intention to introduce the bioenergy innovation.

A major limitation of the survey is the relatively small sample size due to the limited number of experts in the energy field in Ethiopia despite the focus on the two leading areas of the country. Nonetheless, this study provides specific information on the decision-making process concerning the adoption of new bioenergy solutions and also offers relevant insights to researchers and policymakers regarding orientation of or support for technological changes. A second limitation is the lack of information on the socio-demographic characteristics (i.e., age, gender, ethnicity, and education) of the respondents. We refrained from asking such detailed questions, as respondents would be less likely to participate in the survey. Nevertheless, a few questions, such as respondents' sector or organization size, were included. Unfortunately, the response rate was very poor and not sufficient to be reported in this study. However, according to the TPB, these attributes "are considered background factors," affecting the individual preferences and behavior "only indirectly," with their effect captured by the behavioral precursors this study analyzes (Ajzen, 2015). A third limitation is the possibility that respondents reveal high interest in both the innovations (brand new and upgraded). For this particular class of respondents, it is challenging to associate their subsequent responses (e.g., lack of knowledge) directly to BNT or UBT. In this study, this was the case for a few respondents (8%) that were classified as BNT adopters. Finally, it was not feasible to disentangle the respondents' personal opinion from the interest of their organization/community.

3.3.2 Data Analysis

This study implements a two-phase data analysis using Stata/SE 15.0 to analyze the main determinants of the bioenergy innovation process and to identify the relevant behavioral patterns affecting the innovators' decision-making. First, similar to (Akimoto et al., 2014), this study conducts an exploratory FA to achieve a better understanding of the general obstacles and drivers that influence the introduction and diffusion of new bioenergy-centered solutions in Ethiopia. Factors with eigenvalue greater than one are retained in the model. Second, ordered logit estimations are drawn to detect the major behavioral precursors fostering or inhibiting the local adopters' choice when facing prospective bioenergy alternatives and the related risks and opportunities. With reference to the FA, the methodology determines core unobservable factors (i.e., the continuous latent variables F_j, Hutcheson and Sofroniou, 1999) explaining the variance and correlations of a large set of observed variables (Bartholomew et al., 2008; Tryfos, 1998). Two tests are applied to check the robustness of the developed FA models: Bartlett's test of sphericity that enables rejecting the hypothesis that the variables are uncorrelated (1% of significance level), and the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy that measures the data suitability for the FA. In this study, the determinants (i.e., obstacles and drivers) of the introduction and diffusion of bioenergy innovation are described by the manifest variables (x_i) that FA groups into latent factors (F_j), as in the following linear function:

$$X_i = \beta_{i_0} + \beta_{i_1} F_1 + \beta_{i_2} F_2 + \beta_{i_3} F_3 + \;---\; + \beta_{i_j} F_j + \epsilon_i \tag{3.1}$$

where β_{i_j} represents the factor load for each X_i, and ϵ_i the error term.

After extracting the general factors F_j affecting the possible evolution of the Ethiopian bioenergy sector, this study develops two ordered logit regression models to scale down the analysis to the behavioral precursors of the individual innovation-decision process. The related outcome variables are defined by the respondents' intention to adopt a new bioenergy technology (i.e., BNT or UBT). In particular, three possible degrees mirror their self-evaluated level of preference for the proposed two types of innovations. If the respondent's intention to adopt the innovation is higher than the 75^{th} percentile (between the 75^{th} and 50^{th} percentiles, or below the 50^{th} percentile), then the underlying motivation is assumed strongly (moderately, or weakly) oriented toward that type of innovation. Afterward, the intention to deploy the two types of innovations is regressed on explanatory variables(x_i) derived from the set of the respondents' evaluations [4]. Finally, the significant variables elicited (x_i) are associated with the corresponding behavioral antecedents (attitudes, subjective norms, and perceived behavioral control) for each of the two types of innovations. From this behavioral perspective, the general regression model is expressed by equation 3.2:

$$Z_{(B,U)} = \alpha_{(B,U)} + \delta_{(B,U)}\, attitude + \eta_{(B,U)}\, subjective\ norm + \theta_{(B,U)}\, Behavioral\ control + \epsilon_{(B,U)} \quad (3.2)$$

where $Z_(B,U)$ represents the respondents' intention to adopt a brand new or an upgraded bioenergy innovation, respectively, while δ, η, and θ are the coefficients of the explanatory variables, i.e., the behavioral antecedents of the related innovation-decision process. Moreover, in order to ease the interpretation, the odds ratio is computed and discussed. The Brant test of parallel regression assumption is applied to test the proportional odds assumption. Finally, a robustness check is conducted by developing logit models as alternative estimation techniques.

3.4 Results

The results achieved through the FA and the ordered logit models are based on the evaluations made by a sample of 95 experts who completed the questionnaire. The respondents are local experts in the energy field such as entrepreneurs (7 respondents), private and public consultants (64), and policymakers (12); while the remaining subjects (12) belong to other professional profiles. About a half of the respondents (51%) show a high or medium level of interest in adopting a BNT,

[4] Please see the questionnaire in the appendix

whereas the equivalent share for the UBT is about 64%. In general, traditional societies are more likely to have low interest in adopting innovations. This generally weak propensity to adopt an innovation suggests an expected low acceptance rate for new, sustainable bioenergy solutions in Ethiopia. This leads to the hypothesis that the potential adopters may face numerous obstacles affecting their choice to deploy new technologies (e.g., limited financial support, risk aversion, and lack of knowledge of the bioenergy domain) that are not counterbalanced by adequate motivations or supportive conditions. This hypothesis finds confirmation in the respondents' evaluation on the barriers to and drivers of the introduction of bioenergy innovation. Table 3.1 shows that inadequate contributions from research and development (R&D), and lack of access to information on bioenergy innovations are identified as the major obstacles to the innovation adoption. Moreover, the lack of knowledge of environmental and public benefits, the limited access to public financial facilities, the unavailability of skilled manpower, and risk aversion are the additional obstacles the respondents recognize.

Table 3.1: Obstacles to the introduction of bioenergy innovation

Variables	Mean	S.Deviation
Unavailable qualified staff	7.21	2.47
Low benefit/cost ratio	6.12	2.28
Risk due to technology	7.04	2.49
Risk due to market conditions	5.57	2.54
Limited access to private financing	7.03	1.92
Limited access to public financing	7.11	2.38
High fiscal burden	5.10	2.32
Lack of information on bioenergy innovations	7.63	2.00
Lack of knowledge of environmental benefits	7.32	2.13
Lack of knowledge of public benefits	7.09	2.27
R&D not addressing the business' needs	7.69	2.10

Table 3.2 describes the drivers favoring the introduction of bioenergy innovation. Accordingly, the increasing energy demand and the interest to reduce the GHGs emissions stand out as the main fostering factors. Moreover, the respondents assign a high score to the contribution the bioenergy

technologies make to the environmental safeguard and to the quality of life.

Table 3.3 below shows the respondents' perception of the main drivers contributing to the diffusion of the bioenergy innovation across the community/country. The increasing demand of energy access and use in Ethiopia emerges as the most important incentive for spreading the new bioenergy technologies.

Table 3.2: Drivers of the introduction of bioenergy innovation

Variables	Mean	S.Deviation
Energy demand	8.42	1.58
Financial support to investments	6.90	2.15
R&D	6.32	2.32
Contribution to quality of life	7.60	1.67
Contribution to environmental quality	7.74	1.81
Reduction of GHGs emissions	8.02	1.85
Social acknowledgment	6.29	2.06
Collaboration with providers/technical assistants	6.36	1.87
Collaboration with customers	7.61	1.85
Collaboration with other enterprises	6.66	1.72
Collaboration with institutions	6.79	1.89
Collaboration with local universities	6.87	1.97
Collaboration with foreign universities	6.87	2.16
Economic return	7.02	1.67
Social responsibility	7.75	1.87

Table 3.3: Drivers of the diffusion of bioenergy innovation

Variables	Mean	S.Deviation
Growing of energy demand	8.14	1.49
Entrepreneurs' imitative willingness to change	7.44	1.74
Human resources(skills)	7.26	1.74
Contribution to quality of life	7.62	1.57
Contribution to environmental quality	7.79	1.43
Reduction of GHGs emissions	7.98	1.87
Social acknowledgment	6.27	2.07
Social responsibility	7.39	2.14
Organizational strategies	7.50	1.76
R&D	7.04	1.93
Social norms and local partners	6.75	1.88
Social norms and foreign partners	6.89	1.99
Policy incentives	6.58	1.84
Public investments (infrastructures)	6.59	1.74
Private investments	6.06	1.88
Credit availability	6.93	2.11

3.4.1 Behavioral Precursors in the Innovation Decision-making Process: Factor Analysis and Regression Results

This section aims at detecting and analyzing the behavioral precursors of the bioenergy-oriented innovation-decision process. Firstly, from a general perspective the FA elicits the overall obstacles and drivers associated with the introduction and diffusion of bioenergy innovations. Secondly, a distinction between types of innovations and between adopters is made and specific regression models are developed so at to identify the behavioral precursors underlying the intention to adopt a BNT and an UBT.

3.4.1.1 Behavioral precursors in the innovation decision-making process: FA results

The rotated factor matrix in Table 3.4 lists the factor loadings for the first FA model concerning the assessed obstacles to the introduction of bioenergy innovation in Ethiopia, namely the lack of knowledge and the (limited) financial facilities. Based on the modeled linear combination of the observed variables, these two factors explain the 43% of the total variance of the respondents' evaluations of obstacles to innovation adoption.

The first factor, knowledge and risk (F1.1, at 33%), reveals how much the respondents value the full understanding of the innovation's effects in their decision-making. Limited access to information on technological issues, and possible environmental and public benefits, as well as the gap between public R&D and business' needs hinder the introduction of modern bioenergy solutions in the country. In addition, the risk related to the new technology is moderately associated with F1.1. This prime obstacle (the lack of knowledge of the innovation's opportunities, thus the lack of awareness of the implications for the society) limits the strength of the behavioral beliefs (the capacity to link choice and its outcomes), thus feeding (from a TPB perspective) unfavorable attitudes toward the decision to adopt the innovation. The second factor, (limited) financial facilities (F1.2, at 9.6%), relates to the difficulties in obtaining affordable capitals for investment purposes(i.e., limited access to private and public financing). These two obstacles (F1.1 and F1.2) show that individual behavioral attitudes (i.e., uncertainties related to the innovations, and knowledge of the outcomes the decision produces) prevail over the situational and operational concerns (i.e., financial and fiscal conditions affecting the agent's behavioral control) in the decision-making process dealing with the choice to introduce bioenergy innovation in Ethiopia.

Table 3.4: Obstacles to the introduction of bioenergy innovation.

Variables	KMO	Communality (Share of Variance)	Factor 1.1 "Knowledge and risk"	Factor 1.2 "Financial facilities"
Unavailable qualified staff	0.845	0.291	0.455	0.29
Low benefit/cost ratio	0.834	0.269	0.454	0.25
Risk due to technology	0.689	0.264	0.514*	0.007
Risk due to market conditions	0.807	0.376	0.363	0.494
Limited access to private financing	0.663	0.569	0.004	0.754**
Limited access to public financing	0.804	0.562	0.318	0.679*
High fiscal burden	0.632	0.22	0.107	0.457
Lack of information on bioenergy innovations	0.831	0.542	0.687*	0.265
Lack of knowledge of environmental benefits	0.828	0.695	0.746*	0.372
Lack of knowledge of public benefits	0.738	0.639	0.797**	-0.06
R&D not addressing the business needs	0.793	0.303	0.507**	0.213
No of Variables			11	11
Eigenvalue			3.67	1.06
Variance (extraction capacity)			2.84	1.89
Total variance explained (%)			0.33	0.096
Cummulative variance (%)			0.33	0.43

Note: Bartlett's test of sphericity:chi square=296.35; df=55; P-Value= 0.0000; KMO = 0.78. Factor loadings (i.e., measures of the relationship between the observed variable and the factor F) with value ≥ 0.75 **, 0.75 - 0.5 *, and 0.5 - 0.3 are considered "strong," "moderate," and "weak" loadings, respectively.

The second FA model, based on the respondents' assessments of the innovation-decision drivers, identifies two main factors that explain the 57.8% of the total variance: networking and environmental concern (Table 3.5).

The first factor, networking (F2.1, at 49%), emerges as the major driver of innovation introduction in Ethiopia emphasizing the necessity for potential adopters to establish collaborations with institutions and other operators. Specifically, the results suggest that these interrelationships should be dual-goal oriented and include collaborations with research centers and universities (to acquire knowledge in choosing and deploying the new bioenergy solution), and various technical-support services provided by public and private organizations (to develop skills and ability necessary to manage the innovation, while limiting the inherent uncertainty). In addition to the collaboration with relevant stakeholders, the "economic return" and "financial support to investments" variables also show a high correlation with F2.1. A positive attitude toward new bioenergy solutions is detected by the second factor, environmental and socio-economic concerns (F2.2, at 8.8%), that outlines the adopters' consideration for the sustainability of the outcomes (e.g., increased environmental quality, reduction of emissions, improvement of the quality of life, and meeting the energy demand) (Goldsmith and Goldsmith, 2011) the envisaged innovation can produce.

Regarding the main drivers of the diffusion of bioenergy innovation across the country, the third FA model identifies two main factors (external conditions and social motivations) that explain 54.8% of the total variance (Table 3.6). The first factor, external conditions (at 45%), gathers a series of contextual variables that foster the innovation propagation and is mainly attributable to public policies supporting the adopters' investment choice (incentives and investments, F3.1). Together with these measures, a set of situational conditions are identified as additional determinants of the innovation diffusion such as the availability of private financing, accessibility to R&D findings, and professional skills. These elements (policy measures and contextual conditions) enhance the innovators' capacity and limit the investment risks, making the adopters' behavioral performance (perceived behavioral control) the crucial behavioral antecedent affecting the innovation diffusion. Moreover, FA identifies socio-economic motivations (F3.2, at 9.8%) as another driver of innovation propagation. This factor links together environmental, economic, and social evaluations (from GHGs reduction to imitation) that in the experts' opinion can motivate the entrepreneurs' decision to adopt the bioenergy innovation, thus contributing to its diffusion.

Table 3.5: Drivers of the introduction of bioenergy innovation.

Variables	KMO	Communality (Share of Variance)	Factor 2.1 "Networking"	Factor 2.2 "Environmental and socio-economic concerns"
Energy demand	0.865	0.491	0.369	0.596*
Financial support to investments	0.818	0.483	0.621*	0.312
R&D	0.768	0.666	0.816**	0.025
Contribution to quality of life	0.846	0.534	0.246	0.688*
Contribution to environmental quality	0.888	0.691	0.298	0.776**
Reduction of GHGs emissions	0.865	0.588	0.218	0.735**
Social acknowledgment	0.772	0.295	0.325	0.435
Collaboration with providers and technical assistants	0.807	0.524	0.688*	0.225
Collaboration with customers	0.799	0.633	0.324	0.727**
Collaboration with other enterprises	0.896	0.689	0.674	0.484
Collaboration with institutions	0.902	0.744	0.792**	0.343
Collaboration with local Universities	0.889	0.782	0.811**	0.353
Collaboration with foreign Universities	0.882	0.666	0.694*	0.43
Economic return	0.908	0.345	0.538*	0.236
Social responsibility	0.896	0.534	0.234	0.692*
No of Variables			15	15
Eigenvalue			7.345	1.32
Variance (extraction capacity)			4.633	4.03
Total variance explained (%)			0.49	0.088
Cummulative variance (%)			0.49	0.578

Note: Bartlett's test of sphericity: chisquare= 935.5; df=105; P-Value=0.0000; KMO= 0.86 Factor loadings (i.e., measures of the relationship between the observed variable and the factor F) with value ≥ 0.75 **, 0.75-0.5 *, and 0.5-0.3 are considered "strong," "moderate," and "weak" loadings, respectively.

The results of the three FA models detect different behavioral precursors influencing the innovation-decision process. On the one hand, the weak individual attitude towards new bioenergy solutions (caused by the lack of knowledge, thus of awareness of the consequences that the choice can generate) negatively affects the motivations to adopt the innovation. On the other hand, the adopters' perceived behavioral control proves to be the major behavioral driver of innovation introduction and diffusion. This ability to perform the behavior is recognized not just as an individual quality the adopter innately possesses, but also as a resource that strongly depends on two different contextual conditions. With reference to innovation introduction, the individual capacity to deal with new solutions stems from the collaboration with institutions and other operators. Regarding the innovation diffusion, the adopters' perceived behavioral control relies on targeted supporting policy measures. The emerging difference between these two phases of the innovation adoption path stresses the opportunity to further investigate the behavioral precursors that characterize the decision to adopt a BNT or an UBT, separately.

Table 3.6: Drivers of the diffusion of bioenergy innovation.

Variables	KMO	Communality (Share of variance)	Factor 3.1 "External conditions"	Factor 3.2 " Socio-Economic motivations "
Growing of energy demand	0.866	0.386	0.26	0.564*
Entrepreneurs' imitative behavior	0.812	0.65	0.329	0.736*
Human resources(skills)	0.868	0.579	0.673*	0.354
Contribution to quality of life	0.878	0.599	0.345	0.693*
Contribution to environmental quality	0.83	0.649	0.17	0.787**
Reduction of GHGs emissions	0.867	0.568	0.039	0.753**
Social acknowledgment	0.828	0.425	0.405	0.511*
Social responsibility	0.823	0.578	0.27	0.711*
Organizational strategies	0.941	0.488	0.512*	0.476
R&D	0.852	0.619	0.737*	0.276
Social norms and local partners	0.903	0.545	0.616*	0.406
Social norms and foreign partners	0.814	0.475	0.61*	0.322
Policy incentives	0.82	0.506	0.704*	0.101
Public investments (infrastructures)	0.804	0.601	0.756**	0.17
Private investments	0.852	0.633	0.781**	0.151
Credit availability	0.887	0.391	0.534*	0.326
Number of variables			16	16
Eigenvalue			7.16	1.57
Variance(extraction capacity)			4.53	4.16
Total variance explained (%)			0.45	0.098
Cummulative variance (%)			0.45	0.548

Note: Bartlett's test of sphericity: chi square=854.17; df=120; P-Value= 0.0000; KMO = 0.852. Factor loadings (i.e., measures of the relationship between the observed variable and the factor F) with value $\geq$ 0.75 **, 0.75-0.5 *, and 0.5-0.3 are considered "strong," "moderate," and "weak" loadings, respectively.

3.4.2 Behavioral Precursors of the Intention to Adopt a BNT and an UBT: Regression Results

The main variables that challenge and/or drive the adoption of the two types of bioenergy innovations are identified by developing two distinct ordered logit models, and analyzed from a behavioral perspective. According to the assumed research hypotheses, the results of this study confirm that the intention to adopt a BNT is mainly and significantly correlated with extrinsic conditions (the perceived behavioral control and subjective norms), whereas the intention to adopt an UBT is mainly and significantly correlated with intrinsic factors such as the individual's attitude toward new technological solutions and their outcomes. Moreover, the results also suggest that more complex interactions between specific behavioral precursors characterize and further differentiate the two innovation-decision processes. For the sake of completeness, the results include both the odds ratios and the regression coefficients. Throughout this study, the odds ratio compares the probability of high intention versus the combined middle and low intention to adopt the considered innovation.

3.4.2.1 Intention to adopt a BNT

Based on the results of the first ordered logit model, the intention to adopt a BNT is regressed against a series of contextual determinants (Table 3.7). Specifically, the related odds ratios (column 2) show that the probability of a high level of intention to adopt a BNT increases as the availability of R&D advancements improves, the potential of reduction of GHGs emissions increases, and the opportunities of establishing a collaboration with the consumers become concrete. Therefore, three main determinants motivating the innovation-oriented behavioral performance are identified. First, the contribution that a BNT can offer to the environmental quality is significantly and positively associated with the favorable attitude to adopt it.[5]

Second, the access to cutting-edge technologies (perceived behavioral control) is a reliable factor directly linked to the motivation to introduce a BNT. Third, the direct relationship with

[5]Similarly, Kang et al. (2015); Bale et al. (2013) identify the climate change issues (such as the emission reduction) as the major driving factors to adopt energy innovations.

the closer stakeholders(i.e., the customers: subjective norm) can further contribute to orienting the decision toward a BNT-centered investment. On the contrary, the social acknowledgement(i.e., the overall approval or disapproval of the society for an innovative solution: subjective norm) is significantly but negatively associated with the intention to adopt a BNT. Accordingly, the odds ratio indicates a link between the social rejection of new technologies and the innovators' propensity to introduce a BNT. This antagonistic behavioral precursor reveals a gap between the mainstream idea of energy access and use in the Ethiopian society (focused on providing/gaining access to conventional, traditional sources, thus on a general lack of knowledge of modern, sustainable energy opportunities) and the innovators' open orientation toward the bioenergy-centered innovations.

Table 3.7: Behavioral precursors of the intention to adopt a brand new bioenergy technology (BNT).

	(1)	(2)	(3)
Variables	Coefficient	Odds Ratio	Behavioral Precursors
Lack of information on bioenergy innovations	-0.0398	0.961	
	(0.857)	(0.857)	
Lack of knowledge of public benefits	0.0251	1.025	
	(0.879)	(0.879)	
Reduction of GHGs emissions	1.163**	3.198**	Attitude
	(0.030)	(0.030)	
Organizational strategies	-0.264	0.768	
	(0.143)	(0.143)	
R&D	0.893***	2.442***	Behavioral Control
	(0.000)	(0.000)	
Collaboration with customers	0.648**	1.912**	Subjective Norm
	(0.025)	(0.025)	
Collaboration with foreign universities	0.0924	1.097	
	(0.722)	(0.722)	
Limited access to public financing	0.0171	1.017	
	(0.919)	(0.919)	
Social acknowledgment	-0.490**	0.613**	Subjective Norm
	(0.037)	(0.037)	
cut1	16.39***	16.39***	
	(0.002)	(0.002)	
cut2	18.40***	18.40***	
	(0.001)	(0.001)	
N	71	71	
pseudo R^2	0.295	0.295	
Likelihood ratio chi square	44.03		
P-Value	0.000		

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Brant test of parallel regression assumption: chi square= 7.61; P-Value=0.574. The dependent variable is a categorical variable with three levels that describes the intention to adopt a brand new innovation.All the independent variables are considered as continues variables.Column (1) shows the coefficients of the ordered logit estimation. Column (2) shows the odds ratio. Column (3)associates each significant explanatory variable with a behavioral precursor.

3.4.2.2 Intention to Adopt an UBT

The results of the second regression model reveal a specific and composite set of significant variables and of related behavioral precursors that explain the intention to introduce an UBT (Table 3.8). A first group of variables concerns the outcomes the adoption of an UBT is expected or not to produce. On the one hand, the UBT contribution to quality of life shows a positive correlation with the propensity for its deployment and the odds ratio suggests that the probability of this decision increases as the envisaged effect is valued. On the other hand, the lack of knowledge of public benefits displays a negative correlation with the motivation to adopt an UBT as the odds ratio proves (the higher the unawareness of the positive externalities generated by the innovation, the lower the probability of a high level of intention to adopt UBT). Moreover, the reduction of GHGs emissions results negatively associated with the preference for the UBT and the related odds ratio indicates that as the individuals' concern for the climate change increases, their intention to adopt an UBT decreases. This first group of explanatory variables describing the evaluation of the effects that an UBT can generate at individual level (quality of life) or miss at societal level (public benefits and reduction of emissions), respectively, highlights the role that the favorable/unfavorable attitudes play as behavioral precursors in this innovation-decision process.

A second group of variables significantly associated with the UBT-oriented decision involves the relationships with other stakeholders. Specifically, the collaboration with foreign universities as well as the collaboration with customers show a positive significant correlation with the intention to adopt an UBT. Coherently, the related odds ratios indicate that the probability of a high level of this intention to innovate increases as the synergies with the academic world and the sympathy with the economic referents (i.e., market-oriented considerations) improve. These two variables focused on the collaborations the innovators can establish suggest that the intention to adopt an UBT is further associated with the precursors behavioral control and subjective norms, respectively.

Table 3.8: Behavioral precursors of the intention to adopt an upgraded bioenergy technology (UBT).

Variables	(1) Coefficient	(2) OddsRatio	(3) Behavioral Precursors
Lack of information on bioenergy innovations	0.136	1.146	
	(0.615)	(0.615)	
Contribution to quality of life	1.333***	3.793***	Attitude
	(0.002)	(0.002)	
Lack of knowledge of public benefits	-0.783**	0.457**	Attitude
	(0.014)	(0.014)	
Reduction of GHGs emissions	-1.449***	0.235***	Attitude
	(0.001)	(0.001)	
Organizational strategies	0.0434	1.044	
	(0.782)	(0.782)	
Collaboration with customers	1.197***	3.310***	Subjective norm
	(0.004)	(0.004)	
R&D	-0.0777	0.925	
	(0.761)	(0.761)	
Limited access to public financing	0.0397	1.041	
	(0.807)	(0.807)	
Collaboration with foreign universities	0.903***	2.467***	Behavioral control
	(0.004)	(0.004)	
Social acknowledgment	0.299	1.349	
	(0.175)	(0.175)	
cut1	10.38***	10.38***	
	(0.002)	(0.002)	
cut2	12.93***	12.93***	
	(0.000)	(0.000)	
N	70	70	
pseudo R^2	0.321	0.321	
Likelihood ratio chi square	49.07		
P-Value	0.000		

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Brant test of parallel regression assumption: chi square= 9.14; P-Value=0.519.The dependent variable is a categorical variable with three levels that describes the intention to adopt an upgraded bioenergy innovation.All the independent variables are considered as continuous variables. Column (1) shows the coefficients of the ordered logit estimation. Column (2) shows the odds ratio.Column 7 associates each significant explanatory variable with a behavioral precursor.

As alternative estimation technique aimed at testing the robustness of the two developed ordered logit models, this study implements two additional logit models.[6] The first logit model confirms that R&D, reduction of GHG emissions, and collaboration with customers are significantly and positively correlated with the adoption of a BNT in line with the main findings, with the only exception for social acknowledgement that results not significant (column 1, table A4). Similarly, the second logit model shows estimations consistent with the main obtained results except for the variables lack of knowledge of public benefits and collaboration with foreign universities, which are not significantly correlated with the intention to adopt an UBT (column 2, table A4). In general, while only few variables do not emerge as explanatory regressors in the logit models, the robustness check validates the main significant results achieved through the ordered logit models that prove to be comparatively more performing in fitting the observations.

3.5 Conclusions

This study relies on data collected from local experts belonging to the energy or related sectors in two areas of Ethiopia, and implements a two-step approach to investigate their intention to adopt alternative bioenergy innovations. First, the FA models detect from a general perspective the overall factors affecting the introduction and diffusion of new bioenergy technologies. Second, we separately look at the decision-making processes guiding the introduction of two different types of bioenergy innovations: specifically, the ordered logit models identify the main behavioral precursors of the individuals' motivations to adopt brand new and upgraded bioenergy innovations.

Three main orders of findings are achieved through the FA. First, the lack of knowledge stands out as the major factor explaining the total variance of the respondents' evaluation of obstacles in introducing bioenergy innovation. From a TPB perspective, the lack of knowledge of the technological innovation and its opportunities feeds unfavorable attitudes towards the decision to adopt the innovation. Second, the results indicate that networking is the most important driving factor of bioenergy innovation introduction in Ethiopia. The two conditions that networking embodies

[6] In the logit models, the outcome variable is a binary variable (0, 1) with value 1 describing the respondent's interest to adopt the innovation when it is greater than the medium value.

–R&D and collaboration with public bodies– reveal the attention that the adopters pay to the operational issues the innovation introduction implies. Thus, the current capacity to deal with the innovation adoption (i.e., the perceived behavioral control) emerges as the decisive behavioral precursor of the related decision-making process. Third, regarding the experts' evaluation of the main drivers favoring the diffusion of the bioenergy innovation in Ethiopia, a set of situational variables are identified such as the availability of private financing and public supports, the accessibility to R&D findings, and the presence of adequate professional skills. These elements (expressed by the factor "external conditions") are expected to enhance the innovators' capacity and limit the investment risks, and confirm the crucial role that the perceived behavioral control plays as behavioral antecedent of the decisions enabling the innovation diffusion.

As per the distinction between the two types of bioenergy innovations, the regression results show that the behavioral antecedents associated with the individuals' intention to adopt a BNT and an UBT let emerge differences in the related innovators' decision-making processes. On the one hand, general contextual conditions matter to the adoption of a BNT. Specifically, the innovators' propensity toward a BNT is linked to the availability of cutting edge technologies and to the expected reduction of global pollutants emission. On the other hand, more specific contextual conditions as well as idiosyncrasies are crucial to the intention to adopt an UBT. In fact, the motivations generating this decision are positively correlated to the collaboration with the customers and to the outcomes achievable at small scale level (contribution to the community's quality of life), whereas the UBTs are considered ineffective when the benefits are evaluated at large scale (e.g., reduction of GHGs). Moreover, the individual knowledge and awareness of the implications that this type of innovation envisages are relevant to the UBT-oriented innovators' choice. This dichotomy leads to two orders of considerations. First, the behavioral precursors of the individual decision-making process are combined with situational conditions that differ according to the type of bioenergy innovation the adopter evaluates. Second, BNTs characterized by notable good environmental performances are more likely to be attractive for potential innovators.

On the basis of the achieved findings the following main implications and energy strategies can be drawn. First, the adverse individual attitude toward the bioenergy innovations and, specifically, the lack of knowledge and awareness about the out comes they generate are the primary obstacle to their introduction. The regression results reveal that this behavioral precursor is crucial when the choice concerns the adoption of an UBT. The results show that the weak attitude the potential adopters manifest suffers from an inadequate information on the functioning of the technological innovation, thus from an insufficient understanding of the deriving public benefits and positive environmental externalities. This cultural obstacle in the innovation-decision process requires an adequate dissemination of information on the nexus between bioenergy and sustainability by implementing training initiatives (e.g., technical educational programs and lifelong learning programs) targeting local operators.

Second, the behavioral control factors are decisive in facilitating the innovation-oriented choices, which are conditioned by the collaboration with other actors. In this regard, the results identify the universities/research centers as the essential sources of new technological solutions and know-how, the service providers and consultants for the technical assistance, the public institutions for their role in shaping favorable external conditions, and the other enterprises for creating synergies and sharing risks. Networking is the main driver that can heighten the behavioral performances in the bioenergy innovation realm. The adopters' need to set up innovation-centered interrelationships calls for university and public policies that include the creation/enhancement of targeted structures (e.g., extension services and new decision-making bodies together with producers' associations) and the implementation of tailored tools (e.g., smart systems and social events).

Third, the adopters' innovation-decision processes reveal different behavioral patterns in function of the technological characteristics of the bioenergy solution taken into consideration. Prospective research and policy strategies aimed at supporting the adoption of BNTs should consider the relevant underlying behavioral precursors focusing on R&D efforts, bridging the gap between research and business, and giving priority to the environmentally friendly solutions. Differently, strategies oriented toward the introduction of UBT-centered innovations should aim at building the adopters' abilities and capacity to deploy and manage the innovative technologies, ensuring their operability and scalability, and increasing the knowledge of the social benefits these solutions can generate.

One has to be cautious when interpreting these results because of the following limitations. This study used a relatively small sample size, and it assumes that the role of socio-demographic characteristics is captured (as "background factor") by the behavioral precursors. Therefore, it is a viable avenue for future research to adopt large sample size, and explicitly measure the socio-demographic effects on the bioenergy innovation adoption decision. Moreover, this study associates the identified variables with the TPB behavioral precursors. However, there is a need for further research to directly investigate these behavioral precursors through other appropriate approaches and methodologies (e.g., behavioral economics experiments).

Chapter 4

Social Networks, Altruism, and Information Propagation

Atsede Ghidey Alemayehu and Marco Setti

Abstract

Information can be easily spread through social connections by targeting central individuals in the network. Different standard centrality measures (SCMs) are used to select these central nodes. These SCMs, however, are based on the network topology—shaped only by the number of connections—and fail to incorporate the intrinsic motivations of the informants. In this study, we introduce an augmented centrality measure (ACM) by modifying the eigenvector centrality measure through weighting the adjacency matrix with the altruism levels of connected nodes. Using primary data collected from 3,693 high school students in Ethiopia, we found no significant correlation between the level of altruism and popularity. Moreover, we show that, when the subject concerns environmental issues, the use of the ACM in selecting central informants allows for effective information diffusion.

Keywords: Social networks, Centrality, Altruism, Information diffusion, Ethiopia

4.1 Introduction

The adoption of environmentally friendly innovations is vital to minimizing the adverse effects of climate change (Popp, 2006; Gebreegziabher et al., 2017). Nevertheless, several factors may hamper this decision, including financial constraints, the availability of alternative technologies, and risk aversion (Feder et al., 1985; Guerin and Guerin, 1994; Coad et al., 2009; Cuerva et al., 2014). Moreover, recent studies have shown that the lack of relevant information hinders a proper awareness of climate-driven impacts, as well as the introduction of suitable solutions (Noppers et al., 2014; Currarini et al., 2016; Alemayehu et al., 2020).

Information availability and knowledge are key issues in the economic analysis of decision-making by individuals (Jackson, 2014). Individuals may learn about new facts and opportunities directly from their friends and acquaintances, and may gain awareness of alternative options through social connections (Nyblom et al., 2003; Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Banerjee et al., 2013; Kim et al., 2015; Magnan et al., 2015 BenYishay and Mobarak, 2019). The role that social networks play has been proven to be significant, especially when institutions are missing or weak in their strategy, which often occurs in developing countries (Beaman and Dillon, 2018). In these contexts, individuals with a central position in their networks (i.e., central nodes) can effectively serve as informants to the benefit of their community (Banerjee et al., 2013; Beaman et al., 2018). A few individuals selected as informants (i.e., injection points) might be able to successfully spread information (Cai et al., 2015; Akbarpour et al., 2020).

This approach offers several advantages, including feasibility and cost-effectiveness. Indeed, as central individuals are, in general, trusted in their networks (Riyanto and Jonathan, 2018; Banerjee et al., 2019), connected persons are more receptive to the information they provide. Further, central individuals are more likely to have access to diverse sources of knowledge and ideas (Calvó-Armengol et al., 2009;Kratzer and Lettl, 2009). Their privileged position may allow them to recognize the importance of the inputs and to pass clear information to their network. However, information diffusion through central individuals can have two main drawbacks: First, the information may not reach all groups or individuals, due to network segregation, narrow channels, and isolated clusters. For instance, Beaman and Dillon (2018) found that diffusion declines with social distance from the injection points and that the related learning process can discriminate against specific categories (e.g., women). Second, the influence the central node can exert and social pressure, such as the insistence of others on conforming, can lead to uncritical acceptance of the provided information (Akerlof, 1991).

Due to the importance of the central nodes in spreading information, it is crucial to identify them though appropriate centrality measures (Banerjee et al., 2013; Jackson, 2014). The literature on social networks has recognized different centrality measures (e.g., degree, closeness, betweenness, eigenvector, and Bonacich) (Jackson, 2010; Jackson, 2014), which are based on objective and static parameters, such as the number of linkages between nodes; for example, the degree centrality measure identifies pivotal persons in a network, taking into consideration only the number of friends or social connections they have. Similarly, the Bonacich and eigenvector centrality measures select the central nodes on the basis of the number of social connections their friends have. While these standard centrality measure (SCMs) offer clear operational benefits, in terms of their definition and implementation, their effectiveness strictly depends on the assumption that popularity (i.e., network position) alone can trigger the information transmission process. In general, all the above-listed measures fail to take into account the person's intrinsic motivations and the potential establishment of relationships. Indeed, specific social contexts or information contents can require the identification of central nodes by combining network position with other attributes, such as the individual's social preferences. Specifically, when the information concerns the commons, which are strictly related to the well-being of others, such as the management of environmental resources (Setti and Garuti, 2018), the selection of central nodes that express a high level of altruism (Andreoni and Miller, 2002; Bourlès et al., 2017; Carrera et al., 2018) can significantly contribute to propagating the information across social networks.

In this regard, recent studies have shown that the behavioral attributes of informants affect the diffusion of information (Chen et al., 2014; Shikuku et al., 2019; Banerjee et al., 2019). Nevertheless, this research line does not consider the role that the informant's network position can play.

Differently, some studies have used economic experimental approaches to examine the relationships between social networks and social preferences (DellaVigna et al., 2012; Baldassarri, 2015; Candelo et al., 2018) and evaluate the level of altruism and commitment of individuals in a position of social influence (Brañas Garza et al., 2006; Caria and Fafchamps, 2019). However, none of these studies have analyzed the effect of the altruism of the central individuals on information diffusion. To the best of our knowledge, there exists no research that shows whether the combination of network centrality measures and behavioral attributes is associated with information propagation.

This study intends to contribute to the social network analysis literature by implementing an augmented centrality measure (ACM) that combines the SCM with a propensity toward altruism. Specifically, we refer to altruism in its larger context, leaving aside the differences between pure and impure altruism (Bénabou and Tirole, 2006). To incorporate altruism into centrality measures, we assume that information propagation is not only positively affected by the altruism of central individuals, but also by the altruistic attitudes of their friends, friends of friends, and so forth. Thus, the ACM is a modified eigenvector centrality measure (ECM), where ties between two connected individuals are weighted by the level of their altruism. The individual's altruism is supposed to fuel the propagation of information relevant to the benefit of others (Foster and Rosenzweig, 2001. Chen et al., 2014; Ma and Chan, 2014). Under these assumptions, this study addresses two research questions: First, it looks at whether popular individuals who have a central position in their network are also altruistic. If popularity is not associated with altruism, then it could be the first evidence for the importance of incorporating altruism into network analyses when information diffusion is relevant to social well-being. Second, this study examines whether selecting informants through the ACM performs better than using the ECM in terms of information diffusion. It is expected that informants with a high ACM are more likely to spread other-regarding information (e.g., regarding health improvement or climate change adaptation) than individuals with high standard centrality measures.

To empirically test the above hypotheses, primary data were collected by conducting a survey in 2019 with 3,693 ninth-grade students in Bahir Dar, Ethiopia. All students were from eight high schools studying in 68 classrooms. The survey involved both baseline and follow-up phases. During the baseline survey, information related to social networks, altruism, baseline knowledge about climate change, and socio-demographic characteristics of individuals were collected. To construct the network structure of each class, students were asked to provide a list of their friends among their classmates. After the baseline survey, one student was randomly selected from each class as an informant. The informants were provided with training about climate change causes, repercussions, and preventative actions, and were advised to share the information with others. Two weeks after completion of the training, a follow-up survey was conducted to assess the climate change knowledge of the entire population of students.

The results showed that altruism is not correlated with popularity (degree centrality). This implies that students who have a central position in their network can have either self- or other-regarding preferences, and suggests that altruism can serve as additional leverage in the propagation of commons-centered information. Second, consistent with our hypothesis, a comparison between the ECM and ACM of informants showed that the latter was associated with a larger diffusion of information among their classmates. In fact, we did not find a significant correlation between the ECM of informants with the diffusion of information among their classmates. Furthermore, the altruism of informants alone had no significant association with information diffusion. The results were robust when controlled for alternative individual characteristics (e.g., scholastic achievement, gender, religion, and so on) and the inclusion of class characteristics. The results suggest that policy-makers and practitioners should consider both altruistic attitudes and network position when selecting informants, in order to effectively trigger the dissemination of information; especially when it is relevant to social well-being.

The remainder of this study is organized as follows: Section II details the research design and data collection. Section III presents the econometric strategy. Section IV presents and discusses the results. Finally, Section V reflects on the implications and main conclusions.

4.2 Experimental Design and Data Collection

For this study, we used primary data sources. The data were collected from 3,693 students (aged around 16) belonging to 68 ninth-grade classrooms of the eight high schools in Bahir Dar, capital of the Amhara Region, Ethiopia. Students were chosen as a target group for a series of reasons. As students are the future citizens and decision-makers who will be asked to cope with climate change, understanding their current knowledge of weather events and their impacts, as well as testing interventions aimed to improve their awareness of climate change, are crucial for the introduction of mitigation and adaptation measures. This is especially relevant in a country like Ethiopia, where extreme phenomena are expected to impact the already weak local environmental and socio-economic systems. Moreover, students spend more than half of their time at school with their peers. Thus, from a methodological perspective, this sample made it easier to detect who is a friend of whom and to construct their social networks at the classroom and school levels. In order to reduce the risk of missing influential individuals in the network, the survey included the entire population of ninth-grade students living in the city (Chandrasekhar and Lewis, 2011; Hsieh et al., 2018). Furthermore, we do not expect a contamination effect from non-ninth-grade students for two reasons: First, the buildings hosting ninth- and tenth-grade students were separately located from the other grade student classrooms. Second, during the survey period, all tenth-grade students ended their lessons in April (to take the national high school leaving exam in May) and were not coming to school anymore. Therefore, only ninth-grade students attended classes throughout our survey period.

As our research involved human subjects, all procedures were performed in compliance with relevant laws, institutional guidelines, and ethics issues. Specifically, the purpose and the contents of the activities were advertised beforehand to the parents of the young students, teachers, and school principals, and only the students whose parents did not opt-out were included in the survey. Overall, no one was excluded for this reason, and all students gave their assent to participate. Moreover, the privacy rights of participants were guaranteed and always observed during the processing of personal data, which was carried out in such a way as to eliminate any reference that may allow the reconnection of individual statements to a specific person, through pseudonymization and full anonymization. Furthermore, any paper document will be destroyed.

The data were collected in 2019, using a self-administered questionnaire in a two-phase survey (baseline and follow-up). A pilot survey was conducted to make sure that the actual survey ran smoothly. Figure 5.1 shows the survey timeline. The baseline survey was conducted in April. Three weeks later, a training on climate change issues was provided to randomly selected students (who served as informants to their classmates). Two weeks after the training, the follow-up survey was conducted to investigate the variation in the climate change-related level of knowledge in students. In order to ensure the regular running of the surveys, all students filled out the questionnaires at the same time, as each school provided one hour of their schooling time for this purpose (for each phase). Proper training was offered to 68 teachers (one teacher in each classroom), in order to facilitate the survey filling process, and eight supervisors (trained graduate students) maintained the integrity of the process and provided the selected informants with a training session. The facilitators were assigned to their own classrooms and were in charge of providing students a brief introduction to the questionnaires, with clarifications whenever requested, and monitoring of the students while filling the questionnaire properly and without speaking each other. After checking possible parental dissent and gathering student assent to participate, students were informed that they would receive a pre-paid mobile phone voucher card (unitary value: 20 Birr is equivalent to 0.75€) as initial endowment to be used during the survey. Students spent 45 minutes, on average, answering the questionnaires in each phase.

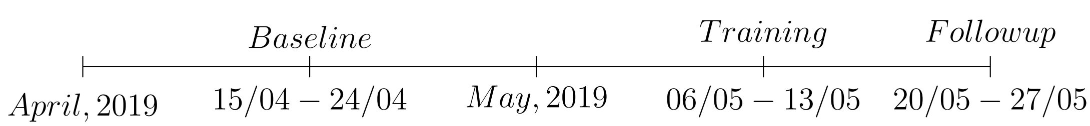

Fig. 4.1: Survey timeline

The first phase was conducted with the aim of collecting four types of information (see Appendix 4). First, participants were asked to provide insights on their individual characteristics and their family background. Second, by referring to their classmates as the social network of the student, they were asked to identify their friends and most frequented peers (e.g., different network-related questions, such as who their friends were among their classmates, with whom they were used to sharing a table or chair with in class, or who they would play with during break/lunch hours at school). Third, according to the incentivized social value orientation approach, adopted to elicit the level of altruism of students (SVO slider measure) (Murphy et al., 2011), participants were asked in which measure they wanted to give their initial endowment to an anonymous peer. Fourth, students were asked questions about climate change issues (the training topic), in order to measure their baseline knowledge of the subject.

From each class, one student was randomly selected, secretly contacted by the teachers (i.e., facilitators) before the training date, and asked for her/his assent to participate in the training. Out of the total students contacted, 59 students (informants) participated in the training; hence, the social network analyses were conducted in these classes.[1] With reference to the main lack of knowledge regarding climate change which emerged from the baseline survey within the population of students, the training was organized by the supervisors, which provided the selected informants with relevant elements; specifically, the determinants, consequences, and strategies to adopt, in order to mitigate the adverse effects of climate change (e.g., droughts and floods). The sessions were supported with short informative slides (notes), made available as printed learning materials to each trained student (see Appendix 6). In order to enhance the motivations to spread this climate change-centered information, the trained informants were all told that the propagation of such elements would contribute to mitigating the adverse effects of climate change for the benefit of their classmates and the community as a whole. As they were confidentially contacted by their teachers and the training was provided out of school hours, their classmates ignored the event, thus reducing their expectations and possible pressures on the trained students to obtain the information. Finally, to investigate to what extent the trained students spread the information in their classes, a follow-up survey was conducted two weeks after the training session. Through this survey, all students were asked climate change-related questions, extracted from the informative notes used during the training session. The results were then used to measure the variation of knowledge of students regarding climate change in each class (social network) and to assess the

[1] Nine students who gave their consent to participate in the training did not show up on the training date. Therefore, the information was not diffused in their classes.

association with the informant's network position (with respect to the ECM and ACM).

4.2.1 Socio-demographic characteristics: Overall students

Table 4.1 reports the statistical summary of the individual and network characteristics of the sample of students involved in this research (see Table B1 for variables description). The average age of the students was around 16 and varied from 14 to 25. The gender distribution showed that 54 percent of the respondents were female. The religion composition of respondents was highly dominated by Orthodox Christians (88%), followed by Muslims and Protestants. Students were asked to self-assess their academic performance using a five-point scale, and most students evaluated their current achievement as average or above average. Regarding the education level of their parents, on average, they had completed at least a primary school education. The distance from school to home was, on average, a 28-minute walk; however, some students walked two hours to reach school.

4.2.2 Knowledge of the intervention topic

The dependent variable is the follow-up climate change knowledge of students, in order to detect a possible association with information propagation across the network. In the Ethiopian education system, learning activities on climate change or environment-related topics are not included in the study programs. However, students might be able to learn about climate change from formal and/or informal information sources. At baseline, their knowledge on the topic scored, on average, 3.5 points out of 9 (Table 4.1; Appendix 4). In the follow-up, their knowledge/awareness of the topic was assessed by asking 18 questions extracted from the informative notes used during the training sessions with the informants (Appendix 5). On average, they scored 5.6 out of 18.[2]

4.2.3 Altruism

In order to elicit the altruism level of students, the SVO slider measure was used. This measure contains six primary items, where each item represents a set of choices relating to payoff alloca-

[2] It is difficult to evaluate the knowledge change of students by just comparing their scores pre- and post-training, as the level of difficulty of the questions in the second phase was higher than in the first wave.

tion to themselves and others (Murphy et al., 2011). During the baseline survey, students were endowed a mobile phone voucher (20 Birr) and asked to make a decision about the share to be gifted by choosing among the alternatives proposed by each of the six primary items of the SVO slider measure included in the questionnaire. The students were informed that this decision would determine their reward for their participation and, after the survey, each student was provided the reward gained independently.

According to Murphy et al. (2011), the six allocative choices made by the students were converted to the SVO index (i.e., the function of the ratio between the average payoffs allocated to others and to themselves: The higher the SVO index, the higher the level of altruism). On average, the SVO index of students was equal to 0.44, with a few students having a negative SVO index—indicating their self-oriented preference, where their objective was to make others worse off at any cost (Table 4.1).[3]

4.2.4 Network centrality measures

In this study, we use the network centrality of trained nodes to analyze their association with the information diffusion, according to the relevant literature (Ammermueller and Pischke, 2009; Bifulco et al., 2011), referring to the connections between the classmates as the basic social network. In fact, as high school students are assigned to a specific classroom for the whole school year and they spend more than half of their day at school with their classmates, it is fair to assume that—at the survey period—noteworthy relationships were established at the class level. In order to derive the network structure of each classroom, students were asked to provide a list of their friends among their classmates and the network ties, represented by undirected links (Jackson, 2010).[4] On this basis, the networks are described by adjacency matrices, the elements of which

[3]If the level of altruism was higher than the 75th percentile of the altruism level of their classmates, they received the lowest value mobile phone voucher (5 Birr); whereas, if they were below the 25th percentile, they received the highest value of the voucher (20 Birr). Students received a voucher with a value of 10 Birr or 15 Birr when their level of altruism was between the 75th and 50th percentile, or between the 50th and 25th percentile, respectively.

[4]As someone cannot be related to another without the second having a relation with the first, friendship was represented by undirected links (Jackson, 2010). In undirected links, if a student A mentions student B as a friend,

take the value of one if the two corresponding classmates are connected, otherwise it is equal to zero.

Figure 4.2 depicts the friendship network of students in one of the analyzed classes, where a yellow circle represents the trained student and the blue circles represents the classmates, with some of them showing a limited number of social connections.

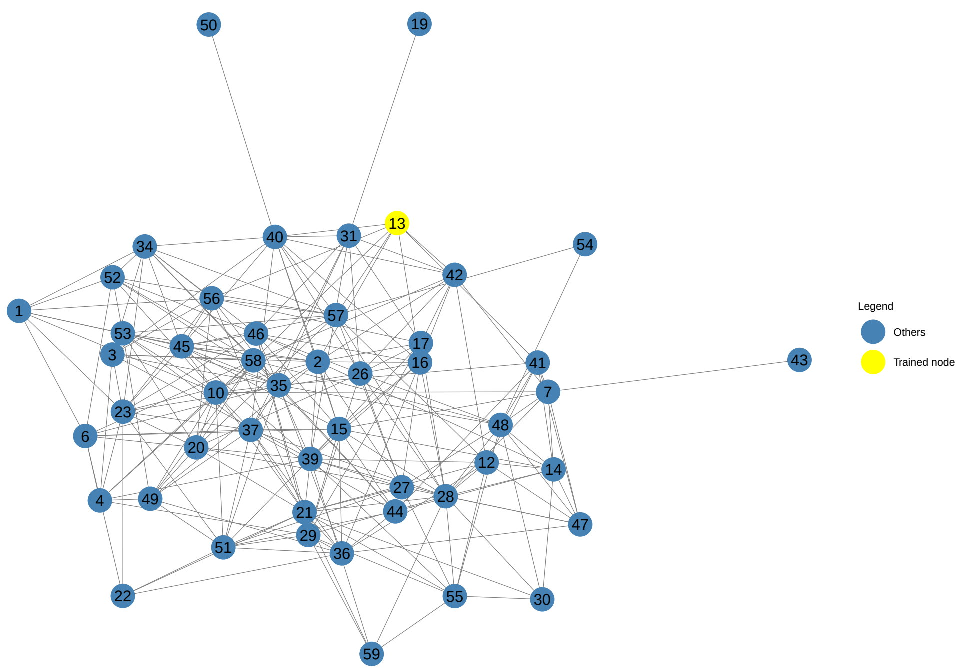

Fig. 4.2: Students friendship network with their respective classmates

Degree Centrality measure (DCM) : An individual's DCM is the number of friends (connections) the subject has. It provides useful information about their personal popularity in a network; however, it only considers the number of immediate contacts, thus failing to provide full information about how well a node is connected in a network (Jackson, 2010). In this study, the DCM of students was computed using undirected links: on average, students listed nine friends among their classmates, with large variability across the students; see Table 4.1.

then the two are assumed to be friends; even if student B has not mentioned student A as a friend. Therefore, in the case of undirected links, it does not matter who is mentioned as a friend.

Eigenvector centrality measure (ECM) : The ECM of an individual i is defined as the proportional sum of their friends' centrality (Jackson, 2010), as described by Equation 4.1. An individual with a high ECM can be considered an influential person in the network, as the positions of their friends are noteworthy within the network. Using undirected links, student i's ECM with classmates j is computed as:

$$Eigenvector_i = \sum_{i \neq j} G_{ij} * Eigenvector_j(g), \tag{4.1}$$

where G_{ij} and g are the adjacency matrix and vector of centrality, respectively.

Augmented centrality measure (ACM) : The proposed ACM combines the network centrality measure of nodes with their behavioral attributes. Specifically, in order to integrate the level of altruism with the ECM, the adjacency matrix (i.e., the undirected network graph) is weighted by the SVO index of students.[5] This study assumes that, when the information concerns subjects relevant to the well-being of others (e.g., environmental issues), the intensity of information sharing between two nodes depends on the altruism level of both nodes. If two nodes are connected, their link is weighted by the sum of their level of altruism (SVO index); otherwise, it is equal to zero. Specifically, student i's ACM with classmates j is computed as:

$$ACM_i = \sum_{i \neq j} WG_{ij} * ACM_j(g), \tag{4.2}$$

where WG_{ij} is the adjacency matrix weighted by the altruism values of nodes, and g is the ACM vector.

Thus, the higher the student's ACM, the higher the potential influence of their position in the network due to the quantitative and qualitative social relationships shared with the classmates. With reference to the analyzed data, on average, the students had lower ACM, compared to their ECM (see Table 4.1), thus indicating the role that behavioral attributes can play in defining the network position of individuals and in selecting the central informants, as shown in Figure 4.3.

[5] Before weighting the adjacency matrix, the altruism variable is re-scaled to avoid negative values.

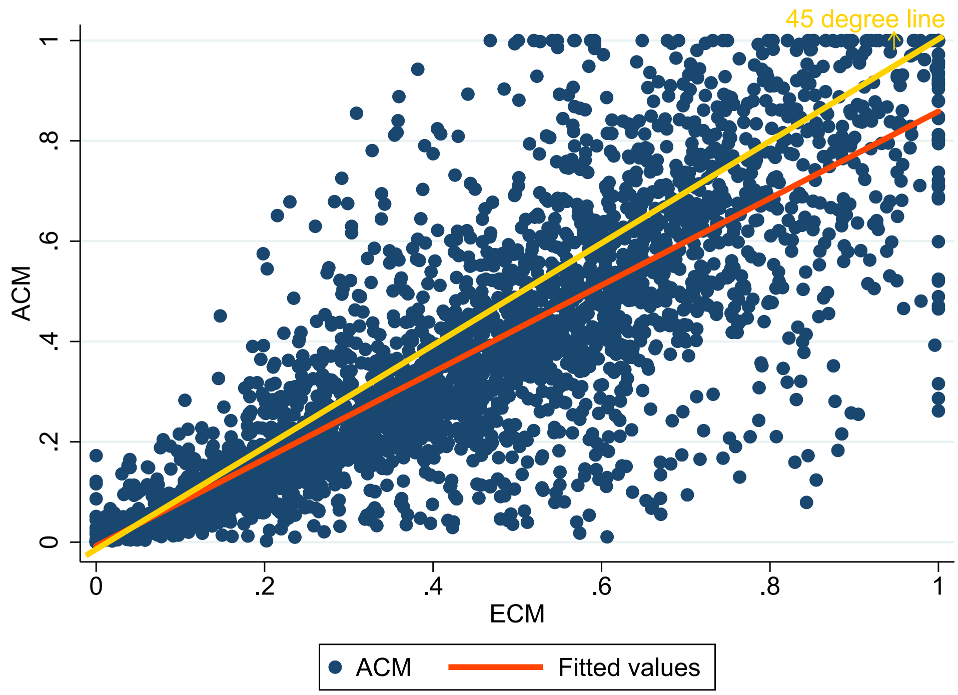

Fig. 4.3: The relationship between ACM and ECM

Table 4.1: Socio-demographic characteristics: overall students

	Mean	S.D	Min	Max	N
Baseline climate knowledge	3.47	1.47	0.00	7.00	2767
Followup climate knowledge	5.64	2.58	0.00	15.00	2532
DCM	8.62	4.01	0.00	24.00	3187
ECM	0.43	0.26	0.00	1.00	3188
ACM	0.36	0.27	0.00	1.00	3188
Altruism(SVO index)	0.44	0.28	-1.46	1.48	2758
Age	16.41	1.41	14.00	25.00	2864
Female	0.54	0.50	0.00	1.00	3030
Catholic	0.01	0.09	0.00	1.00	2773
Muslim	0.09	0.28	0.00	1.00	2773
Orthodox	0.88	0.33	0.00	1.00	2773
Other religions	0.01	0.07	0.00	1.00	2773
Protestant	0.02	0.15	0.00	1.00	2773
Current scholastic grade	3.28	0.92	1.00	5.00	2771
Past scholastic grade	3.38	0.98	1.00	5.00	2773
Parents' education	2.29	1.94	0.00	7.00	2506
Home school distance	27.51	17.34	1.00	120.00	2750

Note: only students in classes with informants are included. Given some students did not provide full information, the number of the observation (N) differs across variables.

4.2.5 Socio-demographic characteristics: trained informants and their classmates

The trained informants (randomly selected students) performed slightly better than their classmates in the baseline climate-change knowledge assessment; see Table 4.2. Similarly, their DCM values indicate that they were more connected than the others (on average, 12 against 9 friends, respectively). Further, the trained students also registered a relatively higher ECM, thus indicating that they play a more central role in their network, as they had friends who were more connected in their network. Accordingly, Figure 4.4 shows that the trained students were characterized by a reduced social distance with their classmates, 20 percent of which were direct friends (social distance is equal to one).[6] Moreover, while almost 50 percent of the students had a friend who was a friend of the trained students (i.e., social distance equal to two), there were a few students who are not either directly or indirectly connected to the trained nodes. Table 4.2 shows that the trained students were less altruistic than the other students. However, their ACM was comparatively higher than that of others, due both to the ECM component and, possibly, to the fact that many of their friends may be more altruistic than the friends of other students.

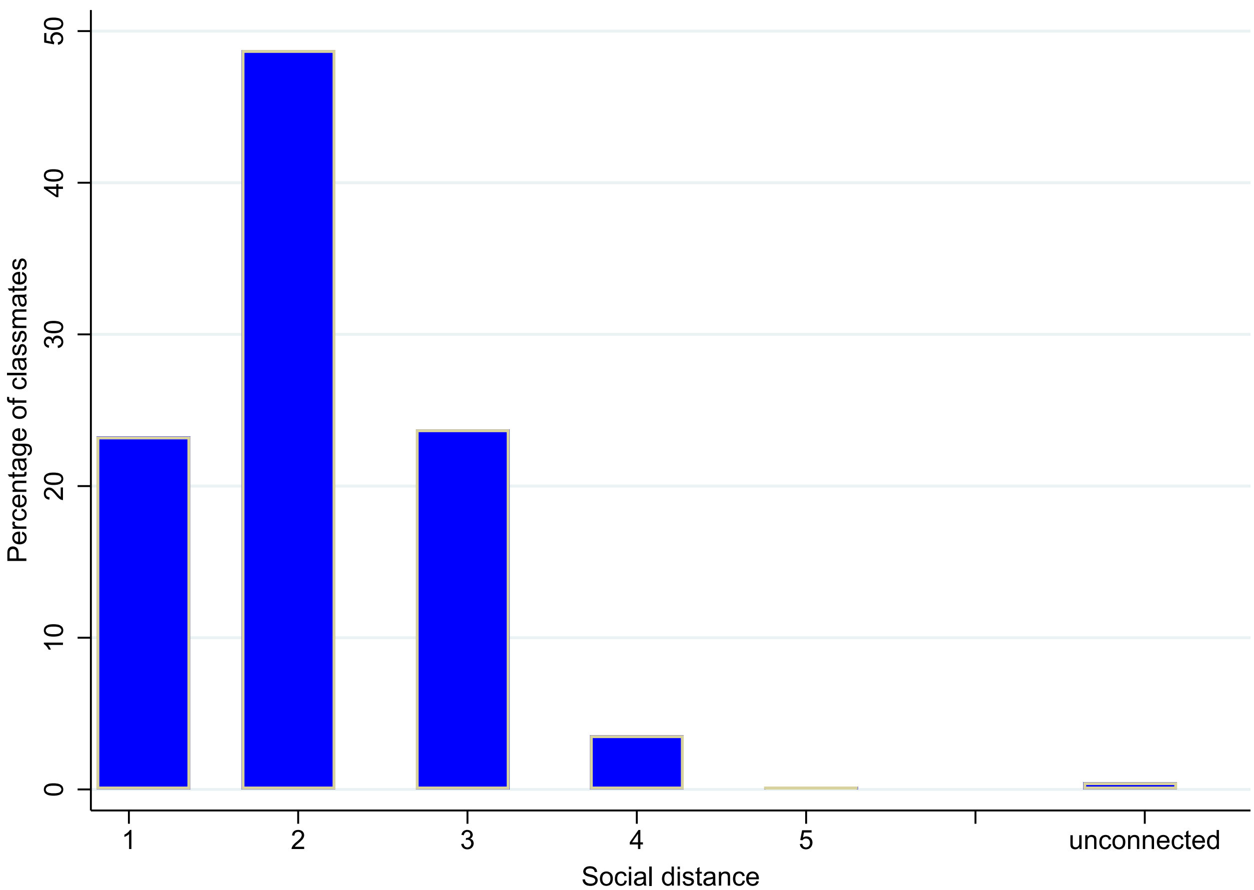

Fig. 4.4: Social distance between trained students and thier classmates

[6]Social distance is the measure of the path length linking the trained and other nodes: It is equal to one between closest friends and increases with weaker connections.

Table 4.2: Socio-demographic characteristics of informants and their classmates.

	Trained students			Other students		
	Mean	SD	N	Mean	SD	N
Baseline climate knowledge	3.97	1.35	58	3.46	1.48	2709
Followup climate knowledge	8.52	2.41	54	5.57	2.55	2478
DCM	12.54	3.89	59	8.54	3.98	3128
ECM	0.67	0.27	59	0.42	0.26	3129
ACM	0.64	0.30	59	0.36	0.27	3129
Altruism(SVO index)	0.39	0.24	59	0.44	0.28	2699
Age	16.17	1.43	58	16.41	1.41	2806
Female	0.41	0.50	59	0.55	0.50	2971
Catholic	0.00	0.00	59	0.01	0.09	2714
Muslim	0.10	0.30	59	0.09	0.28	2714
Orthodox	0.88	0.33	59	0.88	0.33	2714
Other religions	0.00	0.00	59	0.01	0.07	2714
Protestant	0.02	0.13	59	0.02	0.15	2714
Current scholastic grade	3.61	0.81	59	3.28	0.93	2712
Past scholastic grade	3.66	0.92	59	3.37	0.98	2714
Parents education	3.31	2.03	52	2.27	1.93	2454
Home to school distance	25.59	16.40	59	27.55	17.36	2691

4.3 Empirical Specifications

For this study, we developed two regression models: The first aimed to answer whether popular students were also altruistic and to identify the main attributes characterizing popular individuals, while the second compared the use of ECM and ACM in selecting informants and its implications for information diffusion. Far from being two distinct issues, it is argued that, in order to understand the source of popularity in a network, the network centrality of individuals and their behavioral patterns should be jointly analyzed. It is expected that some individuals might have a large number of friends as they possess intrinsic motivations and they care about other people. However, there may also be individuals who are self-centered (individualist), but who are still popular and influential in their network due to other factors (Faris and Felmlee, 2011). For instance, students may often need to be a friend of proficient classmates, such that they can learn more from them. Moving on from this hypothesis, in order to investigate the correlation between popularity and altruism, the first regression model is expressed by Equation 4.3:

$$Y_i = \alpha + \beta_1 altruism_i + \beta_2 scholastic\ grade_i + \beta_3 X_i + \rho FE_c + \epsilon_i, \tag{4.3}$$

where Y_i is student i's popularity, measured by the DCM (both the number of friends who mentioned student i as a friend, and the number of friends named by student i). The explanatory variable, $altruism_i$, represents student i's social preference (SVO), while $scholastic\ grade_i$ indicates the self-evaluated scholastic achievement of student i. The variable X_i represents a set of other individual characteristics of student i, such as the student's gender, age, and education of parents. FE_c is a set of class fixed effects, which was used to capture the class characteristics (both observed and unobserved) that may be associated with the student's popularity (e.g., the class size and whether the student's class was in a public or private school). After controlling all other factors, β_1 identifies the association between altruism and popularity. To further examine the possible associations between the level of altruism of individuals and their network position, we ran the regression model (4.3) by adopting the student i's ECM as the response variable Y_i.

Once it was established whether popularity was associated with social preferences, the follow-up knowledge of students regarding climate change was analyzed, in order to compare alternative criteria to select informants and diffuse information. As the trained informants were randomly selected, we ran the model in two rounds, using their network centrality measures (ECM and ACM) separately. The model included other individual characteristics that might affect the knowledge scores of students, such as their baseline knowledge, their scholastic proficiency, age, religion, and gender (female students may have a narrower social network and may not receive the information accurately). Similarly, the model comprised other contextual characteristics, such as education level of parents and distance of the school from home. Class fixed effects were included to control class characteristics, as it was expected that they could affect the network structure of the class and, as a result, the information diffusion. Specifically, the following model was developed:

$$Z_{ic} = \alpha + \beta_1\, centrality_c + \beta_2\, baseline\ knowledge_{ic} + \beta_4\, scholastic\ grade_{ic} + \beta_5 X_{ic} + \rho F E_c + \epsilon_{ic}, \quad (4.4)$$

where Z_{ic} is the class c student i's follow-up knowledge score. The variable $centrality_c$ is the class c informant's network centrality (ACM or ECM). The $baseline\ knowledge_{ic}$ is the class c student i's baseline understanding/awareness of climate change issues, while $scholastic\ grade_{ic}$ is the scholastic achievement. X_{ic} represents a sets of personal and socio-economic characteristics of student i, such as gender, age, and others. FE_c is a set of class fixed effects that accounts for class specific characteristics.

In addition, potential mechanisms that support the importance of combining social network analysis with behavioral attributes when aiming at diffusing information are also presented. First, whether the role of ACM might simply be due to its altruism component could be questioned. As such, there could be the option to select the informants only on the basis of their level of altruism, an hypothesis which can be addressed by replacing the ACM with the altruism of informants in Equation (4.4). Second, in order to exclude the possibility of biased estimations due to omitted factors, on one hand, the social distance of students from the informants was examined; on the other hand, a placebo test was conducted to investigate the association between the ACM of randomly selected non-trained students and the knowledge scores of their classmates.

4.4 Results

The results obtained from the two orders of elaboration are presented in this section. First, the correlation between popularity and altruism is discussed. Second, considerations facilitating the information propagation are derived, through an analysis of the role that alternative centrality measures play in selecting the informants.

4.4.1 Popularity and altruism

Figure 4.5 shows no evident differences in the distribution of the level of altruism (SVO) across the number of friends of students, thereby illustrating a smooth relationship between the two variables. Specifically, students with nine friends or more (distributed over the 50th percentiles) had the same average level of altruism as students with less than nine friends, thus suggesting that popular individuals are not characterized by relatively higher other-regarding preferences, such that other factors may contribute to their popularity.

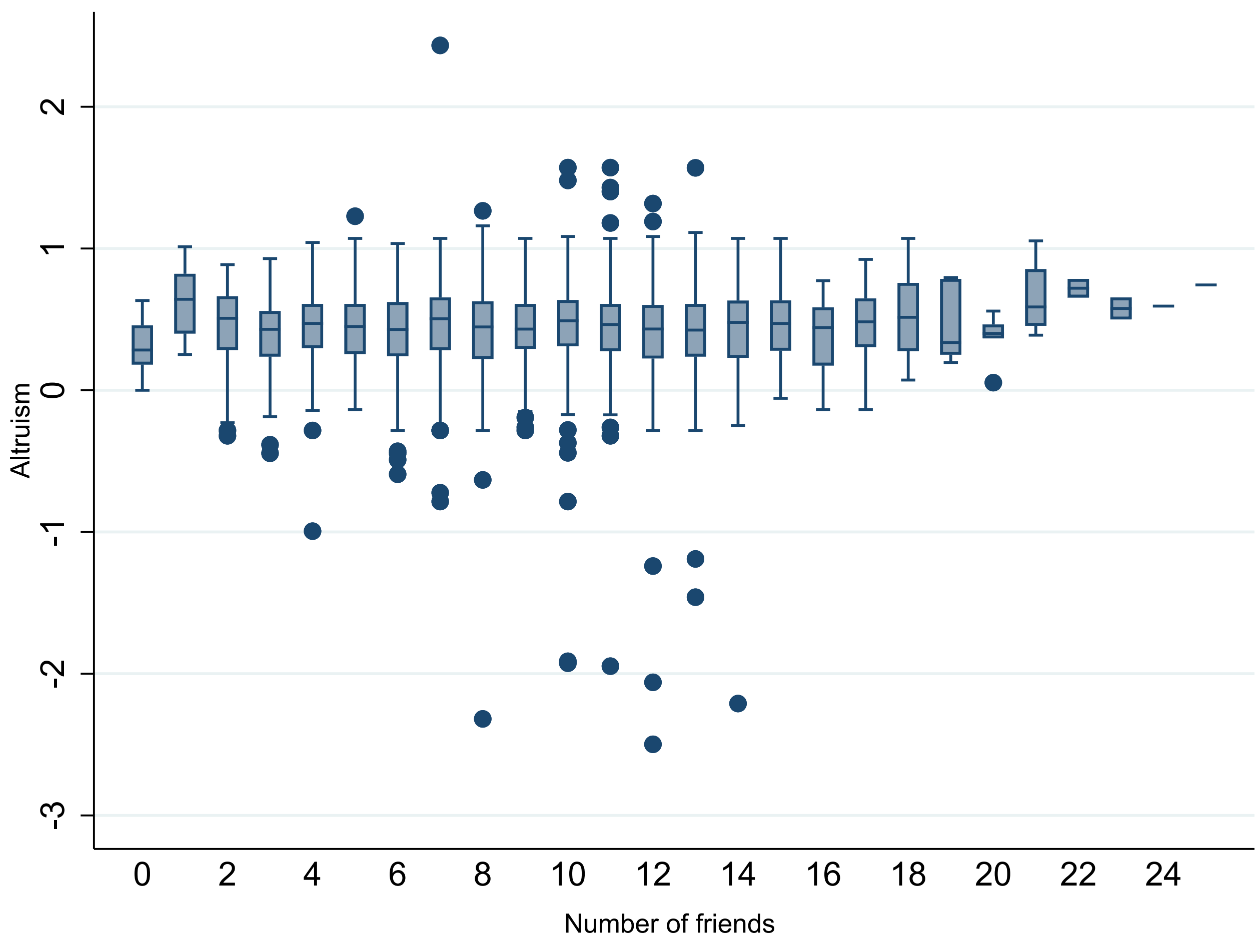

Fig. 4.5: Altruism level over number of friends
(Note: dots are outliers)

The results obtained from the regression model (4.3) showed that altruism has no significant correlation with popularity (Table 4.3, column 2). According to Caria and Fafchamps (2019), this suggests that popular individuals may or may not be motivated by other-regarding preferences when requested to invest effort into projects relevant to social well-being (e.g., sharing information on common resources). Yet, this contributes to explaining why the identification of the central nodes is usually based only on their (more easily measurable) degree of popularity. Nevertheless, Faris and Felmlee (2011) showed that aggressiveness is positively associated with network centrality and that popularity can be linked with the capacity to influence or manipulate others.

Table 4.3 also shows other individual and contextual determinants associated with popularity. For instance, scholastic grade was significantly and positively correlated with the number of friends of students. Besides personal prestige, the opportunity for classmates to establish a connection with the more proficient students, in order to receive support, may explain the observed correlation. Moreover, the education level of parents was positively associated with popularity too; similarly, belonging to major religions, in a religious society like Ethiopia, is related to a high degree of social connections. This also suggests that religious affiliations did not contribute to establishing inclusive (i.e., inter-religion) contexts for the students. Furthermore, being female showed a significant negative correlation with popularity. According to (Brinkerhoff, 2011; Marcus et al., 2015), this result confirms that, in Ethiopia, girls are less likely to have a large number of friends and their social networks are narrower, when compared to those of their male classmates. Similarly, the age variable suggested that the older students had fewer friends and were less popular than their younger classmates. The distance from a student's home to school also mattered, with students closer to school being more popular. A possible explanation derives from the higher transportation costs and amount of time taken to get to school when the distance increases. Thus, students living further away from school are less likely to participate in after-school activities or to spend much time with their classmates. Therefore, they may be forced to have a more limited social network in their classrooms.

In order to detect and better understand the factors associated with the influential power of students within their social networks (classrooms), Equation (4.3) was estimated by adopting their ECM as the dependent variable. Table 4.3 (column 4) suggests that the network centrality of students was not associated with altruism but, rather, was explained by other individual and socio-economic characteristics.

Table 4.3: Students' popularity(DCM) and their influential power(ECM)

	(1)	(2)	(3)	(4)
Altruism	0.20	-0.029	0.002	-0.009
	(0.36)	(0.91)	(0.88)	(0.56)
Age		-0.13**		-0.013***
		(0.02)		(0.00)
Female		-0.49**		-0.054**
		(0.01)		(0.04)
Current scholastic grade		0.23***		0.018***
		(0.01)		(0.01)
Past scholastic grade		0.10		0.0043
		(0.21)		(0.49)
Religion		1.80**		0.15***
		(0.02)		(0.00)
Parent's education		0.17***		0.013***
		(0.00)		(0.00)
Home to school distance		-0.011***		-0.00087***
		(0.00)		(0.01)
Constant	8.01***	7.59***	0.47***	0.47***
	(0.00)	(0.00)	(0.00)	(0.00)
N	2721	2225	2721	2225
R^2	0.19	0.22	0.12	0.17

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column 1 and 2, the dependent variable is degree centrality. In column 3 and 4, the dependent variable is eigenvector centrality. All columns include class fixed effects. Standard errors are clustered at class level.

4.4.2 Centrality measures and information propagation

The selected informants were trained and provided with insights on climate change-relevant issues, such as global and local determinants and repercussions at both the individual and societal scale. As mentioned in Section 4.2, nine of the 68 informants did not participate in the training; thus, the information was not diffused into their classes. By using the difference-in-differences (DID) method, we compared the knowledge scores of students belonging to classes with and without informants, in order to assess the efficacy of the training activity in triggering the information propagation. The results showed that the performance of the students in classes with informants was significantly higher than in those without informants. Table 4.4, Column 2 shows that students with informants scored 11% higher than those without informants.[7] This indicates that the informants increased their knowledge of climate change, thanks to the training, and transferred this information to their classmates.

Table 4.4: The climate change knowledge difference between students in classes with and without injected node

	(1)	(2)
Post training	1.76***	0.34***
	(0.00)	(0.00)
Class with informants	-0.098	-0.038
	(0.33)	(0.13)
Post training*Class with informants	0.42***	0.11***
	(0.00)	(0.00)
Constant	3.58***	1.21***
	(0.00)	(0.00)
N	2994	2994
R^2	0.21	0.16

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Both classes with and without informants are included in this analysis. In Column 1, the dependent variable is students' knowledge scores. While in column 2, the dependent variable is students' knowledge scores in logarithmic form.

Figure 4.6 shows the relationship between the centrality measures (and levels of altruism) of informants and the follow-up knowledge score of their classmates (class average). Two main issues emerged: First, the standard network centrality measures (DCM and ECM) of informants show a slight downward slope. This implies that, as the number of friends (DCM) of informants or

[7] The constant coefficient (3.58) indicates the baseline knowledge of students without informants. As column 1 shows, before the training, the knowledge score for students with informants was lower than that of the other group by 0.09; thus, this group's baseline knowledge was 3.58 - 0.098 = 3.48. After training, students in classes with informants performed at 5.66 (3.48 + 1.76 + 0.42), whereas the other group's knowledge score post-training was 5.34.

their influential power (ECM) increased, the average knowledge score of their classmates slightly declined. Second, ACM and altruism showed a positive slope; that is, the higher the altruism-centered centrality of informants, the higher average knowledge score of their classmates. Moving on from this duality, we argue that, when the information involves other-regarding preferences—such as in the case of common resources like climate—informants with a central network position may not represent the best injection points to ensure effective information propagation. Indeed, the evidence suggests that selecting informants by adopting standard centrality measures that incorporate altruism can boost the diffusion of this specific type of information, which is especially relevant to developing countries. However, the information transmission could vary, due to the influence that other individual characteristics and contextual conditions can exert. Therefore, it is important to systematically explore how the different criteria used to choosing the informants (ACM vs. ECM) can contribute to the information diffusion.

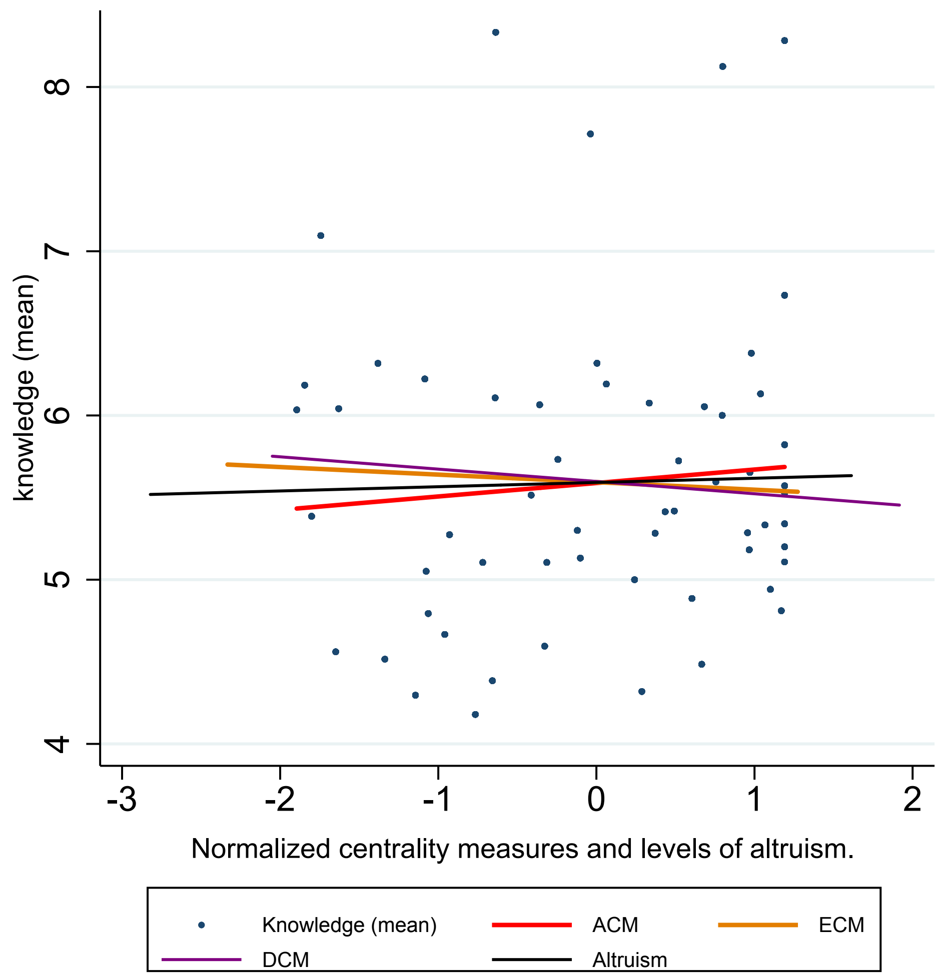

Fig. 4.6: Informants' centrality measures and classmates' knowledge scores.

With this aim, we implemented two alternative regression models—described by Equation (4.4)—both in three different versions (Tables 4.5 and 4.6). The first versions (column 1) only estimated the association between the centrality measures (ACM and ECM) of informants and the follow-up knowledge scores of their classmates; the second versions (column 2) additionally included the baseline climate change knowledge of students; and the third versions (column 3) encompassed all the individual and situational characteristics that may be correlated with the climate change-related knowledge of students. The class fixed effects are always included, in order to control for observed and unobserved class-specific factors.

The results obtained from the first model showed that, in all its versions, the ACM of informants was positively correlated with the follow-up knowledge scores of students (Table 4.6). Moreover, in version 3, an additional set of covariates were positively associated with the dependent variable; namely, the baseline knowledge, current and past scholastic grades, and education levels of parents of student. Differently, a negative coefficient was associated with the female gender and the follow-up knowledge scores of students. According to Beaman and Dillon (2018), female students are less likely to receive information than male students, thus confirming the gender divide the narrower social networks of girls suggested (Table 4.3).

In general, the results confirmed the hypothesis that informants who combine a central network position with a high level of altruism can effectively spread climate change-oriented information among their peers. However, it is debatable whether this finding can be ascribed only to the network centrality component of the ACM (thus, with no or marginal contribution given by the individual's altruism). As a result, choosing the informants only on the basis of their network position would also be sufficient to ensure proper information diffusion, when this concerns environment-relevant subjects. Therefore, it is worthwhile analyzing the role that the informants played when expressing their network position through a standard ECM.

The results of the second regression model were centered on the ECM of informants and varied across the implemented versions; see Table 4.6. In the first version (column 1), before modeling any other relevant characteristics, the ECM was negatively associated with the follow-up knowledge score of classmates (according to Figure 4.6). However, unlike Banerjee et al. (2013), after including the whole set of relevant covariates in the third version (column 3), the eigenvector centrality of informants had no significant correlation with the follow-up knowledge, whereas other explanatory variables were associated with the response variable, consistent with version 3 of the first model (Table 4.5).

Table 4.5: Augmented centrality measure and information diffusion

	(1)	(2)	(3)
ACM	1.62***	0.94***	0.97***
	(0.00)	(0.00)	(0.00)
Baseline climate knowledge		0.34***	0.29***
		(0.00)	(0.00)
Age			-0.064
			(0.19)
Female			-0.43***
			(0.00)
Current scholastic grade			0.30***
			(0.00)
Past scholastic grade			0.18**
			(0.02)
Religion			-0.42
			(0.55)
Parent's education			0.12***
			(0.00)
Home to school distance			0.0017
			(0.66)
Constant	3.91***	3.12***	2.96**
	(0.00)	(0.00)	(0.02)
N	2532	2313	1908
R^2	0.12	0.16	0.20

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is the students' follow-up knowledge. The ACM is normalized. All regressions include class fixed effects. Standard errors are clustered at class level.

The comparison between the results of the two models confirmed that selecting the informants by means of the ACM ensures that their role is associated with the environment–related knowledge of their peers and, therefore, is appropriate for the diffusion of this type of information. Similar results were obtained after controlling the DCM of informants by including it in Equation 4.4: Table B2, columns 1 and 2 show that the ACM of informants was positively correlated with the knowledge score of their classmates, while their ECM was not significantly associated with the knowledge score. As Table B2 (column 3) shows, the results were consistent when DCM, ECM, and ACM were included jointly in the model. Moreover, the suitable use of ACM was further confirmed by modeling the DCM of informants (see Appendix, Table B3). In accordance with Banerjee et al., 2012, the results show that the DCM is negatively correlated with the follow-up knowledge of students, thus confirming that informants with a large number of friends are less likely to spread climate change-oriented information to the benefit of their classmates.[8]

In general, and consistently with the hypothesis formulated in this study, when the information to be disseminated concerns the commons, the ACM outperformed the SCMs. This implies that, in the given circumstances, it is important to select the informants by considering both their contextual (e.g., network centrality) and individual (e.g., level of altruism) characteristics as underlying conditions for effective information diffusion.

[8]Banerjee et al. (2012) found a negative correlation between DCM and information diffusion, although this result was not statistically significant.

Table 4.6: Standard centrality measure and information diffusion

	(1)	(2)	(3)
ECM	-0.86***	0.15**	-0.13
	(0.00)	(0.03)	(0.46)
Baseline climate knowledge		0.34***	0.29***
		(0.00)	(0.00)
Age			-0.064
			(0.19)
Female			-0.43***
			(0.00)
Current scholastic grade			0.30***
			(0.00)
Past scholastic grade			0.18**
			(0.02)
Religion			-0.42
			(0.55)
Parent's education			0.12***
			(0.00)
Home to school distance			0.0017
			(0.66)
Constant	5.42***	4.30***	4.04***
	(0.00)	(0.00)	(0.00)
N	2532	2313	1908
R^2	0.12	0.16	0.20

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is the students' follow-up knowledge. The ECM is normalized. Regressions include class fixed effects. Standard errors are clustered at class level.

4.4.3 Robustness check

In order to check the robustness of the developed models, we explored two alternative mechanisms that may potentially explain information diffusion across a social network. On one hand, it could be observed that, when the subject of the information is relevant to the benefit of others, adopting the level of altruism as a unique criterion to select informants might be a simpler way to inject and diffuse the information than by the ACM. Moreover, this study proved that the ECM (i.e., the network-position component of the ACM) was not correlated with the target population's follow-up knowledge; thus, it could be argued that the ACM was, indeed, dominated by its other-regarding preference component. To test this hypothesis, we explored the correlation between the altruism of informants and the knowledge score of their classmates by adapting Equation (4.4). The results indicated that no association between these two variables emerged (Table 4.7, column 1), thus providing no counterfactual evidence against the achieved results: The selection of the informants based on the intersection of their network position and behavioral attributes can trigger the effective passing of information to the advantage of the recipients.

On the other hand, given the complexity of the social networks, the students could obtain the information not only from the informants, but also from other unobservable sources affecting the diffusion process. In order to address this hypothesis, two additional robustness checks were conducted. First, the social distance between informants and other students was analyzed, under the following assumptions: (i) Closer network ties imply that the classmates are more likely to obtain the information generated by the informants; and (ii) the transmission of accurate and correct information declines over social distance. Therefore, it is expected that the higher the social distance, the lower the final knowledge score. With reference again to a modified equation (4.4), the assessed negative correlation between these two variables indicated that the students increased their knowledge of climate change thanks to the social links they had with the informants (Table 4.7, column 2). Second, a placebo test was conducted, in order to verify whether other overlooked factors played a role in information diffusion. This was analyzed by examining the correlation between the ACM of non-informant students and the follow-up knowledge score of their classmates. For this reason, one student who did not participate in the training was randomly selected from each class, and their ACMs were used in Equation 4.4, replacing those of their informants. Table 4.7 (column 3) shows no significant correlation, thus providing further confidence that the main study results were unbiased: The climate change-related knowledge of students was positively correlated with the ACM of their fellow class informants.

Table 4.7: Altruism, social distance, and randomly students' ACM, and information diffusion

	(1)	(2)	(3)
Altruism	-0.911		
	(0.458)		
Social distance		-0.231***	
		(0.002)	
ACM			0.297
			(0.458)
Baseline climate knowledge	0.286***	0.278***	0.286***
	(0.000)	(0.000)	(0.000)
Age	-0.0644	-0.0587	-0.0644
	(0.194)	(0.232)	(0.194)
Female	-0.435***	-0.373***	-0.435***
	(0.001)	(0.004)	(0.001)
Current scholastic grade	0.303***	0.300***	0.303***
	(0.000)	(0.000)	(0.000)
Past scholastic grade	0.184**	0.178**	0.184**
	(0.021)	(0.022)	(0.021)
Religion	-0.420	-0.527	-0.420
	(0.547)	(0.457)	(0.547)
Parent's education	0.122***	0.111***	0.122***
	(0.003)	(0.007)	(0.003)
Home to school distance	0.00174	0.00175	0.00174
	(0.658)	(0.662)	(0.658)
Constant	4.516***	4.688***	3.948***
	(0.003)	(0.001)	(0.002)
N	1908	1908	1908
R^2	0.196	0.202	0.196

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is the students' follow-up knowledge scores. Column 1, and 2 show the effect of social distance, and trained students' altruism on knowledge diffusion. Column 3 presents the results of a placebo test where ACM is for a randomly selected non-trained students. The ACM is normalized. All regressions include class fixed effects. Standard errors are clustered at the class level.

4.5 Conclusions

This study contributes to the social network and development economics literature by showing the importance of combining the network position and level of altruism of individuals, in order to properly select the central nodes (informants) and achieve better information diffusion, especially when this concerns the welfare of others. In addition, we argued that the propagation of this kind of information also depends on network position and level of altruism of their friends. Under these hypotheses, we proposed an augmented centrality measure (ACM), which is a modified version of the eigenvector centrality measure (ECM) that incorporates the other-regarding preferences of informants and their network neighbors. We provided the first empirical evidence on the advantage that the ACM approach provides in facilitating the dissemination of environmental-centered information.

This study used primary data collected from 3,693 ninth-grade students residing in Bahir Dar, Ethiopia, including both baseline and follow-up surveys. At baseline, we collected information on personal and socio-economic characteristics, network position in each classroom, level of altruism, and knowledge of climate change-related issues. After providing updated information on this subject to randomly selected informants, we administered a follow-up survey that measured the related knowledge of students, thus allowing for a comparison between the ex-ante and ex-post performances of students, which we associated to the network centrality measures of their fellow informants.

This study provides answers to two research questions: First, we investigated the relationship between the standard network centrality of individuals and their level of altruism; second, we analyzed alternative centrality measures as a means to select the central nodes (informants) in charge of diffusing the information. The results showed that there was no significant relationship between popularity and altruism. This suggests that combining altruism with network position can increase the capacity to identify the informants and contribute to effective information dissemination, especially in developing societies.

In order to investigate whether this combination of behavioral attributes and social connections was associated with the information diffusion, we implemented the ACM, which is an augmented version of the ECM, where the adjacency matrix is weighted by the altruism of each connected node. A comparison between ACM and ECM showed that the ACM of informants was positively correlated with the follow-up knowledge of recipients, whereas no significant correlation emerged for ECM. The results showed that combining a structural condition—such as the informant's position inside the social network—with a behavioral precursor—such as their other-regarding preference—can lead to an effective selection of the central nodes, when the information they spread is relevant to the well-being of others. Indeed this is a frequent circumstance, which includes both commons-related topics (e.g., environmental resource management and adaptation to climate change), healthcare, and technological innovations (e.g., energy access and sustainable intensification of production activities). A series of robustness checks were conducted, in order to address potential biases and confirm the consistency of the achieved results.

Nevertheless, this study showed some limitations. First, some students took part in the baseline survey but not in the follow-up survey, and vice versa. Hence, the data were exposed to some attrition problems, even if students were not pre-informed about the dates of the surveys and, so, the absenteeism was random and less likely to affect the results. Similarly, as the data were collected using a self-administered questionnaire, there were also some respondents who did not answer all questions. For this reason, the results are based on inputs from those respondents who participated in both waves and who completed the questionnaire. Moreover, the robustness check shows that the main findings are unchanged even excluding from the sample the data collected from the school with the highest student-attrition rates (see Table B4). Second, we assumed that students were less likely to have friends from other classes or schools. If this was not true, students could have heard the information from other social connections, instead of from their informant and classmates (i.e., contamination effect). In this regard, the results showed that the knowledge score of students was correlated with their social distance from their informants, thus suggesting that they were most likely to obtain the information inside their classroom; that is, the elected social network (Table 4.7, column 2). However, this may need further investigations, in order to control the role of student friendships at the school level. Third, this study referred to randomly selected informants, in order to analyze the associations between their ACM and ECM and information diffusion, but missed measuring cause and effect relationships, thus disclosing the need for further research and suitable methodological approaches, such as a random control trial (RCT). Fourth, this study focused on the level of altruism of young students to augment the ECM. Altruism is a product of caring for others, based also on cognitive components concerning the comprehension of the situations of others. As a young person's cognitive capacity is still in development, they may not have the skill to understand complex social situations and, thus, to behave in an altruistic manner. As such, the implications of using ACM to examine the information diffusion may be more significant, in relation to altruism of adults. This is another research topic that needs to be investigated further.

Chapter 5

Social networks, altruism, and information inequality across genders: Evidence from Ethiopian students

Atsede Ghidey Alemayehu and Marco Setti

Abstract

In conservative societies such as Ethiopia, friendships tend to be gender-biased. In particular, females are expected to be shy and to have a small circle of friends. Do these gender differences affect the structures of social networks and the diffusion of relevant information? To answer this question, we randomly selected students (as informants to their classmates) from 68 classrooms across eight high schools in Ethiopia and trained them on climate change issues, in order to examine how information passes through in-class friendship networks. Our analysis shows that, as the informant's network centrality measure increases, females are involved into the information diffusion process to a lesser extent than males, which calls for a better alternative to target informants. Accordingly, we provide empirical evidence which shows that the selection of informants through the proposed augmented centrality measure (ACM), which combines the network position of informants with their level of altruism, is associated with a broader information diffusion for both gender, thus abating the information inequality.

Keywords: Information inequality, Gender, Social networks, Altruism, Ethiopia

5.1 Introduction

The decision-making processes and behaviors of individuals are greatly influenced by their social relationships and friendships (Robnett and Leaper, 2013), as well as by socio-cultural norms and customs. Indeed, the literature has shown that social learning can significantly affect the achievable outcomes in education (Calvó-Armengol et al., 2009; Boucher et al., 2014), professional activities (Bramoullé and Huremović, 2017), and can alter the propagation of technological innovations (Conley and Udry, 2010; Foster and Rosenzweig, 2010). Especially in developing countries or remote communities, the role that some individuals play in the diffusion of information can be pivotal for its transmission across a social network, and their identification as central nodes can be strategic to injecting and propagating information, as has been documented in the literature (Banerjee et al., 2013; Jackson et al., 2017; Beaman et al., 2018; Akbarpour et al., 2020).

It is also well-known that the social linkages between individuals who share the same socio-demographic characteristics (e.g., gender, race, or religion) are stronger (McPherson et al., 2001; Currarini et al., 2010; Bramoullé et al., 2012; Aiello et al., 2012; Baccara and Yariv, 2013; Dehghani et al., 2016; Jackson et al., 2017), and exert a significant influence on individuals' social learning processes (Beaman et al., 2018; Jackson and López-Pintado, 2013; Smith, 2000). In fact, some social groups, such as female and minority groups, are more likely to be members of narrow social networks, thus hindering their social learning opportunities (Smith, 2000; Katungi et al., 2008); for example, Beaman and Dillon (2018) showed that women are less likely to receive information when it is diffused through a social network. Moreover, individuals can develop strong preferences for and be biased towards their own groups (Smith, 2000; Bramoullé et al., 2012), and their attitudes towards friendship can be influenced by gender-shaped judgments (Almquist et al., 2014). Therefore, the selection of central nodes exclusively based on the number of social links may cause unintended discriminations against social groups; for instance, widening the information inequality between genders.

One possible remedy to address this challenge is to consider the behavioral attributes of individuals as additional criteria in selecting the central nodes. For instance, altruistic persons are expected to have deeper intrinsic motivations to help others (i.e., other-regarding preference; Foster and Rosenzweig, 2001; Carrera et al., 2018) and to devote greater efforts to ensuring everyone is provided the information (Wu et al., 2009; Chen et al., 2014; Ma and Chan, 2014; Obrenovic et al., 2020; Suwanti, 2019). Hence, altruistic individuals with a central network position could play a significant role in closing the information gap between groups by spreading the information to all members of the community, regardless of their gender, religion, and so on.

Few studies have investigated the effect of network centrality measures on information diffusion across genders (Katungi et al., 2008; Beaman et al., 2018), while none of them have extended their analysis to the contribution that the other-regarding preferences of informants can provide in order to overcome information inequality conditions. To the best of our knowledge, this paper is the first study that examines these relationships and attempts to fill this research gap by combining social network analysis with behavioral economics.

We implement an experimental design to address two main research questions: First, we aim to explore the role that gender plays when the level of information inequality is considered. In a conservative society, such as that in Ethiopia, females are less likely to receive information when it is diffused through social networks, as they are expected to be self-restrained and less sociable (Brinkerhoff, 2011; Marcus et al., 2015). Moreover, parents are often over-protective of their daughters and may limit their opportunities to build social connections. This means that females are restrained from establishing social relationships with their male peers (Camfield and Tafere, 2011) and are less likely to receive information from them (Almquist et al., 2014; Yang et al., 2019). On the contrary, males are expected to be social, which leads them to cultivate relationships with their peers (Marcus et al., 2015). Psychological studies have also shown that the friendships of females are focused on the quality of the relationship, rather than on the number of social ties (Stokes and Levin, 1986; Bell, 1991; Thomas and Daubman, 2001). In general, female friendships are small in size, oriented toward the same gender, and intimate. As a result, female informants are expected to spread information to a lesser extent than male informants. There also exists evidence that girls are less shy and more likely to have strong ties with their same-gender peers

(Marianne, 2011; Camfield and Tafere, 2011; Yang et al., 2019). Therefore, it is also expected that females may receive information better when it is provided by female informants.

Second, this study compares the information inequality between males and females when the informants are selected through alternative measures of their network position—that is, standard centrality measures (SCMs) vs. the augmented centrality measure (ACM)—where the latter parameter combines network centrality with the level of altruism. The hypothesis looks at the possibility that informants with a high level of network centrality (SCMs) are more likely to pass information to their same-gender peers, even though these informants are expected to have many male and female friends. Alternatively, the informants with a central network position and other-regarding preferences (ACM) may be more likely to diffuse the information across genders (Chen et al., 2014), thus reducing the information inequality.

To answer these research questions, primary data were collected from 3,693 students, 54 percent of which were female, aged around 16 years in 68 classes across eight high schools in Bahir Dar, Ethiopia. The study involved a baseline and a follow-up survey, which took place five weeks apart. In the first phase, we collected information regarding the personal profiles, in-class friendship networks, levels of altruism, and prior climate change issue-related knowledge of students. Three weeks after the baseline survey was completed, one student was randomly selected from each class and taught about climate change, with the aim that they would spread the newly found information to the rest of their classmates, thus serving as informants. The follow-up survey was conducted two weeks after the training, in which the ex-post knowledge was measured for the entire population of students to evaluate possible associations with the alternative network centrality measures of informants.

The results show that when social networks are used as instruments to diffuse information, female students perform lower than their male counterparts. This highlights that the information inequality across genders occurs and discriminates against females. Moreover, informant gender is positively associated with their same-gender classmates' knowledge score, which indicates that classmates' friendship is gender biased.

In line with our hypothesis, the higher the informants' network centrality measure, the greater the information inequality between their male and female classmates. Specifically, the informants' degree centrality measure shows a higher negative correlation with their female classmates' knowledge scores than with males' knowledge score. In contrast, the informants' ACM is positively correlated with the knowledge scores of both male and female classmates, and no differences emerge across genders. This implies that selecting informants focusing on their levels of altruism and network position (ACM) can reduce the information inequality between males and females.

The remainder of this paper is organized as follows: Section II describes the data source and the experimental design, while Section III shows how the variables were constructed. Section IV explains the empirical strategy adopted to answer the research questions. Finally, Section V discusses the results and Section VI provides some final considerations.

5.2 Experimental Design and Data Collection

The primary data were collected in 2019 from 3,693 students residing in Bahir Dar, which is one of the largest cities in Ethiopia. The participants consisted of all the ninth-grade students enrolled in the eight different high schools of the city. Assuming that the social networks of students were described by their classrooms, the inclusion of all the students (aged 16 years) minimized the risk of missing relationships relevant to the analysis (Chandrasekhar and Lewis, 2011; Hsieh et al., 2018).[1]

The study activities were explained to the parents, teachers, and school principals beforehand, and only the students whose parents did not opt-out were included in the sample (no-one opted out). Moreover, all students gave their assent to participate. The privacy rights of participants were guaranteed and always observed during the processing of personal data, which was carried out in such a way as to eliminate any reference that may allow for the reconnection of individual

[1] Bahir Dar is the capital of the Amhara Region, one of the federal regional states in Ethiopia. There are eight high schools in the city: Bahirdar Academy, Bahir Dar Preparatory, BGMCS (catholic), Fasilo, Ghion, Millennium, SOS, and Tana Haik.

statements to a specific person, through pseudonymization and full anonymization. Any paper document will be destroyed.

We recruited, trained, and rewarded 68 high school teachers as facilitators and eight graduate students as supervisors for the conduction of the survey. The survey was conducted during school hours and in a well-supervised environment, in order to avoid cheating. Moreover, a pilot was conducted, to make sure that the actual data collection process ran smoothly. The facilitators were assigned to their own classrooms and were in charge of providing students with a brief presentation of the aims and contents of the survey, giving clarifications whenever they had questions or raised concerns, and monitoring the students while filling the questionnaire properly and without speaking with each other. The students were informed that they would be given a "mobile credit card" as a reward for their participation in the study, and were told that they could withdraw from the study at any time. On average, the students took 45 minutes to complete each survey.

The baseline survey collected information regarding the socio-economic characteristics and conditions of students, their friendships with their classmates (i.e., their social networks), their levels of altruism, and their baseline knowledge of climate change issues (see Appendix 4). The six slide measures of the social value orientation (SVO) method were used to elicit the levels of altruism of students. According to the proposed SVO pattern, the students were invited to decide which part of their initial endowment (the "mobile credit card") to donate, if any. They were informed that the value of the incentive for their participation would be determined by their resource allocation decision.

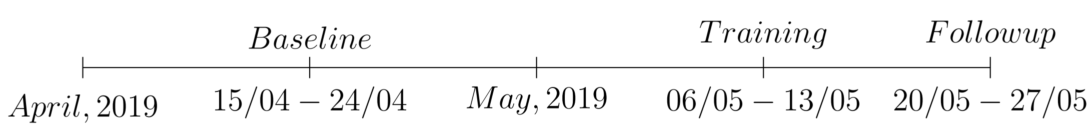

Fig. 5.1: Survey timeline

Three weeks after completing the baseline survey, one student from each class was randomly selected. Before scheduling the training date, the selected students were secretly contacted by their teachers and asked for their consent to participate in the training. Fifty-nine out of the 68 students who were contacted attended the training session.[2] Therefore, the final analysis was based on these 59 classes. The selected students were given training focused on climate change issues; specifically, the determinants, consequences, and strategies to adapt to and mitigate its adverse effects, such as drought and flood. The training was supported by informative notes as learning materials, and was conducted by trained graduate students (see Appendix 6). At the end of the training session, the trained students were asked to take the printed learning materials with them and were informed of the importance of sharing such information with others, in order to minimize the adverse effects of climate change. The trained students were considered as the injection points (informants) for diffusing this information among their peers. Two weeks after the training session, the follow-up survey was conducted with the entire population of students, in order to re-evaluate their levels of knowledge in climate change-relevant issues (see Appendix 5). Specifically, the follow-up survey included questions based on the informative notes used during the training sessions and given to the trained informants.

5.3 Construction of Variables

5.3.1 Altruism

This study used the incentivized SVO slider measures to elicit the students' levels of altruism. Specifically, the SVO six primary items were proposed to offer possible choices to allocate a joint payoff between the potential donor and an anonymous recipient (Murphy et al., 2011). The task was administered as part of the baseline survey, and the students were asked to select the best self vs. other payoff combination among the available alternatives. They were informed that their decision would determine the value of the reward for their participation in the survey (the

[2] Nine out of the 68 students who were invited to participate in the training did not show up on the training day. Thus, the information was not diffused in their classes. We later used these classrooms as a control group to analyze the role the informants played in disseminating information, by comparing the performance of students in classes with and without informants.

maximum value was 20 Birr).[3] It was expected that the altruistic students would donate a large part of their endowment, even at a cost to themselves. On the basis of choices made privately, the SVO index assesses an individual's level of altruism as the ratio between the average allocation to others and the average outcome to the self (Murphy et al., 2011), i.e., the higher the SVO index, the higher the level of altruism. After the survey, each student was informed independently about the reward gained.

5.3.2 Network graphs and centrality measures

In Ethiopian high schools, students spend most of their school time with their classmates and stay in the same classroom for the whole school year. Hence, it is fair to assume that the class represents a privileged social environment for students to build friendships. Moreover, while students could have friends in another class, they may not spend a lot of time with them, given that there is no ample free time in the Ethiopian school schedule. Moving from these contextual conditions, we selected the classroom as the student's social network and, according to Jackson (2010), assumed friendship as an example of an undirected network graph[4]. Hence, students were asked to identify their friendships with classmates, in order to describe the network structure of the class through an adjacency matrix. This matrix maps the ties between the nodes, with a value of one representing a friendship between two students and a value of zero representing no friendship. With reference to the individual's network of friendships with the classmates, both the standard (degree and eigenvector) and the augmented centrality measures were computed.

Degree centrality measure, DCM : The DCM is defined by a person's number of friends (links). As the DCM considers only the individual's direct contacts, it does not provide full information about the real centrality of the node inside the network, as a node with a low degree centrality may have important position in the network by having a link with other central nodes Jackson (2010). We used undirected links to compute the degree centrality, where a person's degree centrality implies both the number of friends they mentioned, as well as others who mentioned

[3]The students with high levels of altruism received the lowest value mobile credit card (5 Birr), while those with low levels of altruism received the highest value (20 Birr).

[4]According to undirected graphs, two nodes are connected if one of them is linked. Therefore, if student A mentions student B as a friend, then B is considered to be a friend of A.

them as a friend.

Eigenvector centrality measure, ECM : The ECM is defined by the weighted sum of the centrality of an individual's friends (Jackson, 2010). As this measure depends on the number of links a node and its connected nodes have (Bonacich, 1987; Jackson, 2010), according to the ECM, individuals are considered influential if they have many contacts with other central individuals in the network. Student i's ECM with classmates j is computed by Equation 5.1:

$$Eigenvector_i = \sum_{i \neq j} G_{ij} * Eigenvector_j(g), \tag{5.1}$$

where G_{ij} and g are the adjacency matrix and the centrality vector, respectively.

Augmented centrality measure, ACM : In order to use an alternative network centrality measure that combines quantitative parameters (e.g., the number of connections) with qualitative characteristics (e.g., an individual's other-regarding preferences), we developed the ACM as an augmented version of the ECM, where the elements of the adjacency matrix are weighted by the level of altruism (SVO index). We assumed that, when the information is related to environmental issues, the intensity of the information sharing between two individuals depends on the altruism level of the two. Specifically, we adopted undirected links to construct the weighted adjacency matrix (WG_{ij}), where the link of two connected nodes is weighted by the sum of their level of altruism (SVO index); otherwise, it is equal to zero. Student i's ACM with classmates j can be represented by Equation 5.2:

$$ACM_i = \sum_{i \neq j} WG_{ij} * ACM_j(g), \tag{5.2}$$

where WG_{ij} is the adjacency matrix weighted by the altruism levels of nodes, and g is the vector of centrality.

Therefore, the proposed ACM derives the network centrality position of nodes, not only as a function of the number of their social connections, but also of their altruistic attitude, as well as that of their friends.

5.4 Empirical Specification

According to the hypotheses outlined in Section 5.1, we developed two regression models. The first model analyses the relationships between female students and follow-up knowledge related to climate change issues. The second model compares the level of information inequality across gender associated with alternative network centrality measures (i.e., SCMs vs. ACM) driving the selection of the informants.

5.4.1 Gender and information inequality

As Ethiopian women and girls are not encouraged to initiate conversations with peers of the opposite gender, they are supposed to have limited social connections (Brinkerhoff, 2011). Hence, the probability of females receiving and spreading information is expected to be relatively lower than that for males, thus creating conditions of information inequality between the genders. We tested this first hypothesis by using the following equation:

$$Y_{ic} = \alpha + \beta_1 \ female_{ic} + \beta_2 \ female_c + \beta_3 \ X_{ic} + \rho FE_c + \epsilon_{ic}, \tag{5.3}$$

where the dependent variable, Y_{ic}, is the follow-up knowledge score of student i in class c, while $female_{ic}$ and $female_c$ are the female student and informant in class c, respectively. The variables X_{ic} and FE_c represent sets of individual characteristics and class fixed effects, respectively. These explanatory variables allowed us to control for possible associations between personal and contextual factors and the knowledge of students. For instance, students with better baseline knowledge or scholastic proficiency were also more likely to perform well during the follow-up session, whereas minorities, such as followers of less diffused religions, may pertain to narrow social networks with scarce access to information. In addition, class characteristics, such as the gender composition, might explain the knowledge scores of students; thus, class fixed effects were included, to control for both observable and unobservable class characteristics.

As noted above, in Ethiopia, the relationships of females are mostly same-gender based. Therefore, female students are expected to belong to narrow social networks and to be more involved in the information transmission process when their class informant shares the same gender. In this regard, we investigated whether the gender of informants could explain possible differences in the knowledge score between their male and female classmates. To test this second hypothesis, the following regression form was specified:

$$Y_{gic} = \alpha + \beta_1 \; female_c + \beta_2 \; X_{ic} + \rho \; FE_c + \epsilon_{ic}, \tag{5.4}$$

where Y_{gic} is the follow-up knowledge score of student i with gender g and studying in class c. The other variables are the same as in (5.3).

5.4.2 Network centrality measures and information inequality

The information inequality across genders can be analyzed through the network centrality measure adopted to select the informants. It was assumed that informants with many contacts were more likely to have friends of both genders. However, the strength of the friendship between males and females can be different, and a preference for conveying information to classmates of the same gender can arise. Even though males and females have the same social distance from their informants, the informants may not pass the information to both genders equally. On the contrary, altruistic individuals have intrinsic motivations to make everyone better off, even at their personal cost. Therefore, altruistic informants with a central network position are expected to be socially oriented toward both genders and more likely to convey the information more fairly. This hypothesis was tested by comparing the role of alternative centrality measures (SCMs vs. ACM) and by introducing an interaction term linking the SCMs and ACM of informants with the gender of their classmates, as specified by the following regression form:

$$Y_{ic} = \alpha + \beta_1\, network\ centrality_c + \beta_2\, female_{ic} + \beta_3\, (female_{ic} * network\ centrality_c) + \beta_3\, X_{ic} + \rho\, FE_c + \epsilon_{ic}, \tag{5.5}$$

where Y_{ic} is the climate change knowledge score of student i in class c, $female_{ic}$ indicates a female student i in class c, and the variable $network\ centrality_c$ represents the SCMs (DCM and ECM) or ACM of the informant in class c, which are introduced in the specification separately. The three network centrality measures (DCM, ECM and ACM) are computed as described in Section 5.3.2. The other variables are the same as in Equation (1). The coefficient β_1 identifies the association between the centrality of informants and the knowledge score of male students, after controlling for all other factors. β_3 identifies the association between the centrality (SCMs or ACM) of informants and the knowledge scores of female students, compared to those of the male students, assuming all other factors to be the same. Therefore, a negative β_3 indicates that the centrality of informants is associated with gender inequality in favor of male students.

5.5 Results

In this section, both descriptive statistics and regression results are discussed. The first subsection describes the differences between male and female students across a range of variables, including socio-economic factors, network position, and behavioral characteristics (see Table B1 for variables description). The second subsection presents the results generated by the regression analyses.

5.5.1 Descriptive analysis

Table 5.1 shows the statistical summary of the characteristics of respondents by gender. Female students accounted for 54% of the total population. With reference to the baseline knowledge of climate change issues, male students performed significantly better than female students. The gap further increased in the follow-up survey, suggesting that the male students might have had an advantage over the female students in receiving the information from their class informants. Moreover, the network centrality measures showed that male students had higher connections with classmates than female students. Female students are more altruistic than male students, according to the literature (Poulin and Pedersen, 2007; Aguiar et al., 2009; Marianne, 2011; Falk and Hermle, 2018). All the personal characteristics of students showed differences between genders, except for religion. Regarding school proficiency, male students self-reported slightly higher grades than female students. Moreover, parents of males possessed higher educational levels than parents of females. Female students walked a longer time between their homes and their schools.

Table 5.1: Respondents' characteristics by gender

	Mean (Male)	Mean (Female)	Difference	p-value	N
Climate Knowledge					
Climate knowledge(Baseline)	3.62	3.47	0.16**	0.01	2304
Climate knowledge(followup)	5.93	5.43	0.5***	0.00	2442
Network Centrality					
Degree	9.46	9.11	0.35**	0.02	2442
Eigenvector	0.49	0.44	0.05***	0.00	2442
ACM	0.43	0.37	0.06***	0.00	2442
Behavioral Attributes					
Altruism	0.43	0.45	-0.02*	0.06	2309
Personal Characteristics					
Age	16.6	16.15	0.45***	0.00	2329
Catholic	0.01	0.01	-0.001	0.71	2314
Muslim	0.08	0.07	0.01	0.34	2314
Orthodox	0.89	0.89	-0.005	0.70	2314
Other religions	0.006	0.004	0.002	0.40	2314
Protestants	0.02	0.026	-0.007	0.30	2314
Academic grade	3.35	3.28	0.075*	0.05	2314
Parents' education	2.51	2.19	0.32***	0.00	2103
Distance home to school	26.62	28.37	-1.75**	0.02	2303

*, ** and *** denote significance at 10%, 5%,and 1% levels, respectively. Given some students did not provide full information, the number of the observation (N) differs across variables.

Table 5.2 presents the main variables describing the randomly selected trained students (i.e., informants). In general, male and female informants obtained higher knowledge scores than their classmates, especially when comparing the increase from baseline to follow-up (see Table 5.1). The informants empowerment, which can be assumed to be associated with the provided training, revealed a significant difference between genders, with a higher knowledge score for males on average. However, the knowledge gap between male and female informants narrowed after the training sessions. Both male and female informants shared similar individual and socio-economic characteristics, network centrality, and level of altruism. The only exception was the distance between their homes and schools, with male informants having to walk further.

Table 5.2: Informants' characteristics by gender

	Mean (Male)	Mean (Female)	Differences	p-value
Climate Knowledge				
Climate knowledge(Followup)	9.100	7.792	1.308**	0.046
Climate knoweldge(Baseline)	4.294	3.500	0.794**	0.026
Network Centrality				
Degree	12.543	12.542	0.001	0.999
SCM (Eigenvector)	0.688	0.632	0.056	0.448
ACM	0.649	0.630	0.019	0.820
Behavioral Attributes				
Altruism	0.382	0.395	-0.013	0.846
Personal Characteristics				
Age	16.412	15.833	0.578	0.130
Catholic	0.000	0.000	0.000	.
Muslim	0.086	0.125	-0.039	0.631
Orthodox	0.886	0.875	0.011	0.903
Other religion	0.000	0.000	0.000	.
Protestant	0.029	0.000	0.029	0.412
Academic grade	3.600	3.625	-0.025	0.908
Parent education	3.273	3.368	-0.096	0.872
Distance home to school	28.714	21.042	7.673*	0.077
Class size	49.629	53.875	-4.246	0.156
N	35	24		

*, ** and *** denote significance at 10%, 5%,and 1% levels, respectively.

Figures 5.2 and 5.3 illustrate the social network structures of two randomly selected but archetypal classes with male and female informants, respectively. In general, it can be observed that the social connections between classmates were highly gender-biased. For instance, the figures show that the two informants (yellow circles) built friendships mostly oriented towards their own gender. This was consistent with our expectation, as well as with the homophily principle, stating that individuals prefer to establish ties with similar persons (McPherson et al., 2001; Jackson et al., 2017).

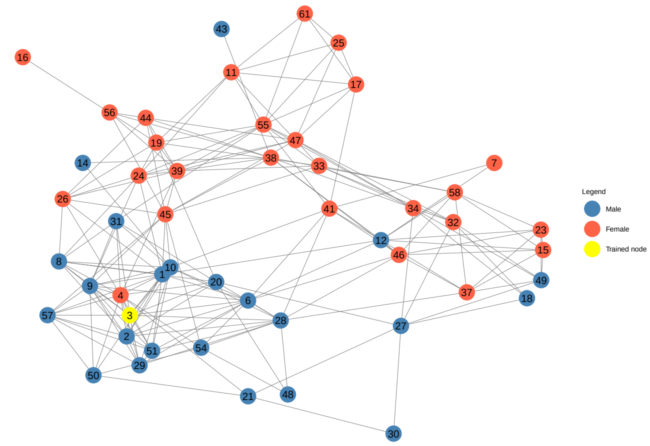

Fig. 5.2: A class with a male informant.

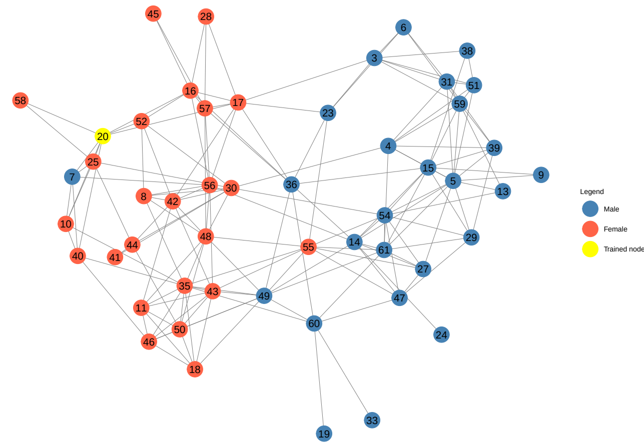

Fig. 5.3: A class with a female informant.

5.5.2 Estimation Results

In order to check the effectiveness of the information transmission process across the networks and triggered by the informants (i.e., the randomly selected injection nodes), we compared the baseline and follow-up knowledge scores of classmates of informants with the scores achieved by the students not involved in the analysis. Notably, the 59 classrooms with informants represented the treatment group, whereas 9 classrooms—the selected students of which did not show up at the training and, thus, were excluded—defined the control group. With this aim, we adopted the difference-in-differences (DID) estimation method. The results are presented in Table 5.3. As column (1) shows, the control group scored, at the follow-up, 5.34 points; while the classmates of informants scored 5.66 points.[5] In column (2), the dependent variable expresses the log knowledge score: The treatment group scored 11% higher than the control group. The results show statistical significance, thus confirming not only that the informants benefitted from attending the training, but also that they effectively passed relevant information to their classmates, who also increased their knowledge.

[5]At baseline, the treatment group's knowledge score was 0.098 points lower than the control group (i.e., 3.48 and 3.58, respectively). The treatment group's follow-up score results were equal to $3.48 + 1.76 + 0.42 = 5.66$.

Table 5.3: Treated and control groups' knowledge scores: difference in differences.

	(1)	(2)
Post training	1.76***	0.34***
	(0.00)	(0.00)
Class with informants	-0.098	-0.038
	(0.33)	(0.13)
Post training * Class with informants	0.42***	0.11***
	(0.00)	(0.00)
Constant	3.58***	1.21***
	(0.00)	(0.00)
N	2994	2994
R^2	0.21	0.16

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Both classes with and without informants are included in this analysis. In Column 1, the dependent variable is students' knowledge score. While in column 2, the dependent variable is students' knowledge score in logarithmic form.

Focusing on the treatment group, the results, derived from Equations 5.3 and 5.4, in Table 5.4 identify the main factors associated with the follow-up knowledge score for the entire sample of students (column 1) and the two sub-samples characterized by gender (columns 2 and 3), respectively. Consistently with our hypothesis, the regression showed that female students performed lower than their male counterparts, as per the negative coefficient of the female dummy in column (1). Similarly, the female informants spread the information to their classmates to a lesser extent than the male informants.

The coefficients reported in columns (2) and (3) show that the female informants were negatively associated with the knowledge scores of male students, but positively with the outcomes of female students. These findings suggest that the information diffusion between male and female students is strongly correlated with their class informant's gender. Specifically, the benefit to students was higher when their class informant shared the same gender. In accordance with (Patacchini and Zenou, 2012a), these results indicate that individuals are biased toward others similar to themselves when they pass useful information to others. Moreover, a positive correlation between the baseline and follow-up knowledge scores emerged for both male and female students.

Again, with no gender differences, the scholastic grade of students was positively correlated with their knowledge score. In general, the level of altruism of students was positively correlated with their climate change knowledge score, thus suggesting that this other-regarding attitude motivated students to be concerned and aware of the environmental challenges and to be open-minded toward relevant information. Education levels of parents were also positively associated with the knowledge scores of both male and female students. This suggests that students from educated families may have a background that allows them to learn more, when compared to other students; that is, social conditions matter. The coefficient of the female ratio in the class indicates that both genders were more advantageous to hear the information when many of their classmates were of their same gender. For female students, knowledge scores were negatively associated with age. This indicates that older female students performed worse than younger female students. This may indicate a stronger cultural influence on the older females, causing them to be less sociable and less likely to receive information than the younger females.

Table 5.4: Information inequality across gender

	(1) Total stuents	(2) Male students	(3) Female students
Climate knowledge (Baseline)	0.29***	0.34***	0.24***
	(0.00)	(0.00)	(0.00)
Female	-0.45***		
	(0.00)		
Female informant	-0.62***	-1.96***	0.28**
	(0.00)	(0.00)	(0.04)
Age	-0.056	-0.0072	-0.19**
	(0.26)	(0.91)	(0.02)
Altruism	0.47**	0.70**	0.51**
	(0.02)	(0.03)	(0.04)
Academic grade	0.39***	0.43***	0.36***
	(0.00)	(0.00)	(0.00)
Religion (Majority=1)	-0.34	-0.60	-0.26
	(0.62)	(0.59)	(0.76)
Parent's education	0.12***	0.11*	0.13**
	(0.00)	(0.08)	(0.02)
Distance home to school	0.0018	-0.00050	0.0025
	(0.64)	(0.94)	(0.59)
Class's female ratio	0.28	-3.44***	2.29***
	(0.43)	(0.00)	(0.00)
Constant	3.48***	7.56***	2.56
	(0.01)	(0.00)	(0.16)
N	1902	813	1089
R^2	0.20	0.22	0.22

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In all columns the dependent variable is the students' follow-up knowledge scores. All regressions include class fixed effects standard errors are clustered at class level.

In order to further investigate and detect possible drivers of information (and knowledge) inequality across genders, the association of network centrality measures of informants with the knowledge scores of their male and female classmates was analyzed. Figure 5.4 shows that the higher the three centrality measures, the higher the level of knowledge inequality. This suggests that the most connected and influencing informants were more likely to pass the information to their male classmates, rather than to their female classmates. However, it is important to explore the association between the network centrality measures of informants and information inequality across genders after controlling for the roles of other individual and contextual factors.

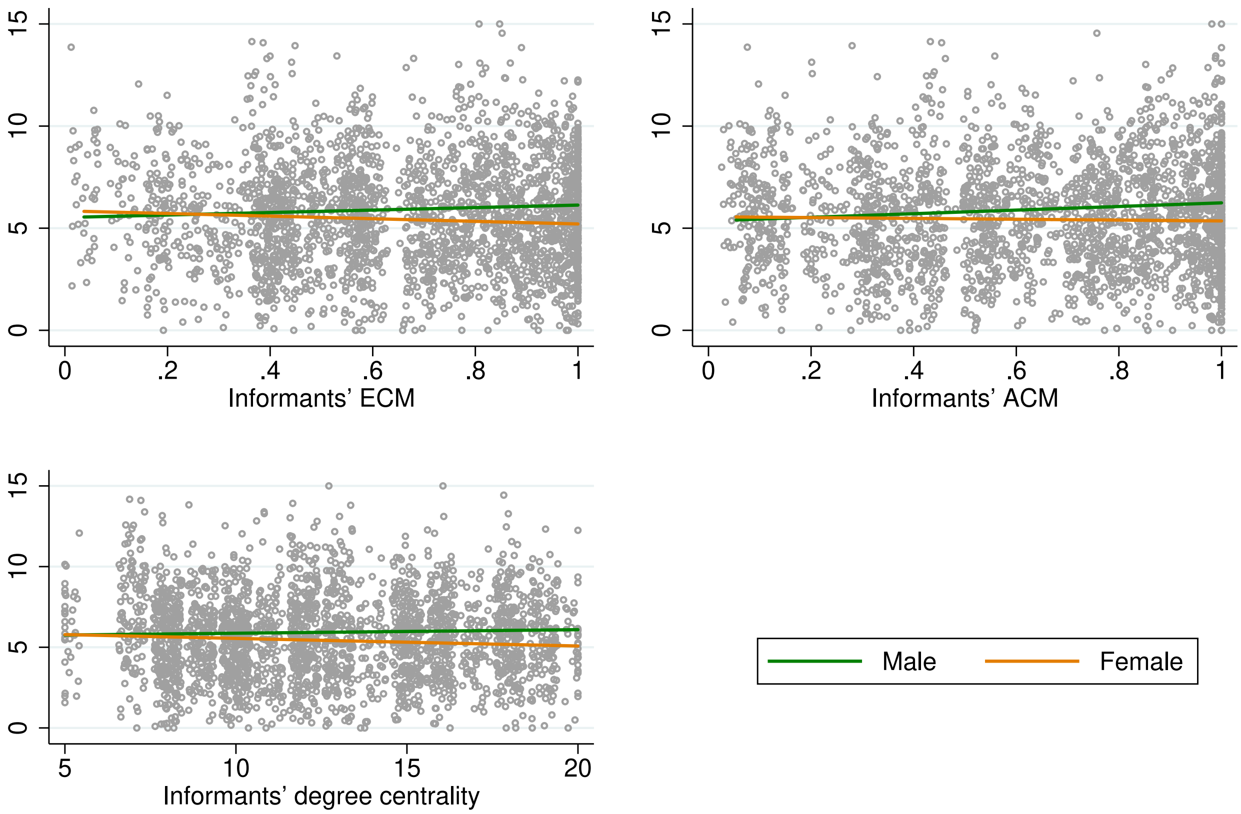

Fig. 5.4: Informant network centrality and information inequality between genders.

With this aim, Table 5.5 presents the results derived from Equation 5.5, where the follow-up knowledge score of students is the dependent variable. Specifically, the interaction of the DCM, ECM, and ACM of informants with the gender of their classmates is introduced in three separate models (columns). Moreover, the correlation between the above measures and the outcomes of female students was tested using the Wald test, as presented in the second part of the table.

In column (1), the results show a negative correlation between the DCM of informants and the follow-up knowledge of their male classmates. The correlation for female classmates was even more negative, as captured by the coefficients of the interaction term (Female*Degree).[6] In general, this indicates that the higher the informant's number of connections, the less likely it is that they will pass the information to their classmates. Column (2) replicates the analysis for ECM. The results show no significant association between the performance of male students and the ECM of their informants. The coefficient of the interaction term (Female*ECM) indicates that the knowledge score of females was lower than that of males when the ECM of their informants is high. Therefore, the results suggest that the ECM of informants widens the difference in knowledge scores between female and male students. Column (3) shows that, unlike the SCMs, the ACM of informants was positively correlated with the performance of their classmates, regardless of their gender. The variable Female*ACM was not statistically significant, thus indicating that there was no evidence of the association between the ACM of informants and information inequality across genders. Notably, the adoption of the ACM in selecting the informants ensured that the empowerment of female students was stronger, compared to all the other SCMs considered.

[6] The coefficient of DCM (-0.72) is the association between the DCM of informants and the knowledge scores of male students. The association of the DCM of informants and knowledge score of females is the sum of the coefficients for DCM plus Female*DCM (-0.72 + -0.061= -0.78).

Table 5.5: The informants network and information inequality across gender

	(1)	(2)	(3)
Climate knowledge(Baseline)	0.29***	0.29***	0.29***
	(0.00)	(0.00)	(0.00)
Female	0.33	0.20	-0.10
	(0.46)	(0.57)	(0.75)
Degree	-0.72***	-0.59***	-0.47***
	(0.00)	(0.00)	(0.00)
Female*Degree	-0.061*		
	(0.07)		
ECM		0.080	
		(0.91)	
Female*ECM		-0.96**	
		(0.04)	
ACM			1.46***
			(0.01)
Female*ACM			-0.52
			(0.20)
Degree + Female*degree	-0.78***		
	(0.00)		
ECM + Female*ECM		-0.88	
		(0.23)	
ACM + Female*ACM			0.94**
			(0.028)
N	1902	1902	1902
R^2	0.20	0.20	0.20

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In all columns the dependent variable is the students' follow-up knowledge scores. All regressions include class fixed effects and all individuals characteristics that are included in table 5.4, and standard errors are clustered at class level

5.5.3 Robustness Check

In order to check the robustness of the analyzed results, we ran ancillary elaborations addressing two main issues, by adapting Equation 5.5. First, it can be stated that male students performed better because, in general, they were part of wider social networks than females and were used to obtaining information not exclusively from their classmates, thus marginalizing the role of the informant. To address this concern, we calculated the social distance of each student from the informant.[7] If the information was not disseminated by the informants, then there should be no correlation between the social distance from the informant and the observed difference between the performance of male and female students. In other words, the score difference between pairs of male and female students should not systematically vary along with the distance from the informants. By using the interaction terms of social distance and gender (Female*Distance from informants), column (1) shows the correlations between the distance from informants and the knowledge of male and female students, in order to identify any gendered differences. The results showed that male students who were closer to the informants disproportionately benefited, compared to their female counterparts with similar distances.

Second, we argue that the proposed ACM could reduce the information inequality between males and females by combining the network centrality of informants with their behavioral traits. However, it could be remarked that the altruism of informants could be sufficient to reduce information inequality across genders, regardless of their network position. To address this concern, we used the interaction terms between the level of altruism of informants and the gender of students to investigate their correlation with the knowledge of male and female students. If the level of altruism is a sufficient selection criterion for the purpose, it should be positively correlated with the knowledge score of the students, and no gender should be benefitted disproportionately. The results in column (3) show that the coefficients for both altruism, and its interaction with the female dummy were not significant, indicating that altruism alone was not correlated with the knowledge of male or female students.

[7] Social distance is the measure of the path length linking trained and other nodes. For instance, the social distance between informants and their closest friends is equal to 1.

Table 5.6: Social distance, altruism and information inequality across genders

	(1)	(2)	(3)
Climate knowledge(Baseline)	0.28***	0.29***	0.28***
	(0.00)	(0.00)	(0.00)
Female	-0.96***	-0.58**	-0.37***
	(0.01)	(0.04)	(0.00)
Distance from informant	-0.47***		-0.29***
	(0.00)		(0.00)
Female*Distance from informant	0.31*		
	(0.09)		
Informant altruism		-1.22	
		(0.36)	
Female*informant altruism		0.35	
		(0.50)	
Distance from informant + Female*Distance from informant	-0.16		
	(0.165)		
Informant altruism + Female*Informant altruism		-0.87	
		(0.5)	
N	1892	1902	1892
R^2	0.20	0.20	0.20

Note: p-values in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In all columns the dependent variable is the students' follow-up knowledge scores. All regressions include class fixed effects and all individuals characteristics that are included in table 5.4, and standard errors are clustered at class level.

5.6 Conclusions

Information diffusion through social networks has been adopted to a great extent, especially in remote communities and in developing countries. Such approaches have been used to accelerate the adoption of technological innovations and the diffusion of microfinance services, as well as other development-related projects. In fact, leveraging social networks for the purpose of propagating information offers several advantages, relating, for example, from the feasibility of the process to its cost-effectiveness. However, this study showed the unintended implications of such an approach that can be derived from the criterion adopted in selecting the injection points (informants); in particular, how information inequality between genders can arise in given circumstances. We explored this drawback and contributed a possible solution to minimize the derived differences among groups.

We used primary data collected from all grade-nine students residing in Bahir Dar, Ethiopia. It covered eight high schools and 3,693 students. The data collection involved both baseline and follow-up surveys, where the former was used to gather data on the personal and socio-economic characteristics, network positions, levels of altruism, and climate change-related knowledge of students. After completing the baseline survey, one informant per class was randomly selected and given training on climate change topics, with the aim of diffusing the information to their respective classmates. A follow-up survey was administered, in order to evaluate the climate change-related knowledge of students after the information diffusion generated by the informants. Moreover, we developed an augmented (altruism weighted) centrality measure, to show the advantages of selecting informants according to their level of altruism and network centrality over the SCMs, when addressing information inequality.

We found that female students performed lower than male students when information was diffused through a social network. This was in line with previous findings, indicating that information diffusion using central nodes selected through SCMs puts women and minorities at a competitive disadvantage (Beaman and Dillon, 2018). We further investigated whether the informant's gender was associated with the information diffusion, and found that female informants were less likely to spread the information than male informants. Our findings also suggest that students were more likely to receive the information when their class informants shared the same gender. Next, we considered whether the choice of the network centrality measure (i.e., the criterion adopted to select the central nodes) was relevant to the generation of information inequality. The results showed that the SCMs of informants was more negatively associated with the climate change-related knowledge of female students, compared to male students. Therefore, we augmented the eigenvector centrality measure with the level of altruism of individuals and found that, as the ACM of the informant increased, so did the performance of both male and female students.

Our findings lead to two main implications: From a methodological perspective, the integration of social network analysis with behavioral economics can offer the opportunity to reduce the information inequality between genders, thus enhancing information propagation across the network. We show that the choice of behavioral precursor (in this study, altruism) can effectively contribute to the purpose, even though this does not characterize the central nodes (the randomly selected informants revealed a level of altruism lower than that of the sample of students). In this regard, a motivational linkage between the behavioral precursor and the subject of the information (in this study, climate change) seems sufficient. However, the definition of the ACM requires an adequate design, as well as the conduction of appropriate behavioral economic experiments in order to elicit the relevant preferences of the individual. In operational terms, the combination of social network analysis with behavioral economics implies a quite complex procedure to be implemented in the field, but offers an opportunity to boost information diffusion in a number of circumstances (e.g., combining public goods and altruism or innovation adoption and risk preferences; Croson and Gneezy, 2009; Scrogin, 2018; Hillesland, 2019; Friedl et al., 2020); mainly, to contribute to reducing the information inequality between social groups and especially that across genders.

Nevertheless, the following caveats apply to this study: First, the Ethiopian school absenteeism rate is relatively high. Therefore, some students attended the baseline survey but missed the follow-up survey, and vice versa. However, we argue that this did not affect our results, as the students had no prior knowledge of the data collection dates, making the absenteeism random. The second limitation concerns the unavailability of clear control groups to analyze the cause and effects of SCMs and ACM on the information inequality across genders; thus, randomized controlled trials with an appropriate selection of the informants (i.e., treatment and control groups) should be implemented. Third, we identified the classroom as the social network, thus assuming that students were less likely to have social connections with peers from other classes. If this is not true, students could obtain relevant information not exclusively from their informants or classmates, and the meaning of the correlation between centrality measures and knowledge score could be altered. Even though the robustness check showed that the access to information was negatively associated with the social distance between students and their informants (Table 5.6, column 3), further research aimed at investigating the information flows, either at an appropriate scale (e.g., at school level) or in isolated social networks, should be conducted.

Chapter 6

General conclusions

This study presents the roles of social networks and behavioral attributes on information diffusion. It aims to show the importance of selecting informants by considering both their network position and their altruism level to diffuse information effectively. The thesis consists of three empirical papers.

The first article (chapter 3) provides a general understanding of the main behavioral attributes that affect individuals' intentions to adopt a brand new (BNT) and an upgraded bioenergy innovation (UBT). This study uses primary data collected from Ethiopian experts in the energy field and implements a two-step approach to investigate the intention to adopt the two types of innovations. In the first step (the factor analysis results), among other factors, lack of knowledge about the innovations and their opportunities affects the adopters' intentions through creating unfavorable attitudes toward the innovation. The second step's results, using an ordered logit regression, reveal that the behavioral precursors of adopters are related to contextual conditions and differ according to the type of bioenergy innovation. Specifically, individuals' intentions to adopt BNT are related to global contextual conditions, such as the potential of the innovation to reduce global pollutant emissions. For the UBT, the adopters' intentions are associated with more specific contextual conditions, for instance, their benefit to the community's quality of life. In general, results suggest spreading information (knowledge) about the innovation's benefit to increase its adoption rate.

The second article is presented in chapter 4 shows the importance of combining both social network and behavioral attributes to effectively diffuse information, especially when the information is related to environmental issues. To date, literature has shown the role of network positioning to select central individuals (informants) to disseminate information through social networks. However, such approaches do not factor in the behavioral attributes of the informants, which could have repercussions both on the effectiveness and equity of information diffusion. Given that altruistic individuals care for the well-being of others, this study proposed the altruism augmented centrality measure (ACM), which is a modified version of the eigenvector centrality measure (ECM), by incorporating the level of altruism of informants and their network neighbors. The aim of this study is to compare the effectiveness of the ACM and the standard centrality measures (SCMs) to spread information, notably on environmental issues. Using 3,693 Ethiopian high school students' altruism and their friendship networks among classmates, we provide the first empirical evidence on the relative advantages of the ACM over the SCMs to diffuse climate-change information. The results also show that there is no association between individuals' network positioning and their altruism levels. The results have crucial policy implications by indicating that when the information is related to environmental issues such as climate change, it is important to select informants considering not only their network position but also their altruism level.

The third article (chapter 5), examines the impacts of gender on the social network structures and on the information diffusion process. Particularly, it aims to investigate if information diffusion through social networks puts women at a competitive disadvantage. It also compares the information inequality between male and female students when informants are selected by the SCMs and the ACM. This study uses the same data set that is used for the analysis of our second article, the Ethiopian high school students' social networks and altruism to address the above research questions. The results show that female students are less advantaged when the information is diffused through social networks using central individuals. Our findings also suggest that students are more likely to receive the information when their class informants share the same gender. We further investigate if informants' network centrality could explain the information inequality between males and females, and we find that relying on network position to select informants exacerbates the information inequality between genders. Specifically, females are less advantaged in receiving information when it is diffused through central individuals in the network, which calls for a better approaches to selecting informants. Accordingly, we provide empirical evidence that shows selecting informants based on ACM, which combines network position and altruism level of informants, leads to a broader information diffusion and lowers the inequality between genders.

To summarize, the thesis suggests that policymakers and practitioners should target different instruments to diffuse innovations depending on their nature. Moreover, it advises practitioners to select informants by combining network position and behavioral attributes to effectively and equitably diffuse information, compared to relying on network centrality measures alone - notably when the information is concerned with environmental issues.

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Appendices

Appendix 1

Table A1: Description of the obstacles to the introduction of bioenergy innovations.

Variables	Description
Unavailable qualified staff	Difficulties to find qualified staffs in the local market to develop products or assist activities in bioenergy.
Competition with food	The potential risk related to cultivating land for biomass instead of crops.
Low benefit/cost ratio	Low economic return from bioenergy investment.
Risk due to technology	Potential risk related to lack of knowledge of the technology to generate energy from biomass.
Risk due to market conditions	Risk perception related with local demand for bioenergy product and or producers competition.
Limited access to private financing	Difficulty to get financial support from private financial sectors to invest on bioenergy.
Limited access to public financing	Difficulty to get financial support from public financial sectors to invest on bioenergy.
High fiscal burden	High tax rate.
Lack of information on bioenergy innovations	Imperfect information/knowledge on new/upgraded bioenergy innovations.
Lack of knowledge of environmental benefits	Imperfect knowledge on environmental benefit derives from bioenergy innovations.
Lack of knowledge of public benefits	Imperfect knowledge on the public benefits derive from adopting the bioenergy innovation.
R & D not addressing the business' needs	Research and development activities not addressing the needs of the enterprises.

Table A2: Description of the drivers of the introduction of bioenergy innovations.

Variables	Description
Energy demand	An increasing of energy demand in the study area.
Financial support to investments	A potential financial support to invest on bioenergy.
R &D	Supports from research and development institutions
Contribution to quality of life	The innovations' Contribution through improving community's quality of life.
Contribution to environmental quality	Intention to improve environmental quality.
Reduction of GHGs emissions	The contribution of the innovation through reducing of CO2 and such emissions released from traditional energy sources.
Social acknowledgment	Obtaining social recognition.
Collaboration with providers	Availability of collaboration with and technical assistants the innovations suppliers and technical assistant providers.
Collaboration with customers	Existence of collaboration with customers.
Collaboration with other enterprises	Collaboration with other enterprises such as private firms that are investing on bioenergy innovations.
Collaboration with institutions public organizations	Collaboration with other institutions such as that have positive influence to introduce bioenergy innovations.
Collaboration with local Universities	Existence of direct link with local research centers & universities that share knowledge & resources.
Collaboration with foreign Universities	Existence of collaboration with foreign research centers & universities that shares knowledge and resource.
Economic return	Profitability of bioenergy innovation investment.
Social responsibility	A responsibility to improve well-being of the society.

Table A3: Description of the drivers of the diffusion of bioenergy innovations.

Variables	Description
Growing of energy demand	An increasing of energy demand.
Entrepreneurs' willingness to imitative	Behavior of entrepreneurs(availability to change,willingness to change,imitation).
Human resources(skills)	Availability of skilled man power.
Contribution to quality of life	An interest to improve wellness of the local community.
Contribution to environmental quality	An intention to improve environmental quality.
Reduction of GHGs emissions	An interest to reduce emission from traditional energy source.
Social acknowledgment	An interest to obtain social recognition.
Social responsibility	A responsibility to improve social well-being.
Organizational strategies	Clearly defined vision/strategies, established norms for innovation promotion.
R &D	Availability of R & D to solve to overcome challenges.
Social norms and local partners	Availability of social capital and local partnership.
Social norms and foreign partners	Existence of social capital and foreign partners.
Policy incentives	Incentives such as subsidy and fiscal deduction.
Public investments (infrastructures)	Availability of infrastructure such as road, telecommunication.
Private investments	Availability of private investors in the bioenergy sector.
Credit availability	Availability of financial facilities.

Table A4: Logit model: factor affecting the intention to adopt a BNT and an UBT.

Variables	(1) BNT	(2) UBT	(3) Behavioral Precursors
Lack of information on bioenergy innovations	0.0919	-0.122	
	(0.717)	(0.702)	
Lack of knowledge of public benefits	-0.0347	-0.440	
	(0.863)	(0.187)	
Reduction of GHGs emissions	1.237**	-0.846**	Attitude
	(0.035)	(0.048)	
Organizational strategies	-0.287	0.0467	
	(0.142)	(0.790)	
R&D	0.648***	-0.0832	Behavioral Control
	(0.010)	(0.771)	
Collaboration with customers	0.565*	0.928**	Subjective Norm
	(0.087)	(0.029)	
Collaboration with foreign universities	-0.100	0.494	
	(0.718)	(0.102)	
Limited access to public financing	0.101	0.165	
	(0.569)	(0.368)	
Social acknowledgment	-0.433	0.318	
	(0.130)	(0.191)	
Contribution to quality of life		0.748*	
		(0.090)	
Constant	-14.99***	-7.594**	
	(0.005)	(0.045)	
N	71	70	
pseudo R^2	0.286	0.294	

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In column (1) and (2), the dependent variables are the intention to adopt a BNT and UBT, respectively. It is a binary variable (0,1) with value 1 when the respondent's intention to adopt the innovation is greater than the medium value. All the independent variables are considered as continues variables. Column (1) and (2) show the coefficients of the logit. Column 3 shows the behavioral precursors category of statistically significant variables.

Appendix 2

Table B1: Description of variables

Variables	Description
Followup climate knowledge	Climate change knowledge score after training provided to selected informants
Baseline climate knowledge	Climate change knowledge score before training provided to selected informants
Degree	Degree centrality; both number of friends who mentioned a student as a friend and number of friends named by himself
ECM	Eigenvector centrality is computed as described in Section 4.2.4 and 5.3.2
ACM	Augmented centrality measure is computed as described in Section 4.2.4 and 5.3.2
Altruism	Altruism value measured by the SVO index (i.e., SVO index = arctan $\left(\frac{average\ allocated\ to\ others-50}{average\ allocated\ to\ self-50}\right)$)
Age	Age
Female	gender, it takes value 1 if a student is female
Religion	A dummy variable, it takes value of 1 if a student is a follower of Orthodox, Protestant or Islam religions, otherwise 0.
Current scholastic grade	Using five ordinal scales, students' self-evaluation for their academic performance in 2019 (during the survey period).
Past scholastic grade	Using five ordinal scales, students' self-evaluation for their academic grade for academic year 2018.
Parent's education	Parent's education level,using ordinal scale.
Home school distance	Minutes take to walk from students' home to their school.

Note: in Ethiopia, a large proportion of the population are follower of Orthodox, Islam and Protestant, while the other religions have minor followers.

Table B2: Augmented and standard centrality measures, and information diffusion

	(1)	(2)	(3)
ACM	0.391***		0.222**
	(0.006)		(0.042)
ECM		-0.132	-0.132
		(0.458)	(0.458)
DCM	-0.533***	-0.713***	-0.507***
	(0.000)	(0.000)	(0.000)
Baseline climate knowledge	0.286***	0.286***	0.286***
	(0.000)	(0.000)	(0.000)
Age	-0.0644	-0.0644	-0.0644
	(0.194)	(0.194)	(0.194)
Female	-0.435***	-0.435***	-0.435***
	(0.001)	(0.001)	(0.001)
Current scholastic grade	0.303***	0.303***	0.303***
	(0.000)	(0.000)	(0.000)
Past scholastic grade	0.184**	0.184**	0.184**
	(0.021)	(0.021)	(0.021)
Religion	-0.420	-0.420	-0.420
	(0.547)	(0.547)	(0.547)
Parent's education	0.122***	0.122***	0.122***
	(0.003)	(0.003)	(0.003)
Home to school distance	0.00174	0.00174	0.00174
	(0.658)	(0.658)	(0.658)
Constant	9.503***	11.88***	9.355***
	(0.000)	(0.000)	(0.000)
N	1908	1908	1908
R^2	0.196	0.196	0.196

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is the students' follow-up knowledge. In column 1 and 2, show the role of ACM and ECM after controlling degree centrality. In column 3, ACM, ECM and DCM are included jointly in the model. All columns include class fixed effects and standard errors are clustered at class level.

Table B3: Degree centrality and information diffusion

	(1)	(2)	(3)
DCM	-1.503***	-0.867***	-0.896***
	(0.000)	(0.000)	(0.000)
Baseline climate knowledge		0.342***	0.286***
		(0.000)	(0.000)
Age			-0.0644
			(0.194)
Female			-0.435***
			(0.001)
Current scholastic grade			0.303***
			(0.000)
Past scholastic grade			0.184**
			(0.021)
Religion			-0.420
			(0.547)
Parent's education			0.122***
			(0.003)
Home to school distance			0.00174
			(0.658)
Constant	22.36***	13.77***	13.95***
	(0.000)	(0.000)	(0.000)
N	2532	2313	1908
R^2	0.121	0.155	0.196

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is students' follow-up knowledge. Regressions include class fixed effects. Standard errors are clustered at class level.

Table B4: Augmented and standard centrality measures, and information diffusion

	(1)	(2)	(3)
ACM	1.044***		
	(0.000)		
ECM		-0.205	
		(0.287)	
DCM			-0.967***
			(0.000)
Baseline climate knowledge	0.296***	0.296***	0.296***
	(0.000)	(0.000)	(0.000)
Age	-0.0636	-0.0636	-0.0636
	(0.270)	(0.270)	(0.270)
Female	-0.413***	-0.413***	-0.413***
	(0.004)	(0.004)	(0.004)
Current scholastic grade	0.277***	0.277***	0.277***
	(0.000)	(0.000)	(0.000)
Past scholastic grade	0.234***	0.234***	0.234***
	(0.007)	(0.007)	(0.007)
Religion	-0.871	-0.871	-0.871
	(0.245)	(0.245)	(0.245)
Parent's education	0.105**	0.105**	0.105**
	(0.016)	(0.016)	(0.016)
Home to school distance	0.00151	0.00151	0.00151
	(0.720)	(0.720)	(0.720)
Constant	3.261**	4.399***	15.14***
	(0.018)	(0.002)	(0.000)
N	1622	1622	1622
R^2	0.194	0.194	0.194

Note: p-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable is students' follow-up knowledge scores. A school with highest students' attrition rate is not included in the sample. Class fixed effects are included in all columns. Standard errors are clustered at class level.

Appendix 3: Questionnaires

Sample of the questionnaire of bioenergy innovation in Ethiopia

The questionnaire you are kindly asked to answer is focused on the diffusion of innovation in the agro-energy sector.

A number of stakeholders interested in the energy sector have been asked to participate in the same interview. This interview is anonymous. The information you provide will not affect your right to any services you are receiving or may receive from the government. Please provide an answer for each of the following questions:

Please provide an answer for each of the following questions:

- In the case of Section 1 you should choose your profile;
- In the case of Section 2 (if you selected the profile "entrepreneur") you should indicate the number of employees of your company and the business sector;
- For **Sections** from 3 to 6 you should mark the most appropriate answer where:
  1 = not relevant
  9 = extremely relevant

1. Your profile									
Expert / researcher (researcher, consultant)									
Policy maker / civil servant of "non-research" public institutions									
Expert of "non-research" private institutions (e.g. association)									
Entrepreneur (farmer, manager, etc)									
Other (please specify)									
2. If you have selected the category "entrepreneur" could you									
Please indicated the number of employee of the farm/enterprise you are running/working for?	0 - 4	5 - 9	10 - 19	20 - 49	50 - 99	100 - 199	200 - 249	250 - 499	> 500
Please indicate your business sector									
3. what kind of innovation of the bio-energy domain (energy from renewable bio-sources) is more interesting for your Company and/or for the Ethiopian agro-energy sector?									
Organizational innovation (e.g.: new forms of internal and/or external collaborations)	1	2	3	4	5	6	7	8	9
Incremental biomass and / or bio-energy product (amelioration to an already existing product)	1	2	3	4	5	6	7	8	9
Radical innovation of biomass and / or bio-energy product (development of a new product)	1	2	3	4	5	6	7	8	9
Incremental biomass and / or bio-energy process innovation (amelioration to an already existing process)	1	2	3	4	5	6	7	8	9
Radical biomass and / or bio-energy process innovation (introduction of a new process)	1	2	3	4	5	6	7	8	9
Other kind of innovation (please specify):	1	2	3	4	5	6	7	8	9
4. what are the major obstacles to the introduction of bio-energy innovation?									
Resources availability (land, water, …)	1	2	3	4	5	6	7	8	9
Ethical reasons (i.e. risk for food security due to food vs fuel competition)									
Difficulties to identify qualified staff	1	2	3	4	5	6	7	8	9

Potential competition with food crops	1	2	3	4	5	6	7	8	9
High cost - benefit ratio (low economic return)	1	2	3	4	5	6	7	8	9
High perceived risk due to financial conditions	1	2	3	4	5	6	7	8	9
High perceived risk due to technological availability	1	2	3	4	5	6	7	8	9
High perceived risk due to market variability	1	2	3	4	5	6	7	8	9
Difficulties to obtain private financial support	1	2	3	4	5	6	7	8	9
Difficulties to obtain public financial support	1	2	3	4	5	6	7	8	9
High fiscal burden (heavy taxation)	1	2	3	4	5	6	7	8	9
Difficulties to reorganize the production process	1	2	3	4	5	6	7	8	9
Lack of information on innovative solutions / technologies	1	2	3	4	5	6	7	8	9
Lack of clear knowledge on the deriving environmental benefits for your area	1	2	3	4	5	6	7	8	9
Lack of clear knowledge on the deriving public benefits for your community / for the society	1	2	3	4	5	6	7	8	9
Lack of providers or of services of technical assistance	1	2	3	4	5	6	7	8	9
Market difficulties (lack of market knowledge; competition with leading enterprises)	1	2	3	4	5	6	7	8	9
Lack of linkages with universities/research centers	1	2	3	4	5	6	7	8	9
Research and development activities not addressing the needs of the enterprises	1	2	3	4	5	6	7	8	9
Difficulties to develop technical and financial partnerships	1	2	3	4	5	6	7	8	9
5. In your opinion, what are the major factors that favored / can favor the <u>introduction</u> of the bio-energy innovation?									
Growing energy needs	1	2	3	4	5	6	7	8	9
Investments / financial support	1	2	3	4	5	6	7	8	9
Research and development	1	2	3	4	5	6	7	8	9
Contribution to the quality of life / wellness of your community	1	2	3	4	5	6	7	8	9
Contribution to the environmental quality of your region	1	2	3	4	5	6	7	8	9
Reduction of green-house gases emissions	1	2	3	4	5	6	7	8	9
Obtaining public or social acknowledgement	1	2	3	4	5	6	7	8	9
Collaboration with providers and technical assistants	1	2	3	4	5	6	7	8	9
Collaboration with customers	1	2	3	4	5	6	7	8	9
Collaboration with other enterprises	1	2	3	4	5	6	7	8	9
Collaboration with Institutions	1	2	3	4	5	6	7	8	9
Collaboration with local research Centers and Universities	1	2	3	4	5	6	7	8	9

Collaboration with foreign research Centers and Universities	1	2	3	4	5	6	7	8	9
Expected economic returns	1	2	3	4	5	6	7	8	9
Social responsibility (benefit for the entire society)	1	2	3	4	5	6	7	8	9
6. In your opinion, what are the main factors stimulating the <u>diffusion</u> of innovation in the bio-energy field?									
Expected increase of energy demand	1	2	3	4	5	6	7	8	9
Behavior of entrepreneurs (availability to change; willingness to change; imitation)	1	2	3	4	5	6	7	8	9
Human resources (skills)	1	2	3	4	5	6	7	8	9
Contribution to the quality of life / wellness of the local communities	1	2	3	4	5	6	7	8	9
Contribution to the environmental quality of the region	1	2	3	4	5	6	7	8	9
Reduction of green-house gases emissions	1	2	3	4	5	6	7	8	9
Obtaining public or social acknowledgement	1	2	3	4	5	6	7	8	9
Social responsibility(benefit for the entire society)	1	2	3	4	5	6	7	8	9
Organizational strategy (clearly defined vision/strategy; established norms for innovation promotion)	1	2	3	4	5	6	7	8	9
Research and development	1	2	3	4	5	6	7	8	9
Social capital and partnerships (with local partners)	1	2	3	4	5	6	7	8	9
Social capital and partnerships (with foreign partners)	1	2	3	4	5	6	7	8	9
Policy measures (subsidies; fiscal deductions; norms and regulations)	1	2	3	4	5	6	7	8	9
Public investments (infrastructural investments)	1	2	3	4	5	6	7	8	9
Private business investments	1	2	3	4	5	6	7	8	9
Credit availability	1	2	3	4	5	6	7	8	9

Appendix 4: Questionnaires II

Sample of Questionnaire social networks, altruism and knowledge of climate change.

Baseline Questionnaire

መጠይቅ

መግቢያ:

የተከበራችሁ ተሳታፊወች:

ስሜ አፀደ ይባላል። ጣልያን ውስጥ በሚገኘው ቦሎኛ ዩኒቨርሲቲ የዶክትሬት ተማሪ ስሆን በአሁኑ ጊዜ ለመመረቂያ ጽሁፌ ግብዓት የሚሆን መረጃ በመሰብሰብ ላይ እገኛለሁ። የጥናታዊ ጽሁፌ በማህበረሰባዊ ግንኙነት ላይ ያተኩራል። ትምህርት ቤቶች የግንኙነት መዋቅርን ለማጥናት ምቹ ስለሆኑ የጥናታዊ ጽሁፌ የናንተን ጨምሮ በባህርዳር ከተማ የሚገኙ ሁለተኛ ደረጃ ትምህርት ቤቶችን ያካትታል። በመሆኑም እናንተም የዚህን ጥናት መጠይቅ በመሙላት እንድትተባበሩኝ በአክብሮት ተጋብዛችኃል።

መጠየቁን ለመሙላት በአማካኝ ከ 40-50 ደቂቃ ይወስዳል። በመጠይቁ ላይ ያሉትን ጥያቄወች በሙሉ በተገቢው መንገድ ሞልታችሁ ከጨረሳችሁ በዓይነት ክፍያ ይኖራችኃል። የምታገኙት የክፍያ አይነት የሚወሰነው በመጠይቁ ክፍል 3 ላይ በሚቀርቡላችሁ የሀብት ክፍፍል አማራጮች ላይ በምታሳልፉት ዉሳኔ መሰረት ይሆናል ። (ዝርዝሩ በክፍል 3 መግቢያ ላይ የሚገለጽ ይሆናል።)

በዚህ መጠይቅ ላይ ለሚቀርቡላችሁ ጥያቄዎች የምትሰጡት ምላሽ በሚስጥር የሚጠበቅ እና ለዚህ ጥናት አገልግሎት ብቻ የሚውል ይሆናል። መረጃው ከተሰበሰበ በኋላም ማንኛውም ግለሰባዊ መረጃወች ለምሳሌ ሙሉ ስም ና ተራ ቁጥር ወደ ሚስጥራዊ መለያ ከተቀየሩ በኋላ የሚወገዱ ይሆናል፡፡ በተጨማሪም እንደ ዕምነት ፡ የወላጅ ትምህርት ደረጃ ና ስራ ሁኔታ .. የመሳሰሉት ምላሾች በቡድን መልክ ከተደራጁ በኋላ ለትንታኔ የሚውሉ ይሆናል፡፡ ለመሳተፍ ከመረጣችሁ እና ክፍያ ለማግኘት ከፈለጋችሁ፤ እባካችሁን መጠይቁን በተቻለ መጠን በተገቢው ከሞላችሁ በኋላ ለተገቢው አካል መልሱ። ተሳትፏችሁ ፍፁም ፈቃደኝነትን መሰረት ያደረገ ሲሆን ፍቃደኛ ያልሆነ ተሳታፊ በማንኛውም ጊዜ ማቋረጥ ይችላል።

ጊዜያችሁን ሰውታችሁ መጠይቁን ለመሙላት ፍቃደኛ ስለሆናችሁ እና የጥናታዊ ጽሁፌን ዓላማ እንዳሳካ ስለተባበራችሁኝ እጅግ አድርጌ አመሰግናችኃለሁ።

ክፍል 1

1. ሙሉ ስም : ____________________	የክፍል ተራ ቁጥር :____________
2. ፆታ	ወንድ☐ ሴት☐
3. ዕድሜ	
4. ከእድሜ እኩዮችሽ/ህ አንፃር የአካላዊ እድገትሽ/ህ (ቁመትሽ/ህ) እንዴት ትገመግሚዋለሽ/ህ ?	ከብዙወቹ አንፃር ትንሽ ሁኘ እታያለሁ☐ ከጥቂቶቹ አንፃር ትንሽ ሁኘ እታያለሁ☐ መካከለኛ ሁኘ እታያለሁ☐ ከጥቂቶቹ አንፃር ትልቅ ሁኘ እታያለሁ☐ ከብዙወቹ አንፃር ትልቅ ሁኘ እታያለሁ☐

5. ከእድሜ እኩዮችሽ/ህ አንፃር የአካላዊ እድገትሽ/ህ (ክብደትሽ/ህ) እንዴት ትገመግሚዋለሽ/ህ ?	ከብዙወቹ አንፃር ቀጭን ሁኘ እታያለሁ☐ ከአንዳንዶቹ አንፃር ቀጭን ሁኘ እታያለሁ☐ መካከለኛ ሁኘ እታያለሁ☐ ከአንዳንዶቹ አንፃር ወፍራም ሁኘ እታያለሁ☐ ከብዙወቹ አንፃር ወፍራም ሁኘ እታያለሁ☐
6. የምን ሃይማኖት ተከታይ ነሽ/ህ ?	ካቶሊክ☐ ሙስሊም☐ ኦርቶዶክስ☐ ፕሮቴስታንት☐ ሌላ________
7. ከአማርኛ በተጨማሪ መናገር የምትችይዉ/ለዉ ቋንቋ አለ?	አለ☐ የለም☐
7.1. ለጥያቄ ቁጥር 7 መልስሽ/ህ አለ ከሆነ፣ ምን ምን ተጨማሪ ቋንቋዎች መናገር ትችያለሽ /አለህ?	______________________ ______________________
8. የቤተሰብሽ/ህ አባላት ቁጥር ስንት ነዉ?	______________________
9. ከአንተ/ቺ በተጨማሪ እዚህ ት/ቤት የሚማሩ እህቶች /ወንድሞች አሉሽ/ህ?	አለ☐ የለም☐
10. በትምህርትሽ/ህ ጥሩ ዉጤት ለማምጣት ምን ያህል ጥረት ታደርጊያለሽ/ህ?	ምንም አይነት ጥረት አላደርግም ☐ እምብዛም ጥረት አላደርግም ☐ እሞክራለሁ ነገር ግን የአቅሜን ያህል አይደለም ☐ አቅሜ የሚፈቅደልኝ ያህል እሞክራለሁ ☐
11. ወቅታዊ የትምህርት ዉጤትሽን/ህን መሰረት በማድረግ ራስሽን/ህን እንዴት ትገመግሚያለሽ /ማለህ?	ከመካከለኛ ተማሪ ያነሰ ☐ ከመካከለኛ ተማሪ በመጠኑ ያነሰ ☐ መካከለኛ ተማሪ ☐ ከመካከለኛ ተማሪ በመጠኑ የተሻለ ☐ ከመካከለኛ ተማሪ እጅግ በጣም የተሻለ ☐

12. ያለፈ አመት የትምህርት ዉጤትሽን/ህን መሰረት በማድረግ ራሰሽን/ህን እንዴት ትገመግሚያለሽ/ ትገመግማለህ?	ከመካከለኛ ተማሪ ያነሰ ☐ ከመካከለኛ ተማሪ በመጠኑ ያነሰ ☐ መካከለኛ ተማሪ ☐ ከመካከለኛ ተማሪ በመጠኑ የተሻለ ☐ ከመካከለኛ ተማሪ እጅግ በጣም የተሻለ ☐
13. በዚህ አመት ምን አይነት የትምህርት ዉጤት ለማስመዝገብ አቅደሻል/አቅደሃል?	ከመካከለኛ ተማሪ ያነሰ ☐ ከመካከለኛ ተማሪ በመጠኑ ያነሰ ☐ መካከለኛ ተማሪ ☐ ከመካከለኛ ተማሪ በመጠኑ የተሻለ ☐ ከመካከለኛ ተማሪ እጅግ በጣም የተሻለ ☐
14. እባክሽን/ህን የሚከተሉትን የትምህርት አይነቶች የትምህርት ዉጤትሽን/ዉጤትህን መሰረት በማድረግ የደረጃ ቅደም ተከተል ስጫቸዉ/ስጣቸዉ :: ለምሳሌ እንግሊዝኛ በአብዛኛው ከሁሉም የትምህርት ዓይንቶች ይልቅ የተሻለ ዉጤት የምታስመዘግቢበት/ብበት የትምህርት አይነት ከሆነ አንደኛ ደረጃ ስጪዉ/ስዉ :: እንግሊዝኛ 1	አማርኛ ☐ ኬሚስትሪ ☐ ሕብረተሰብ ☐ ስነ-ህይወት ☐ ስነ-ዜጋና ስነ-ምግባር ☐ እንግሊዝኛ ☐ ታሪክ ☐ ሒሳብ ☐ ፊዚክስ ☐ የሰዉነት ማጎልመሻ ☐
15. የአባትሽ/አባትህ የትምህርት ደረጃ ምንድን ነዉ?	ምንም: ያልተማረ ☐ የባህላዊ ትምህርት ☐ አንደኛ ደረጃ (1-8ኛ ክፍል) ☐ ሁለተኛ ደረጃ (9-12ኛ ክፍል) ☐ ዲፕሎማ ወይም TTI ☐ የመጀመሪያ ዲግሪ ☐ የማስተርስ ዲግሪ ☐ የዶክትሬት ዲግሪ ☐ ጥያቄዉ አይመለከተኝም ☐

16. የእናትሽ/እናትህ የትምህርት ደረጃ ምንድን ነዉ?	ምንም: ያልተማረ☐ የባህላዊ ትምህርት☐ አንደኛ ደረጃ (1-8ኛ ክፍል)☐ ሁለተኛ ደረጃ (9-12ኛ ክፍል)☐ ዲፕሎማ ወይም TTI ☐ የመጀመሪያ ዲግሪ☐ የማስተርስ ዲግሪ☐ የዶክትሬት ዲግሪ☐ ጥያቄዉ አይመለከተኝም ☐
17. የአባትሽ/አባትህ የስራ መደብ ምንድን ነዉ? ለምሳሌ መምህር፣ አካውንታንት፣ ሹፌር ...	________________________________
18. የእናትሽ/እናትህ የስራ መደብ ምንድን ነዉ? ለምሳሌመምህር፣ አካውንታንት፣ ሹፌር ...	________________________________
19. በአብዛኛዉ ከቤት ወደ ትምህርት ቤት ስትንቀሳቀሺ/ስትንቀሳቀስ ምን አይነት የትራንስፖርት መንገድ ትጠቀሚያለሽ/ትጠቀማለህ?	የትምህርት: ቤት: አዉቶቢስ☐ ታክሲ☐ የቤተሰብ: መኪና☐ ባጃጅ☐ በእግር☐
20. በአብዛኛው በአማካይ ከቤት ወደ ት/ቤት ለመሄድ ምን ያህል ጊዜ(በደቂቃ) ይወስድብሻል/ይወስድብሃል?	________________________________
21. አሁን የምትማሪበት ትምህርት ቤት መማር ከጀመርሽ/ከ ስንት አመት ሆነሽ/ህ?	
22. ከዚህ በፊት ሌላ ትምህርት ቤት ተምረሽ/ህ ታውቂያለሽ/ታውቃለህ?	አዎ ተምርያለሁ☐ አልተማርኩም☐
23. ለጥያቄ 22 መልስሽ/ህ አዎ ተምርያለሁ ከሆነ፤ የትምህርት ቤቱን/ቹን ስም ጥቀሺ/ስ?	________________________________

ክፍል 2

24. እባክሽን/ህን ከአንቺ/ተ ክፍል የሚማሩ የቅርብ ጓደኞችሽን/ጓደኞችህን ሙሉ ስም ዘርዝሪ/ር::	______ ______ ______ ______ ______ ______ ______ ______ ______ ______
25. እባክሽን/ህን በአንድ ጠረጴዛ /ዴስክ ላይ አብረዉሽ/ህ የሚቀመጡ ተማሪወችን ሙሉ ስም ዘርዝሪ/ር ::	______ ______ ______ ______
26. እባክሽን/ህን ከአንቺ/ተ ጀርባ በሚገኘዉ ዴስክ ላይ የሚቀመጡ ተማሪወች ሙሉ ስም ዘርዝሪ/ር::	______ ______ ______ ______
27. እባክሽን/ህን ከአንቺ/ተ ፊት በሚገኘዉ ዴስክ ላይ የሚቀመጡ ተማሪወች ሙሉ ስም ዘርዝሪ/ር ::	______ ______ ______ ______

28. እባክሽን/ህን ከአንቺ/ተ ጋር በአብዛኛው በቡድን ስራ ወይም አሳይመንት (assignment) አብረዉሽ/ህ የሚሳተፉ የክፍልህ/ሽ ተማሪወችን ሙሉ ስም ዘርዝሪ/ር ።	
29. እባክሽን/ህን ከአንቺ/ተ ጋር በአብዛኛው በትምህርር ቤት ቅጥር ግቢ ዉስጥ አብረዉሽ/ህ የሚጫወቱ የክፍልህ/ሽ ተማሪወችን ሙሉ ስም ዘርዝሪ/ር ።	
30. እባክሽን/ህን ከአንቺ/ተ ጋር ከቤት ወደ ት/ቤት አብረዉሽ/ህ የሚሄዱ የክፍልህ/ሽ ተማሪወችን ሙሉ ስም ዘርዝሪ/ር ።	

31. እባክሽን/ህን በአንቺ/ተ መማሪያ ክፍል ዉስጥ ዝነኛና ብዙ ተማሪዎች አብረዋቸው የሚሆኑ ተማሪዎችን ሙሉ ስም ጥቀሺ/ስ::	
32. እባክሽን /ህን በአንቺ/ተ መማሪያ ክፍል ዉስጥ ብቸኛና ተማሪዎች ጋር ብዙም ማይቀራረቡ ተማሪዎችን ስም ጥቀሽ/ስ::	
33. አስተማሪያችሁ ድንገት ድንገተኛ ፈተና (quiz) በነገዉ እለት ሊሰጧችሁ አስበዋል እንበል፡፡ ከመካከላችሁ ሦስት ተማሪወች ፈተናዉ ከየትኛዉ ምዕራፍ እንደሚመጣ መረጃ ደርሷቿል እንበል ፡፡ እነዚህ ተማሪወች እነማን ቢሆን ትመርጫለሽ/ህ? በሌላ አነጋገር ከክፍልሽ/ህ ዉስጥ እነማን እንደዚህ አይነት መረጃ ቢደርሳቸው ለሁሉም የክፍሉ ተማሪ መረጃዉን ያሰራጫሉ?	

34. እባክሽን/ህን **አንቺ/ተ ትምህርት ቤት ነገር ግን ሌላ ክፍል** ውስጥ የሚማሩ የቅርብ ጓደኞችሽን/ጓደኞችህን ሙሉ ስም ዘርዝሪ/ር::	______________________ ______________________ ______________________ ______________________ ______________________ ______________________ ______________________ ______________________ ______________________ ______________________

ክፍል 3

መመሪያ ፤

ከዚህ በመቀጠል በምናከናዉነዉ ተግባር ከአንድ ፈፅሞ ከማታዉቂዉ/ቀዉ የእድሜ እኩያሽ/ህ ከሆነች ወይም ከሆነ ተማሪ ጋር ትጓደኛለሽ/ህ። ይህን ሰዉ **ሌላኛዉ ተሳታፊ** ብለን እንጠራታለን/ እንጠረዋለን፡፡ሌላኛዉ ተሳታፊ ፈጽሞ ማንነትሽን/ህን አታቅም/አያዉቅም ፡፡ ተከታዩን ተግባር በምናከናውንበት ጊዜ የምትወስኚዉ/ነዉ ዉሳኔዎች በሙሉ በሚስጥር የተጠበቁ ናቸው ። ሌላኛ ተሳታፊ አንቺ/ተ ስለወሰንሽው/ስለወሰንከው ዉሳኔ ምንም አይነት መረጃ ወይም እዉቀትአይኖራትም(አይኖረዉም) ፡፡ ከአንቺ/ተ የሚጠበቀዉ ተግባራዊ ዉሳኔ እንደሚከተለዉ ነዉ፡፡ በ አንቺና/ተና በሌላኛው ተሳታፊ መካከል የሚኖርን የሃብት ክፍፍል እንድትወስኚ/ን እድል ይሰጥሻል/ሃል ። ይህንን ለማድረግ እንዲያስችልሽ/ህ በተከታታይ ልዩ ልዩ የሃብት ክፍፍል አማራችጮች ይቀርቡልሻል/ሀል፡፡ ለእያንዳንዱ ጥያቄ (ማስመሪያ መሰል የሀብት ክፍፍል አመላካች)፤ ለአንቺ(ተ) ተስማሚ ነው የምትይውን(ለውን) አማራጭ በማክበብ ወይም በማጥቆር ታመለክቻለሽ(ታለህ)፡፡

እያንዳንዱ ዉሳኔሽ(ህ) አንቺ/ተ የምታገኚውንም (የምታገኘውንም) ሆነ ሌላኛው ሰው የሚያገኘውን የገንዘብ መጠን ይወስናል፡፡ለምሳሌ ከዚህ በታች ማየት እንደሚቻለዉ አምስተኛ አማራጭ ተጠቁሯል፡፡ይህ ማለት ለአንቺ(ተ) ሃምሳ ነጥብ ሌላኛዉ ሰዉ ደግሞ አርባ ነጥብ ቢወስድ ደስ እንደሚልሽ\ህ ይገልፃል፡፡በግልጽ ማየት እንደሚቻለው ዉሳኔሽ/ህ የአንቺ(ተ) ሆነ የሌላኛዉ ሰዉ የሚያገኘዉን የገንዘብ መጠን ይወስናል ፡፡ በእነዚህ ዉሳኔወች ዉስጥ ትክክል ወይም ስህተት የሚባል አማራጭ የለም ፡፡ እባክሽን/ህን የመረጥሽውን ወይም የመረጥከውን የሀብት የክፍፍል ውሳኔ መሰረት በማድረግ ከእያንዳንዱ አማራጭ በስተቀኝ በኩል በተሰጠዉ ክፍት ቦታ ላይ ለአንቺ/ተ እንዲሁም ለሌላኛው ተሳታፊ የሚደርሰውን የነጥብ መጠን ጻፍ/ጻፊ፡፡ ከዚህ ላይ የምታገኚው/ኘው የነጥብ ድምር ወደ ገንዘብ ተቀይሮ ክፍያ ይፈጸምልሻል(ሀል)፡፡ አንድ ነጥብ ምን ያህል ብር (ሳንቲም) እንደሚያወጣ ከተግባሩ በኋላ የሚገለጽ ይሆናል፡፡

ለምሳሌ

ለአንቺ/ተ	30	35	40	45	50	55	60	65	70	አንቺ/ተ= 50
ሌላኛዉተሳታፊ	80	70	60	50	40	30	20	10	0	ሌላኛዉተሳታፊ =40

35.

ለአንቺ/ተ	85	85	85	85	85	85	85	85	85	____________
ለሌላኛዉ ተሳታፊ	85	76	68	59	50	41	33	24	15	____________

36.

ለአንቺ/ተ	85	87	89	91	93	94	96	98	100	____________
ለሌላኛዉ ተሳታፊ	15	19	24	28	33	37	41	46	50	____________

37.

ለአንቺ/ተ	50	54	59	63	68	72	76	81	85	________
ለሌላኛዉ ተሳታፊ	100	98	96	94	93	91	89	87	85	________

38.

ለአንቺ/ተ	50	54	59	63	68	72	76	81	85	________
ለሌላኛዉ ተሳታፊ	100	89	79	68	58	47	36	26	15	________

39.

ለአንቺ/ተ	100	94	88	81	75	69	63	56	50	________
ለሌላኛዉ ተሳታፊ	50	56	63	69	75	81	88	94	100	________

40.

ለአንቺ/ተ	100	98	96	94	93	91	89	87	85	________
ለሌላኛዉ ተሳታፊ	50	54	59	63	68	72	76	81	85	________

ክፍል 4

41. በአንቺ/ተ አስተያየት፣ የአየር ንብረት ለዉጥ በአሁን ጊዜ እየተከሰተ ነዉ?
    ሀ. አዎ ለ. አይደለም ሐ. አላዉቅም

42. የአየር ንብረት ለዉጥ -------------------------------ነዉ?
    ሀ. በተፈጥሮ የሚፈጠር ሂደት ነዉ።
    ለ. በሰዉ ሰራሽ የሚፈጠር ሂደት ነዉ።
    ሐ. በተፈጥሮና በሰዉ ሰራሽ የሚፈጠር ሂደት ነዉ።
    መ. ከላይ የተጠቀሱት አማራጮች ዉስጥ መልሱ የለም።
    ሠ. አላውቅም

43. ከሚከተሉት አማራጮች ውስጥ ሰው ሰራሽ ካርቦን ዳይ ኦክሳይድ ልቀት መንስኤ የሆነው(ኑት) የትኛው ነው(ናቸው) ?
    ሀ. ከኢንዱስትሪዎች የሚወጣ ጭስ
    ለ. ከማገዶ እንጨት የሚወጣ ጭስ
    ሐ. ሁሉም
    መ. አላዉቅም

44. እንደ ሰዉ ሰራሽ የልቀት መንስኤወች ሁሉ ተፈጥሯዊ የሆኑ ካርቦን ዳይ ኦክሳይድ ልቀት መንስኤዎች ይገኛሉ ።
    ሀ. እዉነት ለ.ሀሰት

45. የሳልፈር ዳይ ኦክሳይድ ልቀት ምክንያት የትኛዉ ነዉ?
    ሀ. ከኢንዱስትሪዎች የሚወጣ ጭስ።
    ለ. ከመኪናዎች የሚወጣ ጭስ።
    ሐ. ከማገዶ እንጨት የሚወጣ ጭስ።
    መ. ሁሉም
    ሠ. አላዉቅም

46. የአየር ንብረት ለዉጥን ለሰዉ ልጅ እጅግ አሰሳቢ ጉዳይ የሚያደርጉት ዋና ዋና ምክንያቶች የትኞቹ ናቸው?
    ሀ. የባህር ጠለል እና የከባቢ አየር ሙቀት መጨመር
    ለ. የባህር ጠለል እና የዉቂያነሶች አሲዳማነት መጨመር
    ሐ. የከባቢ አየር ሙቀት እና የዉቂያነሶች አሲዳማነት መጨመር
    መ. የባህር ጠለል፣ የከባቢ አየር ሙቀት እና አውሎ ንፋስ መጨመር
    ሠ. በርሃማነት

47. እጅግ በጣም በሰፊዉ የሚገኘዉ የግሪን ሀዉስ ጋዝ የትኛዉ ነዉ?
    ሀ. ካርቦን ዳይ ኦክሳይድ
    ለ. ሚቴን
    ሐ. ሳልፈር ዳይ ኦክሳይድ
    መ የውሀ ተን
    ሠ. አላውቅም

48. በአለም ላይ እጅግ በጣም ከፍተኛ ካርቦን ዳይ ኦክሳይድ ብክለት የምታስከትለዉ ሀገር የትኛዋ ናት?
    ሀ. ኳታር ለ. አሜሪካ ሐ.ህንድ መ. ቻይና
    ሠ. አላውቅም

49. ከሚከተሉት ውስጥ የአይር ንብረት ለወጥ ስለሚያስከትላቸው ተጽኖዎች እዉነት የሆነዉ የትኛዉ ነዉ?
    ሀ. ሳንሳዊ መረጃ የተገኘለት የአየር ንብረት ለዉጥ ተፅዕኖ እስካሁን አልተገኘም።
    ለ. የባህር ጠለል መጨመር፣ የደን መልሶ ልማት እና የከተማ ልማት።
    ሐ. የባህር ጠለል መጨመር ፣የከባቢ አየር ሙቀት መጨመር እና አውሎ ንፋስ መጨመር።
    መ. መልስየለም።
    ሠ. አላውቅም

Appendix 5: Questionnaires III

Questionnaire (Follow-up)

መጠይቅ

መግቢያ

<u>የተከበራችሁ ተሳታፊወች:</u>

ስሜ አፀደ ይባላል። እንደምታስታውሱት ከ 1 ወር በፊት ተመሳሳይ መጠይቅ ይዘን መጠን የነበረ ሲሆን ይህም መጠይቅ ሁለተኛው ክፍል ነው። መጠየቁን ለመሙላት በአማካይ ከ 40-50 ደቂቃ ይወስዳል።

ይህ መጠይቅ ከመደበኛ የትምህርት መርሃ ግብራቹህ (ፕሮግራማቹህ) ጋር ምንም አይነት ግንኙነት የሌለውና በዚህ መጠይቅ ላይ ለሚቀርቡላችሁ ጥያቄዎች የምትሰጡት ምላሽ ለዚህ ጥናት አገልግሎት ብቻ የሚውል ይሆናል። መረጃው ከተሰበሰበ በኋላም ማንኛውም ግለሰባዊ መረጃወች ለምሳሌ ሙሉ ስም ና ተራ ቁጥር ወደ ሚስጥራዊ መለያ ከተቀየሩ በኋላ የሚወገዱ ይሆናል።

እባካችሁን እንደተለመደው መጠይቁን በተቻለ መጠን በትክክል ከሞላችሁ በኋላ ለተገቢው አካል መልሱ። ተሳትፏችሁ ፍፁም ፈቃደኝነትን መሰረት ያደረገ ነው።

ጊዜያችሁን ሰውታችሁ መጠይቁን ለመሙላት ፍቃደኛ ስለሆናችሁ እና የጥናታዊ ጽሁፌን ዓላማ እንዳሳካ ስለተባበራችሁኝ እጅግ አድርጌ አመሰግናችኃለሁ።

<u>ክፍል 1.</u>

50. ሙሉ ስም : ______________________	የክፍል ተራ ቁጥር :______________
51. የትውልድ ዘመን	ወር ________ ዓ.ም ______________
52. የክፍል አለቃ ነህ/ሽ?	አወ ☐ አይደለሁም ☐
53. ስለቆሻሻ በአይነት በአይነት መለየትና መሰብሰብ ጥቅም እንዳለው ከጎደኞችሽ/ህ ሰምተሻል/ሀል? 4.1 ለጥያቄ ቁጥር 4 መልስሽ/ህ ሰምቻሁ ከሆነ፤ እባክሽን/ህን የነገሩሽን/ህን ከጎደኞችሽ/ህ ስም ጥቀሽ/ስ ::	ሰምቻለሁ ☐ አልሰማሁም ☐ 1. ______________ 2. ______________ 3. ______________ 4. ______________
54. ስለየአየር ንብረት ለውጥና ተፅዕኖዎቹ ከጎደኞችሽ/ህ ሰምተሻል/ሀል? 4.1 ለጥያቄ ቁጥር 5 መልስሽ/ህ ሰምቻሁ ከሆነ፤ እባክሽን/ህን የነገሩሽን/ህን ከጎደኞችሽ/ህ ስም ጥቀሽ/ስ ::	ሰምቻለሁ ☐ አልሰማሁም ☐ 1. ______________ 2. ______________ 3. ______________ 4. ______________

55. ከወር በፊት በተካሔደው መጠየቅ በመሣተፍሽ/ህ የምታገኝውን/የምታገኘውን ሽልማት በችግኝ ተቀይሮ ቢሰጥሽ/ህ ትመርጫለሽ/ትመርጣለህ?	እመርጣለሁ ☐ አልመርጥም ☐

ክፍል 2፡
እባክሽን/ህን ለሚከተሉት ጥያቄዎች ትክክለኛ መልስ ነው የምትይውን/ለውን ምርጫ አክብቢ/አክብብ ።

1. ባለፉት 100 አመታት የአለም የሙቀት መጠን ------- ጨምረል ።
   ሀ. በ 2 ዲግሪ ሰልሽየስ
   ለ. በ 1.5 ዲግሪ ሰልሽየስ
   ሐ. በ 1 ዲግሪ ሰልሽየስ
   መ. ምንም የሙቀት መጠን ለውጥ የለም
   ሠ.አላውቅም

2. ከሚከተሉት የጋዝ አይነቶች ዉስጥ ለአየር ንብረት ለዉጥ መንስኤ ያልሆነው የትኛው ነው ?
   ሀ. ሚተን
   ለ. ናይትረስ ዳይ ኦክሳይድ
   ሐ. የ ውሃ ትነት
   መ. ሁሉም የጋዝ አይነቶች መንስኤ ናቸው
   ሠ. አላውቅም

3. ለአንዳንድ አካባቢወች የሙቀት መጨመር አወንታዊ ተፅእኖና አገራቱን(ቦታዎቹን) ለመኖር ምቹ ሊያደርገው ይችላል።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

4. ከሚከተሉት ውስጥ የአየር ንብረት ለውጥ ለመቀነስ መፍትሔ ያልሆነው የትኛው ነው?
   ሀ. ዛፎችን መትከል
   ለ. ሐይል ቆጣቢ የሃይል ምንጮችን መጠቀም
   ሐ. አነስተኛ ብክለት የሚያስከትሉ የሀይል አማራጮችን መጠቀም
   መ. ምንም የሀይል ምንጮች አለመጠቀም

5. አትሞስፌር ውስጥ እጅግ በብዛት የሚገኘው የጋዝ አይነት የትኛው ነው?
   ሀ. ውሃ ትነት
   ለ. ካርቦን ዳይ ኦክሳይድ
   ሐ. ናይትረስ ኦክሳይድ
   መ. ሁሉም
   ሠ. አላውቅም

6. የተፈጥሮ የካርቦን ልቀት መንስኤወች መካከል የሆኑት የትኞቹ ናቸው?
   ሀ. የማገዶ እንጨት ፍጆታ ጭስ ና የሰው ልጅና እንስሳት ትንፋሽ
   ለ. የማገዶ አንጨት ፍጆታ ጭስ ና የ አፈር መሸርሸር
   ሐ. የሰው ልጅና እንስሳት ትንፋሽ ና የእሳተ ጉመራ ጭስ
   መ. የተፈጥሮ መንስኤወች የሉም

7. ካርቦን ዳይ ኦክሳይድ ለአጭር ጊዜ በአትሞስፌር የሚቆይ የጋዝ አይነት ነው።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

8. ከፍተኛ የካርቦን ልቀት በማስመዝገብ ቀዳሚ አገር የሆነችው ማን ናት?

ሀ. ጀርመን
ለ. ህንድ
ሐ. አርጀንቲና
መ. ቻይና
ሠ. አላውቅም

9. ካርቦን በውስጣቸው የያዙ የሚቃጠሉ አካላት በመቃጠል ሂደት ላይ ከሳልፈር ጋር ሲዋሀዱ ለካርቦን ዳይ ኦክሳይድ ጭስ ልቀት ምክንያት ይሆናል።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

10. የሰው ሰራሽ የካርቦን ዳይ ኦክሳይድ ምክንያት የትኛው ነው?
   ሀ.ከኢንዱስትሪ የሚለቀቁ ፈሳሽ ቆሻሸዎች
   ለ. የማገዶ እንጨት ፍጆታ ጭስ
   ሐ. የሙቀት መጨመር
   መ. ሁሉም መልስ ናቸው

11. የናይትሮስ ኦክሳይድ ጭስ መንስኤወች መካከል የሆነው የትኛው ነው?
   ሀ. የሰው ልጅና እንስሳት ትንፋሽ
   ለ. የተፈጥሮ ማዳበሪያ
   ሐ. የእሳተ ጉመራ ጭስ
   መ. የተፈጥሮ መንስኤወች የሉትም
   ሠ. አላውቅም

12. ክሎሮፍሎሮ ካርቦን በሰው ሰራሽ ምክንያት ብቻ ወደ አትሞስፌር የሚለቀቅ የጭስ አይነት ነው።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

13. የሰው ሰራሽ የናይትሮስ ኦክሳይድ ምክንያት የትኛው ነው?
   ሀ. ከኢንዱስትሪዎች የሚለቀቁ ፈሳሽ ቆሻሸዎች
   ለ. ብስባሽ አካላትን ወደ ነዳጅ ምንጭ የመለወጥ ሂደት
   ሐ. የሙቀት መጨመር
   መ. ሁሉም መልስ ናቸው
   ሠ. አላውቅም

14. የናይትረስ ኦክሳይድ ጭስ አምብዛም ጉዳት የማያደርስ የጭስ አይነት ነው።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

15. ሚቴን አትሞስፌር ውስጥ ያለው ድርሻ አነስተኛና ከካርቦን ዳይ ኦክሳይድ አንፃር እምብዛም ጉዳት የማያደርስ ጭስ ነው ።
   ሀ. እውነት
   ለ. ሐሰት
   ሐ. አላውቅም

16. የኦዞን ሽፋንን በመጉዳት ከፍተኛ ድርሻ ያለው አደገኛ ጭስ የትኛው ነው?
   ሀ. ካርቦን ዳይ ኦክሳይድ
   ለ. ክሎሮፍሎሮ ካርቦን
   ሐ. ሚቴን
   መ. ናይትረስ ኦክሳይድ
   ሠ. አላውቅም

17. የሰው ሰራሽ የሚቴን ጭስ መንስኤ የትኛው ነው?
   ሀ. ከኢንዱስትሪ የሚለቀቁ ፈሳሽ ቆሻሸዎች
   ለ. የማገዶ እንጨት ፍጆታ ጭስ
   ሐ. የደረቅ ቆሻሻ ክምሮች የሚለቀቅ ትነት
   መ. ሁሉም መልስ ናቸው
   ሠ. አላውቅም

18. የአየር ንብረት ለውጥ የሚያስከትላቸው ቀጥተኛ አሉታዊ ተፅእኖዎች መካከል ያልሆነው የትኛው ነው?

   ሀ. የሙቀት መጨመር

   ለ. የዝናብ ውደት ማዛባት

   ሐ. የዱር እንስሳትን ህልውና አደጋ ላይ መጣል

   መ. አሲድ ያዘለ ዝናብ

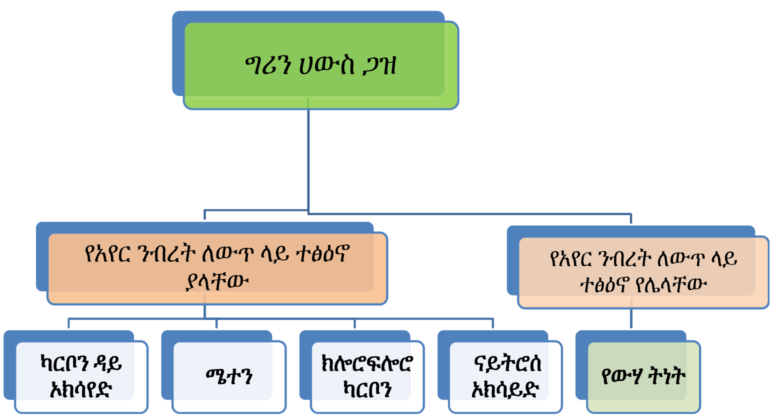
Appendix 6: Training notes

የ አየር ንብረት ለውጥ

ምክንያቶችና ተፅዕኖች

የአየር ንብረት እውነታዎች

- ባሳለፍነው 100 ዓመታት ውስጥ የ መሬት ሙቀት መጠን በ1 ድግሪ ሴልሸየስ ጨምሯል፡፡
- በ2010 -2016 ዓ.ም እጀግ ከፍተኛ የሙቀት መጠን የተመዘገበበት ተከታታይ ዓመታት ናቸው፡፡
- በ2016 ዓ.ም ከፍተኛ ሙቀት የተመዘገበበት አመት ነው፡፡



የአየር ንብረት እውነታዎች

- የውሃ ትነት በብዛት ሚገኝ የግሪን ሀውስ ጭስ አይነት ነው፡፡
- ሙቀት የውሃ ትነትን ወደ ዝናብ ወይም ደመናነት ይቀየራል፡፡
- ስለዚህም የውሃ ትነት አየር ንብረት ላይ ምንም አይነት አሉታዊ ተፅእኖ አያሳድርም፡፡
- በሌላ በኩል የሙቀት መጨመር ግን በአትሞስፌር የሚገኙውን የውሃ ትነት ይጨምረዎል፡፡

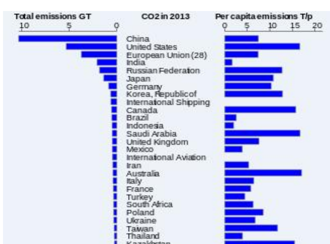
የአየር ንብረት ለውጥ ዋና ዋና መንስኤዎች

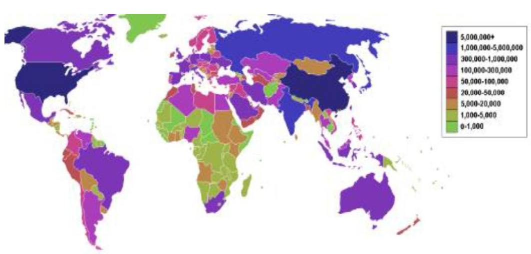
- **ካርቦን ዳይ አክሳየድ :**
- በተፈጥሮና በሰው ሰራሽ ምክንያቶች ወደ አትሞስፌር የሚለቀቅ የጭስ አይነት ነው ::
- በተፈጥሮ ከሚለቀቁ የካርቦን ዳይ አክሳየድ ምክንያቶች ውስጥ የእሳተ ገሞራ ጭስ እና ከሰው ልጅና እንስሳት ትንፋሽ ተጠቃሾች ናቸው::
- ከሰው ሰራሽ ምክንያቶች መካከል ደግሞ ከኢንዱስትሪወችና የማገዶ እንጨት ፍጆታ የሚወጡ ጭሶችና የሚጠቀሱ ናቸው ::
- ካርቦን ዳይ አክሳየድ ለረጅም ጊዜ በአትሞስፌር ውስጥ የሚቆይ ና ለአየር ንብረት ለውጥ በምክንያትነት በዋናነት የሚጠቀስ የጭስ አይነት ነው ::

የአየር ንብረት ለውጥ ዋና ዋና መንስኤወች

- ካርቦን በውስጣቸዉ የያዙ የሚቃጠሉ አካላት (እንደ የድንጋይ ከሰል እና ነዳጅ ,ጋዝ) በመቃጠል ሂደት ላይ ከኦክስጂን ,ጋር ሲዋሀዱ ለካርቦን ዳይ ኦክሳይድ ጭስ ልቀት ምክንያት ይሆናል ::
- የእርሻ መሬት ማስፋፊያና የኢንዱስትሪዎች መጨመር ለደን ጭፍጨፋ ብሎም ለካርቦን ዳይ ኦክሳይድ ልቀት ዋና የሰው ሰራሽ መንስኤወች ናቸው::
- የ2017 ኢ.ም መረጃ እንደሚያመለክተው ከፍተኛ የካርቦን ልቀት የሚያስከትሉ አገራት በደረጃ ቻይና፣ አሜሪካና ህንድ ሁነው ተመዝገበዋ::

የአገራት የካርቦን ልቀት ድርሻ

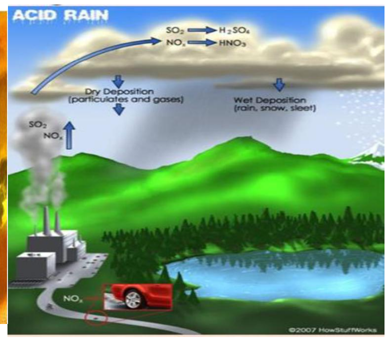




የአየር ንብረት ለውጥ የሚያሳድራቸው ተፅእኖወች

- የአየር ንብረት ለውጥ ቀጥተኛና ቀጥተኛና ያልሆኑ ተፅዕኖወች ያስከትላል::
- እንደ ሙቀት መጨመር፤ አሲድ የቀላቀለ ዝናብ፣ የዝናብ ኡደት መዛባት ና የመሳሰሉት ከቀጥተኛ ተፅኖወች መካከል ዋና ዋናወቹ ናቸው::
- የ ሙቀት መጨመር ተፅእኖ ከቦታ ቦታ ሊለያይ ይችላል:: ለምሳሌ: በበረዶማ አካባቢወች ሙቀት መጨመር ቦታውን ለመኖር ምቹ ስለሚያደርገው አወንታዊ ተፅእኖ ይኖረዋል::
- በአብዛያው የአለም ክፍሎች ግን የሙቀት መጨመር አሉታዊ የሆነ ተፅእኖ ያሳድራል ::

በፊት በኋላ



የሰው ልጅ ጤና ላይ የሚያሳድረው ተፅእኖ፡

- በሞቃት አካባቢወች የሙቀት መጨመር በሙቀት ምክንያት ለሚመጡ በሽታወች ያጋልጣል፡፡
- ለምሳሌ፡ በምድር ወገብና አካባቢው የሚገኙ እንደ ኢትዮጵያ ያሉ አገራቶች የሙቀት መጨመር ለወባ መሰል በሽታ ያጋልጣል፡፡
- በተመሳሳይ በአየር ንብረት መለወጥ ምክንያት ለጎርፍ አደጋ መከሰትና ለሰው ልጅ ሒወት መጥፋት ያጋጥማል ፡፡

አካባቢዊ ተፅእኖ ፡

- የአየር ንብረት ለውጥ የተለያዩ አካባቢዊ ለውጦችን ያስከትላል፡፡ ከነዚህም መካከል የአፈር መሸርሸር ፤የእህል ምርት መባከንና የዱር እንስሳት ሞት/ስደት ተጠቃሾች ናቸው፡፡
- ለምሳሌ፡ በከባድ ዝናብና ጎርፍ ምክንያት ኢትዮጵያ በአመት ከ1.5 ሄክታር በላይ ለም አፈር ይሸረሸራል፡፡
- የአየር ንብረት መለወጥ የዱር እንስሳትንና እፅዋትን ህልውና አደጋ ላይ በመጣል ከምድረ ገፅ ያጠፋል፡፡

- ለምሳሌ የኢትዮጵያ ምቹና ልዩ የአየር ሁኔታ በመለወጡ ምክንያት ብዛት ያላቸው እንስሳትና እፅዋት በመመናመን ላይ ይገኛሉ ፡፡
- በአጠቃላይ የአየር ንብረት ለውጥ የሚያሳድረው አሉታዊ ተፅእኖ ታዳጊ አገራት ላይ እጅግ የከፋ ነው፡፡ ምክንያቱም የታዳጊ አገራት ኢኮኖሚ በእርሻ የተመሰረተና የዝናብ ወቅትና መጠን መለዋወጥ የምርታማነት መጠንን ይጎዳል ፡፡
- ለምሳሌ፡ በተለያዩ የኢትዮጵያ ክፍሎች ባጋጠመው የዝናብ እጥረት ምክንያት በተለያዩ ጊዚያትና በተደጋጋሚ ድርቅ ሊከሰት ችሏል ፡፡

- በሌላ በኩል ደግሞ ጎርፍን ያስከተለ ዝናብም የአፈርን ምርታማነትን ይቀንሳል፡፡

- ለምሳሌ፡ በ2006 ጋምቤላ ክልል ውስጥ ባጋጠመው ጎርፍ ምክንያት ከፍተኛ የሆነ የበቆሎና ሌሎች እህሎች ምርት ጥቅም ላይ እንዳይውል አድርጎል፡፡

- ቀጥተኛ ያልሆኑ ተፅዕኖች መካከል ደግሞ እንደ የውሃ ወለድ ና ምግብ መመረዝ የመሳሰሉ በሽታወች በተደጋጋሚ እንዲከሰቱ መንስኤ ይሆናል ፡፡

- ለምሳሌ 2016 አ.ም የተከሰተው ጎርፍ በጋምቤላ፣ አርሲ፣ አሮሚያና አዲስ አበባ የአሜባና ጃርዲያ በሽታ መንስኤ ሊሆን ችሏል ፡፡

መፍትሔወች

- ለአየር ንብረት ለውጥ ዋነኛ ምክንያት በካይ ሆኑ ጭሶች ወደ አትሞስፌር መለቀቅ ነው፡፡ ስለዚህ በካይ ጭሶችን መቀነስ ዋነኛ መፍትሔው ነው፡፡
- በሚከተሉት መንገዶች የአየር ንብረት ለውጥን (በካይ ጭሶችን) መቀነስ ይቻላል፡-

  – ዛፎች መትከል
  – የአካባቢን ነፅህና መጠበቅ
  – የሀይል ፍጆታ መቀነስ
  – አማራጭ የሐይል ምንጮችን መጠቀም

ዛፍ መትከል

- እንደ ካርቦን ዳይ ኦክሳይድ ያሉ በካይ ጭሶችን ለመቀነስ መፍትሔ ነው፡፡
- በአየር ንብረት ለውጥ ምክንያት የሚመጣን እንደ የአፈር መሸርሸርና የመሳሰሰሉት አሉታዊ ተፅእኖ ይቀንሳል፡፡

የሀይል ፍጆታ መቀነስ

- ሐይል ቆጣቢ ምድጃዎችን፣ መኪናወች(የትራንስፖርት መንገድ) መጠቀም

አማራጭ የሐይል ምንጮችን መጠቀም

- አነስተኛ የአየር መበከል የሚያስከትሉ የሐይል ምንጮችን መጠቀም