Can Biases in Perceived Attitudes Explain Anti-Conformism?

Guillaume Deffuant, Omid Roozmand, Sylvie Huet, Kamilla Khamzina, Armelle Nugier, and Serge Guimond

***Abstract*—In two studies about farming practices, the respondents who are particularly favorable to organic farming tend to have a higher intention to convert their farm to organic when they perceive other farmers as not very favorable to this practice. This intention can be considered as anticonformist, as it is in opposition to the general view of others. This article hypothesizes that this phenomenon can be explained by some biases on the perceptions of attitudes. It proposes an agent-based model which computes an intention based on the theory of reasoned action (TRA) and assumes some biases in the perception of others' attitudes according to the social judgment theory. It investigates the conditions on the model parameter values for which the simulations reproduce the features observed in the studies. The results show that perceptual biases are a possible explanation of anticonformist intentions.**

***Index Terms*—Anticonformism, organic farming, perceptual bias, social judgment theory, theory of reasoned action (TRA).**

I. Introduction

CLIMATE change, energy, and food requirements of a growing world population could lead societies to operate deep social changes. In general, social changes start from activist minorities which challenge the established norm and adopt anticonformist behaviors. It is therefore important to better understand the emergence and the development of such behaviors. In this article, we focus on a specific understanding of anticonformism, in which intention to act appears reinforced by the perception of others' opinion as against this action. The purpose of this article is to investigate the hypothesis that such anticonformist intentions can be generated by biases in the perception of attitudes.

We first show the existence of anticonformist intentions in two already published studies [1], [2] (the datasets are publicly available [3]) that build on previous research about perceived group norms (PGNs) and pluralistic ignorance [4], [5]. The first study is about Eastern European farmers' intention to convert to organic farming ($N = 269$) and the second about French agricultural college students intention to become an organic farmer ($N = 220$). Indeed, both datasets share the following features.

1) Among participants whose personal attitude about organic farming is higher than the average, the intention to become an organic farmer is negatively correlated with the PGN. The PGN is the perceived average opinion of the other farmers. In other words, when participants are in favor of organic farming more than the average, the less they think others are in favor of organic farming, the higher is their intention to become an organic farmer. Therefore, their intention tends to be reinforced when it is against the PGN, which can be seen as an anticonformist intention.
2) Among participants whose personal attitude about organic farming is lower than the average, on the contrary, the intention is positively correlated with the PGN. In this case, the intention is rather conformist, which is more usual.

We hypothesize that some biases on the perception of attitudes could explain these observations. More precisely, we assume that, because of the bias, agents tend to perceive far attitudes further than they are and close attitudes closer than they are. Therefore, the perception of the attitudes of close others, which have a strong influence on the intention, is modified differently by the bias than the perception of the attitude of others in general, which determines the PGN. In some cases, this difference could lead to a negative correlation between intention and PGN.

To investigate this hypothesis, we adopt a modeling approach.[1] We design computational models of the perceptual biases, the intention and the PGN. We simulate a population of virtual agents holding these perceptual biases impacting their intention and PGN. We determine for which parameter values the model displays correlations that are similar to the ones measured on the case studies. Such agent-based approaches are now rather common [6]–[8].

The model of biases on the perception of attitudes is inspired by the theory of social judgment [9]. This theory assumes, in the light of robust observations, that people tend to perceive (or judge) close attitudes closer than they are, and far attitudes further than they are. Moreover, the limit

[1]The R program of the model can be found at https://www.comses.net/codebases/d46c8a84-f54a-400e-8599-f2228ceaa677/releases/1.0.0/

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This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

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between close and far depends on the extremity of the attitude (Theory of Social Judgment, p. 139). People with extreme attitudes tend to perceive most of other attitudes as further while people with moderate attitudes perceive most other attitudes as closer (these observations are also often related to ego-involvement [9]–[11]).

The model of intention is based on the theory of reasoned action (TRA) [12], assuming that the intention is mainly determined by the attitude of the considered agents and the perceived attitudes of their important others, the subjective norm (SN). Here, it is important to stress the difference between the SN, which is based on the perceived attitudes of close or important others, from the PGN, which is based on the perceived attitudes of other group members, beyond close others (e.g., other farmers). We choose the TRA rather than the more complete theory of planned behavior (TPB) [13] because in our case studies, the anticonformist intentions are observed only at early stages of decision processes. Indeed, the first case study only includes answers from farmers who have not envisaged the conversion to organic farming yet and in the second case study, the participants are students in an agricultural college who are not yet farmers. Therefore, in both case studies, the perceived behavioral control, added to the TRA in the classical TPB [13], is likely to play a negligible role in the determination of the intention. Indeed the perceived behavioral control measures the perceived easiness to perform the action in practice hence it supposes to envisage with some details the practical implications of the action. People who are at the beginning of the process of changing their behavior are not likely to have in mind the many practicalities that could hamper the behavioral change. The situations that we consider can be seen as the first step toward a potential major change [14] or a transformational adaptation [15]–[17]. The TPB received considerable empirical support in a large variety of studies, some of which related to organic farming adoption [18]–[21].

We study the agent-based model through specific simulation experiments. Our method involves two main steps as follows.

1) We first adopt an approximate Bayesian computing (ABC) approach [22]–[25]. We uniformly draw a large number of parameter values in chosen intervals and we select the ones that lead to simulations reproducing the features of the data. The results show that only the parameter settings corresponding to a significant perceptual bias are selected. The average of the distribution of attitudes should be significantly positive to get anticonformist intentions among agents of high attitudes and it should be significantly negative to get anticonformist intentions among agents of low attitudes.
2) We then select the parameter settings leading to regression coefficients that are close to the ones obtained in each case study. Then for each case study, we analyze how the perceptual biases modify differently the SN and PGN for individuals with more or less extreme attitudes and we relate this to the emergence of the anticonformist intention.

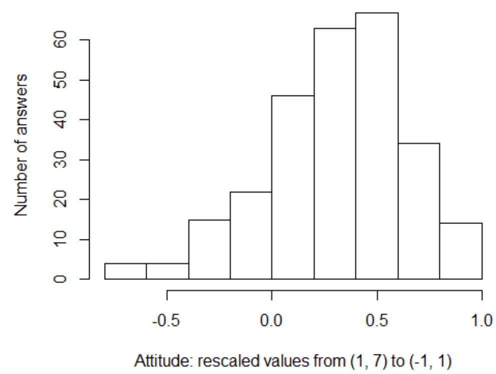


Fig. 1. Distribution of attitudes for case study 1: eastern European farmers.

This article is organized as follows. Section II presents the two case studies showing anticonformist intentions. Section III describes the model. Section IV explains the method adopted for studying the model. Section V reports the results. Section VI discusses these results and draws some future perspectives.

II. Two Case Studies Showing Anticonformist Intentions

A. Case Study 1: Intention to Convert to Organic Farming Among Eastern European Farmers

We only summarize the survey since all the details are already published [1] and focus on the relation between intention and PGN. The survey took place in 2007 in Estonia, Hungary, Latvia, Lithuania, Poland, and Slovenia with, respectively, 187, 182, 170, 193, 192, and 157 farmer interviews. The questionnaires were designed in a large part in the framework of the TPB [13], thus they provide the necessary information for applying the TRA, as the TPB extends the TRA. They include questions about personal attitude toward organic farming, SN, perceived behavioral control and behavioral intention toward organic farming. They include additional questions about the PGN.

The questions use seven-point Likert scale where one indicates *extremely unlikely* or *disagree* or *bad* and seven indicates *extremely likely* or *agree* or *good*. We computed the personal attitude of a farmer as the average of the four questions about different aspects of the personal attitude and the attitude of important others (SN) as the average of the six questions about different aspects of the SN. The perceived attitude of other farmers in general (PGN) was asked in a single question as well as the intention to convert to organic farming. We restrict our study to the farmers who are at the very beginning of the decision process and have not concretely envisaged to convert to organic farming yet. The size of the sample is 269.

Fig. 1 shows the distribution of the personal attitudes translated into a range between -1 and $+1$. It is noted that the average of the personal attitudes is significantly positive ($\bar{a}_1 = 0.336$) and the standard deviation is $\sigma_1 = 0.332$. The shape of the attitude distribution appears reasonably close to the one of a Gaussian.

TABLE I

REGRESSION COEFFICIENTS OF INTENTION BY PGN FOR FARMERS WITH LOW (c_l^1 TOP LINE) AND HIGH ATTITUDES (c_h^1 BOTTOM LINE), FOR CASE STUDY 1

	Estimate	Std. Error	t value	Pr(>|t|)
Low attitudes	$c_l^1 = 0.3243$	0.1406	2.307	0.0232 *
High attitudes	$c_h^1 = -0.28801$	0.09776	-2.946	0.00381 **

Table I shows the coefficients of linear regressions of the intention to convert to organic farming as a function of the PGN for low and high attitude farmers. The low attitudes a are such that $a < \bar{a}_1 - 0.2\sigma_1$ and the high attitudes are such that $a > \bar{a}_1 + 0.2\sigma_1$. The regression coefficient for the low attitudes is positive (0.32), while the regression coefficient for high attitudes is negative (-0.29). These results suggest that the intention to convert increases with the PGN for farmers with a low attitude while it decreases in the contrary for farmers with a high attitude. The latter case is more significant and probably more surprising. It indicates indeed a tendency which is antagonist to the one of the group, hence an anticonformist intention.

B. Case Study 2: Intention to Become an Organic Farmer Among French Agricultural College Students

Like previously, we only summarize the study, focusing on the relation between intentions and PGN. The sample includes 220 participants from agricultural colleges in Rhône-Alpes, France, surveyed in 2017. The study assesses personal attitudes toward organic farming using an 11 items scale with three reversed items (e.g., "Organic farming practices are desirable for the region's future"). It assesses PGN about organic farming by transforming the personal attitudes questions into measures of the perception of others' attitudes by adding the phrases such as "most farmers believe that..." or "my friends believe that..." at the beginning of each item in place of "I believe." The items starting with "Most farmers" contribute to the PGN while the ones starting with "My friends" contribute to the SN. Fig. 2 represents the histogram of attitudes on a scale between -1 and $+1$ (translated from the 5-item Likert scale). The distribution of attitudes has a mean of $\bar{a}_2 = 0.278$ and standard deviation of $\sigma_2 = 0.372$. On average, the attitudes about organic farming are positive, like in the previous survey.

Table II shows the regression of the intention as a function of PGN for low and high attitudes. The low attitudes are attitudes a such that $a < \bar{a}_2 - 0.2\sigma_2$ and the high attitudes are such that $a > \bar{a}_2 + 0.2\sigma_2$. For high attitudes, the regression coefficient is negative (-0.71) while it is positive for low attitudes (0.40). The coefficient for the high attitudes is more significant than the positive coefficient for low attitudes (see Table II).

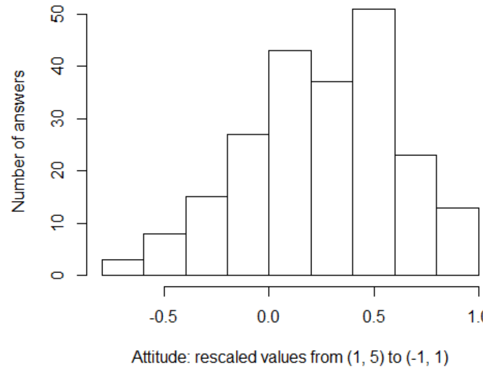


Fig. 2. Distribution of attitudes for case study 2: agricultural college students.

TABLE II

REGRESSION COEFFICIENTS OF INTENTION BY PGN FOR FARMERS WITH LOW (c_l^2 TOP LINE) AND HIGH ATTITUDES (c_h^2 BOTTOM LINE), FOR CASE STUDY 2

	Estimate	Std. Error	t value	Pr(>|t|)
Low attitudes	$c_l^2 = 0.4002$	0.1633	2.451	0.0161 *
High attitudes	$c_h^2 = -0.7100$	0.1510	-4.702	8.82e-06 ***

III. MODEL

The model includes a population of virtual agents, each holding an attitude, drawn from a Gaussian distribution. Each agent is connected to a set of other agents, representing her acquaintances in the group at large. A subset of these acquaintances represents her close or important others. The SN and PGN are average of the perceived attitudes of, respectively, the close others and the whole set of acquaintances. The intention is the average of the attitude and the SN, following the TRA. The perception of the attitudes is biased in accordance with the social judgment theory.

A. Attitudes and Biased Perception of Attitudes

The model includes n virtual agents and each agent i is characterized by an attitude a_i. In practice, we draw the attitudes a_i at random from a Gaussian distribution of mean $0 < \delta < 0.5$ and of standard deviation σ. The scale of attitudes is continuous on the segment $[-1, 1]$ (attitude -1 being very against while 1 is very favorable to the issue). Only the values drawn from the Gaussian distribution that fall within the segment of attitudes $[-1, 1]$ are kept. Therefore, the average attitude $\bar{a}$ of the population is generally a bit different from δ.

The attitude a_j of agent j perceived by agent i is denoted $p^i(a_j)$ and it depends on threshold τ_i, as follows.

1) If the difference between a_i and a_j is lower than τ_i then the perception $p^i(a_j)$ of a_j by agent i is closer to a_i than a_j is.
2) If the difference between a_i and a_j is on the contrary greater than τ_i, then the perception $p^i(a_j)$ of a_j by agent i is further from a_i than a_j is.

The threshold τ_i is large when the attitude a_i is close to 0 and small when the attitude is close to the extremes (-1 or $+1$). It is assumed to increase linearly for a_i between -1 and 0 and to decrease linearly for a_i between 0 and 1. More

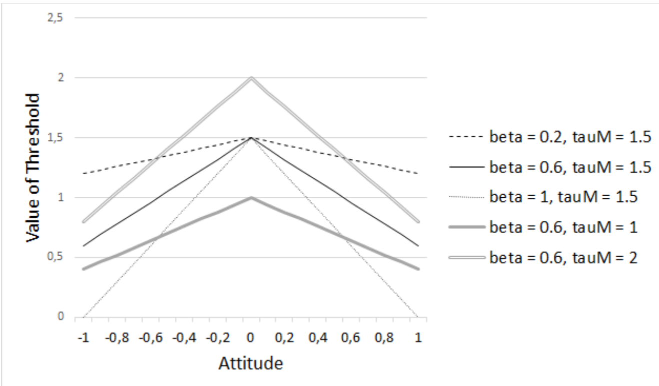


Fig. 3. Examples of function determining the perception threshold τ_i for parameters β equal 0.2, 0.6, and 1, and τ_M equal 1, 1.5, and 2.

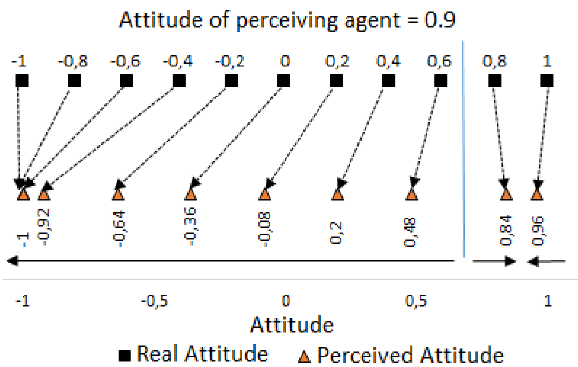


Fig. 4. Example of how real attitude is perceived: attitude of perceiving agent = 0.9.

precisely (β and τ_M being parameters of the model), we have

$$\begin{cases} \tau_i = \tau_M(1+\beta a_i), & \text{if } a_i < 0 \\ \tau_i = \tau_M(1-\beta a_i), & \text{if } a_i \geq 0. \end{cases} \tag{1}$$

Fig. 3 represents how parameters β and τ_M affect the value of the threshold τ_i based on the given attitude. Parameter β defines the slope of the segments. Parameter τ_M, the maximum threshold which corresponds to the neutral attitude 0.

Then, $p^i(a_j)$, the attitude of j perceived by i, is given by (ρ being a parameter)

$$\begin{cases} p^i(a_j) = a_j + \rho(a_i - a_j), & \text{if } \tau_i > |a_i - a_j| \\ p^i(a_j) = a_j - \rho(a_i - a_j), & \text{otherwise.} \end{cases} \tag{2}$$

To be compatible with the extreme ends of attitude's scale, $p^i(a_j)$ is blocked in the range $[-1, 1]$.

Fig. 4 shows how one agent with a high attitude (attitude = 0.9) perceives (red triangles) the attitude of others (black squares). Fig. 5 shows the same for an agent with a neutral attitude (attitude = 0). We observe that the agent of attitude 0.9 perceives most of the others' attitudes further and only a few closer than they are. The agent of attitude 0 perceives all other attitudes closer than they are.

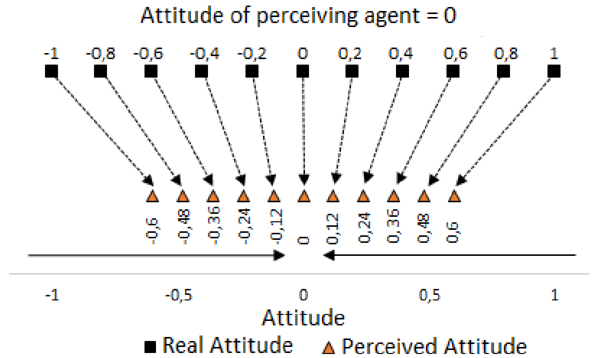


Fig. 5. Example of how real attitude is perceived: attitude of perceiving agent = 0.

B. Subjective Norm, Perceived Group Norm, and Intention

For each agent i we draw uniformly in the population a set R_g^i of agents that represents the acquaintances of agent i in the whole group. The model assumes that these acquaintances give the agent an idea of the average attitude in the group hence it assumes that the average perceived attitude of these acquaintances is the PGN. The size s_g of this set is assumed the same for all the agents. The PGN N_g^i of agent i is modeled as the average of the attitudes in the set R_g^i as perceived by agent i

$$N_g^i = \frac{1}{s_g} \sum_{j \in R_g^i} p^i(a_j). \tag{3}$$

A subset R_c^i of R_g^i represents the important others (close to the considered agent) who are the base for the computation of the SN. We assume that the attitude of the important others is likely to be close to the one of the considered agent, especially if the issue at stake is important. Indeed, important others are likely to have a background which is similar to the one of the considered agent which increases the probability to be aligned on important issues. Therefore, the set R_c^i is built by drawing at random s_c agents j in the set R_g^i with a probability decreasing with the absolute value of the difference between a_i and a_j

$$\mathbb{P}\big(j \in R_c^i\big) = \exp\big(-\alpha|a_i - a_j|^2\big). \tag{4}$$

The SN is finally computed as the average of the attitudes of important others (in set R_c^i) as perceived by agent i. It is denoted by N_c^i

$$N_c^i = \frac{1}{s_c} \sum_{j \in R_c^i} p^i(a_j). \tag{5}$$

The intention I^i of agent i to act (e.g., intention to convert to organic farming) is approximated from the TRA as the sum of the agent's attitude and the SN

$$I_i = \frac{1}{2}\big(a_i + N_c^i\big). \tag{6}$$

Table III breaks down the parameter definitions.

TABLE III
BREAKDOWN OF MODEL PARAMETERS

Symbol	Definition
n	Size of the population
δ	Mean of attitude distribution
σ	Standard deviation of attitude distribution
s_c	Size of the set of close others R_c^i
s_g	Size of the set acquaintances in the whole group R_g^i
α	Coefficient ruling probability to be in close other set R_c^i
β	Slope of the perception threshold function τ_i
τ_M	Maximum perception threshold (for attitude equal 0)
ρ	Coefficient ruling the difference between attitude and perceived attitude

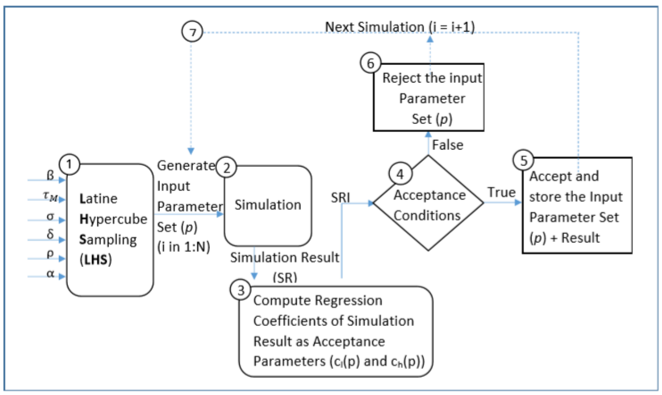


Fig. 6. Schema of ABC for accepting/rejecting parameter settings.

IV. METHOD FOR STUDYING THE MODEL

We use an ABC approach to determine the conditions on the parameter values that are necessary to generate the features observed in the case studies. Then we study in more detail specific models that closely represent each case study.

A. Parameter Selection by Approximate Bayesian Computing

ABC is a class of methods rooted in Bayesian statistics that is used to estimate the distribution of model parameter settings for which the model satisfies some criteria. Starting from a large number of parameter settings, each drawn uniformly in a chosen interval (prior distribution), we select the parameter settings for which the simulation shows the features identified in the case studies and this determines the approximation of the posterior distribution.

We have chosen to investigate parameter settings: $p = (\sigma, \delta, \beta, \tau_M, \rho, \alpha)$ (Table III recalls the meaning of each parameter symbol). The parameters related to the population and agent connections are set to the following values:

$$n = 1000 \text{ (number of agents)} \tag{7}$$

$$s_c = 5 \text{ (size of the set of close others)} \tag{8}$$

$$s_g = 30 \text{ (size of the set of acquaintances in the whole group)}. \tag{9}$$

Fig. 6 describes the items of the ABC process as follows.

1) Generate $N = 25$ million parameter settings p using the Latin hypercube sampling (LHS) package in R.
2) Run the model for parameter setting p.
3) Compute the regression coefficients $c_l(p)$ and $c_h(p)$ of the intentions as a function of the PGN for, respectively, the low and the high attitudes, derived from the simulation run with parameter set p. The low attitudes a are such that $a < \hat{\delta} - 0.2\hat{\sigma}$ and the high attitudes such that $a > \hat{\delta} + 0.2\hat{\sigma}$ ($\hat{\delta}$ and $\hat{\sigma}$ are, respectively, the average and standard deviation of attitudes).
4) Compute the acceptance criteria which are the following conditions on the coefficients of the regressions of the intentions by the PGN:

$$c_l(p) > 0.2 \text{ and } c_h(p) < -0.2. \tag{10}$$

These criteria ensure the conformist intention of agents with low attitude and anticonformist intention for agents with high attitude.
5) If criteria (10) are satisfied, then parameter set p is accepted.
6) Otherwise it is rejected.

The approximate posterior distribution provides the conditions on the parameters for which the features found in the case studies are reproduced by the simulations. It can be visualized by representing the density of selected parameter settings in 2-D spaces defined by pairs of parameters. A posterior distribution extended in the parameter space indicates that the features are likely to be observed in many cases. This would suggest that case study 1 and 2 represent common situations. On the contrary, a very narrow posterior distribution indicates that the features observed in these case studies are exceptional.

B. Selecting a Parameter Setting for Each Case Study

For each case study, we select the parameter setting for which the regression coefficients are the closest to the ones observed on the data. In the 6-D parameter space (σ, δ, β, τ_M, ρ, α), for each case study, we define $10^4 = 10\,000$ 6-D boxes as follows.

1) For each parameter $\omega \in \{\sigma, \delta, \beta, \tau_M, \rho, \alpha\}$, let s_ω be the size of the box on the dimension defined by the parameter. The value of s_ω is the range of the prior distribution of parameter ω divided by 10

$$s_\omega = (\omega_h - \omega_l)/10 \tag{11}$$

where ω_h and ω_l are, respectively, the maximum and minimum of the interval of the prior distribution for parameter ω.
2) The values of δ and σ of points located in the boxes satisfy the following conditions:

$$\delta \in \left[\delta_1 - \frac{s_\delta}{2}, \delta_1 + \frac{s_\delta}{2}\right] \text{ and } \sigma \in \left[\sigma_1 - \frac{s_\sigma}{2}, \sigma_1 + \frac{s_\sigma}{2}\right] \text{ for case study 1} \tag{12}$$

$$\delta \in \left[\delta_2 - \frac{s_\delta}{2}, \delta_2 + \frac{s_\delta}{2}\right] \text{ and } \sigma \in \left[\sigma_2 - \frac{s_\sigma}{2}, \sigma_2 + \frac{s_\sigma}{2}\right] \text{ for case study 2} \tag{13}$$

where δ_1 and δ_2 are the means of the attitudes for case studies 1 and 2 and σ_1 and σ_2 are their standard deviations.

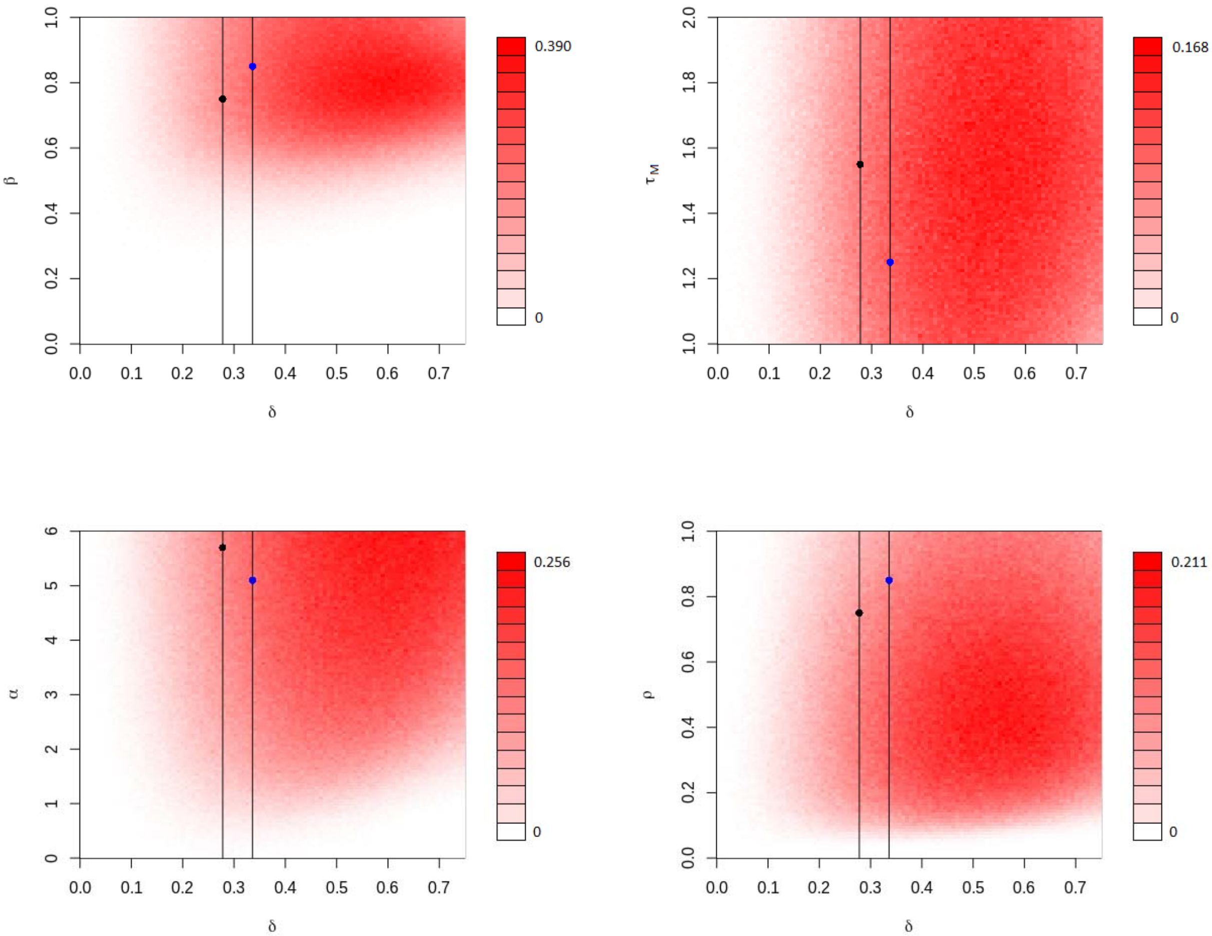


Fig. 7. Results of ABC: proportion of accepted simulations presented on 2-D spaces where δ is on the horizontal axis and β, τ_M, α, or ρ are on the vertical axis.

3) Then each box is defined by four integers $k_\omega \in \{1, \ldots, 10\}$, for $\omega \in \{\beta, \tau_M, \rho, \alpha\}$

$$\omega \in [\omega_l + (k_\omega - 1)s_\omega, \omega_l + k_\omega s_\omega] \quad \text{for } \omega \in \{\beta, \tau_M, \rho, \alpha\} \text{ and } k_\omega \in \{1, \ldots, 10\}. \tag{14}$$

Among the $10^4 = 10\,000$ boxes, we select the ones for which all parameter settings of the box are accepted and the number of parameter settings in the box is higher than 15. Then, among these boxes, we select the one for which the parameter setting at the center of the box provides regression coefficients that are the closest to the ones derived from the corresponding dataset (using the average of absolute value of the difference of coefficients). More precisely, the boxes are obtained by computing

$$\min_{k_\beta, k_{\tau_M}, k_\rho, k_\alpha} \left|c_l(k_\beta, k_{\tau_M} k_\rho, k_\alpha) - c_l^1\right| + \left|c_h(k_\beta, k_{\tau_M}, k_\rho, k_\alpha) - c_h^1\right|, \quad \text{for case study 1} \tag{15}$$

$$\min_{k_\beta, k_{\tau_M}, k_\rho, k_\alpha} \left|c_l(k_\beta, k_{\tau_M} k_\rho, k_\alpha) - c_l^2\right| + \left|c_h(k_\beta, k_{\tau_M}, k_\rho, k_\alpha) - c_h^2\right|, \quad \text{for case study 2} \tag{16}$$

where $c_l(k_\beta, k_{\tau_M}, k_\rho, k_\alpha)$ and $c_h(k_\beta, k_{\tau_M}, k_\rho, k_\alpha)$ are the regression coefficients of intention by PGN for, respectively, the low and high attitudes obtained with the parameters given by the center of the box defined by $(k_\beta, k_{\tau_M}, k_\rho, k_\alpha)$ and averaged on 1000 replicas and c_l^1, c_h^1, c_l^2 and c_h^2 are the regression coefficients computed on case studies (see above).

C. Explaining the Anticonformist Tendency on Simulations for Models Representing the Case Studies

We consider each model corresponding to a case study and we analyze in detail the correlations between the attitudes and the norms to better understand, in this particular case, the role of the perceptual biases in the emergence of anticonformist intentions.

For that, we repeat the computation of the norms with many different draws of the attitudes and sets of connected agents. The large number of repetition reduces the variability of the norms for a given agent and the distributions of the norms look almost like curves. The effect of the perceptual biases on both norms appears then clearly. Moreover, we can easily identify parts of curves which are almost linear and the sign of the corresponding slope. Thus, we can identify more easily how the PGN correlates with the attitudes or with the SN and therefore with the intention. Therefore, we can identify a causal link between the biases and these correlations and

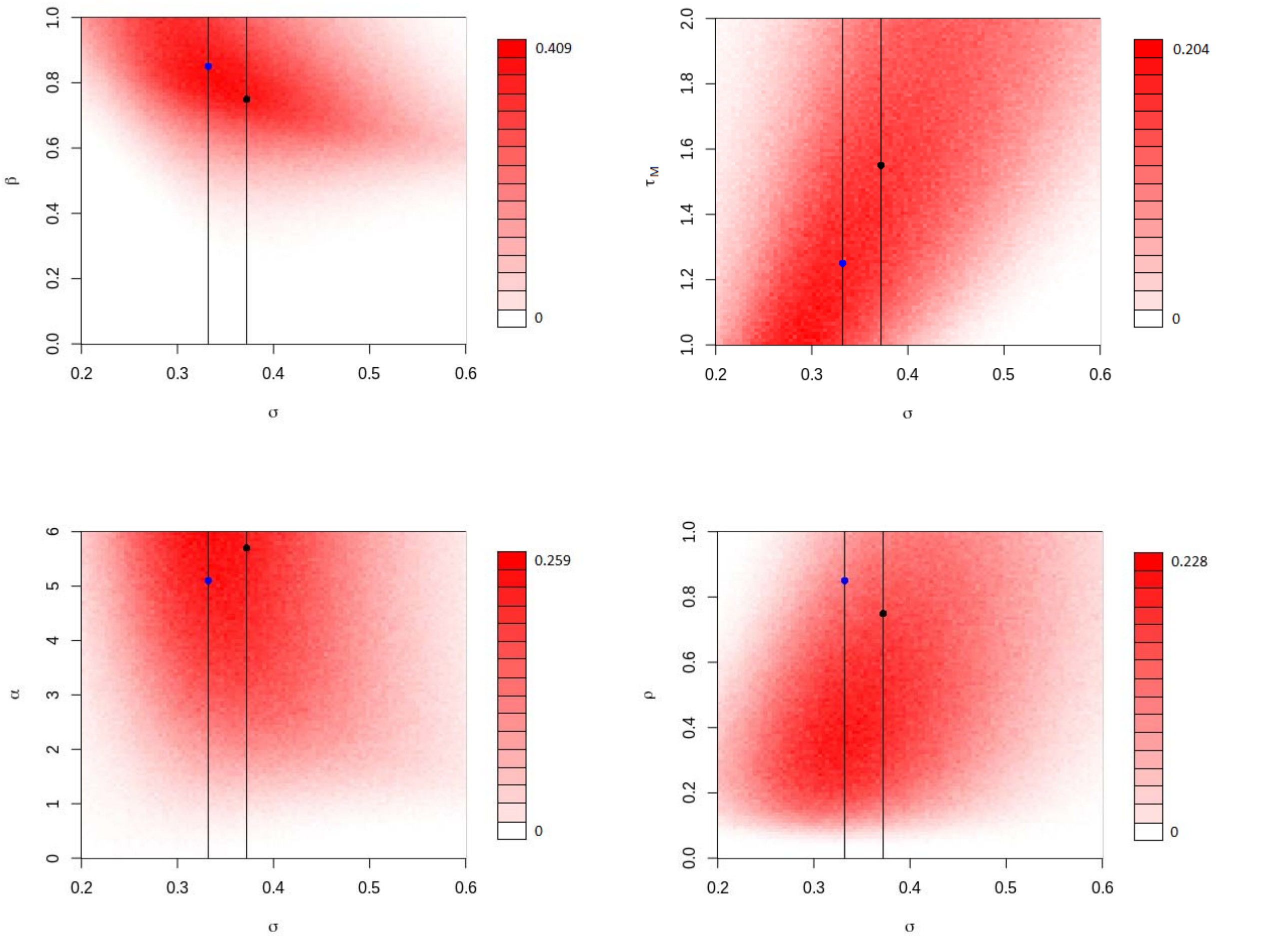


Fig. 8. Results of ABC: proportion of accepted simulations presented on 2-D spaces where σ is on the horizontal axis and β, τ_M, α or ρ are on the vertical axis (see comments in text).

more particularly the correlation defining the anticonformist intention. More precisely, the procedure is the following.

1) Draw a set of 1000 attitudes from the Gaussian distribution, corresponding to 1000 agents. Let (a_i^0), $i \in \{1, 1000\}$ be this set of attitudes.
2) Repeat for j from 1 to 1000 (j is the index of the replica) as follows.
   a) Draw at random from the Gaussian distribution a set of 1000 attitudes: (a_i^j), $i \in \{1, 1000\}$.
   b) For i from 1 to 1000, for attitude (a_i^0) compute the PGN N_g^{ij} and the SN N_c^{ij} from the set of attitudes (a_i^j).
3) Compute the average PGN $\bar{N}_g^i$ and average the SN $\bar{N}_c^i$ over the 1000 populations

$$\bar{N}_g^i = \frac{1}{1000}\sum_{j=1}^{1000} N_g^{ij} \text{ and } \bar{N}_c^i = \frac{1}{1000}\sum_{j=1}^{1000} N_c^{ij}. \tag{17}$$

V. Results

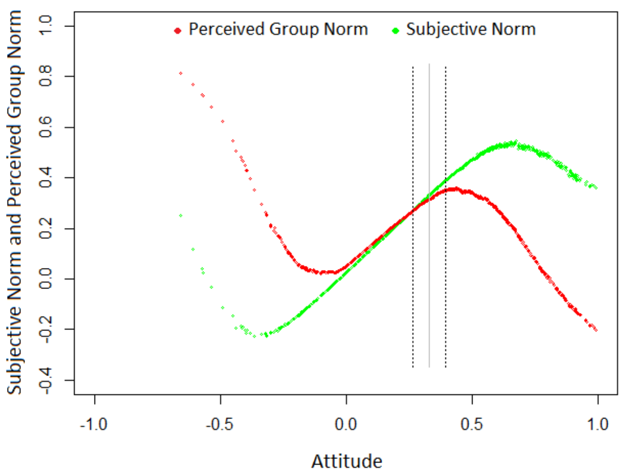
A. Parameters Settings for Which the Simulations Reproduce the Features of the Case Studies

The 2.2 million parameter settings have been selected among the 25 million tested in the ABC process. Figs. 7 and 8 show the distribution of these selected settings projected on the planes defined by eight pairs of parameters which include δ or σ. Each panel of Figs. 7 and 8 shows a 2-D map of 100 $\times$ 100 cells representing the proportion of accepted parameter settings in the cell. The color ranges from white to red as the proportion of accepted parameter sets increases. The white color indicates that no parameter settings located in the cell has been accepted. The red color thus corresponds the highest proportion of accepted simulations among all the cells of the considered 2-D map. The legend indicates this maximum. The lines show the points for which the values of δ or σ are the ones of our case studies, datasets 1 and 2, respectively (dataset 1: $\delta = \delta_1 = 0.336$ and $\sigma = \sigma_1 = 0.332$, and dataset 2: $\delta = \delta_2 = 0.278$ and $\sigma = \sigma_2 = 0.372$). The point on each of these lines is the parameter setting leading to the regression coefficients that are the closest to the ones of the corresponding case study (see details further).

Figs. 7 and 8 suggest the following comments (Table III recalls the definition of each parameter).

1) Parameter δ should be larger than approximately 0.05 and parameter σ should be larger than approximately 0.25. Importantly, as the model is symmetric with respect to $\delta = 0$, for $\delta < -0.25$ and the other conditions satisfied, we would get an anticonformist intention in

Case-study 1



Case-study 2

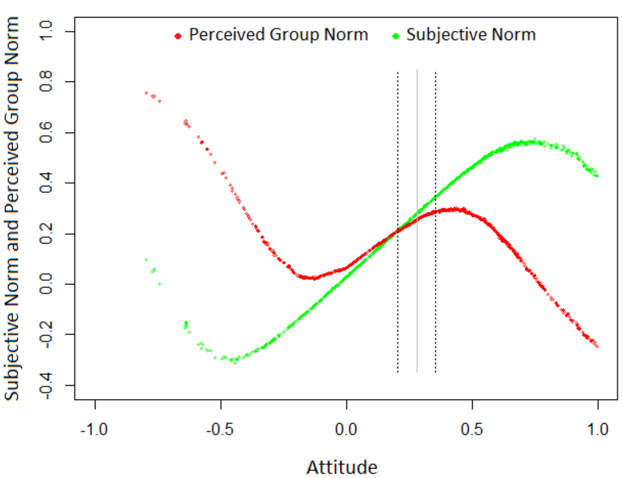


Fig. 9. SN (in green) and PGN (in red) as a function of attitude averaged over 1000 replicas of 1000 agents drawn from the Gaussian distribution. The two dotted black verticals lines indicate the thresholds for low (on the left) and high (on the right) attitudes with, in the middle the gray plain line indicating the average of the attitude distribution. Top panel: case study 1. Bottom panel: case study 2.

the low attitudes and a conformist intention in the high attitudes.

2) Parameter β, which defines how the bias threshold decreases when the attitude becomes extreme, should be larger than approximately 0.3. This indicates that the perceptual bias should be significantly different at the extremes of the opinion range.
3) The graph in the space δ, τ_M does not provide any condition on τ_M. However, τ_M should increase with σ.
4) For low values of both δ and α, and also low values of both σ and α, no parameter set is accepted. By increasing these two parameters, the number of accepted results increases. This indicates that the attitudes of the close others should be significantly correlated with the attitude of the considered agent.
5) For $\beta < 0.3$ and $\sigma < 0.25$ no parameter set is accepted. By increasing these two parameters, the number of accepted results increases and then decreases for very high β and very high σ.

TABLE IV

CENTER OF BOXES FOR WHICH THE REGRESSION COEFFICIENTS OF INTENTION BY PGN ARE THE CLOSEST TO THE ONES OF THE CASE STUDIES

Case-study	nb.	δ	σ	β	τ_M	α	ρ	Dist
1	25	0.336	0.332	0.85	1.25	5.1	0.85	0.108
2	26	0.278	0.372	0.75	1.55	5.7	0.75	0.185

B. Selecting a Single Parameter Setting for Each Case Study

Table IV shows the center of the selected boxes. In the last column of Table IV, "Dist." indicates the distances defined by (15) and (16). These points are visualized in Figs. 7 and 8.

C. Analyzing the Model for the Selected Parameter Values

Fig. 9 shows the average over 1000 replicas of the whole population and averaging the PGN and the SN over the 1000 populations ($\bar{N}_g^i$ and $\bar{N}_c^i$ in the procedure described in the section about the method for studying the model), for the selected parameter settings corresponding to case studies 1 (top panel) and 2 (bottom panel) shown on Table IV.

The general shapes of the curves shown on the top and bottom panels of Fig. 9 look very similar on both case studies. Let us first consider the PGN (red curve). Without perceptual bias, this curve would be constant at the value of the average attitude. Instead, considering attitudes from -1 to $+1$, the PGN curve starts at its highest value, decreases until a local minimum located just below 0 then increases until a local maximum located just above the average attitude and finally decreases until reaching its lowest value for the highest attitude 1. These changes of slope can be explained by the perceptual bias. In the first decreasing part of the PGN, the agents tend to predominantly perceive others' attitudes as higher than they are. Moreover, when their attitude increases, the proportion of others' attitudes perceived higher decreases, hence the PGN decreases. In the increasing part of the curve, the agents predominantly perceive others' attitudes as closer than they are with no strong bias on their average and the curve is similar to a local average, hence increasing. In the last decreasing part, the agents predominantly perceive others' attitudes as lower than they are. As their attitude increases the proportion of attitudes perceived lower increases hence the PGN decreases.

Without perceptual bias, the SN (green curve) should be close to a local average of the attitude distribution, because the close others tend to have attitudes which are close to the one of the considered agent. Hence it should be growing with the attitude. Instead, because of the perceptual bias, like the PGN, the SN initially decreases until a minimum, then increases until a maximum and finally decreases again. The minimum of the

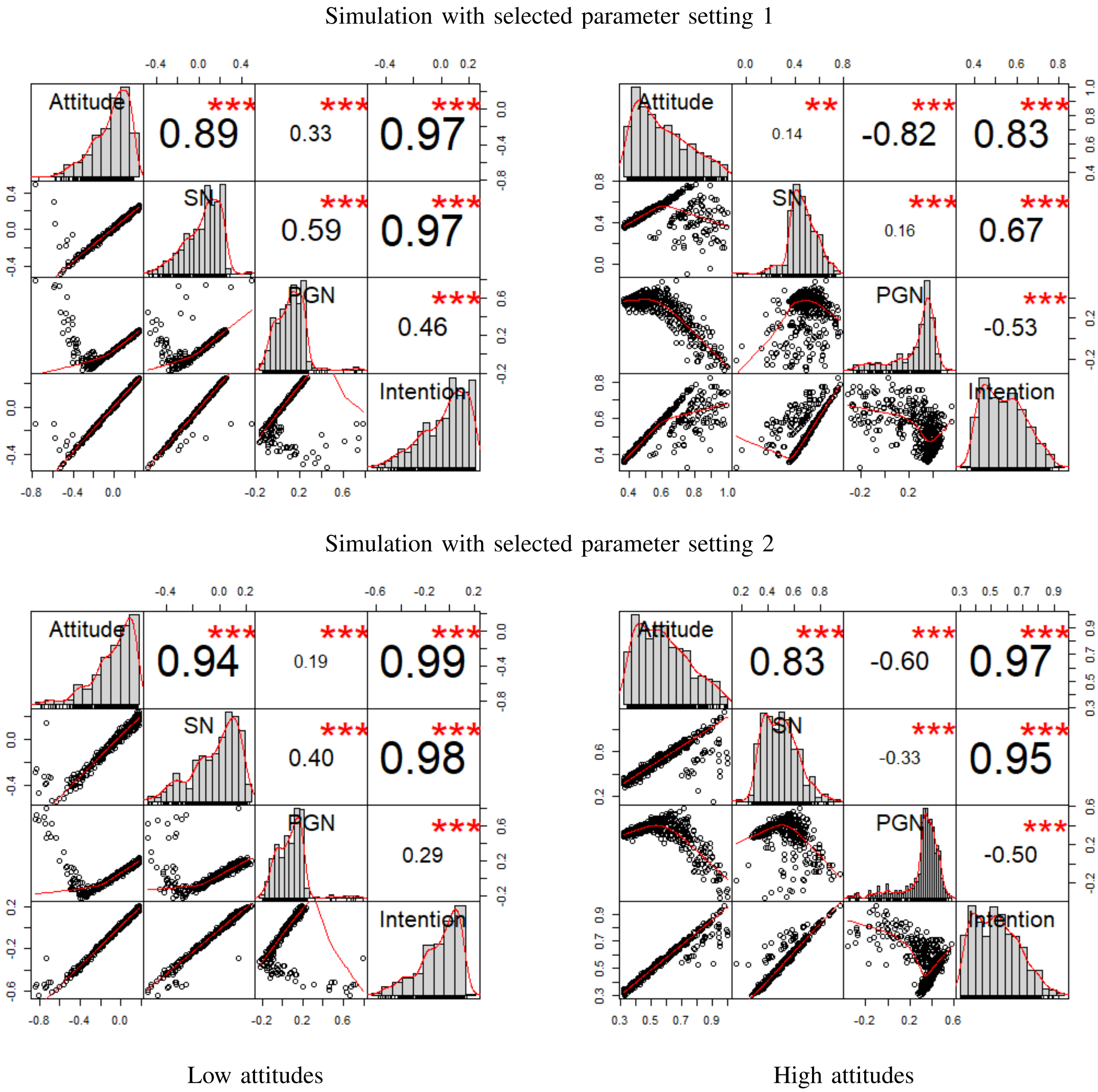


Fig. 10. Correlations between the different variables for low attitudes (on the left), high attitudes (on the right), for an example of simulation with the selected parameter settings 1 and 2 (see Table IV).

SN is lower than the one of the PGN and reached for a lower value of attitude, while the maximum is higher and reached for a higher attitude. Overall, the effect of the bias is smaller on the SN than on the PGN because the attitudes taken into account for computing the SN are closer on average to the considered agent's attitude and the results is therefore closer to a local average.

The most striking difference between the top and bottom panels of Fig. 9 relates to the SNs: for case study 2 (bottom panel), the maximum is higher and the minimum lower than for case study 1 (top panel). This difference comes from the difference of the value of parameter α ($\alpha = 5.1$ in setting 1 and $\alpha = 5.7$ in setting 2). With parameter setting 2, the attitudes of the close others are on average closer to the considered agent than with parameter setting 1; therefore, the effect of the bias is smaller on the SN and there is a bigger difference between the SN and the PGN. This difference explains why the regression coefficient of intention by PGN is more negative for setting 2 than for setting 1.

We can relate more precisely the features of the curves shown in Fig. 9 to the correlations between the different variables. Fig. 10 shows these correlations computed for an example of simulation for each of the selected parameter settings (see Table IV).

Indeed:

1) In the low attitudes (below the left dotted vertical line), both norms first decrease and then increase together, which explains the positive correlation between them.
2) On the contrary in the high attitudes (above the right dotted vertical line), the PGN is significantly decreasing, explaining a negative correlation (-0.82 for setting 1, -0.60 for setting 2) of the PGN with the attitudes, while

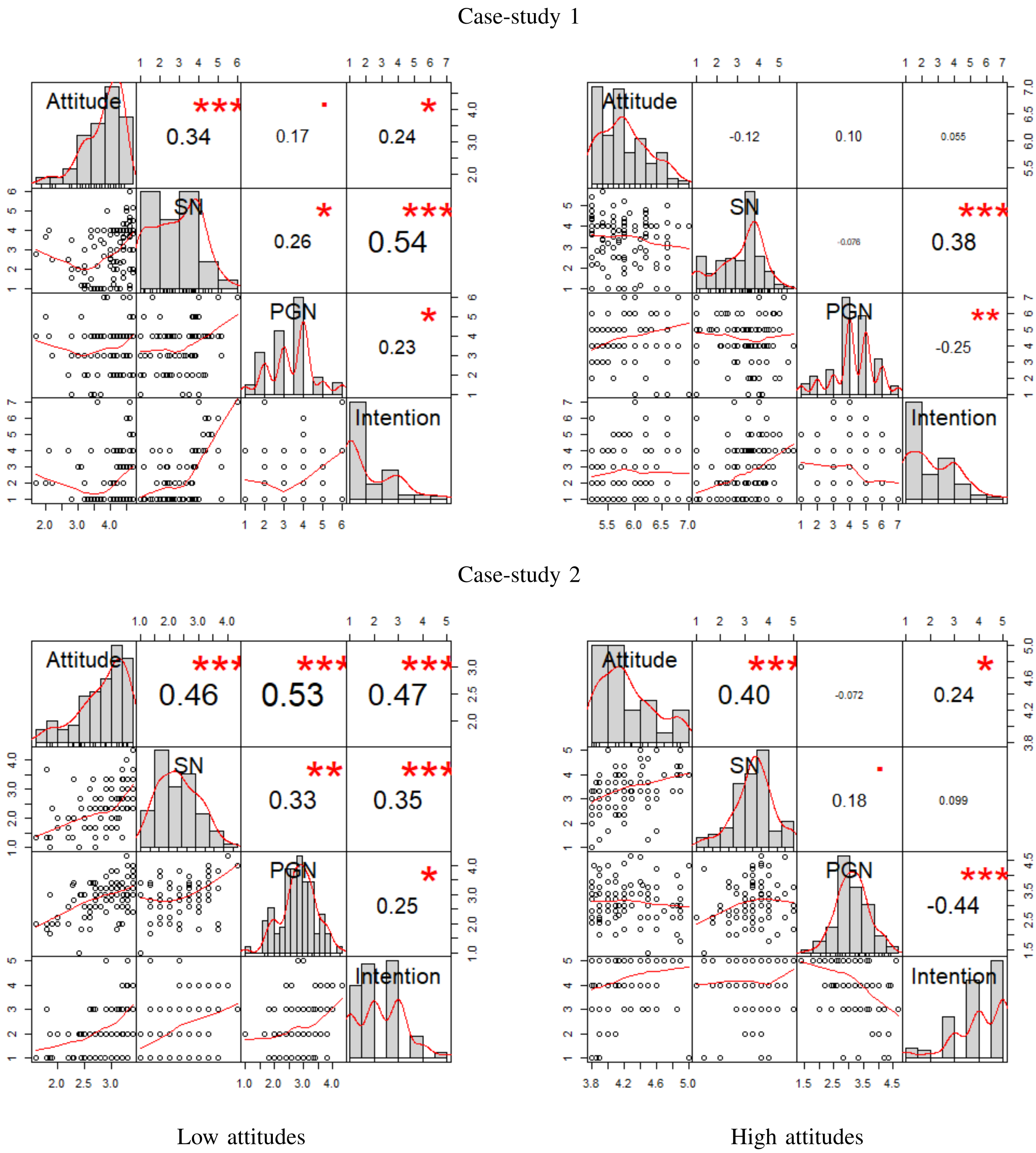


Fig. 11. Correlations between the different variables for low attitudes (on the left) and high attitudes (on the right), for case studies 1 and 2.

the SN first increases and then decreases, explaining low (0.16 for setting 1) or negative correlation (−0.33 for setting 2) between the PGN and the SN.

These observations suggest the following explanations of conformist and nonconformist intentions.

1) The conformist intention (positive correlation between intention and the PGN) within low attitudes is mainly driven by the positive correlation between the PGN and the SN.
2) The anticonformist intention (negative correlation between intention and the PGN) within high attitudes is mainly driven by the negative correlation between the PGN and attitudes and to some extent (in setting 2) by the negative correlation between the PGN and the SN.

This analysis can be qualitatively summarized as follows: when the distribution is not centered, a significant bias on the perception of attitudes generates a negative correlation between the PGN and attitudes and a small or negative correlation between the PGN and the SN, in the high attitudes. Therefore, the intention is negatively correlated with the PGN (anticonformist intention). In the low attitudes, both norms are mainly increasing with the attitude hence they are both positively correlated with the attitudes and with each other. Therefore, the PGN is positively correlated with the intention (conformist intention).

VI. Conclusion

The exploration of the model parameters by the ABC approach suggests that getting anticonformist intentions on one side of the attitudes and conformist intentions on the other side is a common and robust situation. The main conditions on the parameters values are: an average attitude significantly different from 0, a significantly stronger perceptual bias for agents with extreme attitudes and a significant probability that the attitude of the important others is close to the one of the agent. These conditions guarantee that the PGN decreases with the attitudes when the attitude is close to the high extreme (when the average attitude is positive) or the low extreme (when the average attitude is negative) and does not correlate with the SN. In particular, the models representing the case studies display a negative correlation between the attitude and the PGN for agents of high attitudes, which causes the negative correlation between the PGN and the intention.

Comparing the full patterns of correlation generated by the model to the ones observed on the case studies (see Fig. 11), yields more information about the relevance of the model. For low attitudes, the correlation patterns of the case studies are qualitatively similar to the ones of the simulations, with all correlations positive. For high attitudes, the correlation between the PGN and the intention is significantly negative for both case studies, which was expected because the regression coefficient of the intention by the PGN is negative. In case study 1, the correlation of the PGN with the SN is almost 0 and the SN has the highest correlation with the intention (0.38). For case study 2, the correlation of the PGN with the attitudes is almost 0 and the attitudes have the highest correlation with the intention (0.24). Therefore, in both case studies, the PGN is not correlated with the determinant of the intention, which makes possible its negative correlation with the intention. This absence of correlation between the PGN and the attitudes or the SN can be an effect of the bias on perceived attitudes, as suggested by the model.

However, it is important to underline the following limitations of our work.

1) We did not compare the distributions of the PGN and the SN from the model with the ones of the case studies. This would require introducing noise into the model of attitude perception.
2) The model assumes that the agents determine their PGN only from direct interactions with other agents of the group. Yet, indirect relations (gossip) and exposure to media can play an important role.

Moreover, different explanations than perceptual biases, related to psychological motivations, can also be considered. For instance, people with a high attitude can feel that they have the moral duty to act (for the good of the planet for instance) and this feeling can be reinforced when they think that most of the others disagree (low PGN), because then, the risk (for the planet) is increased [26], [27]. A related view is that the more people with high attitudes feel in minority (low PGN) the more they feel like pioneers of a just cause and this reinforces their intention to act. These explanations postulate that a low PGN has some causal effect on reinforcing the anticonformist intention.

Our model relies on a very different hypothesis, as it denies any causal relation between the PGN and the intention. Moreover, the perceptual biases do not impact significantly the SN hence they do not impact significantly the intention. Therefore, our approach could appear in direct contradiction with the other explanations.

Actually, both types of explanations could very well be entangled. Indeed, the perceptual biases, as we modeled them, would for instance tend to increase the feeling of being pioneers because it would increase the perceived difference between the agents with a very high attitude and the others, and this could increase even more their intention.

Finally, it should be underlined that this article only establishes the possibility that perceptual biases are an explanation to the observed anticonformist intentions. Better assessing the relevance of the model requires collecting more data about attitudes, intentions and PGNs in different contexts. In particular, the model predicts that, if the average of attitudes is negative ($\delta < 0$) and is sufficiently large, then the anticonformist intention should be expected among agents of low attitude. The model also predicts that, if the average of the distribution of attitudes is located close to the center of the attitude scale ($\delta \approx 0$), then the intention should be either conformist or anticonformist for both low and high attitudes. These predictions can easily be checked on adequate new data collections.

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