ISSN 2279-9362

Collegio Carlo Alberto

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Moreno Mancosu

No. 464
October 2016

Carlo Alberto Notebooks

www.carloalberto.org/research/working-papers

Diffusion of political behaviors and the role of negative word-of-mouth: An agent-based approach*

Moreno Mancosu - Collegio Carlo Alberto

moreno.mancosu@carloalberto.org

Abstract

It has long been accepted that positive and negative word-of-mouth (WOM) play a crucial role in convincing people to adopt innovative behaviors and ideas or to reject them (Rogers, 1983). Although there is some evidence showing that negative WOM follows some sort of dissemination process, limited attention has been paid to the interplay between negative and positive WOM in the diffusion of political innovations. In this study, it will be argued that both the processes might behave simultaneously in a threshold-like fashion. The first part of the study will test, by means of an agent-based model, the theoretical expectations of this argument, while the second part will apply this theoretical model to a case study, the diffusion of the Movimento 5 Stelle in the Italian election campaign of 2013 (Vezzoni and Mancosu, 2016). Calibration parameters of the agent-based model will thus be extracted from survey data. The results support our argument: contrary to being just accidental, both positive and negative WOM behave according to the expectations of a threshold model of diffusion (the first to be converted are the easiest, while the latest are the most difficult). Moreover, when calibrated with real data, the agent-based model predicts quite well the electoral result of the Movimento.

Keywords - agent-based models, social influence, political networks, political innovations, Italy, Movimento 5 Stelle

1 Introduction

This study aims at investigating the diffusion of innovative political behaviors and the mechanisms of interpersonal influence that contribute to foster it. Empirically, it is possible to detect a number of cases in which, apparently, political behaviors diffuse by means of interpersonal relations. Especially in young democracies, sudden explosive performances of newly established parties (see the case of Alberto Fujimori in 1990 and Hugo Chavez in 1998) have been hypothesized to be triggered by micro-social processes of interpersonal communication and influence (Baker, Ames and Renno, 2006). Empirical evidence has been also provided for the increase of preferences during the election campaign of the Movimento 5 Stelle—a new Italian populist party that became the most voted in the country during the 2013 National Elections—could be the result of a diffusion process, triggered by interpersonal communication (Vezzoni and Mancosu, 2016).

Both the sociological and political science literature have largely committed to investigating different aspects of the abovementioned topic in object, but little evidence has focused on the phenomenon as a whole. In particular, sociological literature (as well as the economic/marketing one) investigated the processes of diffusion of innovations, producing an exterminate number

*The paper was originally presented at the 2016 EUSN conference (Paris, June 14-17). The author wants to thank Gianluca Manzo for his useful comments and suggestions.

of contributions (e.g., Rogers, 1983; Granovetter, 1973; Valente, 1996; Föllmer, 1974; Galam et al., 1982). However, the diffusionist literature has little focused on the particular nature of political behaviors by investigating the adoption of innovative non-political goods, such as mobile phones, cohabitations (Guetto et al., 2016), or organic products (Deffuant et al. 2005). At the same time, political science and political sociology literature have committed to assessing the conditions under which political opinions of a collective succeed in influencing an individual (Berelson, Lazarsfeld, and McPhee, 1954; Huckfeldt and Sprague, 1995; Mutz, 2002; Rogowski and Sinclair, 2012; Bello and Rolfe, 2014), without focusing on the temporal succession of these mechanisms (see Bello and Rolfe, 2014). We will argue that both these approaches can be combined to explain mechanisms of political influence, in situations in which an innovative opinion spreads in a social system. It is possible to say that this study aims at investigating a special case of these two branches of the literature. From the diffusionist side, our topic relates to a special case of diffusion process, in which the innovation is represented by a political behavior, whereas from the political network side, it is a special case of political influence of an opinion, which systematically increases its prevalence in a social system.

We will argue that, given the particular nature of political behavior, the role of opinion volatility becomes crucial: during the diffusion of a new political option, it is easier for people to be swung toward the innovation; however, it is also likely to switch from supporting a political party/action to not supporting it (Pedersen 1979; Dejaeghere and Dassonneville, 2015). In this regard, the role that negative word-of-mouth (NWOM, Richins, 1983; Deffuant et al., 2005) has in shaping the pace of a diffusion process will be deepened. It will be also tested whether and in what ways negative word-of-mouth disseminates through a social system and whether the dissemination of negative and positive word-of-mouth can coexist simultaneously in the same system.

2 Background

The object of our study is the diffusion of political behaviors (Sinclair, 2012; Vezzoni and Mancosu, 2016). Examples of these behaviors can be exemplified as vote intentions for a certain party during an election campaign or as a hypothetical choice in a public consultation (one could ask him/herself "If there was a referendum about legalizing gay marriages, would you be for or against?"). Although voting is the most straightforward example of political behavior, the concept can be also extended to other activities such as participating to demonstrations, public rallies, or riots (Granovetter, 1978).

When the prevalence of a behavior (or of the intention to realize it) increases within the population by means of interaction among people, we can say that this behavior diffuses (and that the behavior itself represents an innovation, see Rogers, 1983). Although characteristics of a political innovation and its adoption will be better defined in the following paragraphs, we can introduce them by means of several characteristics that these latter share. First, political behaviors are often potential, that is, are going to happen in the future. Empirically, it is possible to measure a potential political behavior as an intended vote choice expressed by a respondent some time before the election takes place. This operation is widespread in electoral studies surveys, in which is usually asked what party one would vote for if the elections were held the day after the interview (see van der Meer et al., 2012; Veiga and Veiga, 2004; Bélanger et al., 2006).

Second, political behaviors are driven by general individual attitudes towards the political objects (van der Eijk and Franklin, 1996; van der Eijk et al., 2006): the participation to a rally/demonstration or the expressed vote choice for a certain party are a function of people's beliefs, which, in turn, are shaped by a number of individual factors. In an empirical setting, it is possible to realize this relation between attitudes and behaviors in the correlation between, say, vote choice and self-placement in a liberal-conservative scale. People who defined themselves as more liberal will tend to avoid conservative candidates and vice versa (Stimson, 1975; Conover and Feldman, 1981; Poole and Rosenthal, 1984).

Third, political behaviors, among other things, are shaped by the interaction with other in-

dividuals. Immense research (e.g., Berelson, Lazarsfeld, and McPhee, 1954; Huckfeldt and Sprague, 1995; Huckfeldt et al., 2004; Fowler et al., 2011; Rogowski and Sinclair, 2012; Bello and Rolfe, 2014) has showed that discussion networks represent a crucial element by which people change their mind and choices.

In the literature, both the processes of diffusion of (generic) innovations and those of influence of political opinions (and consequent behaviors) have been faced. For what concerns studies on generic diffusion processes, an exterminate literature is present, focusing in particular on physical objects or practices (Rogers, 1983, Blossfeld and Nazio, 2003; Deffuant et al., 2005; Guetto et al., 2016). The literature of changes in opinions and beliefs has been particularly committed to investigating the mechanisms of influence in a temporal vacuum (Vezzoni and Mancosu, 2016), as a result, the diffusionist arguments (which expect an interaction between time and interpersonal influence) took a back seat. Simulation-based studies, by investigating the persistence of disagreement in networks (Huckfeldt et al., 2004; Zuckerman, 2005), do not consider the case in which an idea becomes more prevalent in their simulated system.[1] More recently, the literature on opinion change in political settings has focused more on the processes of influence/selection among people belonging to the same social network. However, the context in which these processes occur has not been considered (Bello and Rolfe, 2014; Rogowski and Sinclair, 2012; Fowler et al., 2011; Mancosu, 2016).

The aim of this study is thus threefold. First, it is aimed at connecting the "diffusionist" and "political networks" lines of research, which have hardly interacted with each other, by investigating the cases in which a new political idea (and not a physical product or a practice) breaks in a social system and acquires support at the expenses of traditional beliefs. Second, the study also aims at integrating diffusion theory and political research arguments concerning the formation of behaviors, especially working on the ways in which political attitudes are translated into actual choices (Tillie, 1995; van der Eijk et al., 2006; Martins et al., 2009) and drawing empirical conclusion on the particular outcomes that this kind of behavior leads to. Third, the study aims to empirically assess the external validity of this model by applying it to real data of the diffusion of the Movimento 5 Stelle (an Italian populist party) that diffused during the 2013 Italian National Election campaign (Vezzoni and Mancosu, 2016).

2.1 New political opinions and behaviors as special forms of innovation

Why should political innovations be different compared to other goods such as new mobile phones or contraceptives? In this study, we argue that political opinions (and behaviors based on these) have particular characteristics that differentiate their diffusion from goods.

It is well known that the evaluation of costs and benefits of the innovative object, based on the information that ego can acquire from the environment, is a crucial force that triggers the spread of new practices. This study will argue that political innovations present a set of costs and benefits that are partially different with respect to other innovations. In addition, it will be argued that these differences can lead to particular patterns of adoption and discontinuity (that is, the act of abandoning the innovation, see Rogers, 1983 and Richins, 1983). The first dimension of this individual calculus is the rational one. People will more likely tend to adopt innovation if they see some form of direct benefit in it in the present or future (Rogers, 1983; Klandermans, 1992). Applying this argument to party choices, it turns out that people vote for the party which is expected to increase their lifestyle or to benefit them in some way (the idea is largely present in electoral studies since the seminal works on the topic. See Downs, 1956 and Campbell et al., 1960). The idea of an expected utility in political behaviors—and, especially, that the economic rationality alone can explain vote—is, however, quite difficult to sustain. First, many political behavior that we adopt do not affect us directly. A heterosexual person sustaining LGBT rights and being available to join a rally/vote in favor of a law that aims at

[1] In his seminal work about the dissemination of culture (1997), Axelrod expressly focuses on mechanisms in which the diverse sets of opinions are going to reach some sort of equilibrium; however, in any case, none of them diffuses at the expenses of others.

legalizing same-sex marriages does not have any practical egoistic benefit from the behavior. In such a case, thus, the egoistic rationality model does not apply completely.[2] Second, classic economic rationality hardly explains why people should engage themselves in political behaviors if their chance to exercising a pivotal vote is very small (a situation also known as the paradox of voting. See Downs, 1957; Edlin, Gelman, and Kaplan, 2007). As largely acknowledged by the public opinion studies, thus, the sole egoistic rationality cannot sufficiently account for the complexity of political behaviors, such as the vote. Others explanations have been proposed to complete the rationality argument in voting behavior. The first one, rooted on the individual level, states that a person, given a set of previously established beliefs will behave coherently with those beliefs. Cognitive dissonance theory (Festinger, 1957), for instance, suggests that people possess an inner drive to hold all their attitudes and beliefs in harmony with their behavior by avoiding inconsistencies among attitudes and between attitudes and behaviors. In other words, liberal voters may be more prone to vote for hypothetical civil rights referendums to maintain coherence of their manifested behavior with their ideological belief system. This could partly account for political behaviors that do not lead to immediate benefits to the ego (see, for instance, theories about expressive benefits; e.g., Fiorina, 1976; Schuessler, 2000). Partially related to this argument is the one that places social pressure as a crucial tool of behavior change and stability. By means of personal interactions and opinions exchange, one can not only be affected about his/her daily life decisions, such as buying a new car, but also change opinions about political matters (Berelson, Lazarsfeld, and McPhee 1954, Zuckerman, 2005; Fowler et. al 2011; Noel and Nyhan, 2011; Fowler and Christakis, 2008; Cacioppo, Fowler, and Christakis, 2009; Klofstad, 2007; Huckfeldt 2014; Bello and Rolfe 2014).
Moreover, in the case of a physical good, the rational/egoistic, expressive, and peer pressure dimensions are relevant in driving one's purchasing decision. What we argue here is that the relative contribution of these dimensions is extremely different if we focus on a political behavior. Contrarily to the case of goods adoption, difficulties in correctly determining the egoistic benefits that a choice could give are expected to lead an individual to consider the higher importance of the expressive and social drivers when evaluating a political behavior.

2.2 The individual decision-making structure of political behavior

Keeping constant the drivers that guide a certain political choice, it is well known in the literature that the decision-making process of a political choice is a complex mechanism. According to the political choice theory (Luce and Suppes, 1965; Manski, 1977; van der Eijk et al., 2006), a vote choice is function of the characteristics of the decision maker, the set of available alternatives, and the decision rule. To make a decision, individuals construct some kind of utility distribution including every alternative. This can be exemplified as a sort of a latent continuum that potentially goes, for every alternative, from "I will never vote from a certain party/support a certain political alternative" to "I will surely vote for a certain party/support a certain political alternative." Given their individual characteristics, which are composed by rational, cognitive and environmental elements, voters construct the utility of each choice in their mind. According to van der Eijk et al. (2006), utilities for different vote choices can be empirically derived by means of the so-called propensities to vote (ptv's). Technically, ptv's are usually collected by means of survey questions: respondents are asked to indicate how likely it is that they will ever vote for several parties on an 11-point scale. An example of the ptv's structure is depicted in Figure 1.

In Figure 1, the right panel shows that ptv's lead only probabilistically to the correspondent vote choice: an undecided person, who has not-so-high propensities to support a certain choice, will be more prone to be swung toward deciding whether or not to choose an alternative with respect to an individual who has a firmly low or high propensity to vote for that party. In many documented cases, indeed, the propensity to vote for a party does not automatically lead to voting for that party in an approaching election (van Der Eijk and Franklin, 1996;

[2] One could argue that participating in LGBT initiatives could benefit heterosexuals by enhancing the sense of justice and the attention for civil rights of these individuals. However, it seems that this meaning of the benefit term stretches the concept too much.

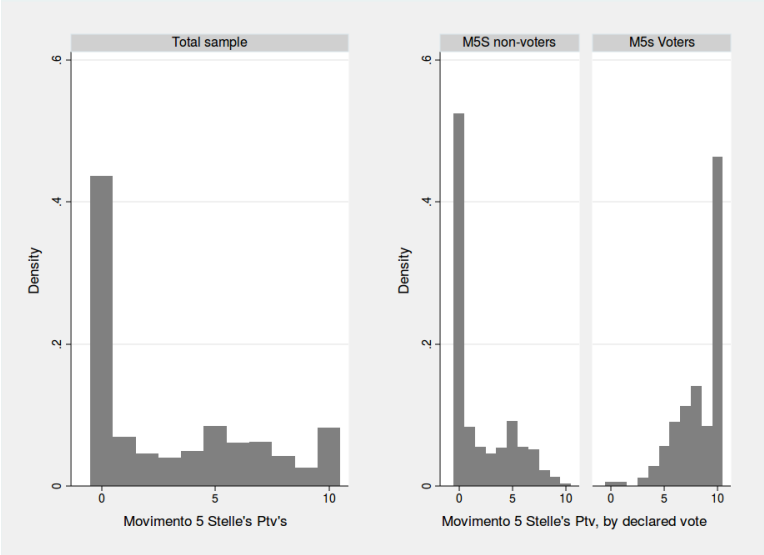

Figure 1: An example of ptv structure: The case of Movimento 5 Stelle in the 2013 elections (RCS data, first 8 days)

Vezzoni and Mancosu, 2016). For what concerns our research topic, we can say that ptv's are nothing more than the party politics version of the "propensities to adopt," which are largely employed in diffusionist research that expects heterogeneous adoption threshold (Goldenberg et al., 2000; Delre et al., 2007; 2010). So far, we can find several elements of this model in the threshold model of diffusion (Granovetter, 1978, Valente, 1996) and the CODA (continuous opinions, discrete actions) theoretical framework proposed by Martins et al. (2009). As in the attitude-behavior models of conditional choices, the threshold and CODA models assume that individuals, independently of their actual behavior, hold a certain exogenous likelihood of being convinced. This likelihood is probabilistically realized in a binomial behavior (adopting or non-adopting the innovation). The larger is the prevalence in the environment, the larger the pressure it will exert on the individual to switch toward that choice. This combination between the exogenous likelihood of adopting and the environment is depicted by Granovetter as the so-called threshold. People with a high threshold will need a larger prevalence of the potential behavior to switch and be converted to the innovation, while people with a low threshold will be more likely converted to the innovative behavior even if the prevalence is smaller. If we integrate this dynamic component into the theoretical argument made in the previous paragraph, we can argue the following theoretical statements:

1. People, during the course of their lives, "construct" a set of utilities for political object and potential choices;
2. These utilities can be easily depicted by a continuum and are given both by individuals and egoistic, rational, and psychological/ideological factors;
3. Utilities do not deterministically drive toward a pre-determined behavior. As long as the utility is higher, probabilistically, one will be more likely to support the adoption of the innovation;
4. This individual calculus is further complicated by the social environment in which one is embedded. When the innovative behavior spreads, as long as the prevalence of that behavior will be higher in the social system, one will be pushed by her discussants toward the innovation;

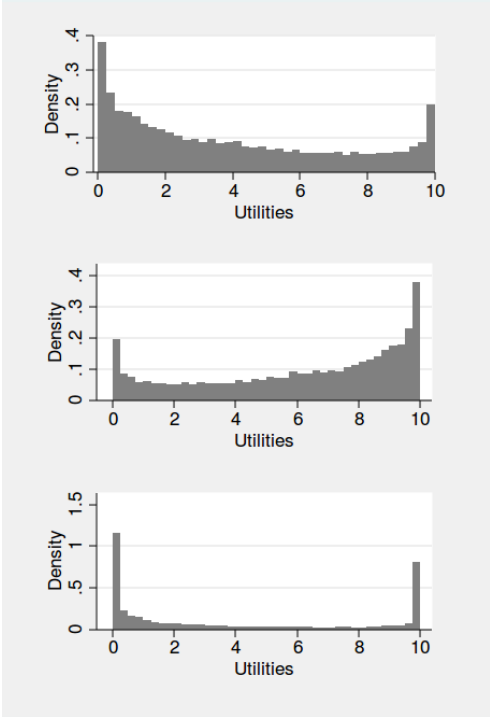

Figure 2: Different shapes of utility distributions. Values created from a non-central Beta distribution with parameters $\alpha = 0.5$; $\beta = 0.7$, $\alpha = 0.7$; $\beta = 0.5$; $\alpha = 0.1$; $\beta = 0.3$

5. Consistent with the threshold model, the utility (the attitude behind the behavior) and the binomial behavior, in a certain moment, are given by the combined effects of individual attitudes and environmental pressures.

In this framework, the relation between utilities and potential behaviors becomes pivotal, especially at the early stages of the diffusion. The structure of these two variables largely affects the likelihood that a certain person can encounter an innovation supporter and can be an innovative option holder. At the aggregate level, the utility distribution can be more or less centered toward high or low utilities, as shown in Figure 2. Assuming a utility of a certain political option ranging from 0 to 10, the utility distribution for the innovation can be similar to those in the top panel or central panel—with a small/large quota of enthusiasts and a large/small part of unpersuaded and almost unpersuadable people. If the former setting is similar to that of a diffusion process that is presumably going to begin, the latter could represent a process that already ran out a large part of its potential.
The second way in which a diffusion process can be diversified by its utilities structure is by changing the variance of utilities. In Figure 2, the top and bottom panel show these two situations. The main difference here is that, in the second case, when the variance is higher, intermediate positions become negligible. This structure is expected to lead to consequences on the nature of the diffusion: in a heavily polarized setting, people can hardly change their ideas (Fiorina and Abrams, 2008). At the beginning of the process, the undecided people, who have not yet switched to the innovation but are generally favorable to it, could be the first to be converted (Granovetter, 1978).

The other variable that affects the pace and reach of diffusion is the decision rule that individuals apply, given a certain utility. Stating that higher utilities lead to higher likelihoods holds qualitatively; however, in quantitative terms, the structure of the decision rule can dramatically change the structure of the diffusion. First, it is important to assess where in the utility function one decides on average to switch (one could have higher propensities to switch once reached 5 or 8 of his/her utility). In the same way, the stochastic nature of the

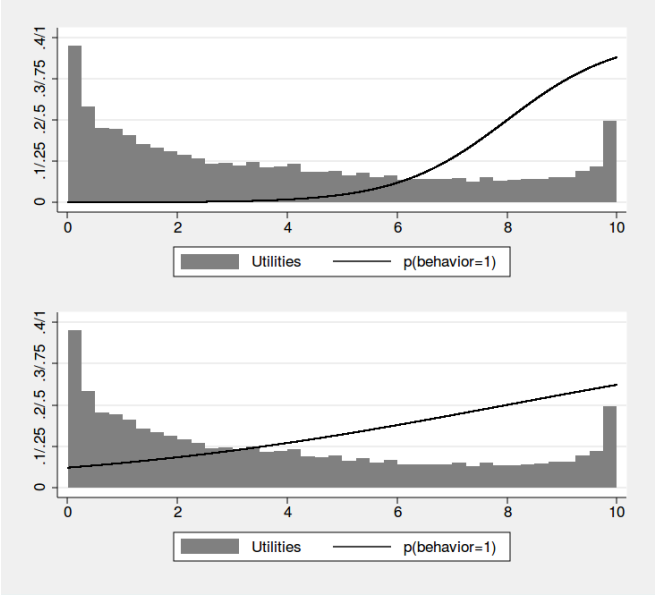

Figure 3: Different shapes of utility distributions

decision rule can be more or less aleatory. Given a decision rule centered on an utility of 8 (the state-of-the-art cut point detected in the voting behavior literature, see van der Eijk and Franklin, 1996; van der Brug, van der Eijk and Franklin, 2007), consider two individuals, one with a utility of 9 and the other with an utility of 7. If the stochastic term of the rule is 0, the "9" individual will automatically behave as 1, and the "7" individual will automatically be 0. In other cases, such as those depicted in Figure 3, a "9" could have around 75% of likelihood to be 1, while a "7" could have 25% likelihood to be 1.

2.3 Mechanisms of political persuasion and negative word-of-mouth

It has been repeatedly stressed that new political behaviors represent a particular form of innovation, with special features. We have stressed that egoistic rationality is insufficient to explain stability and change of political preferences. Other psychological and social elements are in action to convince one to switch to the new behavior, and these elements have a larger weight in the definition of the utility structure and, in turn, of the potential behavior. As mentioned above, political behaviors do not lead to clearly measurable benefits and expected egoistic utilities of a political action are usually difficult to measure (Downs, 1957). Moreover, expressive and social benefits can easily drive individuals in different directions, especially in situations of strong opinion volatility. By taking into account election campaign studies, we can see that these situations are quite common. The Italian National Elections of 2013 showed, for instance, an aggregate level of volatility of 39% from the previous election. In other words, almost 4 out of 10 Italians voted for a different party in 2013, with respect to the previous election (D'Alimonte, Di Virgilio, and Maggini 2013; D'Alimonte 2013). Moreover, it has been shown that several parties, including the populist Movimento 5 Stelle, increased their support by about 30% in the time-span of an election campaign spanning for a month and a half (Vezzoni and Mancosu, 2016). The 2013 Italian case is not the only example in recent politics. Several political exploits can be detected in at least two continents, as, for instance, the growth in consensus of the parties of Alberto Fujimori (Roberts, 1995) and Hugo Chavez (Weyland, 2003) in Peru and Venezuela, respectively, in the 1990s', as well as the victory of Silvio Berlusconi's Forza Italia in Italy in 1994 (Campus, 2004). In a volatile system, a relatively large number of individuals is undecided of behaving in a certain way. In our model, it means that levels of attitudes leading to certain behaviors present average values that range

between maximum and minimum values and/or that the behavior is mildly correlated with utilities. As a result, in a dynamic setting, is it more likely to imagine people who change their potential behaviors. If some sort of innovative opinion increases its prevalence at the detriment of other opinions in this social system (a new party or an innovative option), attitudes will be more directed toward the innovative option. In the diffusionist literature, the engine of this interpersonal influence towards the innovation is called positive word-of mouth (PWOM).
In a situation marked by both a strong role of interpersonal influence, not clearly measurable rational benefits and high volatility, however, the concepts of negative word-of-mouth (NWOM) become crucial. NWOM can be defined as a way that people have to express their dissatisfaction toward an innovation by communicating their negative feelings with others (a mechanism that could eventually result in the conversion of these "others" against the innovative option). A situation of volatility leads to higher likelihoods of changes that go in the opposite way with respect to the innovative opinion. Concerning this point, the sociological and political science literature has been largely noncommittal. A large part of the literature focuses on NWOM of goods, consistently with a marketing-driven approach and on a more individualistic view of the reasons that lead to engage in a NWOM process (Richins, 1983; Goldenberg et al., 2001; 2007; Moldovan and Goldenberg, 2004). Moreover, a small, but important, amount of sociological research aimed at detecting the role of extremist nodes in the system and their support to NWOM (Deffuant et al., 2002; 2005). Both these lines of research are unanimous in assessing the relevance of NWOM in diffusion processes and in detecting some form of dissemination of NWOM: the mechanism is not an accidental nuisance of the process of diffusion but represents a process that disseminates in the system. However, these studies mainly focus on the role of opinion leaders (e.g., Goldenberg et al., 2001; Deffuant et al., 2005), as well as that of weak and strong ties in transmitting the negative information (Goldenberg et al., 2007). Little has been done on interpersonal dynamics that favor or impede the dissemination of opinions and potential behaviors that are inconsistent with the innovative one. In particular, little sociological evidence has been shown to study NWOM political innovations and externally validate these arguments.
Therefore, this article aims at answering three questions: the first concerns the relation between utilities and behaviors and which combination of the two leads to a successful process of innovation. As expected, is the "basin" of people who have mixed feelings toward the innovation and did not decide to switch to it that makes an innovation successful? Or is the sharpness and average level with which people divide themselves as adopters or non-adopters that makes a diffusion process more or less successful (or a mixture of the two)?
The second question concerns the role of the NWOM: the literature, as mentioned above, does not problematize the role of the NWOM in diffusion processes, thereby limiting to focus on the role of certain special groups of adopters (extremists/opinion leaders). In this study, we argue that NWOM, especially in situations with high volatility, represents a pivotal element in the diffusion of innovation. We will ask ourselves whether the NWOM is actually relevant in conditioning the pace and result of a diffusion process and will investigate the nature of a possible dissemination of this process in an exploratory fashion.
The final question concerns the external validity of our results. Is it possible to extend theoretical models exposed above to real case-studies and, more important, does this operation lead to externally valid outcomes?

3 An agent-based model for the diffusion of political behaviors

To answer these questions, an agent-based model was programmed. It simulates a threshold diffusion process, in which the heterogeneity of propensity to adopt an innovation can vary and where the possibility of a NWOM is expected.

Topology. Since a diffusion process has, as a crucial feature, that of being disseminated through

interpersonal relations, the most straightforward topology that one can employ is the network one. Several random networks, however, can be used, and different networks possess different "natural" characteristics. In this case, a simple random network topology has been used: an Erdős-Rényi (1959) random network comprising 1000 nodes with 8 neighbors per node. As pointed out in the previous paragraph, each agent must have both a potential behavior and consistent utility function at t0 concerning the innovative opinion.

Utility function. At the beginning of the diffusion process, the overall distribution of the utilities is expected to see a large number of agent presenting low utilities, a smaller section of the social system of innovation enthusiasts (presenting high utilities), and the rest presenting intermediate utilities (as seen in Figure 1). In this case, we found that a distribution consistent with real data follows a type I non-central Beta distribution with parameters α, β, and λ with a domain of the distribution 0–10, as in (1).

$$u = [1 - Beta(\alpha, \beta, \lambda))] \cdot 10 \text{ [3]} \tag{1}$$

Where α and β are the shape parameters of the distribution and λ is a non-centrality parameter. If utilities are based both on individual and environmental elements, assigning to every node a random realization from the distribution in (1) would lead not to consider the fact that the utilities of ego and alters are correlated. This argument is confirmed by a large amount of literature that argues homogeneity of the networks of opinion (Berelson, Lazarsfeld, and Gaudet, 1948; Huckfeldt et al., 2004). To overcome this problem, the process of utility assignment to every node is divided in two steps:

1. The first step defines a "seed node" i (a random node of the network) for which is drawn an utility value from the distribution in (1);
2. The neighbor node j is thus randomly selected among the available nodes of the network of i. If the node does not possess a valid value yet, the utility drawn for this node is expressed in (2);

$$u_j = rand(u) \ s.t. \ u > u_i - h \ \wedge \ u < u_i + h \tag{2}$$

   In other words, the u_j value is drawn from a truncated beta distribution presented in (1) which is centered in u_i and has range $[u_i - h; u_i + h]$. In this way, h can be seen as a homogeneity factor going from 0 to 10, which represents a random draw from the whole distribution when $h = 10$ and a constant (equal to the value drawn from the first node) when $h = 0$.[4]
3. Once having drawn the value, node j is renamed as node i, and the process is repeated until every node has a non-missing value.

The advantage of this technique is that we obtain a distribution that resembles the original, random one; however, it is arranged to present non-random levels of homogeneity.

Potential behavior. Once having assigned a utility to every subject, it is possible to assign the corresponding potential behavior. Basically, people with high utilities should have higher propensities to accept the innovative behavior. The propensity of being an adopter is modeled by a logistic cumulative function as in (3):

[3] The function is multiplied by 10 to make the utility compatible with the propensity to vote as mentioned above.

[4] In this study, the h parameter is set to 2.5. This means that nodes can have neighbors of which utilities are around the 50% of the distribution (e.g., given a node with a utility of 7, all its neighbors will have utilities between 4.5 and 9.5). Although it is acknowledged that this term can change results of the simulation, it has been decided, for space constraints reason, not to consider this aspect in this study.

$$p(b) = Log(u, \mu, s) \tag{3}$$

Where $p(b)$ is the propensity of being an adopter, u is the utility drawn from the Beta function in (2), μ is the location parameter, and s is the scale parameter that models the steepness of the curve. Once the propensity to be an adopter is obtained, the vector of b is confronted with a random uniform distribution and the binomial values are consistently derived.
Behavioral rules. At t_0, every node in the network has a continuous utility, drawn from the beta distribution in (2) and a consistent potential behavior that is extracted from each node's utility by means of (3). For each time t, every node "tries to persuade" its behavior to one of its neighbors who is randomly selected. We will call the former node "the sender" and the latter "the receiver." The process of persuasion can be depicted by considering at least three scenarios:

1. If the sender and the receiver have the same behavior (sender = 0 and receiver = 0; sender = 1 and receiver = 1), nothing happens and the algorithm passes to the next sender.
2. (a) If sender = 1 and receiver = 0, a random number from a uniform distribution (of domain $[0; 10]$) is sampled.
   (b) The random number is compared to the utility of the receiver: if the random number is larger than the utility of the receiver, nothing happens and the algorithm passes to the next sender node.
   (c) Otherwise, the receiver changes its behavior from 0 to 1 in $t + 1$. Moreover, a new utility of the node is sampled from a normal distribution with mean and standard deviation calculated only among the nodes that have a behavior equal to 1 in t.
3. (a) If sender = 0 and receiver = 1, a random number from a uniform distribution (domain $[0; 10]$) is sampled.
   (b) The random number is compared to the utility of the receiver: if the random number is smaller than the utility of the receiver, nothing happens and the algorithm passes to the next sender node.
   (c) Otherwise, the receiver changes its behavior from 1 to 0 in $t + 1$. Moreover, a new utility of the node is sampled from a normal distribution with mean and standard deviation calculated only among the nodes that have a behavior equal to 0 in t.

We can formalize the second scenario in the following manner:

$$b_{r,t+1(s=1;r=0)} = \begin{cases} b_{r,t} \; if \; rnd > u_{r,t} \\ 1 \; otherwise \end{cases} \tag{4}$$

$$u_{r,t+1(s=1;r=0)} = \begin{cases} u_{r,t} \; if \; rnd > u_{r,t} \\ N(\mu_{b=1}; s_{b=1}) \; otherwise \end{cases} \tag{5}$$

Where $b_{r,t}$ and $b_{r,t+1}$ are behaviors of the receiver at time t and $t + 1$ (in this case, when $s = 1; r = 0$, that is, the sender is an adopter while a receiver is not). $u_{r,t}$ and $u_{r,t+1}$ are utilities in times t and $t+1$. $\mu_{b=1}$ and $s_{b=1}$ are mean and variance of the distribution of people who have $b = 1$. rnd is the random number drawn for every disagreement situation. In the case of $(s = 0; r = 1)$, the only difference is the condition concerning the random number and the utility $(rnd < u_{r,t})$ and the distribution from which mean and variance of utilities is extracted from $(\mu_{b=0}, s_{b=0})$. Two elements concerning the structure of the simulation should be noticed: first, the agent-based model applies the concepts of the threshold model of diffusion in a slightly different way with respect to other studies (Valente and Davis, 1999; Goldenberg et al., 2000; DeCanio et al., 2000). Threshold models are usually deterministically simulated,

given an ego with a certain threshold and prevalence of the innovation in ego neighbors, the ego automatically switches toward the innovation once the prevalence of the neighbors surpasses the threshold. In our case, the process of conversion is stochastic (similarly to Bohmann et al., 2010). Consistent with both the theory of Granovetter and public opinion research, we assume that people do not switch because they simply evaluate the prevalence of the innovation on their neighbors. Actually, the simple evaluation by ego of its network seems a quite poor approximation of the process of conversion of a certain innovation, especially if we deal with a political opinion/behavior. According to the literature, persuasion is definitely a non-deterministic process (Lazarsfeld et al., 1948; Huckfeldt and Sprague, 1995; Bello and Rolfe, 2014). In our simulation, we implicitly assume that to control one's threshold, an individual with a higher prevalence of innovation adopters in her social network will be more likely subjected to innovation adopters, who, in turn, will be more likely to convince her. As a consequence, instead of an automatic switch once the threshold is surpassed, we expect a probabilistic relation between the prevalence of the innovation in the neighborhood, the attitude the individual holds (that can be summarized as the u continuous variable), and the switching likelihood. This can be formally stated as follows:

$$L(S_{w_{t+1,i}}) = f(u_{t,i}, b_{t,j}) \tag{6}$$

Where $L(S_{w_{t+1,i}})$ is the likelihood to switch in $t+1$ for node i, $u_{t,i}$ is the utility the individual i had in the previous time unit and $b_{t,j}$ is the behavior of the surrounding nodes j in the previous time.

Equation (6) does not have a direction of the switching process. As indicated above, especially in highly volatile systems, people can change their minds several times during a single time-span (an election campaign, for instance) and not necessarily always toward the adoption of the innovative opinion/behavior. In the diffusionist literature, these people are usually defined discontinuers, that is, people who refused to adopt an innovation and, after a certain period, stopped adopting it (Leonard-Barton, 1985). The model presented so far allows its nodes to be converted both toward and against the innovation. In particular, we expect, consistently with (6), that the likelihood of discontinuing from the innovation in $t+1$ is the function of the utility possessed by an innovation holder in t and the number of other nodes which do not hold the innovation.

Dynamics. This structure is repeated for 30 time units.

Simulations. For every combination of the calibration parameters, the whole simulation has been repeated 50 times. The following paragraphs, thus, are the averaged results for the 50 repetitions of the Agent-Based Model (ABM).[5]

4 Results of the ABM

It has been argued that the present simulation possesses, at least, four crucial calibration parameters that can alter the pace, levels, and, possibly, mechanisms of influence of the process: the mean and variance of the utility structure and the decision rule (the stochastic function that transforms utilities into potential behaviors). After several sensitivity tests on calibration, it emerged that the most important parameter that affects the diffusion process characteristics and, at the same time, allows to clearly show emerging results of the simulation is the variance of the aggregate utility function.[6] In this first part of the section, results for three parameterizations of the model will be presented. As shown before, α and β parameters define, among other things, how many nodes present intermediate utility positions (and consequently, behavior). We argued that intermediate positions can represent the "fuel" of the innovation

[5] Data on which the simulation is based, scripts of the simulation (in R), and Stata do-files that replicate the analyses in this study are available on request.

[6] For more information about the sensitivity tests conducted and the resulting evidences see Appendix 1

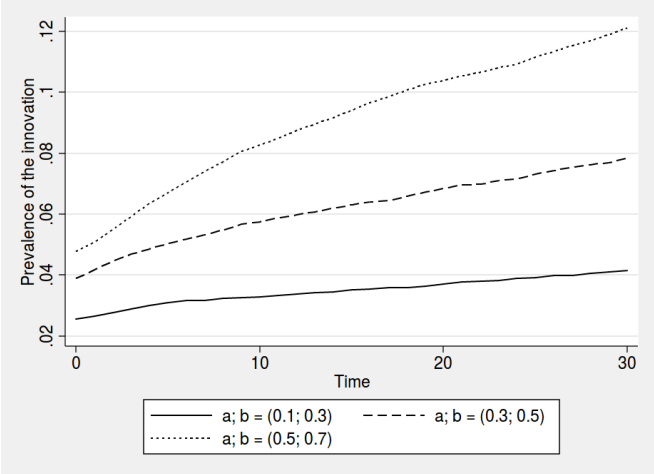

Figure 4: Prevalence and pace of the diffusion and per shape parameters of the utility function

and Figure 4 seems to confirm our hypothesis. [7] In the figure, curves for simulation initialized with $\alpha = 0.1$ and $\beta = 0.3$, $\alpha = 0.3$ and $\beta = 0.5$, and $\alpha = 0.5$ and $\beta = 0.7$ [8] are presented. First, we can see from the top panel of the figure that the structure of utilities/behavior and the mechanisms of influence explained above actually lead to an increase of what we refer to as the potential behavior. The percentage of conversion in the system is larger as long as the diffusion pace is steeper (at the beginning of the process) and gradually lowers when the process tends to stabilize. Interestingly, the pace and incidence of the diffusion process are affected by α and β coefficients: where they are small (0.1 and 0.3) and the aggregate distribution of utilities is more polarized (see Figure 2, bottom panel), the prevalence of the innovation remains negligible (from 2 to 4% of the system). When there are more nodes in between the two extremes (in a situation similar to what is shown in the top panel of Figure 2, with $\alpha =$ 0.5 and β =0.7), the diffusion increases its prevalence by 7 points in the 30 time units.

The main assumption behind an innovation is that it disseminates in a certain social system. This means that people who change their mind with regard to that innovation will affect, in turn, their network neighbors and so on. The first, and easier way to have evidences of this process is by analyzing the effect that the neighbors have on the propensity to switch to the innovation of a node in a certain time unit. To do so, three logistic fixed effect regression models, one for each structure of the utilities, have been fitted.[9] In both the models presented in Table 1, the dependent variable is a dummy that indicates switching towards the adoption from t to $t + 1$, while the main independent variable is represented by the number of neighboring nodes that switched to the innovation in $t + 1$. The variable is constructed in a way that negative figures represent a network in which potential discussants who discontinued are more than those who adopted the innovation and vice versa (see Appendix 2 for the distribution of the variable). An additional variable is the time unit in which the conversion takes place. Our main assumption is that, as long as there is an increase of the prevalence of people who are supporting the innovation in one's ego-network, our ego will be more likely to switch toward that innovation. Results confirm this idea and show a quite similar effect of the neighborhood

[7] A total of 95% of confidence intervals have not been inserted in the figures because the large amount of cases (1,000 by 50 repetitions) are extremely narrow. Except when specified otherwise, the reader must thus be aware that the results possess extremely small sampling errors.

[8] To make the curves starting from roughly at the same point (in this case, about 2–5% of the system) the parameter λ has been changed. For $\alpha = 0.1$ and $\beta = 0.3$, $\lambda = 4$; for $\alpha = 0.3$ and $\beta = 0.5$, $\lambda = 3.5$, and for $\alpha = 0.5$ and $\beta = 0.7$, $\lambda = 3$. Differences in the non-centrality parameters, however, do not change the slope of the process.

[9] Fixed-effect (or within effects) models is a type of regression model focusing only on within-individual variations, which allows to control for omitted/unobserved variables, drastically reducing spurious correlations or alternative explanations and leading to more robust theoretical conclusions (for more information, see Wooldridge, 2012).

persuasion effect. The propensity to switch behavior is 1.4 times bigger ($e^{0.35}$) as long as one more neighbor starts supporting the innovation.

Table 1: Three fixed-effect models to study the adoption of the innovative behavior

	$\alpha;\beta = (.1;.3)$	$\alpha;\beta = (.3;.5)$	$\alpha;\beta = (.5;.7)$
Neighbors who switched in t-1	0.36***	0.36***	0.35***
	(0.06)	(0.03)	(0.02)
Time	-0.03***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)
Observations	42,601	112,897	180,235
Number of nodes	1,469	3,893	6,215

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Since the simulation is designed in a way that leads nodes to be influenced only by other nodes, these results do not surprise us much. However, although we have stated that our model is influenced by the threshold model of diffusion theorized by Granovetter (1978), we did not directly model the diffusion as a threshold model: in the ABM, nodes do not automatically change once they have reached a certain number of neighbors supporting the innovation. On the contrary, they are stochastically affected by their neighbors. As we have seen in the previous table, this holds at the individual level. Another prediction of the threshold model is that, on aggregate, if the diffusion follows the threshold pattern, nodes that are easier to be converted will be converted almost immediately; however, nodes that are more difficult to be converted are expected to need an additional number of convinced neighbors to switch, and therefore, are more likely to be converted in a later time. Results corroborating this hypothesis come from Figure 5, in which the average of the utility of the time unit before the switch toward the innovation at every time unit is plotted. Nodes which are easier to be converted—that is, those who have high utilities for the innovative option, but who have not switched to it—are the first to be converted. As long as the innovation spreads (see Figure 4), nodes which are more difficult to be converted are actually converted. On average, at the end of the time-span, nodes which possess a 2 on a 0–10 scale are converted. This is a proof that our process of innovation spreads in a fashion that is consistent with that theorized by Granovetter and others (Granovetter, 1978; Valente, 1996).

4.1 The pattern of the NWOM: A failed counter-diffusion process

It has been shown that the pattern of the innovation of the PWOM is consistent with the theory of diffusion. However, it has been argued that in the diffusion of a public opinion-based behavior, the balance between negative and positive WOM could be more crucial than in the diffusion of other innovative objects (for the reason that, *ceteris paribus*, it is easier to change your mind during an election campaign than to change a just-purchased 600$ mobile phone). As shown in Figure 6, it is possible to evaluate the incidence of PWOM and NWOM (in terms of the average number of people persuaded toward and against the innovation during the 50 replications) in the simulated system[10] for every time unit.

PWOM is certainly relevant in the system, and shows some sort of declining trend that is consistent with the less steep curve of diffusion in the second part of Figure 4. However, the NWOM pattern remains stable around 5 nodes affected per day (against the 10 nodes "persuaded" to support the innovation). At the beginning of the process, for every two nodes that switch towards the innovation, one chose not to support it anymore.

[10]The following results are based on the $\alpha = 0.5$, $\beta = 0.7$ diffusion process, since no significant differences emerged in testing other parameterizations of the simulation.

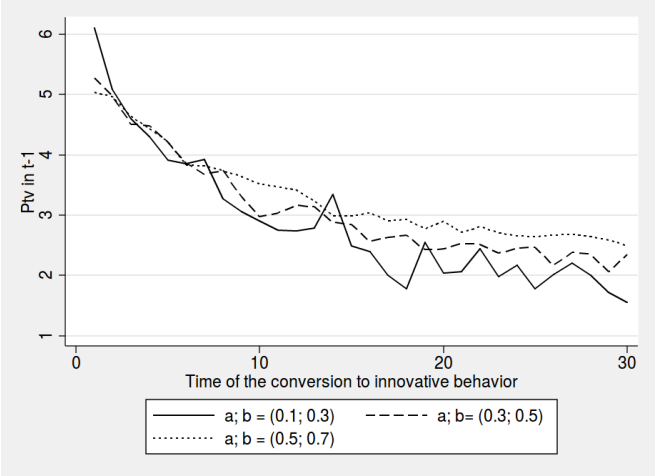

Figure 5: Ptv at t-1 of new adopters per day

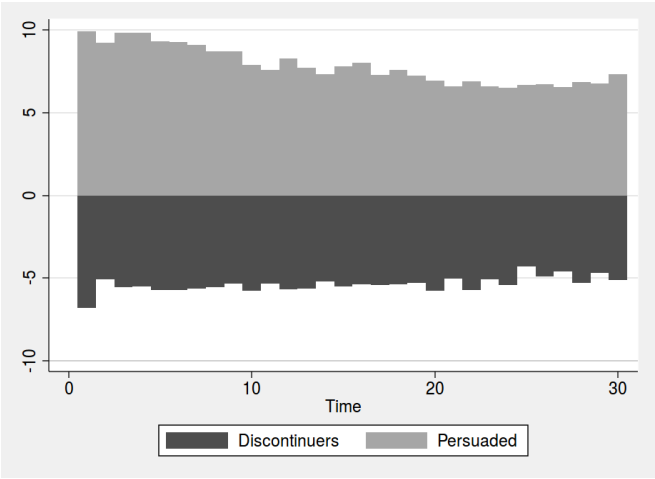

Figure 6: Average discontinuers and adopters per day

However, although relevant, this pattern could be provided by accidental, non systematic factors that do not lead to a real dissemination. To test the dissemination process, we fit a fixed-effect regression model in Table 2 in which discontinuity is modeled (Models 3 and 4) in addition to modeling the persuasion toward the innovation (Models 1 and 2). The first model is equal to model 3 of Table 1; however, the second one adds an interaction between time units and the neighbor prevalence of the innovation. Since the interaction is negative, the effect of the neighbors slightly declines in the second part of the diffusion (the effect of the interaction is at the edge of the 10% significance).
The second set of models aims at assessing an effect on discontinuers. If the NWOM is a simple accident—something that does not diffuse through the network—we would expect a non-significant coefficient. Results show a -0.09 parameter for our variable of interest (as long as one has one less discussant supporting the innovation, its likelihood to discontinue will increase by e-0.09, about 10%) In addition, this parameter does not change with the unfolding of the diffusion, as observed slightly for the PWOM. Models 3 and 4 show us that, the more a network becomes unfavorable to the innovation, the more the likelihood to switch against the innovation rises. This is an indirect proof that discontinuers tend to affect other adopters to make them change their mind and that this process disseminates in a weaker but similar way with respect to the proper diffusion process.

Table 2: Three fixed-effect models to study the adoption of the innovative behavior

	Model 1	Model 2	Model 3	Model 4
	Being persuaded		Discontinue	
Neighbors who switched in t-1	0.35***	0.41***	-0.09***	-0.14***
	(0.02)	(0.04)	(0.02)	(0.05)
Time	-0.02***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
(Nei. switches * Time)*10		-0.04*		0.03
		(0.00)		(0.00)
Observations	180,235		147,552	
Number of nodes	6,215		5,088	

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Figure 7 analyses the utility trend of both adopters and discontinuers with the same logic of Figure 5 (the solid line is equivalent to the $\alpha = 0.7, \beta = 0.5$ line of Figure 5). Here, NWOM patterns behave exactly in a specular way with respect to PWOM. In both cases, the nodes which are easier to be converted are the first to actually discontinue. Regarding discontinuers, however, it is easier to convert those who support a behavior for innovation and possess a utility which is not so high. As long as the innovation occurs, two things happen. First, the trend goes on rising (in the discontinuer's perspective, the more difficult nodes to persuade are those who support the innovation and have a higher utility for it); second, the steepness of the discontinuers curve decreases, making this trend weaker with respect to the trend of the PWOM.[11]

[11] One could argue that the trend of utilities can be an artifact due to the fact that conversion actually change utilities (a single node is converted toward 0/1 with its utility drawn from a normal distribution which has a mean and standard deviations equal to the 0/1 group). However, the difference between the non-adopters group are 0.3 points in the entire time-span of 30 time units, while regarding the 1 group, there is difference of 1 point of utility. The differences presented in Figure 7 are too big to be accounted by the, actually small, differences in the distribution of the utilities.

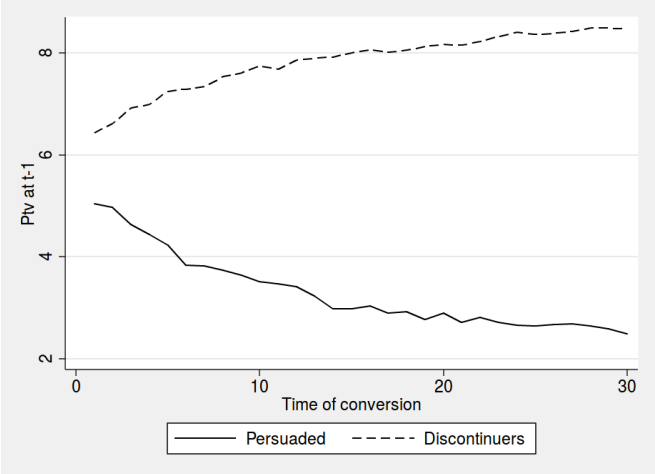

Figure 7: Ptv at t-1 of adopters and discontinuers per day

So far, thus, we can draw two conclusions from the analysis of the results of the ABM. First, the fuel of the diffusion is centered among those people who have intermediate utilities and do not (yet) support the innovation. As long as this basin of potential adopters is populated, the innovation has chances to enlarge its prevalence. Second, NWOM cannot be seen as an "accident," that happens in inconsistent parts of the system. Rather, it can be more correctly defined as a sort of a (failed) process of counter-diffusion. NWOM systematically disseminates in the system (as argued by Richins, 1983; Deffuant et al., 2005). Another result, that has been little investigated by previous literature is that NWOM, consistent with PWOM, follows the expectations of a threshold model, in which the perspective of easy and hard to convert nodes is overturned. In sum, NWOM is a fundamental part of the diffusion process because it contributes to shape (by lowering its potential levels) and counterbalance the diffusion when the fuel of the innovation (the "undecided" nodes) starts to run out.
So far, the ABM has been used to theoretically test what can happen to a generic diffusion process in which both the two-step structure of individual decision-making and the effects of different types of senders (discontinuers and adopters) are taken seriously. The ABM is now calibrated with a real-life case of diffusion of a political option in a situation of high electoral volatility (the increase of the Movimento 5 Stelle in the campaign of 2013). The model employed above will be calibrated with the real data collected at the beginning of the campaign and both the external validity of the model (with respect to the real outcomes of the elections) and the relationship between negative and positive WOM will be tested.

5 The case of Movimento 5 Stelle in 2013

To present a sketched picture of the 2013 Elections, we must stress two elements of the Italian political landscape: from one side, classical political parties—that, together with name changes and internal splits, used to remain more or less stable for more than 20 years—lost a huge quota of their previous strength (ITANES, 2013). From the other side, several scholars (ITANES, 2013) reported a growth of a number of new political parties that criticized the old party system. Undoubtedly, the most successful of these parties in 2013 has been the Movimento 5 Stelle: in a partially unexpected way, the party, led by a former comedian, Beppe Grillo, became the largest party in the House of Deputies, with 25.5% of the votes. The Movimento, presenting itself in the middle of a harsh crisis of representation that invested the entire political landscape (Diamanti, 2014), revealed to be incredibly charming for the electorate. This happened for several reasons. First is because of the figure of Beppe Grillo, a former comedian who, during the past few years, became a foreground character in the political

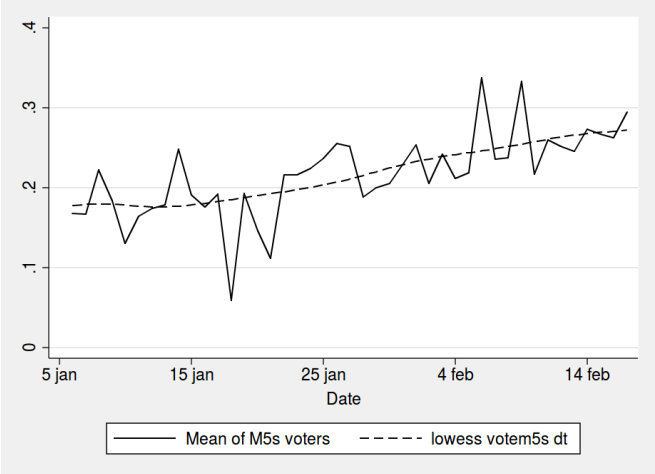

Figure 8: The rise of M5S during the campaign of 2013 with lowess interpolation ($bw = 0.8$)

arena. Beppe Grillo, who defines himself as a simple loudhailer of a "non-party" (Diamanti, 2014), repeatedly refused any institutional mediation between him and his followers, stressing the difference between the Movimento and the old, traditional political arena. Second, Movimento's 2013 election campaign has been based on popular and captivating arguments such as the institution of a basic income for the unemployed and the clampdown on corruption in public administration. The image of the Movimento was also promoted by means of the MPs selection process: to signal a distance between the Movimento and the old political parties, a troop of young citizens, who had never experienced activism in traditional parties, were selected by means of a web-based contest. Grillo's media and political strategies, taken together, led experts to borrow Taggart's (1995) classification in defining the Movimento as a populist (or neopopulist) party (Corbetta and Gualmini; 2013; Biorcio and Natale, 2013; Diamanti, 2014). As pointed out in several other occasions (Diamanti, 2014; ITANES, 2013), characteristics of the 2013 Italian political arena led voters to signal their dissatisfaction in a way that was different with respect to simple abstention: "a vote for the M5S does not reflect identification with it. The last-minute voters and the most peripheral passengers of February 2013 voted for the M5S to express dissatisfaction and anxiety. It was a 'tactical' vote—an alternative to a non-vote—and it was manifested through a non-party" (Diamanti, 2014). From the outcome side, these factors led to a stunning two-month increase of the percentage of vote intentions for the Movimento 5 Stelle as it is possible to see from the 2013 ITANES Rolling Cross-section data (Figure 8), Beppe Grillo's party passes from around the 17% of the first days of January to more than 25% gained between 24 and 25 February.

The—so far not particularly extended—literature that tries to explain Movimento's 2013 exploit employs two main explanatory arguments: several scholars (Diamanti, 2014) argued that Grillo's media-related strategy was one of the key of the Movimento's outcome. Albeit Movimento's candidates did not show in TV debates and talk show, the Movimento and especially its charismatic leader, Beppe Grillo, "has succeeded, indeed, in being visible and making news even without being directly present. He has 'compelled' news broadcasters and talk-show hosts to deal with him, to download his video messages, and retransmit them. Grillo, in fact, exploits television to his own advantage, pushing the lever of communication to 'full on' when an election is in sight" (Diamanti, 2014). This "indirect" media coverage could, indeed, have affected positively voters, who basically heard Grillo's claims without any direct contradiction. This hypothesized mechanism would allow to explain the rise of the Movimento without assuming any discussion network.
Other scholars focused on an internet-based explanation. The employment of the web and its instruments (weblog, social networks, etc.) by the Movimento has been much more intensive

and successful with respect to traditional parties (Nizzoli, 2013; Corbetta and Gualmini, 2013, Diamanti, 2014; Bentivegna, 2014). This element could have been crucial in the success of Movimento 5 Stelle: the Internet becomes a sort of substitute of real interactions (Bentivegna, 2014). According to this explanation, the diffusion process would thus be enacted by means of virtual interactions instead of real-life ones.

These two explanations (the media and the internet) have several drawbacks. The main problem related to the internet explanation is the fact that the web is far from being pervasive in the Italian electoral body. From the demographic perspective, Italy is one of the "oldest" countries in the world and, consistent with this situation, the penetration rate of the web is among the lowest in developed countries (Chen and Wellman, 2004). Moreover, after descriptively analyzing results of the 2013 CAPI survey collected by ITANES (Vezzoni, 2015), we found that only 3.8% of the respondents use Twitter and only 8% of the sample uses the social network Facebook to share political contents or ideas.[12] These results should make us sufficiently aware that, if an internet effect does actually exist, it risks of being lower than expected. The media effect argument drawback, instead of being related to the prevalence of the conversion instrument, could be rather related to the prevalence of the message in the media itself. No doubt that the effect of media, although it is not clear to which measure, can have affected Italians' voting behavior. In the specific case of the Movimento, however, the information has been spread together with huge conflicting opinions that were typically aired after Grillo's speech during the election tour (Diamanti, 2014). In this way, if a media effect was actually present, it was probably against the Movimento itself or, at least, it is difficult to expect that the effect was solely positive. The choice to consider the diffusion of the Movimento as a social process does not neglect, however, the fact that other effects could have been ongoing in the electoral body. More simply, our interpretation is that, among other effects, the social effect can be included as an important factor for an electoral change.

Vezzoni and Mancosu (2016), proposed that, instead of relying on (social) media effects, the success of the Movimento must be interpreted as a diffusion process in which interpersonal relation were crucial in transmitting the anti-political messages of the new party and, eventually, convincing a larger amount of people. In particular, a relation between exposure to weak ties and the increase of the propensity to vote for the party over time has been detected. This outcome is indeed consistent with a process of diffusion, in the meaning provided by Rogers (1983).

An ABM, largely based on that presented above, will investigate the social mechanisms that could underlie the process of diffusion of Movimento's voters behavior. With respect to the previous models, whose main aim was to investigate the emergence of a set of empirical regularities that affect pace and mechanisms that force the process, the model that follows has the additional aim of also being externally valid (Liu, 2011). If the "analytic adequacy" of an ABM (McKelvey, 2002) is not related to real data at all and it is just assessed to prevent illogical emergence processes, external validity requests become more demanding: the data emerging from the real world must be adequately represented in the simulation. This means that the simulation must be first initialized with real data (in other words, starting values must be extracted from real data); second, additional tests must be performed to assess the level of coherence between real data and the simulation (Liu 2011). For this purpose, some of the most important variables of the model (especially the utility and potential behavior data) are adapted from real data. Additionally, the availability of real data allows us to compare the results of the ABM and real results of the Elections to externally validate the model.

[12] Results are based on the author's descriptive analyses of the ITANES' 2013 CAPI survey

6 An empirically-calibrated ABM for modeling the diffusion of Movimento 5 Stelle in 2013

6.1 The real-data calibration of the ABM

The 2013 pre-electoral rolling cross-section (RCS) survey (Johnston and Brady, 2002) seems to be the more promising candidate for collecting the data to calibrate the ABM. The time span of the ITANES' 2013 RCS is of 50 days, from January 5th to February 23rd, a day before the elections (held on February 24–25, 2013). An independent quota sample of approximately 200 interviews was collected each day, excluding Sundays, using the CAWI mode (Computer Assisted Web Interviewing) for a total of 8722 interviews distributed over 43 days.[13] The dataset allows, thus, to provide us the unfolding of the diffusion process. The dataset provides a 0–10 ptv (propensity to vote) for Movimento 5 Stelle. In addition, it accounts for declared voting behavior (the answer of the question is related to the party one is going to vote on the day of the election). The variable can be reduced to a binomial variable which is 1 when the voter declares that he/she is going to vote for the M5s and 0 otherwise. By combining these two pieces of information, we can have a clear idea of what were the balance of forces at every time point in the campaign. To calibrate the ABM, an Erdős-Rényi network of 1,000 cases (with every case having 8 neighbors) was created, and for every node, a propensity to vote and a vote choice were assigned. The assignment was created in a way that every node has the real-data-based joint probabilities of having a certain ptv-vote couple of properties (for instance, being 0.046 the probability of having a ptv = 6 and a vote choice = 0, the algorithm of assignment produces a network in which 4.6% of the nodes have that combination of ptv–vote declaration).[14] Since voters have different levels of interest in the campaign, a real-data driven additional characteristic, the propensity to talk, is added to every voter. If a node "talks about politics" one time per week, the probability that it can start the process of persuasion is lowered to 1/7. The rest of the simulation, namely the persuasion process, is identical to the previous paragraph.[15]

6.2 Results

The most straightforward way to test the external validity of our model is to exploit the data provided by ITANES' 2013 RCS survey. As discussed above, the RCS provides daily estimates of the prevalence of the M5S during the election campaign, and in the calibration process, the first eight days of RCS data have been used. If the simulation sufficiently depicts the unfolding of the process of diffusion, we might thus expect that the shape of the simulated data resembles that of the real data, collected with the RCS. In this way, the simulation predicts data points that have not been used to calibrate the ABM. Figure 9 shows three curves. The solid curve is the mean for every day of innovation in the simulated environment, whereas the broken, dashed line is the point estimate of the M5s from day 9 of the collection (that is, one day after the data employed for the RCS). The smooth dotted line represents a lowess interpolation (bandwidth = 0.8) of the real data. The three curves are extremely similar and especially the lowess interpolation and the simulated data curve present very similar traits.

Table 3 presents the Pearson's correlation of the three variables. The simulated data correlates .62 with the point estimates and .98 with the lowess interpolation of the estimate (n

[13] The RCS data come from a commercial opt-in community. The single daily samples and the overall pooled pre-electoral dataset are thus not representative of the Italian population. Several biases can be detected on several relevant dimensions (such as, for instance, education, age, interest in politics). As a result, the data cannot be used for the estimations that aim at generalize to the population. Biases are however systematic across daily samples (namely, each daily sample can be seen as an independent sample similar in all respects to all other daily samples, except the day of data collection, as requested by the RCS procedure of data collection). The interpretation of the trends of the variables of interest can be thus considered as genuine, although their absolute levels cannot be generalized to the Italian population (see Vezzoni and Mancosu, 2016).

[14] In this case, the homogeneity problem has been disregarded

[15] Propensity to talk variable and the descriptive statistics of real data employed to calibrate the ABM are showed in Appendix 2

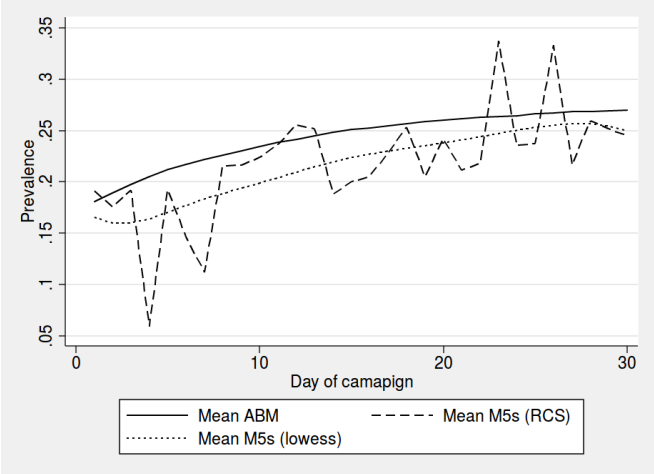

Figure 9: Simulated and real data for the prevalence of M5S during 2013 campaign

= 30). This outcome represents very promising evidence that the simulation predicts well the actual outcome. Regarding the PWOM–NWOM relationship, we can see how the real-data cal-

Table 3: Correlation matrix between simulated and real data (2013 Italian National Election campaign)

	M5s prev.	M5s lowess	Sim. data
M5s prev.	1		
M5s lowess	0.64	1	
Sim. data	0.62	0.98	1

ibrated simulation provides a slightly different situation from the theoretical models presented above (Figure 10). Especially, it is interesting to stress the relevant amount of conversions towards the innovative opinion at the beginning of the time-span (almost 20 per "day"). As long as the steepness of the diffusion pace slows down, the system reaches equilibrium between discontinuers and adopters.

For what concerns the two other outcomes that test the dissemination of positive and negative WOM and the presence of a threshold-like fashion of the diffusion process, Table 4 and Figures 10 and 11 present results that are overall similar to those discussed when the theoretical simulation has been investigated. The prevalence of the changes in time of adopters/discontinuers lead to other adoptions/discontinuances (see Table 4), while the relative prevalence of adopters/discontinuers (Figure 10) and the threshold-like progress of nodes converted towards/against the innovation (Figure 11), although differing quantitatively, can be interpreted in a qualitatively equal fashion. Moreover, for the real-data calibrated diffusion, thus, we can stress the crucial importance of the NWOM in diffusion processes characterized by a strong level of volatility (that can be seen, for instance, by the prevalence of high-utility people who were measured as non-adopters of the innovative party, see Figure 1).

7 Discussion

This study aimed at investigating, by means of both a theoretical and real-data calibrated ABMs, general trends and individual mechanisms that withstand a process of diffusion of political behavior. It has been argued that this particular kind of behavior must be modeled in a slightly different way with respect to the usual diffusionist literature (Martins et al., 2009). At the same time, little discussion has been found, in political behavior literature, about the diffusion of political objects. This study placed itself in between these two research lines,

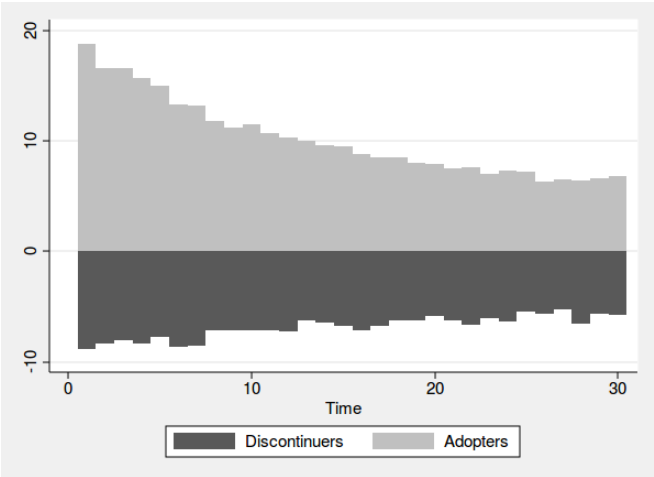

Figure 10: Prevalence of discontinuers and adopters per day (real-data calibrated model)

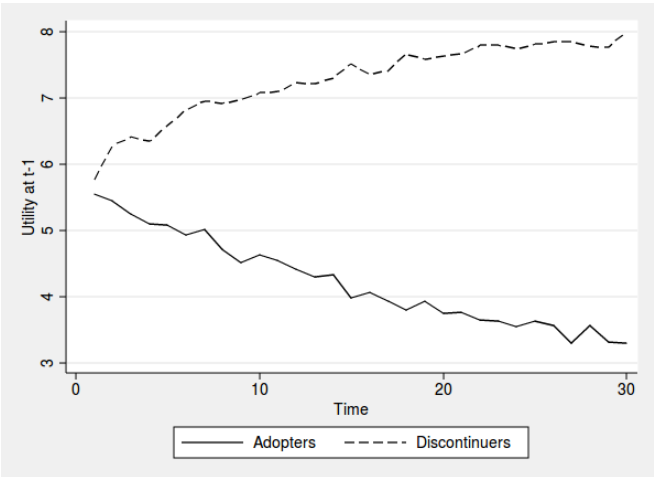

Figure 11: Ptv at t-1 of adopters and discontinuers per day (real-data calibrated model)

Table 4: Two fixed-effect models to study adoptions and discontinuances (real-data-calibrated ABM)

Indep. vars	Model 1 Adopters	Model 2 Discont.
Neighbors who switched in t-1	0.32***	-0.10***
	(0.02)	(0.03)
Time	-0.04***	-0.02***
	(0.00)	(0.00)
Observations	293,741	219,182
Number of nodes	10,129	7,558

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

aiming at providing useful insights for both. At the individual level, it has been argued that the likelihood of a certain behavior is the result of the structure of the utilities one has and the social environment in which this latter is embedded (as stressed by Martins et al., 2009 and van der Eijk et al., 2006). At the aggregate level, we argued that the pace and actual success of a diffusion process could be potentially affected by, at least, two elements: the utilities distribution (and, more clearly, the variance and mean of this distribution) and the decision rule (and, again, what we could call its "mean" and "variance"). Results corroborated our expectations and provided new insights, which emerged from the unfolding of the ABM. The first result concerns the potential of a diffusion process and the characteristics of a system that can favor or obstruct it. We have seen that—given a t_0 with a structure of utilities and expressed (potential) behaviors and keeping all other elements fixed—the diffusion process has higher possibilities to succeed as long as the basin of undecided adopters who have not yet decided to adopt the innovation is larger. Second, it emerges that NWOM, rather than being an accident of the process of diffusion, seems to disseminate in a fashion similar to that of a proper diffusion process. The number of neighboring nodes that discontinue, affects the propensity to discontinue of the ego-node, and the effect, although smaller than the diffusion, is systematic. Moreover, we have seen that the empirical working of the process is similar to that of a diffusion process: easier nodes are the ones which are converted, while more difficult nodes are converted only later. NWOM, thus, represents a (failed, since the diffusion increases its adopters) counter-diffusion process, which crucially contributes to hinder (or better, balance) the diffusion.

These two findings also emerge in a real-data-calibrated ABM, which impressively fits real outcomes that are not statistically correlated with the calibration process. Moreover, in this simulation, the role of NWOM is crucial: keeping into the model the ability for a node to "persuade" another node to discontinue, the simulation fits quite well within the data.

By observing the topic more generally, this study stresses two major theoretical points, which has been little addressed by the literature, that could be interesting for future research. First, this study provides theoretical and empirical instruments that assess whether an innovative opinion has the potential to break into the public by employing data that is largely available in political surveys. People who have medium/high utilities for the innovation but have not yet switched are those who have, in t_0, the larger probabilities to be converted toward the innovation. Second, and more important, this study emphasizes the relation between PWOM and NWOM by showing that one is the reverse of the coin of the other.

This study possesses several limitations. The first, and most gigantic, is that this study treats the diffusion of political behaviors by considering only interpersonal communication as the driver of conversions, while, as we know from the literature, other factors can be pivotal in shaping the diffusion process of a political idea. The media can alter citizens' perceptions and

will to be converted by others (e.g., Schmitt-Beck, 2003). Although the model fits well the data of our case study, it could be not so efficient in modeling situations in which effects of the media largely influence the system. The second, a major limitation, is that it is known that people are not convinced in the same way by any relevant other. People are differently affected by their environment conditionally to the intimacy they share with their alters. A large number of studies (Granovetter, 1973; Erisen and Erisen, 2013; Huckfeldt et al., 1995) have found that being exposed to a disagreeable partner or an intimate relative leads to higher conversion rates than being exposed to friends or co-workers. Evidence of this trend have been also found in studies on diffusion of innovative behaviors (Goldenberg et al., 2001; Vezzoni and Mancosu, 2016).
Some of the limitations of this study, however, could be translated into opportunities by future research. This study focuses on diffusion of political innovations; however, as it has been observed in the results, when the fuel of the diffusion is scarce and conversions towards and against a certain political object equal, the model is able to predict stability (and it can also predict a decrease in people supporting that object). The question that one could ask is whether the model, in the way is designed, can account for general volatility of a party. Moreover, since dealing with a diffusion process, the model systematically disregards other alternatives that are present in a public opinion landscape. In a generalized situation, this would be not sufficient, and the model should be extended to systems in which possible choices (and utilities) are two or more. In this way, it could be possible to take the utility-behavior dualism even more seriously and, at the same time, make the ABM more falsifiable.

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9 Appendix 1 - Sensitivity analyses

As it has been argued above, four elements in the calibration of the ABM can presumably account for differences in the shape and pace of the process. In this Appendix, each of these elements is considered and, whether it is the case, results for the sensitivity analysis are reported (a recap of the analyses is presented in Table 5).

Mean of the utility function (non-centrality parameter, λ). What has been called mean of the utility function is the non-centrality parameter of the non-central beta distribution. It was decided that a sensitivity analysis would not be performed on this feature, mainly because the only shape that is compatible with a diffusion process in one in which, at t0, the diffusion did not started yet to spread or is in an embryonic state. Testing a diffusion with an utility function similar to what presented in the middle panel of Figure 2, although interestingly, it would not be an analysis of a diffusion process anymore.

Table 5: A recap of sensitivity analyses

	Diff. in shape		Diff. in mech.	
	Statistical	Substantive	Statistical	Substantive
Variance of the utility function				
a = 0.3; b=0.5	+	+	+	-
a = 0.1; b=0.3	+	+	+	-
Variance of decision rule function				
s = 0.5	+	-	+	-
Homogeneity				
h = 0.5	+	-	+	-
h = 1	+	-	+	-

Variance of the utility function (α and β coefficients). Regarding the sensitivity analysis of the variance of the utility function, determined by α and β coefficients, we have seen in the text that a different quantity of nodes in between the two extreme utilities changes both the shape and mechanisms of the diffusion process (with special reference to the shape of the utilities of the converted during the time-span of the simulation), even if the latter are not substantially significant (standard errors for 50 repetitions of the same simulation, however, lead to extremely small standard errors, as pointed out in footnote 5; it is thus easy to find statistically significant differences in absence of substantive differences).

Mean of the decision rule (μ coefficient). Similarly to the case of the mean of the utility function, it has been decided to not perform any sensitivity analysis on this topic, assuming that a mean equal to 8 could be sufficient to differentiate nodes which can be easily already supporters of the innovation and those who cannot. The experience of previous research shows that, starting from a ptv of 8, people who have such an high ptv and do not vote for the party represent a minority (see, for instance, van Der Brug et al., 2007).

Variance of the decision rule (s coefficient). Regarding the variance of the decision rule or the uncertainty to which, given a utility, the individual gets a 1 or 0, the sensitivity analysis has been conducted with an s of 0.5. No significant differences from the baseline model (with an $s = 1$) have been recognized in the results.

10 Appendix 2 - Descriptive statistics

Table 6: Theoretical ABM descriptive statistics

	Variable	Mean	S.D.	Min	Max	N (in 1,000)
t_0	Utility	2.3	2.5	0	10	50
	Adoption	.05	.21	0	1	50
t_{30}	Utility	2.6	2.8	0	10	50
	Adoption	.12	.32	0	1	50
Whole system	Neighbors changes	.02	.31	-4	3	1,450
	Adopter	.01	.08	0	1	1,450
	Discontinuer	.01	.07	0	1	1,450

Table 7: Real-data calibrated ABM descriptive statistics

	Variable	Mean	S.D.	Min	Max	N (in 1,000)
Real data	Ptv M5s	3.1	.13	0	10	1.02
	Vote M5s	.17	.37	0	1	1.02
	Talk (n° per week)	.17	.04	1	7	1.02
t_0	Utility	3.2	3.9	0	10	50
	Adoption	.27	.44	0	1	50
Whole system	Neighbors changes	.03	.37	-3	3	1,450
	Adopter	.01	.10	0	1	1,450
	Discontinuer	.01	.08	0	1	1,450