An agent-based model for understanding the influence of the 11-M terrorist attacks on the 2004 Spanish elections

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Abstract

Government, politicians, and mass media generated a large quantity of information after the bombing attacks in Madrid on the 11th of March 2004. This information had two competing dimensions on the terrorist group responsible for the attacks: ETA and Al'Qaeda. The framing theory could explain how this information influenced the Spanish national elections on the 14th of March, three days after the attacks. We propose to analyze this political scenario using agent-based modelling to recreate the environment and framing effect of the three days prior to the elections. Using our model we define several experiments where we observe how media communications influence agent voters after calibrating the model with real data. These experiments are what-if scenarios where we analyze alternatives for mass media communication messages and word-of-mouth behaviours. Our results suggest that the framing effect affected the election results by influencing voters. These results also outline the aggregated impact of mass media channels and the different role of each party segment of voters during this period.

Keywords— Social Simulation, Agent-Based Modelling, Voting, Framing Effect, Terrorist Attack 11-M

1. Introduction

On the 11th of March 2004 (11-M), three days before the Spanish national elections on the 14th of March (14-M), some terrorists exploded various bombs on trains circulating to Atocha

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train station in Madrid. 193 people died and about 2000 were wounded. The attacks changed the electoral process: in the morning of the 11-M, the campaign was suspended; on the 12th of March, there were demonstrations marches against terrorism in the main Spanish cities; and on the 13th of March, there was a demonstration in front of the headquarters of the People's Party (PP), the Spanish right-wing party who was in the government. Finally, voting surveys failed and the results of the 14-M elections revealed an unexpected change of government.

After the attacks took place, a large quantity of information was generated by government, politicians, and mass media. That huge amount of information pushed the 11-M candidates to position themselves in relation to this event. Voters incorporated this political position about the attacks into their voting decision processes [31]. The communicative framework of this event had two political competing dimensions regarding the two terrorist groups which could be responsible for the attacks: ETA and Al'Qaeda. The first position was defended by PP's government, while the second was supported by the left-wing Spanish Socialist Workers' Party (PSOE), the main opposition party, and other opponents [53]. Two main reasons influenced public opinion on PP and PSOE's positions: the evaluation of the management of the government against ETA terrorism and the active participation of Spain in the invasion of Iraq, in March 2003. The majority of the Spanish population positively evaluated the action of the PP government in the fight against ETA. Therefore, President Aznar's bureau declared ETA responsible for the 11-M attacks as an election strategy [36]. On the contrary, the Spanish government's decision to participate in the invasion of Iraq was against the majority of public opinion and political parties.

The presence of terrorism has influenced pre-electoral environments in the past. In the US, the hostage crisis in Iran embassy was few weeks before the presidential elections of November 1980 [64]. In the Netherlands, the mayor of the city of Rotterdam was assassinated nine days before the local elections of 2002 [55]. However, none of the previous cases was comparable to the dimension of the 11-M attacks. As a consequence, the analysis of the turnout of the 14-M elections cannot be performed by comparing it with previous observations because there is not any similar electoral incident.

The post-election studies of the 14-M elections showed that the 11-M attacks influenced the decision of many voters, a thesis that has been corroborated by existing research studies on the 11-M and its impact on the elections [36, 11, 3, 57, 37, 69]. The authors supporting this thesis tend to interpret the elections turnout as a punishment to the ruling party for their mismanagement of the attack, along with their foreign policies. However, no previous study was devoted to explain the framing effect that was generated right after the attack by recreating the main communicative framework. Chong and Druckman [13] defined the framing effect as the psychological process that allows people to develop an *ad hoc* conceptualization of an issue or event, and to readjust their opinion. For instance, an important study showed that 11% of voters changed their minds and decided to go to vote after the attack [10]. This percentage rises to 15.5% in the survey conducted by the Regional Political Observatory [51] but it decreases to 6% in the opinion poll by TNS / Demoscopia [36].

Given the socio-economical and political importance of these facts in the recent Spanish history, the main goal of the current contribution is to analyse the framing effect generated after the 11-M attacks and how it influenced the decision of those who would vote for PP, PSOE, or abstain after the attacks. These two parties and abstention were the three electoral options with the highest support in the 14-M elections. PP and PSOE obtained 81% of votes cast, and 24.83% of the voters abstained. Our analysis involves studying the influence of mass media treatment of the attack's responsibility into voters and how this influence was spread by individual voters.

We propose to model this political scenario using an agent-based model (ABM) methodology [24, 43, 7, 20, 73]. ABM has been broadly applied for social simulation [35, 60, 23, 44] and for modelling political scenarios [38, 41, 49]. The ABM methodology relies on a population of autonomous entities called agents which behave according to simple rules and by interacting with other agents. The aggregation of these simple rules and interactions allow the representation of complex and emerging dynamics as well as defining what-if scenarios and forecasting hypothetical scenarios [32].

By using this ABM framework we simulate the 72 hours next to the attacks and study how this period of time affects the Spanish population when voting for the 14-M elections. The simulated population is segmented using pre-electoral real data to replicate the main political options: PP, PSOE, and abstention. Our ABM simulation framework also reproduces mass media information from real tracking data and the word-of-mouth (WOM) [40, 59] mechanisms by using artificial social networks [4, 72]. Specifically, WOM is modelled by spreading voters perceptions [17, 5] through a scale-free network [4]. We include mass media information by gathering and modelling the main broadcast media involved in the event (i.e., television, radio, and press) for this period within the simulation.

Using pre-electoral real data as our input, we validate our designed model to fit its behaviour to the actual 14-M election results, calibrating its parameters using the election's turnout as the target data. The calibration process tunes model parameters and it is a crucial phase in model validation [52, 61, 56]. More specifically, we have implemented our calibration process using metaheuristics [68]. The selected metaheuristic is a memetic algorithm [48] based on a genetic algorithm [2, 25] and a local search procedure which adjust the main WOM and media parameters to match the reality.

We define several experiments where we observe how media communications influenced voters through their corresponding agents for the ABM-based calibrated simulation model. These experiments are what-if scenarios where we analyze alternatives for mass media communication messages and WOM behaviours. Alternatives for mass media involve different communication strategies, such as alter media messages to favour one of the identified framings. In the case of WOM, these alternative behaviours involve modifying how segmented voters react to WOM. Additionally, the proposed set of what-if scenarios is used for studying the impact of both media treatment and WOM in the 14-M election results. This study is carried out by monitoring the elections turnout for the different scenarios.

The structure of this paper is as follows. Section 2 discusses related work and motivation for analyzing the framing effect in our study. Then we introduce the description of the model and its structure in Section 3. Section 4 presents the model validation with real data. In Section 5, we run the what-if scenarios where we study how the designed model behaves under different communication strategies. Finally, in Section 6, conclusions and final remarks are discussed.

2. Related work and motivation

2.1. ABM for simulating political scenarios and mass-media influence

ABM techniques have been extensively applied in the field of political sciences for dealing with political party competition [33, 34, 38]. These approaches consider both parties and electors as moving entities that make decisions continuously. That is, electors react to politicians behaviour and politicians reconsider their strategy regarding electors decisions. In [49], they extended this approach by including mass media influence. This new role for mass media is focused on campaign organisation, where political parties use media for enhancing their image regarding their voters. The latter studies show how mass media can be useful to add realism to the model and better explain the political scenario. We will explain how we include it in our model in Section 3.4.

In [26], mass media influence is studied by distinguishing two possible behaviours: global and local. The essential differences between these behaviours are focused on how they behave regarding time and space. Mass media effect and the role of mass media during campaigns regarding voters mobilizations is also analyzed in [22]. This approach is interesting because it analyses the abstention factor, instead of focusing on individual voting preferences. Authors of [45], considered the polarization effect of mass media in opinion dynamics to examine how mass media affects individuals. In this model, mass media messages are propagated via social interactions, showing dynamic changes over different scenarios where strongly polarized messages influence the agent population.

In [41], the authors examined how mass media influence the opinion formation through opinion leaders (i.e., influentials) [39]. Using an ABM simulation, the authors highlight the importance of the communication networks used by opinion leaders to influence the public. Another approach to the cascade of influence and its relationship with social networks can be found in [71]. Some contributions like [67] incorporate topology restrictions for structuring social influence into voter communities, creating substructures where agents with similar attributes are grouped. The substructures created this way are applied for modelling agents' social communications and influencing their political decision making.

ABM has been also used for studying the propagation of political perceptions. In [74], the propagation of the agent's knowledge is modelled using a space based approach. In this case, the propagated agents' knowledge depends on the satisfaction of agents with the current political situation. This approach simplifies the topology problem by assigning different radius to each agent, thus some agents will share their perceptions further, reaching more agents. A similar approach is followed in [62], where an ABM models the effect of social influence regarding voting preferences.

2.2. Using the framing effect for explaining the voting process in the 14-M

Due to the special nature of the 14-M elections, several publications were dedicated to study this phenomenon from the political perspective. The main topic of study is to find out if the attacks influenced the election process [36, 11, 3, 69]. Most authors seem to agree on interpreting that the elections turnout involved a punishment to the ruling party for its mismanagement of the attack, along with its foreign policies. The study carried out in [36] showed the influence of the attacks on the voting population when compared to a similar scenario where no attacks had taken place. In this case, authors used counter-factual simulations to analyze the influence of both the information treatment of the attacks and the foreign policies of the government [21], concluding that the management of the attacks by the government could have influenced the voters. However, its experiments did not reproduce the communicative framework and they neither simulated scenarios with alternative information treatments as done in the current contribution.

In our case, we aim at studying this communication environment and information treatment by using the framing theory. The framing theory [19, 13, 12] focuses on how communication can emphasize some features of the transmitted message to influence how this message is perceived. Because of the wide range where it can be applied, studies analysing the framing effect appear in many social disciplines [8, 16, 46]. In the framing effect, two types of subjects take part: i) the speakers, who invoke the communication, and ii) the public opinion, which could modify their political attitude after receiving the informational content. In the 14-M elections, the external event of the campaign was the 11-M attacks; speakers were political elites, mass media, and social activists; and the public opinion were the voters. The psychological process of the framing effect on the 14-M elections assumes that voters received the messages of the communication framework that was generated after the attack [65], but they mainly paid attention on those who helped them decide their vote [30].

The framing theory has been previously applied to the 11-M attacks for studying the integration of the Islamic community living in Spain [18]. The framing effect analyzed in that study is the one generated from the months following the attacks and how it influenced Islamic segregation in Spain. However, there is no previous study about the framing effect generated by the attacks on the 14-M elections.

Most of the publications considering framing theory used other approaches but ABM. Among them, we can distinguish those focused on political party competition over time and its relationship with public opinion [46, 63, 27, 16], and those interested in framing competition [12, 8]. Therefore, the current manuscript presents a methodological novelty for modelling the framing effect in political scenarios.

3. Model description

This section describes the main ABM design's features. Section 3.1 presents the general structure of our model. Section 3.2 describes the mechanics and behaviour of agent's voting. Section 3.3 introduces the artificial social network and its features, and Section 3.4 shows how mass media channels are modelled. Finally, Section 3.5 addresses the calibration process of the model with respect to real data.

3.1. ABM general structure

Our proposed model simulates the 72 hours from the attacks to the election time: from March 11th at 08:00 am to March 14th at 08:00 am. The timestep of the ABM simulation is an hour, as it correctly fits with the mass media schedule. After the 72 steps of the simulation, every agent (representing an individual voter) votes and the simulation outputs the elections' results. During the simulation period, agents receive information from mass media and spread their political perceptions through their social network in a WOM process.

The initial perceptions of the agents of the simulation come from pre-electoral data of the Spanish government [10]. Therefore, the simulation starts with no framing effect over the voters. In order to model the voters (agents' population), we have divided agents into three segments (S): PSOE voters, PP voters, and abstainers. This segmentation is done to better fit the pre-election survey data [10]. Using this segmentation, agent parameters are defined at the segment level, so agents from different segments behave differently. This design decision makes the ABM simulation more realistic and heterogeneous as well as facilitates the definition of the model's parameters.

We use the size of the pre-election survey [10], ie., 24,109 agents, as the ABM population size. This way we ensure enough granularity in the number of agents to represent the political conditions and available data from polls and National studies. Our target real population is the sum of PSOE and PP voters, and abstainers, which represents 29,238,662 people. Thus, the ABM maps one agent/voter with a 1:1,212.77 ratio.

3.2. Agents' state and update rule

Agent population will be influenced by the two framing effects generated after the 11-M attacks: ETA is responsible for the attacks and Al'Qaeda is behind the attacks. Each agent manages the framing effect by the use of a state variable, called **resilience** and encoded in μ, a real-valued variable within interval [0, 10], which represents the amount of external influence needed to change its vote.

$$v_A(\mu_A(t)) = \begin{cases} 0, & \text{if } \mu_A(t) \in [0, 3.3)\,, \\ 1, & \text{if } \mu_A(t) \in [3.3, 6.7)\,, \\ 2, & \text{if } \mu_A(t) \in [6.7, 10)\,. \end{cases} \tag{1}$$

By using the framing effect variable μ we can define the voting alternative by Equation 1, where $v_A(\mu_A(t))$ represents the voting option of agent A at timestep t. This function returns 0 if the the agent votes for PSOE, 1 if the agent abstains, and 2 if the agent votes for PP. Voters can change their vote v from $t-1$ to t, since they can be influenced by different sources (i.e., other agents and multiple mass media channels). The final voting option for agent A will be the result of $v_A(\mu_A(72))$. At the beginning of the simulation, the μ variable is randomly initialized for each agent in each of the three segments using a uniform distribution in the segment-specific interval. These intervals are: [0, 3.3) for agents at the PSOE voters segment, [3.3, 6.7) for abstainers, and [6.7, 10) for agents at the PP voters segment.

If agent A resilience value (μ_A) moved to other segment's interval, it will vote for that segment's party, modifying its behaviour as shown in Table 1. For example, if an agent gets its resilience to a value between 3.3 and 6.7, it will abstain, even if it belongs to PP or PSOE voters segments. Thus, changes affecting resilience (μ) can generate four effects on the vote: reinforcement, conversion, activation [39, 6], and deactivation [14] (see Table 1). Reinforced voters are those who voted the same electoral option at both steps $t = 0$ and $t = 72$. Converted voters are those who reoriented their vote, choosing another option at $t = 72$. Activated voters are those who did not want to vote initially, but chose to vote at $t = 72$. Deactivated voters are those who wanted to vote at $t = 0$, but finally did not vote at $t = 72$.

3.3. Social network of agents

Our agents are placed into an artificial social network [4, 72]. We choose to model this social network using an artificial scale free network [4] because of the lack of information about the real social network in 2004 and the high number of different applications where scale free networks were used [54, 28, 70].

Before the attacks: $V(0)$	**Elections:** $V(72)$	**Framing Effect**
PP	PP	Reinforced voter
PSOE	PSOE	Reinforced voter
Abstention	Abstention	Reinforced voter
PP	PSOE	Converted voter
PSOE	PP	Converted voter
Abstention	PP	Activated voter
Abstention	PSOE	Activated voter
PP	Abstention	Deactivated voter
PSOE	Abstention	Deactivated voter

Table 1: Framing effects in 72 hours for the elections March 14th, 2014.

Scale free networks [4] assign each of its nodes a different degree using a power law distribution. This kind of topology has been pointed out as a realistic way of modelling real networks, where few nodes have many connections and most nodes have few connections. Scale free networks are generated using preferential attachment algorithm that depends on the parameter m, which regulates the network's growth rate and its final density [4].

The agents are able to spread its perceptions during the simulation using the artificial social network. We model this WOM interaction as a contagion process [50]. Every agent A has a talking probability ($p_A(t) \in [0, 1]$) to spread its perceptions about the current framing (i.e., its μ value) during the simulation and at each step. When the probability check passes, the agent will talk with all of its neighbours of the social network. We will model this interaction using a variable called influence change (Δ), which modifies the strength of the agent' influences to its neighbours. This interaction is modelled in a directed way, meaning that the speaking agent influences its neighbours and not in the opposite way. This change of resilience value is depicted in Equation 2, where $\mu_B(t)$ refers to resilience value of the listening agent B when speaking with agent A and Δ refers to the influence change value of agent A.

$$\mu_B(t+1) = \mu_B(t) + (\mu_B(t) - \mu_A(t))\,\Delta_A. \tag{2}$$

We also include in our model a variable called influence decay ($d\Delta$), which modulates how previous influence is forgotten over time. This decay effect is applied at the beginning of each step for every agent, and reduces accumulated influence. Previous accumulated influence ($\delta_A(t)$) is computed following Equation 3 and represents the sum of previous changes to μ performed by WOM from the initial step 0 to current step t. The resilience value change for agent A due to decay is depicted in Equation 4, where $d\Delta$ represents the decay rate which modifies the accumulated influence.

$$\delta_A(t) = \sum_{i=1}^{i=t} \left(\mu_{A_i} - \mu_{A_{i-1}}\right). \tag{3}$$

$$\mu_A(t+1) = \mu_A(t) - (\delta_A(t) d\Delta_A). \tag{4}$$

Let us finally remind that, in order to make the ABM more heterogeneous, each segment of the model can have different values for the talking probability ($p(t)$), influence (Δ), and influence decay ($d\Delta$).

3.4. Modelling the mass media

Registered media audience from 11-M to 14-M is modelled as an external influence for the agents of the ABM simulation [42, 1]. These external influences work as global mass media [26], with the same probability of influencing any agent regardless of the social network and segment. Moreover, these external influences are parameterized to define differences between press, radio, and television[1]. Mass media channels can influence any number of agents at random depending on the channel audience at each step.

The selection of the messages forming the communicative framework that originated after the attack has been performed considering three criteria. First, the communicative diversification, because we analyse the messages broadcast by television, radio and newspapers, instead of focussing on a single type of mass media. Second, we select mass media channels that broadcast at a national scale. Finally, we select messages that respect the plurality of information. Following these criteria, we design a complete communicative framework that covers the main informations broadcast in this period. Specifically, we include the main mass media channels broadcasting in Spain during this period: El Pais (press), El Mundo (press), ABC (press), Cadena Ser (radio), TVE (television) Antena 3 (television), and Telecinco (television). A summary of the selected mass media channels is depicted at Table 2.

Every mass media channel can have different values for its parameters even if they belong to the same media type. For instance, the existing television channels (TVE, Antena 3, and Telecinco)

[1]In 2004, the Internet influence was not strong enough to consider including it in our model. Communications via phone messages are modelled using WOM.

Channel name	**Type**
El Pais	Press
El Mundo	Press
ABC	Press
Cadena Ser	Radio
TVE	Television
Antena 3	Television
Telecinco	Television

Table 2: Selected mass media channels

have different parameter values. These channels will also spread different messages at any step t, depending on which terrorist group is suggested as responsible by its broadcast informations (ETA or Al Qaeda). Each transmitted message by a channel C at a step t shows a **polarization** modelled as $m_C(t) \in [-2, 2]$ representing the information bias (ETA *versus* Al Qaeda). In order to simulate this effect, we reviewed press, radio and television informations during the three days period and scored them wherever they claimed ETA's or Al Qaeda's authority. Our scale assigns -2 if the informations points strongly to Al Qaeda and 2 if it points strongly to ETA. Both -1 and 1 refer to weak authority and 0 refers to not assigning attacks authority to a specific group. As our simulation steps by hour, we use the average polarization for a given time slot when two or more informations appear within it for a specific media.

Additionally, mass media is modelled by the following parameters:

- Reach. This parameter models the maximum amount of people each channel is able to hit. It this sense, some media are able to reach more people than others. Moreover, there is a difference between the amount of people that can be influenced for a given time slot or during the whole simulation. Thus, we use a reach parameter r_{min} for the percentage of agents that may be influenced within an hour (timestep). Another parameter, called r_{max}, is used for the maximum percentage of agents that can be influenced during the simulation. Data for setting the values of the latter two parameters were taken from Zenith study from 2013 [2].

- Influence. When a mass media channel impacts an agent A, its message influences the resilience value of the agent (μ_A). We define the influence change parameter (Δ') to modulate the latter effect. This behaviour is similar to the one defined for the social interaction between

[2] `http://blogginzenith.zenithmedia.es/estudio-zenith-los-medios-en-espana-y-portugal-un-terreno-cambiante/`

agents. This way, resilience change is performed using the received message and the influence change value for the media channel. As the same message could be received multiple times by the same agent, its maximum influence is limited to the maximum influence value (Δ^{max}). Additionally, we represent the previous influence accumulated by the channel (δ') analogously to WOM. The resilience value change of agent A after the influence of channel C is formulated by Equation 5, where $m_C(t)$ refers to the transmitted message and Δ^{max} refers to influence max value.

$$\mu_A(t+1) = \mu_A(t) + (\Delta_C^{max} - \delta'_C)\Delta'_C m_C(t). \tag{5}$$

In addition, agents may forget what they just watched or read. We include a parameter for measuring how media influences can be forgotten by the agents. This effect is modelled as influence decay ($d\Delta'$) which reduces previous influence, similarly to the one defined for social interaction. Equation 6 defines the decay update for agent A due to the influence of channel C.

$$\mu_A(t+1) = \mu_A(t) - (\delta'_C d\Delta'_C). \tag{6}$$

- Buzz. Information during those events can get a critical media impact and may generate a viral buzz effect. We model this effect through a variable called buzz increment (τ_C) for a channel C. This increment is applied to the agents' talking probability as a percentage increment to the initial talking probability ($p_A(0)$) of the agent. In contrast, as information is getting older, its buzz effect decreases over time. In a similar way to media influence, we model this effect with a variable called buzz decay ($d\tau_C$). Buzz decay decreases the talking probability depending on the previous amount of talking probability that has been previously incremented to the agent (σ). The update of the talking probability of agent A due to both buzz increment and decay effects of channel C, is shown at Equations 7 and 8 respectively.

$$p_A(t+1) = \begin{cases} p_A(t) + (p_A(0)\tau_C), & \text{if } (p_A(t) + (p_A(0)\tau_C)) \leq 1, \\ 1, & \text{otherwise.} \end{cases} \tag{7}$$

$$p_A(t+1) = p_A(t) - (\sigma_A d\tau_C). \quad (8)$$

By using these parameters, we can model how media spread their messages to the entire population of agents during the whole period of time. As previously exposed, mass media information during these three days period suffered from strong polarization, moving from one position to the opposite one. At the beginning, media information strongly pointed to ETA's authority, but later declared Al Qaeda's authority. Thus, the message transmitted via a certain mass media channel C will change during the simulation and we model it by scheduling the different message polarization values for each channel ($m_C(t)$).

3.5. Calibration

Automated calibration is a data-rich and computationally intensive process that uses an error measure to compare real-world data to model-data, and then tunes the parameters of the model in order to identify a set of parameters which best match the data [52, 61]. Automated calibration attempts to discover the best parameters of the model that fit the model to the data. Therefore, automated calibration requires an error measure and an optimization method for modifying the parameters in a systematic way in order to minimize the error measure. After calibration is finished, the resulting parameter values need to be reviewed and validated.

With regards to the optimization method, since the parameters in computational models exhibit non-linear interactions, the best option is to use a non-linear optimization algorithm that can search across a large span of the model parameters space [47, 52, 66]. Metaheuristics are a family of approximate non-linear optimization techniques that provide *acceptable* solutions in a reasonable time for solving hard and complex problems in science and engineering [68].

The optimization process will asses the quality of the model by running the computational model and comparing its outputs to the elections data. By doing this, we adjust the parameters of the model to match the model's output with the 11-M reality. The selected parameters for calibration are those related with the parameters that control WOM and mass media diffusion, which are both the most uncertain and the hardest to estimate with the available information. For each defined parameter, we also use a parameter range to set its possible values during optimization. The set of parameters to be calibrated contains 44 elements, being all of them real values. Briefly, they are the following parameters:

- WOM diffusion parameters. For each defined segment S, we will calibrate its initial talking probability ($p_S(t)$), influence change (Δ_S) and influence decay ($d\Delta_S$), i.e., 9 parameters.

- Mass media parameters. For each defined mass media channel C, we calibrate its maximum influence (Δ_C^{max}), influence change (Δ'_C), influence decay ($d\Delta'_C$), buzz increment (τ_C) and buzz decay ($d\tau_C$); i.e., 35 parameters.

The selected automated calibration algorithm is a memetic algorithm [48] composed of a steady state genetic algorithm [2, 25] and a local search procedure. The calibration algorithm initializes its population generating feasible solutions. Thus, every generated individual is a feasible configuration of models' parameters. The creation of the population of the memetic algorithm is randomly performed by selecting a value for each gene between a range of values. The fitness function designed for guiding the optimization algorithm measures the distance between the election results and the simulated output. Fitness values are computed using a symmetric mean absolute percentage error (SMAPE), defined in Equation 9, which facilitates to increase the sensitivity for miss-voting agents. In this equation, A_t represents actual election results and F_t represent the simulated election results. The sensitivity of the calibration is 0.0248% as the mapping ratio between the number of agents and the size of the real population was 1,212.77.

$$SMAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|F_t - A_t|}{(|A_t| + |F_t|)/2}. \tag{9}$$

The algorithm follows a steady state approach with 100 population size and 10.000 evaluations as stopping criteria. It also uses tournament selection, a BLX-α crossover [29], and an uniform random mutation mechanism. The crossover operator generates two offspring by crossing two parents with a probability $p_c = 1,0$. It truncates the selected values over the gene set of feasible values after selecting it from interval $[c_{min} - I\alpha, c_{max} + I\alpha]$, $c_{max} = max(v_i^1, v_i^2)$, $c_{min} = min(v_i^1, v_i^2)$ and $I = c_{max} - c_{min}$. v_i^1, v_i^2 are the feasible decoded values from the genes of the parents. α defines the level of exploration for the operator. If α is set to 0, BLX-α is equivalent to the flat crossover. Regarding mutation operator, we choose to assign mutation probability $p_m = 0,1$ for each gene. When the probability check passes, a new value is generated for that gene using an uniform distribution and the specific range of values for that gene.

4. Validation of the model with elections' data

4.1. Data description

The data we use to set fixed parameter and calibrate the model is obtained from the following sources:

- Final election results to match the model's output [51].
- The voting intention before the 11-M attacks has been extracted from the 2555 study of the Spanish Centre for Sociological Research. This study [10] is a National survey that was executed between January 24 and February 15, 2004, with a sample size of 24,109 interviews. From that interview, we focus on the question regarding who they were willing to vote on the next national elections to be held in March 14th. We use these data to model initial resilience values for the agents' population at step $t = 0$.
- Three different sources have been used for setting the polarization message value of $m_C(t)$ for the whole simulation:
  - We took the television information from the informational volume 19-20 from *Quaderns del Consell de l'Audiovisual de Catalunya* [15].
  - The audio from the radio was gathered from Cadena Ser, since it had the highest audience rate at that moment and received special attention during this period.
  - The information about the chosen newspapers (ABC, El Mundo, and El País) was directly collected from them and can be accessed from the on-line database [3].
- There has been a thorough analysis of the broadcast informational content from 07:30 pm on March 11, until 12:00 am on 14-M, television (Antena 3, Tele 5, and Spanish National Television), radio (Cadena SER), and newspapers (ABC, El Mundo, and El País). The share of the three television channels analyzed exceeded 75% [42]. As said, the most important media were selected for the study according to *Encuesta General de Medios* [1]. For instance, we included Cadena Ser, a radio channel which had an important role for this political event [53]. The three analysed newspapers were the most read ones during this period, reaching 32% of newspaper readers.

[3] This database can be accessed from `http://ugr.mynews.es/hu/`

4.2. Fitting model results

In order to test the model behaviour we show the fitting results using historical voting data as well as different validation scenarios. These validation scenarios are built by removing some components of the ABM simulation model to observe its behaviour with respect to the historical trends. First, we calibrate the ABM with all the designed components. Due to the lack of empirical data regarding the social network of voters before the elections, we choose to set the parameter m for the social network generation to the standard value $m = 2$, resulting in a network density of 0.00033. The value of the parameter m is studied later at Section 5.1, where its influence in the diffusion mechanisms is studied using different values for creating different network configurations. The full list of calibrated parameters with the final values are shown in Table 3, and the values of the parameters manually calibrated taking into account the existing data are shown in Table 4.

Additionally, three validation scenarios are presented: one without mass media, another without WOM diffusion, and the last one with neither mass media nor WOM diffusion. These additional scenarios are variations over the complete model. This way we create new models where certain modules are disabled. By setting these scenarios, the designed model can be validated as a whole, facing its global behaviour with respect to removing any of its main modules.

The scenario without mass media, called "No Media", disables media effect on the agents. Thus, mass media channels will neither influence agents neither increase buzz activity. In this scenario, only WOM diffusion is performed by agents through their social network. The scenario without WOM diffusion, referred as "No Diffusion", does not include agent diffusion through the social network. In this scenario, only mass media channels influence the agent population, but there is not any buzz effect generated from its impact. Last scenario, called "No Influence", does not include neither media effect on the agents nor diffusion through the social network. In this scenario, the agents' population is not exposed to any kind of influence, thus the elections results are those forecasted by pre-election opinion surveys.

The comparison between the whole model and the three additional validation scenarios is shown in Table 5. These results are obtained averaging the results of 30 Monte-Carlo iterations of the ABM simulations. Percentage values represent SMAPE accuracy using final election results, scaling both simulated and real number of votes to the top third. This computation facilitates the understanding of the fitting results in a 0% to 100% scale.

Parameter	Value	Parameter	Value	Parameter	Value
WOM parameters				Cadena Ser	
$p_{PSOE}(0)$	0.04	Δ_{PP}	0.06	Δ_{max}	2.5
$p_{Abtention}(0)$	0.01	$d\Delta_{PSOE}$	0.27	Δ	0.94
$p_{PP}(0)$	0.02	$d\Delta_{Abtention}$	0.1	$d\Delta$	0.18
Δ_{PSOE}	0.19	$d\Delta_{PP}$	0.38	τ	1.6
$\Delta_{Abtention}$	0.11			$d\tau$	0.13
El Pais		El Mundo		ABC	
Δ_{max}	1.5	Δ_{max}	1.6	Δ_{max}	2.1
Δ	0.79	Δ	0.78	Δ	0.81
$d\Delta$	0.16	$d\Delta$	0.21	$d\Delta$	0.25
τ	1.4	τ	0.9	τ	1.4
$d\tau$	0.19	$d\tau$	0.11	$d\tau$	0.19
TVE		Antena 3		Telecinco	
Δ_{max}	4.2	Δ_{max}	3.6	Δ_{max}	3.8
Δ	0.79	Δ	0.87	Δ	0.94
$d\Delta$	0.18	$d\Delta$	0.14	$d\Delta$	0.15
τ	1.8	τ	2.4	τ	0.7
$d\tau$	0.2	$d\tau$	0.18	$d\tau$	0.15

Table 3: List of ABM parameters to be calibrated by the automatic method.

In this Table 5, votes are displayed by party in the first block of the table and computed error is shown in the second block. Fitting results show very good values for the complete model, displaying an accuracy value higher than 99%. This implies that the model is correctly simulating elections turnout. Observed errors also suggest that only WOM or mass media information in isolation are not enough to match final votes, and there is a need to use both modules in the model. In fact, the latter two scenarios have higher PP voters than the final results. That suggests that, when used in isolation, defined dynamics are not modelling voting turnout reality in an accurate way after the attacks. This corroborates our initial assumption that both WOM and mass media information had significant influence on the 14-M election results.

Parameter	Value	Parameter	Value	Parameter	Value
El Pais		El Mundo		ABC	
r_{min} r_{max}	0.396 0.584	r_{min} r_{max}	0.396 0.584	r_{min} r_{max}	0.396 0.584
TVE		Antena 3		Telecinco	
r_{min} r_{max}	0.46 0.995	r_{min} r_{max}	0.46 0.995	r_{min} r_{max}	0.46 0.995
Cadenar Ser		Social network parameter			
r_{min} r_{max}	0.543 0.611	m	2		

Table 4: List of parameters manually calibrated by the modeller using existing data.

	Real Data	**Models**			
Party	**Election Results**	**Complete**	**No Media**	**No Diffusion**	**No Influence**
Votes					
PSOE	11,026,163	11,020,144	10,329,618	10,259,170	9,941,145
PP	9,763,144	9,766,804	10,577,439	10,948,887	11,403,078
ABS	8,449,355	8,451,711	8,331,602	8,030,602	7,894,438
% Total votes					
PSOE	37.71%	37.69%	35.33%	35.09%	34.00%
PP	33.39%	33.40%	36.18%	37.45%	39.00%
ABS	28.90%	28.91%	28.50%	27.47%	27.00%
Global fitting		**99.13%**	**84.49%**	**77.06%**	**68.39%**

Table 5: Fitting values of the calibrated model and three additional model variation scenarios.

4.3. Analysis of the model's outputs

Once we have compared the model results with the real elections data, we will further evaluate the model behaviour to ensure its validity. In the first place, resilience evolution $\mu(t)$ of the population is displayed in Figure 1. Let us remind the reader resilience represents the amount of external influence needed to change its vote. If an agent gets its resilience to a value between 3.3 and 6.7, it will abstain, even if it belongs to PP or PSOE voters segments. In order to compute these values, we average resilience for all the agents of each segment. This evolution is stepped by hours, starting on March 11th at 08:00 am and finishing on March 14th at 08:00 am.

This chart presents stronger changes when news are on television. It corresponds to the prime time for news in Spain by that time. Additionally, the first simulation steps show more intense changes in the perceptions of the agents than the subsequent ones. The main responsible for this behaviour is the polarization of the message transmitted by mass media. This message, that was

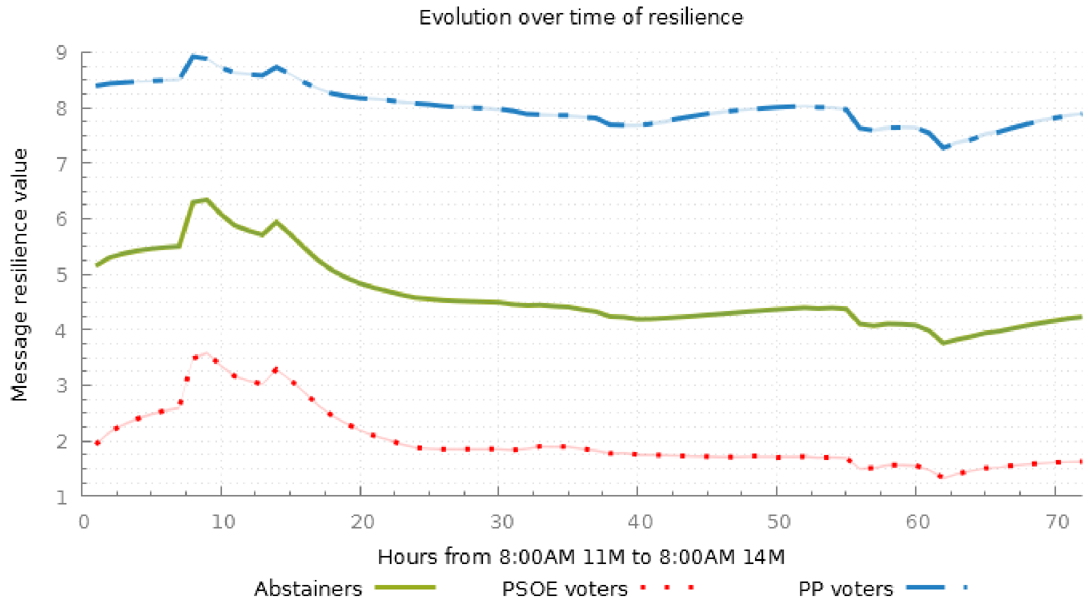

Figure 1: Averaged message resilience (μ) over time for all the agents.

uniform at the start of the simulation, turns mixed at the end, resulting in a smoother curve. Because mass media exposure is not biased by segment, its impact over resilience evolution is similar (averaged resilience curves present similar shape in the three segments). This evolution is slightly softer for the PP voters segment at the beginning of the simulation. This effect can also be observed at the end of the simulation, but for the opposite direction. PSOE voters change their perception smoother than before.

We also present the evolution of the resilience standard deviation in Figure 2 to show variance between segments. This chart shows Monte-Carlo variances as blurred areas. These curves are consistent with perception evolution, because deviation is increased when mass media exposure gets stronger. Again, when resilience gets closer to border values, agents saturate their value, reducing dispersion.

This situation can be observed during the first 20 hours for PP voters and during the final steps for PSOE voters and abstainers. In contrast, variance increases when agents are influenced by the framings. This can be observed between hours 0 and 20 for PSOE voters and abstainers, or from hour 30 for PP voters. In the former case, mass media channels are transmitting a message about the implication of ETA in the attacks. This increments resilience value, increasing PSOE and abstainers variance, and reducing PP variance. In the latter case, the message spread by mass

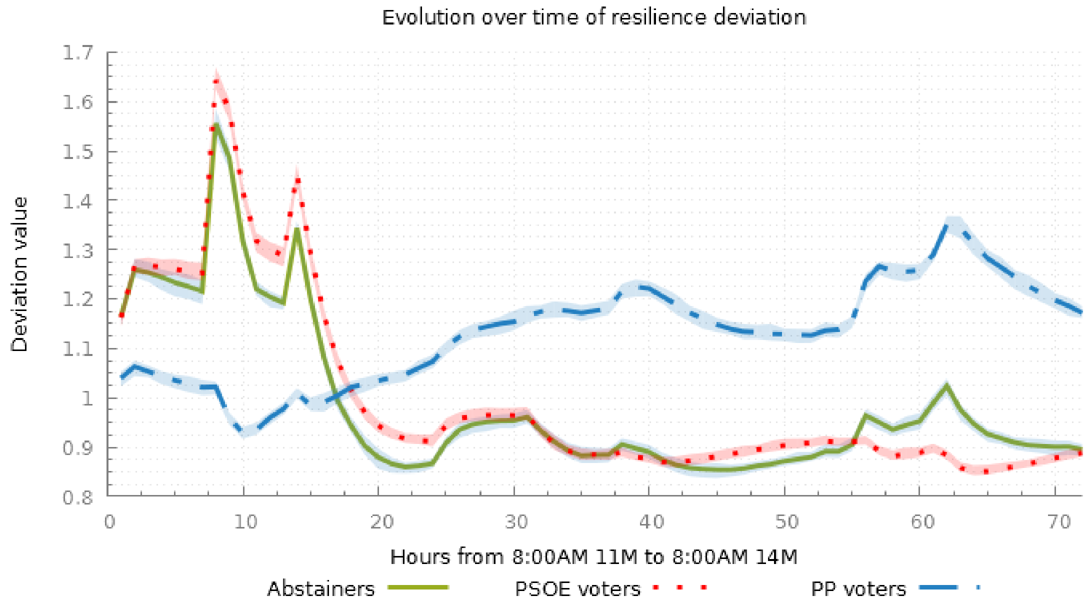

Figure 2: Averaged deviation of resilience (μ) for all the agents.

media gets mixed, transmitting both framings. Eventually the messages from the framing blaming Al Qaeda outnumber the messages blaming ETA, which reduces PSOE dispersion and increases the dispersion of the other segments.

Figure 3 shows the evolution of votes by day, plotting a track of the voters intention every 24 hours. Votes track is done at 08:00 am every day. Tracks for the first day, i.e., 11M, do not have variance as they are collected when the simulation starts. Boxplots of Figure 3 shows how PP decreases their votes in favour of PSOE and abstention along the simulation. This behaviour is consistent with the surveys closer to the elections whose results suggested that the gap between PSOE and PP was reduced as the elections approached [36].

Finally, WOM behaviour is validated using two metrics: number of conversations and sentiment evolution. Figure 4 shows the percentage of conversations by step (also called WOM volume). In these values we can see that the highest buzz is achieved at prime time, just like in the resilience evolution chat. As happened in the deviation chart, blurred areas represent Monte-Carlo variations. This increment in the number of conversation is consistent, as the highest audience level is achieved during these time slots. Figure 5 shows the sentiment of the conversations during the simulation. A positive polarization value (above 0) means that average conversations are increasing resilience value (moving towards 10). Otherwise, polarization suggests that resilience values decrease (moving

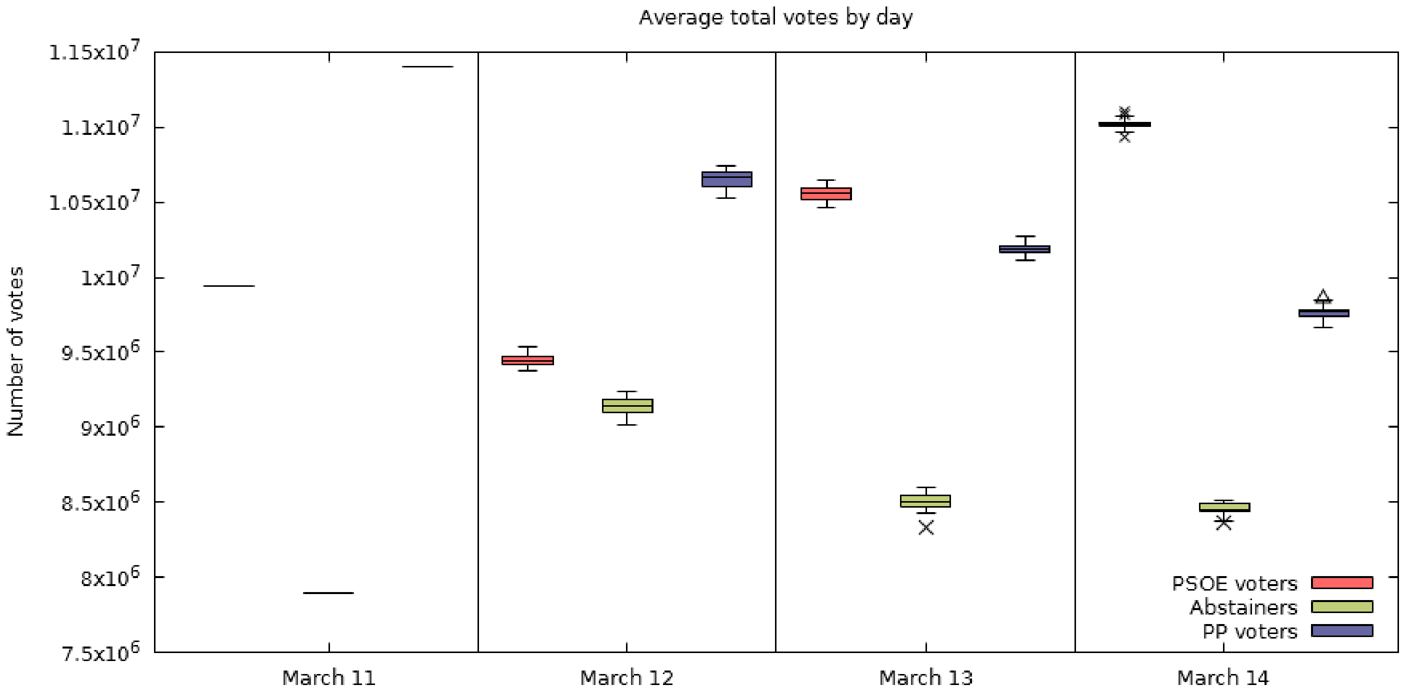

Figure 3: Average votes by political option for every day between the attacks and the elections.

towards 0). The resulting chart looks similar to the ones displaying resilience evolution. These trends show how media influence is affecting conversations in the simulation. Because the sentiment at the end of the simulation is negative (μ), it means that there are more conversations regarding Al Qaeda's involvement in the attacks than conversations regarding ETA's authority. Because Al Qaeda's framing is defended by the PSOE party, this situation increases PSOE votes.

5. Deployment of what-if political scenarios

We will analyse in this section different what-if scenarios using the previously validated model. Our study is mainly focused on two scenarios. First, Section 5.1 analyses WOM influence in the voters' segments. Then, changes on mass media messages are analysed in Section 5.2.

5.1. WOM influence in the voters segments

This scenario is focused on the information spread through the social network. In order to study WOM influence, we perform a sensitivity analysis on the parameters which control the diffusion mechanisms. Those parameters are the talking probability ($p(t)$) and the parameter to generate the scale free social network (m) which affects the social network density and the hubs degree

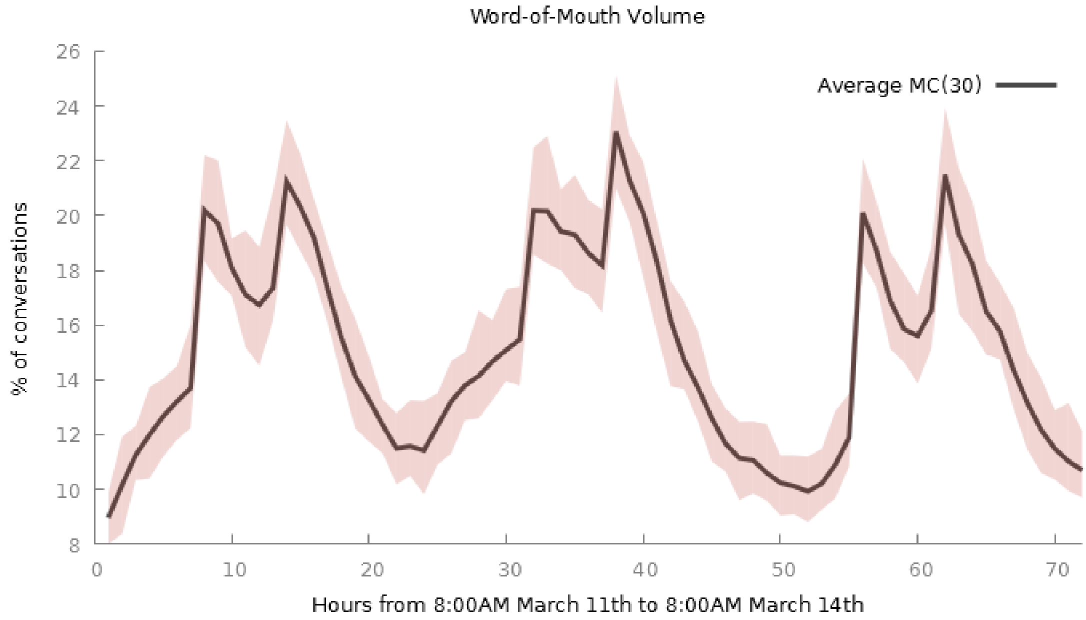

Figure 4: Percentage of conversations made by agents within their social network.

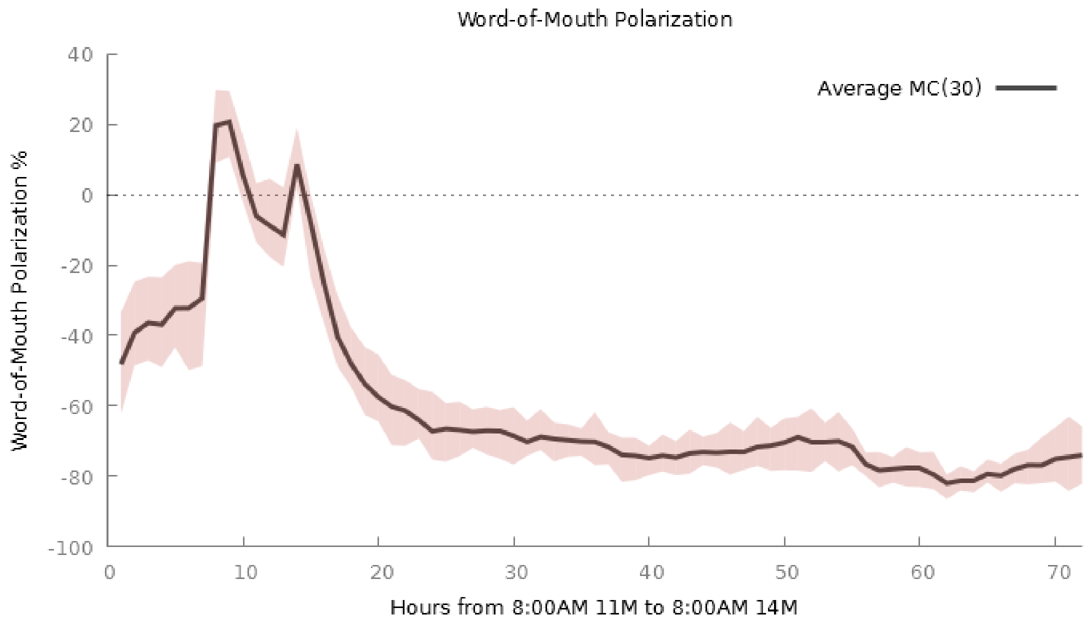

Figure 5: Net variation of the polarization of the message transmitted by the WOM process.

(increasing it), and consequently the speed of the diffusion process. The sensitivity analysis is performed following the one-factor-at-a-time methodology [9] which modifies each parameter in an isolated way by keeping the rest of parameter values fixed.

This experimentation is performed at both segment and global level. First, we will modify m and talking probability for each segment, studying the resulting behaviour of the overall simulation. Later, we will do the same by modifying the model's parameters to all the segments at the same time. In these charts, shown in Figure 6, model's response changes from talking probability are displayed as *lines* and connectivity variations are displayed as *points*.

Chart (a) from Figure 6 shows the simulation results after altering talking probability and m for PSOE voters. These results, where only parameters for the PSOE segment are modified, present strong changes on both PSOE and PP voters, keeping abstentions stable. It is also remarkable to notice that variations on talking probability produce linear variations for PSOE votes, keeping almost the same trend when increasing and decreasing. Variations over connectivity value m behave slightly softer.

Chart (b) of Figure 6 shows the simulation results after altering talking probability and m for PP voters. These results show a different behaviour from the other studied segments. When increasing/amplifying the values of the diffusion parameters, the three political options tend to obtain similar votes, reducing the difference between them. In addition, when decreasing the values of the diffusion parameters, the difference between the three political options rises. However, variations on talking probability and m (i.e., density of the social network) present low differences. In the case of the talking probability parameter, a tilt of its value produces a transition between PSOE votes and abstainers, with a slower transition between abstainers and PP votes. In the case of the parameter m, increasing its value only increases the number of abstentions, while PSOE and PP votes decay. For instance, when m is greater than 5, PP party obtains similar support to the abstention option. This behaviour is also interesting because when the social network has a lower density (lower m value), both PP and PSOE obtain a higher number of votes. Instead of being favoured by more connections, these political options are penalized in a more connected WOM scenario.

We show in chart (c) of Figure 6 the simulation results by modifying the talking probability and m for abstainers. These results show a more stable behaviour for every segment. However, we

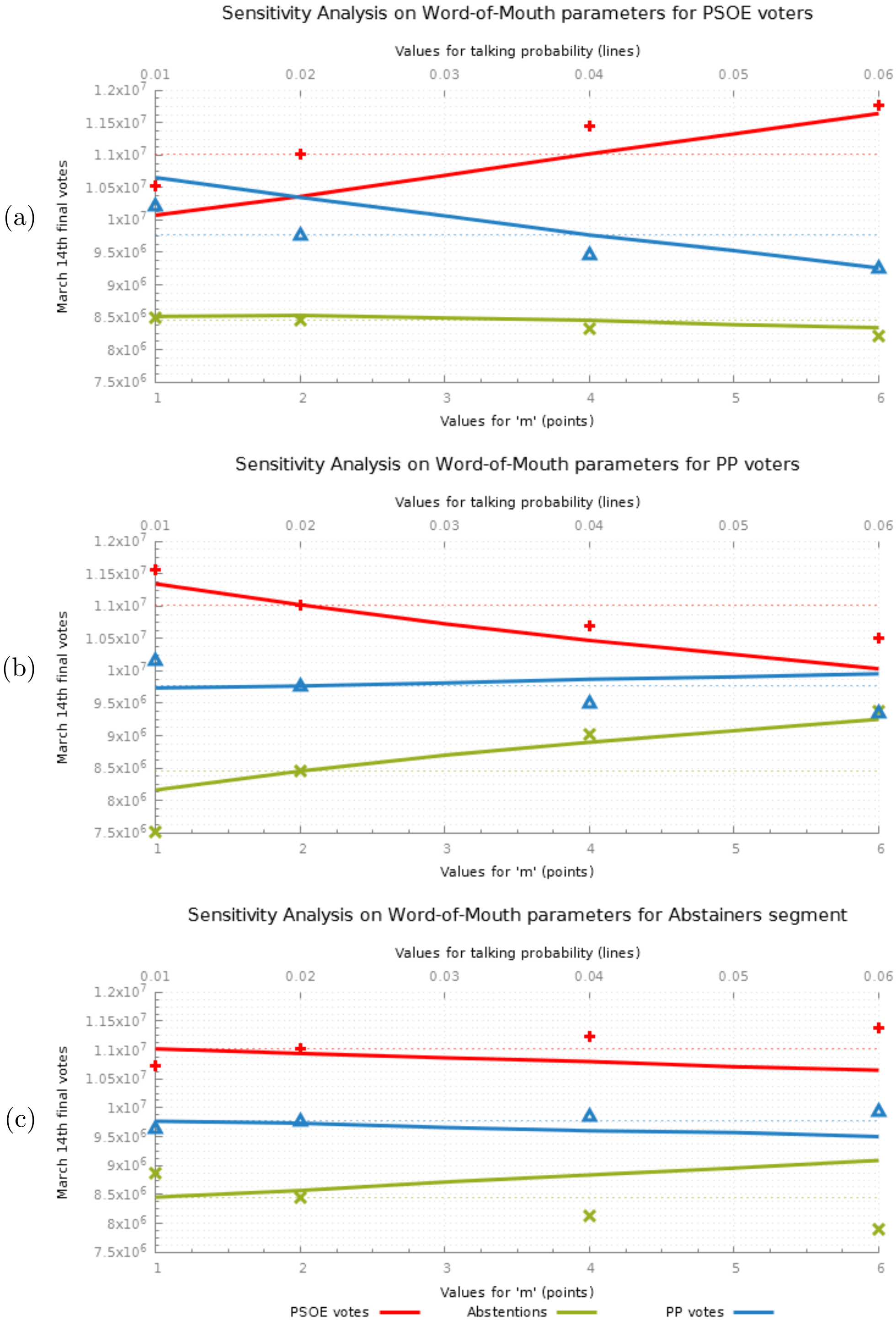

Figure 6: Sensitivity analysis of talking probability and scale free m parameter on the segments' voters.

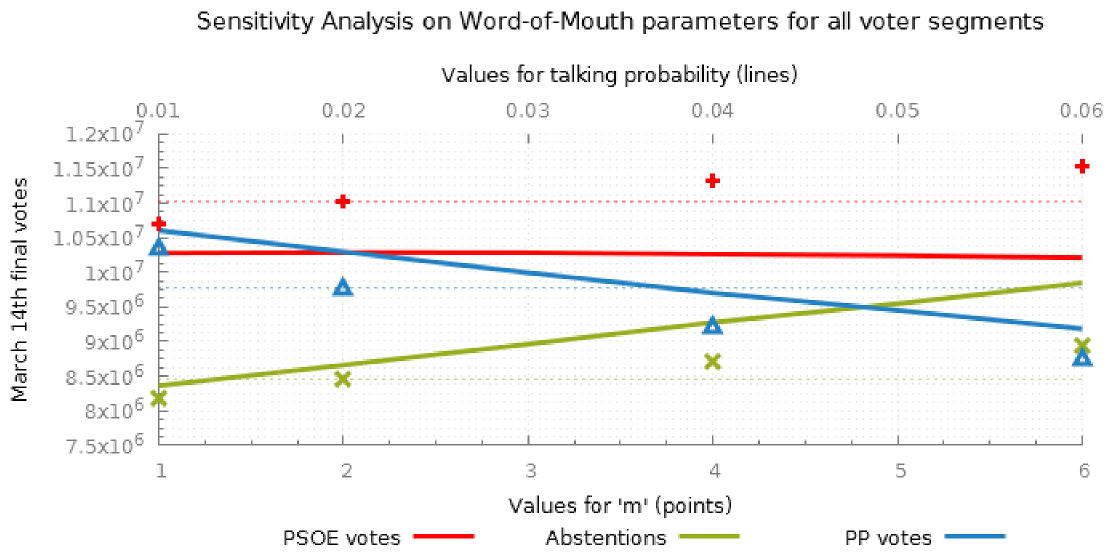

Figure 7: Sensitivity analysis of talking probability and scale free m parameter on every segment.

can notice that changes over talking probability slightly favour different diffusing messages than changes on m. On the one hand, increasing talking probability also increases abstentions, reducing votes for the other political alternatives in a similar way. On the other hand, increasing m reduces abstentions, specially increasing PSOE votes.

Figure 7 shows the simulation results after changing talking probability and m for all the segments of the agent population at the same time. The study, previously applied to segments, is now performed to all the agents of the population at once. The results of this study are in line with those gathered when the variations were only applied to PSOE voters, but keeping some differences. Focusing on the PP response, its evolution follows a similar trend with respect to PSOE. Variations on the social network density (m parameter) produce a fall on PP votes while increasing abstentions and PSOE votes. While PSOE increment is similar to the one showed when altering PSOE values only, abstentions and PP variations are similar to the ones found when only altering PP values.

To sum up with this analysis, we can observe that the model's behaviour and its reality fitting are sensible to changes on the WOM parameters. The three existing segments have different voting results when their parameters are modified. In the case of PSOE voters, it seems to have an important participation in the diffusion process because the number of votes for PSOE party changes rapidly when modifying their diffusion parameters but keeps stable when altering the values of the other segments. With respect to abstainers, modifying its parameters has a relatively small effect on the other segments that could suggest a secondary role in the diffusion process. Finally, in the case of PP voters, these results show a fall in the number of PP votes for most scenarios when diffusion increases. This fact suggests that PP segment cannot influence the other segments even when PP's diffusion parameters have a high value. This could also suggest that message polarization penalizes extreme values when having a highly connected network.

5.2. Changes on the message of mass media channels

These scenarios are focused on the polarization of the message transmitted by mass media channels. As previously explained, message polarization from March 11th to March 14th gradually changed from pointing ETA to pointing Al Qaeda as long as new insights were progressively known from the developed investigation. Using the original polarization as a reference, we perform a sensitivity analysis over the message transmitted by each mass media channel.

Instead of modifying a single parameter, a group of parameters are changed for each scenario [9]. For each mass media category (press, radio, and television), their message polarization is modified towards ETA and towards Al Qaeda. These polarization variations are applied to all the mass media channels and applied to every information transmitted by those mass media channels contained in each category. This experimental design allows us to study polarization influence into simulation results.

The results of this study are shown by political option in Figures 8, 9, and 10. For each option, its evolution of votes is displayed regarding the amount of modified polarization. This way, results obtained with the original message are placed at 0 in the x-axis. This polarization is gradually increased from 0 to 1 and from 0 to -1. Both extremes represent full message content towards Al Qaeda (-1) or ETA (1).

Figure 8 shows the results of the polarization variations for the number of abstentions. Resulting abstentions are displayed by mass media categories: press, radio, television, and all of them together. These results clearly highlight television as the most influencing media channel. Additionally, the joint effect of all the mass media channels seems interesting because its maximum result surpasses individual categories.

This chart is also interesting because its non-symmetric shape. If message polarization is strongly moved towards Al Qaeda (-1 variation), simulation results collapse quickly. There is almost

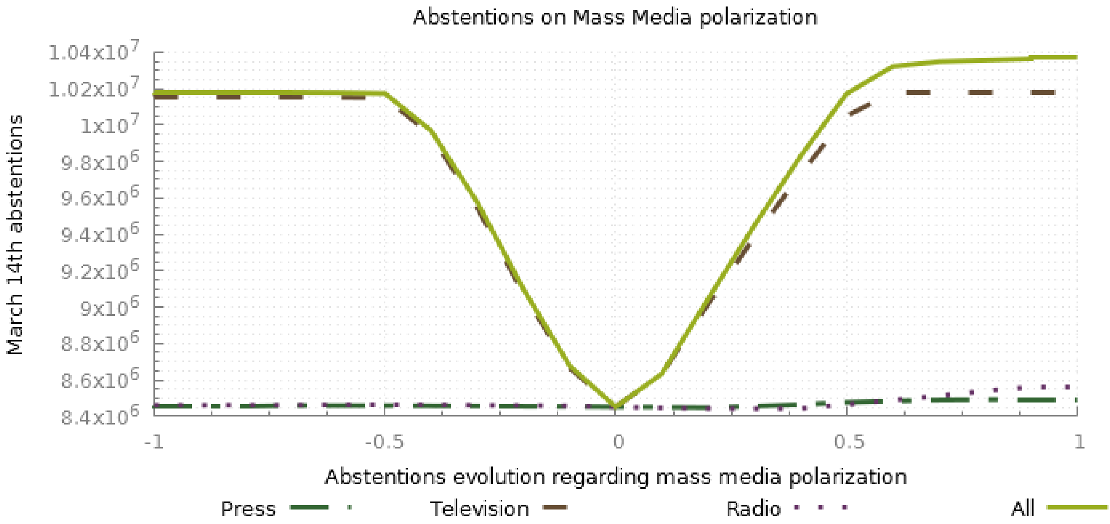

Figure 8: Abstentions resulting from variations on the polarization of mass media messages.

no change in the number of abstentions when message is pushed beyond -0.5. On the opposite, when message is pushed towards ETA (+1 variation), the model's results saturate around 0.9. In the case of television, its results saturate before the rest of the media categories. These results suggest that the number of abstentions is not really influenced by messages towards Al Qaeda, and it is more sensible to messages towards ETA.

Figure 9 shows the results of the polarization variations for the PP voting results. Again in this case, television polarization achieves the highest change. Moreover, this chart also shows a non-symmetric shape, where all categories saturate around -0.5. Most mass media channels seem to have its maximum number of votes close to the maximum influence towards ETA (+1 variation).

We can also notice the amount of votes achieved by increasing the polarization towards ETA is relatively small when compared with the amount of votes lost when decreasing the polarization towards Al Qaeda (-1 variation). This effect may be caused by the original message of some channels like television channels which changed their message during the three days period moving from one framing to the other. Results then show that the number of PP votes is more influenced by polarization towards Al Qaeda than polarization towards ETA.

Finally, Figure 10 shows the results of the polarization variations for PSOE. As happened with previous political options, television is the channel that causes the highest change. In addition, the polarization variations toward ETA involve significant fluctuations. These results also suggest

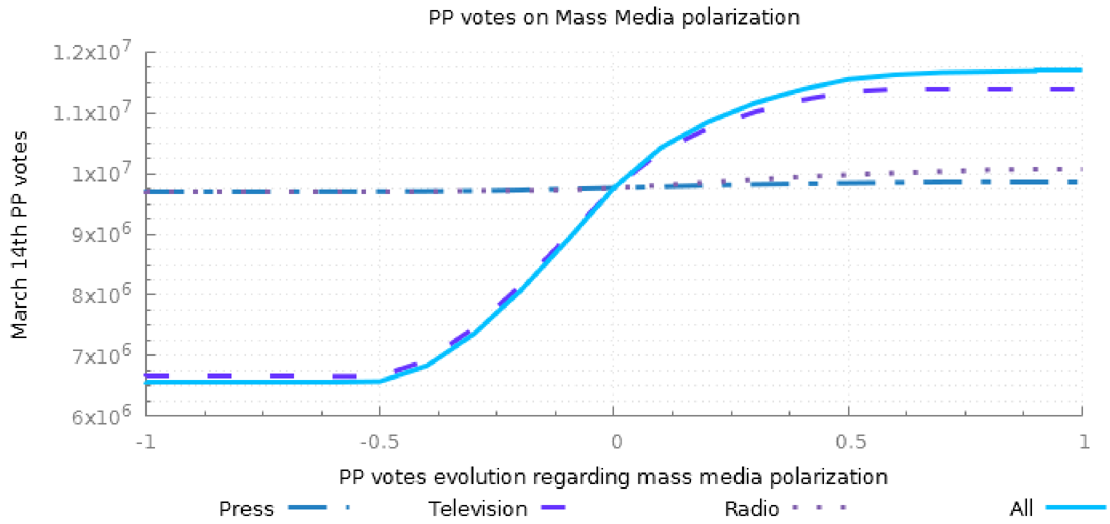

Figure 9: PP votes resulting from variations on the polarization of mass media messages.

a resilient behaviour regarding polarization when pushed to Al Qaeda. In fact, the amount of increased votes is small compared to the amount of votes lost when polarization is pushed towards ETA. This decrement is the highest one of all the political options.

6. Final remarks

In this paper we have presented a study on the framing effect during the 2004 Spanish elections following the 11-M attacks. We have designed and implemented an ABM simulation to replicate electors' behaviour into agents connected by a social network and influenced by the most significant Spanish mass media messages. Our model recreated the environmental conditions from 11-M to 14-M from the mass media information point of view. We calibrated and validated the model by achieving a model fitting of 99.13% and employing different validation cases of the modules of the ABM framework.

The results of the experiments suggest that the framing effect could actually influence the election results by both mobilizing abstainers and deactivating voters from PP party. Other important conclusions of the model's results in our what-if scenarios are:

- Diffusion mechanisms have an important role during this period because a significant swap of votes arises when modifying the density of the social network and dynamics of the WOM process (i.e., m parameter of the social network and talking probability). This conclusion

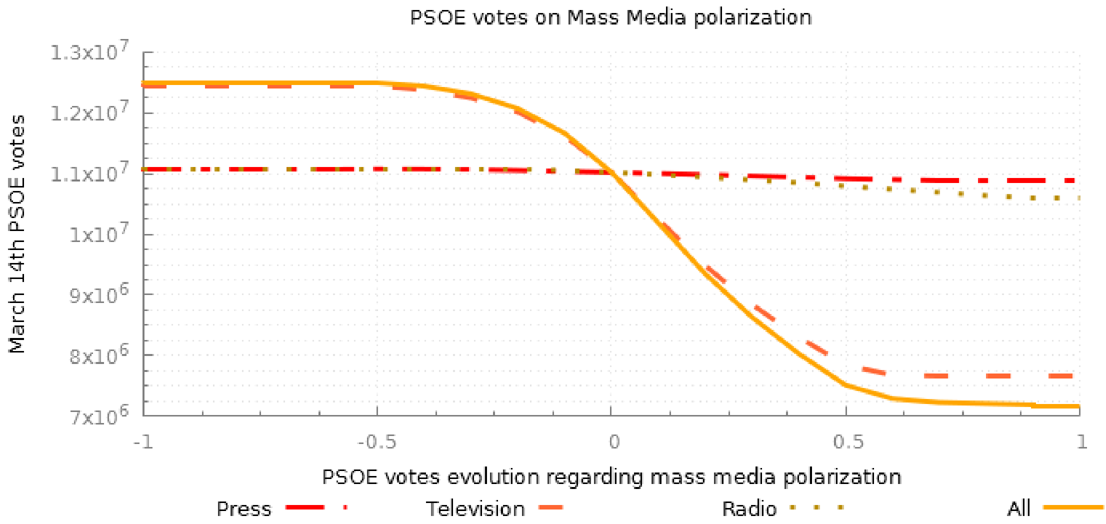

Figure 10: PSOE votes resulting from variations on the polarization of mass media messages.

seems consistent with other works regarding diffusion of political beliefs [62, 67, 74]. Moreover, the experiments we present in this paper show that the social network have a key role when exposing an agent population to highly polarized messages.

- The swap of votes through diffusion does not seem to follow linear increments. Instead, some political options achieve votes when increasing its diffusion rates, but others maintain or barely increase its number of votes. PSOE is the most influenced political option by WOM diffusion.

- In the same way, the diffusion of polarized messages using mass media communications does not produce linear changes of votes. On the one hand, the number of votes for every party reaches its maximum rather quickly when the transmitted message is polarized towards Al Qaeda by not responding to strategies with a stronger message. On the other hand, the number of votes changes smoothly when polarizing the message towards ETA. This behaviour suggests a higher sensitivity of the model when messages are polarized towards Al Qaeda.

- Aggregating mass media channels seems to achieve stronger effects than the addition of those channels applied individually. Even if television is clearly distinguished as the most influencing channel, radio and press increase the aggregated media effect remarkably. This also corroborates that not only television channels had an important role in the diffusion of the 11-M events but the presence of other media channels were decisive for the elections turnout.

Future work will be focused on studying alternative strategies for modelling more complex social network diffusion and voting behaviours for the agents of the political scenario. These more advanced voting mechanics could involve combining the framing effect with the individual political positioning of the individual voters [58]. The latter combination may be useful for extracting additional insights regarding this special elections.

Acknowledgments

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7. References

[1] Asociación para la Investigación de Medios de Comunicación (AIMC), . AIMC February to November 2004. General Recap. EMG. http://www.aimc.es/-Datos-EGM-Resumen-General-.html. Accessed: 2016-03-28.

[2] Back, T., Fogel, D.B., Michalewicz, Z., 1997. Handbook of evolutionary computation. IOP Publishing Ltd., Bristol (UK).

[3] Bali, V.A., 2007. Terror and elections: Lessons from Spain. Electoral Studies 26, 669–687.

[4] Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509–512.

[5] Bass, F.M., 1969. A new product growth for model consumer durables. Management Science 15, 215–227.

[6] Berelson, B., 1954. Voting; a study of opinion formation in a presidential campaign. University of Chicago Press, Chicago.

[7] Bonabeau, E., 2002. Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences 99, 7280–7287.

[8] Borah, P., 2011. Conceptual issues in framing theory: A systematic examination of a decade's literature. Journal of communication 61, 246–263.

[9] ten Broeke, G., van Voorn, G., Ligtenberg, A., 2016. Which sensitivity analysis method should I use for my agent-based model? Journal of Artificial Societies & Social Simulation 19, 5.

[10] Centro de Investigaciones Sociológicas, 2004. Estudio 2555. CIS Data bank.

[11] Chari, R., 2004. The 2004 Spanish election: terrorism as a catalyst for change? West European Politics 27, 954–963.

[12] Chong, D., Druckman, J.N., 2007a. Framing public opinion in competitive democracies. American Political Science Review 101, 637–655.

[13] Chong, D., Druckman, J.N., 2007b. Framing theory. Annual Review of Political Science 10, 103–126.

[14] Martínez i Coma, F., 2008. ¿ Por qué importan las campañas electorales? (in Spanish). Centro de Investigaciones Sociológicas.

[15] Consell de l'Audiovisual de Catalunya, 2004. 11-14M: la construcció televisiva. Quaderns del CAC , 89–204.

[16] Druckman, J.N., Peterson, E., Slothuus, R., 2013. How elite partisan polarization affects public opinion formation. American Political Science Review 107, 57–79.

[17] Duzevik, D., Anev, A., Funes, P., Gaudiano, P., 2007. The effects of word-of-mouth: An agent-based simulation of interpersonal influence in social networks. Word of Mouth Research Symposium .

[18] Edling, C., Rydgren, J., Sandell, R., 2016. Terrorism, belief formation, and residential integration population dynamics in the aftermath of the 2004 Madrid terror bombings. American Behavioral Scientist , in press. DOI:0002764216643127.

[19] Entman, R.M., 1993. Framing: Toward clarification of a fractured paradigm. Journal of communication 43, 51–58.
[20] Epstein, J.M., 2006. Generative social science: Studies in agent-based computational modeling. Princeton University Press.
[21] Fearon, J.D., 1991. Counterfactuals and hypothesis testing in political science. World politics 43, 169–195.
[22] Fieldhouse, E., Lessard-Phillips, L., Edmonds, B., Crossley, N., 2005. The complexity of turnout: An agent-based simulation of turnout cascades. Electoral Studies 24.
[23] Gao, L., Durnota, B., Ding, Y., Dai, H., 2012. An agent-based simulation system for evaluating gridding urban management strategies. Knowledge-Based Systems 26, 174–184.
[24] Gilbert, N., Troitzsch, K., 2005. Simulation for the social scientist. McGraw-Hill Education (UK).
[25] Goldberg, D.E., Holland, J.H., 1988. Genetic algorithms and machine learning. Machine Learning 3, 95–99.
[26] González-Avella, J.C., Cosenza, M.G., Klemm, K., Eguíluz, V.M., San Miguel, M., 2007. Information feedback and mass media effects in cultural dynamics. Journal of Artificial Societies and Social Simulation 10, 9.
[27] Hänggli, R., Kriesi, H., 2010. Political framing strategies and their impact on media framing in a Swiss direct-democratic campaign. Political Communication 27, 141–157.
[28] He, T., Huang, C., Blum, B.M., Stankovic, J.A., Abdelzaher, T., 2003. Range-free localization schemes for large scale sensor networks, in: Proceedings of the 9th annual international conference on Mobile computing and networking, ACM. pp. 81–95.
[29] Herrera, F., Lozano, M., Verdegay, J.L., 1998. Tackling real-coded genetic algorithms: Operators and tools for behavioural analysis. Artificial Intelligence Review 12, 265–319.
[30] Higgins, E.T., 1996. Knowledge activation: Accessibility, applicability, and salience. Guilford Publications.
[31] Holbrook, T., 1996. Do campaigns matter?. volume 1. SAGE publications.
[32] Janssen, M.A., Ostrom, E., 2006. Empirically based, agent-based models. Ecology and Society 11, 37.
[33] Kollman, K., Miller, J.H., Page, S.E., 1992. Adaptive parties in spatial elections. American Political Science Review 86, 929–937.
[34] Kollman, K., Miller, J.H., Page, S.E., 1998. Political parties and electoral landscapes. British Journal of Political Science 28, 139–158.
[35] Kuhn, J.R., Courtney, J.F., Morris, B., Tatara, E.R., 2010. Agent-based analysis and simulation of the consumer airline market share for frontier airlines. Knowledge-Based Systems 23, 875–882.
[36] Lago, I., Montero, J.R., 2006. The 2004 election in Spain: Terrorism, accountability, and voting. Institut de Ciències Polítiques i Socials, Barcelona.
[37] Lago Peñas, I., Montero, J.R., Torcal, M., 2005. Del 11-M al 14-M: Los mecanismos del cambio electoral (in Spanish). Claves de la razón práctica 149, 36–45.
[38] Laver, M., 2005. Policy and the dynamics of political competition. American Political Science Review 99, 263–281.
[39] Lazarsfeld, P.F., Berelson, B., Gaudet, H., 1965. The people's choice; how the voter makes up his mind in a presidential campaign. Columbia Univ. Press, New York.
[40] Libai, B., Muller, E., Peres, R., 2013. Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion. Journal of Marketing Research 50, 161–176.
[41] Liu, F.C., 2007. Constrained opinion leader influence in an electoral campaign season: Revisiting the two-step flow theory with multi-agent simulation. Advances in Complex Systems 10, 233–250.
[42] López García, G., 2004. El 11-M y el consumo de medios de comunicación (in Spanish). Sala de Prensa 71.
[43] Macal, C.M., North, M.J., 2005. Tutorial on agent-based modeling and simulation, in: Proceedings of the 37th conference on Winter simulation, ACM. pp. 2–15.
[44] Martínez-Miranda, J., Pavón, J., 2012. Modeling the influence of trust on work team performance. Simulation 88, 408–436.
[45] Mckeown, G., Sheehy, N., 2006. Mass media and polarisation processes in the bounded confidence model of opinion dynamics. Journal of Artificial Societies and Social Simulation 9, 11–42.
[46] Miceli, M.S., 2005. Morality politics vs. identity politics: Framing processes and competition among christian right and gay social movement organizations, in: Sociological Forum, Springer. pp. 589–612.
[47] Miller, J.H., 1998. Active nonlinear tests (ANTs) of complex simulation models. Management Science 44, 820–830.
[48] Moscato, P., 1989. On evolution, search, optimization, genetic algorithms and martial arts: towards memetic algorithms. Technical Report 826. Caltech Concurrent Computation Program. Pasadena, USA.
[49] Muis, J., 2010. Simulating political stability and change in the netherlands (1998-2002): an agent-based model of party competition with media effects empirically tested. Journal of Artificial Societies and Social Simulation

13, 4.
[50] Newman, M., Barabási, A.L., Watts, D.J., 2006. The structure and dynamics of networks. Princeton University Press.
[51] Observatorio Político Autonómico, 2004. Resultados encuesta postelectoral elecciones generales 14 de marzo de 2004 (in spanish).
[52] Oliva, R., 2003. Model calibration as a testing strategy for system dynamics models. European Journal of Operational Research 151, 552–568.
[53] Olmeda, J.A., 2005. Miedo o engaño: el encuadramiento de los atentados terroristas del 11-M en Madrid y la rendición de cuentas electoral (in Spanish). Boletín Elcano , 47.
[54] Pastor-Satorras, R., Vespignani, A., 2001. Epidemic spreading in scale-free networks. Physical review letters 86, 3200.
[55] Pennings, P., Keman, H., 2003. The Dutch parliamentary elections in 2002 and 2003: The rise and decline of the Fortuyn movement. Acta politica 38, 51–68.
[56] Rand, W., Rust, R.T., 2011. Agent-based modeling in marketing: Guidelines for rigor. International Journal of Research in Marketing 28, 181–193.
[57] i Rigo, E.O., 2005. Aznar's political failure or punishment for supporting the Iraq war? Hypotheses about the causes of the 2004 Spanish election results. American Behavioral Scientist 49, 610–615.
[58] Riker, W.H., Ordeshook, P.C., 1968. A theory of the calculus of voting. American political science review 62, 25–42.
[59] Rogers, E.M., 2010. Diffusion of innovations. Simon and Schuster.
[60] Roozmand, O., Ghasem-Aghaee, N., Hofstede, G.J., Nematbakhsh, M.A., Baraani, A., Verwaart, T., 2011. Agent-based modeling of consumer decision making process based on power distance and personality. Knowledge-Based Systems 24, 1075–1095.
[61] Sargent, R.G., 2005. Verification and validation of simulation models, in: Proceedings of the 37th conference on Winter simulation, pp. 130–143.
[62] Singh, V.K., Basak, S., Modanwal, N., 2011. Agent based modeling of individual voting preferences with social influence, in: Trends in Computer Science, Engineering and Information Technology. Springer, pp. 542–552.
[63] Slothuus, R., de Vreese, C.H., 2010. Political parties, motivated reasoning, and issue framing effects. The Journal of Politics 72, 630–645.
[64] Sorauf, F.F.J., Beck, P.A., 1988. Party politics in America. Scott Foresman.
[65] Stapel, D.A., Koomen, W., Zeelenberg, M., 1998. The impact of accuracy motivation on interpretation, comparison, and correction processes: Accuracy × knowledge accessibility effects. Journal of Personality and Social Psychology 74, 878–893.
[66] Stonedahl, F., Rand, W., 2014. When does simulated data match real data? Comparing model calibration functions using genetic algorithms, in: Advances in Computational Social Science. Springer, Japan. volume 11 of *Agent-Based Social Systems*, pp. 297–313.
[67] Sudo, Y., Kato, S., Mutoh, A., 2013. The impact of exchanging opinions in political decision-making on voting by using multi-agent simulation, in: PRIMA 2013: Principles and Practice of Multi-Agent Systems. Springer, pp. 340–354.
[68] Talbi, E.G., 2009. Metaheuristics: from design to implementation. John Wiley & Sons.
[69] Torcal, M., Rico, G., 2004. The 2004 Spanish General Election: In the Shadow of Al Qaeda. South European Society and Politics 9, 107–121.
[70] Wang, W.X., Wang, B.H., Yin, C.Y., Xie, Y.B., Zhou, T., 2006. Traffic dynamics based on local routing protocol on a scale-free network. Physical Review E 73, 026111.
[71] Watts, D.J., Dodds, P.S., 2007. Influentials, networks, and public opinion formation. Journal of consumer research 34, 441–458.
[72] Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of 'small-world' networks. Nature 393, 440–442.
[73] Wilensky, U., Rand, W., 2015. Introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo. MIT Press.
[74] Zakaria, N., 2014. Modeling political belief and its propagation, with malaysia as a driving context. Open Journal of Political Science 4, 58–75.