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Can biases in perceived attitudes explain anti-conformism?

Guillaume Deffuant^{1,2,*}, Omid Roozmand¹, Sylvie Huet^{1,2}, Kamilla Khamzina¹, Armelle Nugier², and Serge Guimond²

¹Université Clermont Auvergne, INRAE, LISC, Aubière, 63178, France

²Université Clermont Auvergne, LAPSCO, Clermont-Ferrand, 63000, France

*guillaume.deffuant@inrae.fr

ABSTRACT

This paper investigates how anti-conformist intentions could be related to some biases on the perception of attitudes. It starts from two case studies, related to the adoption of organic farming, that show anti-conformist intentions. It proposes an agent-based model which computes an intention based on the Theory of Reasoned Action and assumes some biases in the perception of others' attitudes according to the Social Judgement Theory. It investigates the conditions on the model parameter values for which the simulations reproduce the features observed in the case studies. The results suggest that anti-conformist intentions are indeed likely to be the effect of perception biases.

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 anti-conformist behaviours. It is therefore important to better understand the emergence and the development of such behaviours. In this paper, we focus on a specific understanding of anti-conformism, which is the negative correlation between the intention and the perceived group norm. The purpose of the paper is to investigate the hypothesis that such anti-conformist intentions can be generated by a bias in the perception of attitudes.

We first attest the existence of anti-conformist intentions in two already published case studies¹. One 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 data sets share the following features:

- 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 perceived group norm. In other words, when participants are in favour of organic farming more than the average, the less they think others are in favour of organic farming, the higher is their intention to become an organic farmer. Therefore, their intention tends to be reinforced if it goes against the perceived group norm, which can be seen as an anti-conformist intention.
- Among participants whose personal attitude about organic farming is lower than the average, on the contrary, the intention is positively correlated with the perceived group norm. In this case, the intention is, as more usual, rather conformist.

We make the hypothesis that some biases on the perception of attitudes could explain these observations. Roughly, the bias can increase the difference between the perception of the attitude of close others, which determines the intention, and the perception of the attitude of others in general, which determines the perceived group norm. In some cases, this additional difference could lead to negative correlation.

In order to investigate this hypothesis, we adopt a modelling approach. We design computational models of the perception biases, the intention and the perceived group norm. We simulate a population of virtual agents holding these perception biases that impact their intention and perceived group norm. We determine for which parameter values the model displays correlations between intention and the perceived group norm that are similar to the ones measured on the case studies. Such agent-based approaches are now rather common²⁻⁴.

The model of biases on the perception of attitudes is inspired by the theory of Social Judgment⁵. 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 between close and far depends on the extremity of the attitude (⁵ p. 139). People with extreme attitudes tend to perceive most of other attitudes as farther while people with moderate attitudes see most other attitudes as closer (there is actually an important relation with ego-involvement⁵⁻⁷).

The model of intention is based on the well empirically supported Theory of Reasoned Action (TRA)⁸, assuming that the intention is mainly determined by the attitude of the considered agents and the perceived attitudes of their important others. Here, the subjective norm, based on the perceived attitudes of close or important others, is distinguished from the perceived group norm, based on the perceived attitudes of other group members, beyond close others (e.g., other farmers). We choose the Theory of Reasoned Action (TRA) rather than the more complete theory of Planned Behaviour (TPB)⁹ because in the case studies¹, the anti-conformist 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 behavioural control, added to the TRA in the classical TPB⁹, is likely to play a negligible role in the determination of the intention. Indeed the perceived behavioural 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 behaviour are not likely to have in mind the many practicalities that could hamper the behavioural change. The situations that we consider can be seen as the first step towards a potential major change¹⁰, or a transformational adaptation^{11–13}.

We study the agent-based model by making a large number of simulations. Our method involves two main steps:

- We first adopt an Approximate Bayesian Computing (ABC) approach. We generate a large number of parameter values uniformly drawn from chosen intervals and we select the ones that lead to simulations reproducing the features of the data. The results show that only the parameter sets corresponding to a significant perception bias are selected. The average of the distribution of attitudes should also be significantly positive.
- We focus on a typical selected simulation, and we analyse how the perception biases modify differently the subjective and perceived group norms for individuals with more or less extreme attitudes. We observe that the perception biases create a slope change for both the subjective and the perceived group norm in the vicinity of the extreme opinions. This change takes place further from the extremities for the perceived group norm and this explains the emergence of the anti-conformist intention.

The paper is organised as follows: the next section presents the two case studies showing anti-conformist intentions. Section 3 describes the model. Section 4 explains the method adopted for studying the model. Section 5 reports the results. The final section discusses the results and draws future perspectives.

Two case studies showing anti-conformist intentions

Intention to convert to organic farming among Eastern European farmers

We only summarise the survey and focus on some specific features of the data analysis. All details can be found in¹. 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 TPB⁹, thus they provide the necessary information for applying the TRA, since TPB extends TRA. They include questions about personal attitude towards organic farming, subjective norm, perceived behavioural control and behavioral intention towards organic farming. They include additional questions about the perceived group norm.

The questions use 7-point Likert scale where 1 indicates extremely unlikely/disagree/bad and 7 indicates extremely likely/agree/good. We computed the personal attitude of a farmer as the average of the 4 questions about different aspects of the personal attitude and the attitude of important others (subjective norm) as the average of the 6 questions about different aspects of the subjective norm. The perceived attitude of other farmers at large (perceived group norm) 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.

Figure 1 shows the distribution of the personal attitudes, subjective norm and perceived group norm translated into a range between -1 and +1. Note that the average of the personal attitudes is significantly positive ($\bar{a}_1 = 0.33$) and the standard deviation is $\sigma_1 = 0.33$. The average of subjective and perceived group norms are lower than the one of the attitudes, with a significantly larger number with low values (2 or 3). The shape of the attitude distribution appears reasonably close to the one of a Gaussian.

Figure 2 shows linear regressions of the intention to convert to organic farming as a function of the perceived group norm 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 $a > \bar{a}_1 + 0.2\sigma_1$. On the left the regression involves only farmers with a personal attitude lower than the average and on the right only farmers with a personal attitude higher than the average. The details of the regressions are provided by table 1.

Figure 3 shows the correlations between attitudes, subjective norm, perceived group norm and intention to convert to organic farming. They confirm the regressions: there is a significant positive correlation between intention and perceived group norm within farmers of low attitude while there is a significant negative correlation between the intention to convert and the

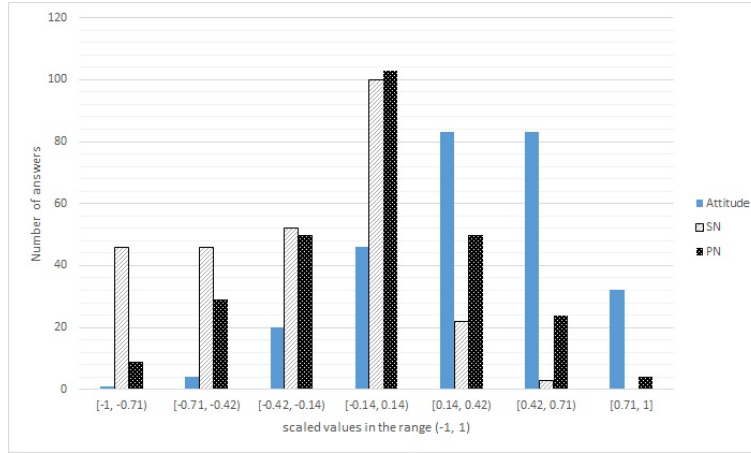


Figure 1. Distribution of attitudes, subjective norms, and perceived group norms of Eastern European farmers

	Estimate	Std. Error	t value	Pr(> t)
(Intercept) Low attitudes	1.1559	0.5096	2.268	0.0255 *
11[, 4] Low attitudes	0.3243	0.1406	2.307	0.0232 *
(Intercept) High attitudes	3.96441	0.43876	9.035	1.94e-15 ***
12[, 4] High attitudes	-0.28801	0.09776	-2.946	0.00381 **

Table 1. Details of the regressions of intention by perceived group norm for farmers with attitudes lower than average (top lines) and higher than average (bottom lines).

perceived group norm within farmers of high attitude. Figure 3 also shows that the intention to convert has an even stronger correlation with the subjective norm, in conformity with the theory of reasoned action.

These results suggest that the intention to convert increases with the perceived group norm 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 anti-conformist intention.

Intention to become an organic farmer among French agricultural college students

Like previously, we only summarise the study, focusing on the main features that will be compared with the model. The sample includes 220 participants from agricultural colleges in Rhône-Alpes, France, surveyed in 2017. The study assesses personal attitudes towards 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 perceived group norm 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 perceived group norm while the ones starting with “My friends” contribute to the subjective norm.

Figure 4 represents the histograms of attitudes, subjective norm, and perceived group norm, on a scale between -1 and +1 (translated from the 5 item Likert scale). In the model, we consider more particularly the distribution of attitudes which has a mean of $\bar{a}_2 = 0.28$ and standard deviation of $\sigma_2 = 0.38$. On average, the attitudes about organic farming are positive, like in the previous survey.

Figure 5 shows the regression of the intention as a function of perceived group norm for low (left) and high attitudes (right). 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 while it is positive for low attitudes. The negative coefficient for the high attitudes is more significant than the positive coefficient for low attitudes (see Table 2).

These features are confirmed by the correlation analysis presented on Figure 6 which shows the correlations between attitude, subjective norm, perceived group norm and intention for low and high attitude respondents. Indeed, a significant negative correlation between the intention and the perceived group norm can be noticed for high attitudes respondents, while this correlation is positive for low attitude respondents. This pattern replicates the observations made with Eastern European farmers. We can note a few other features, that are less important for this paper: There is a significant positive correlation between attitudes and intention as well as between subjective norm and intention for low attitude respondents. The correlation between the subjective norm and the intention is not significant for high attitudes.

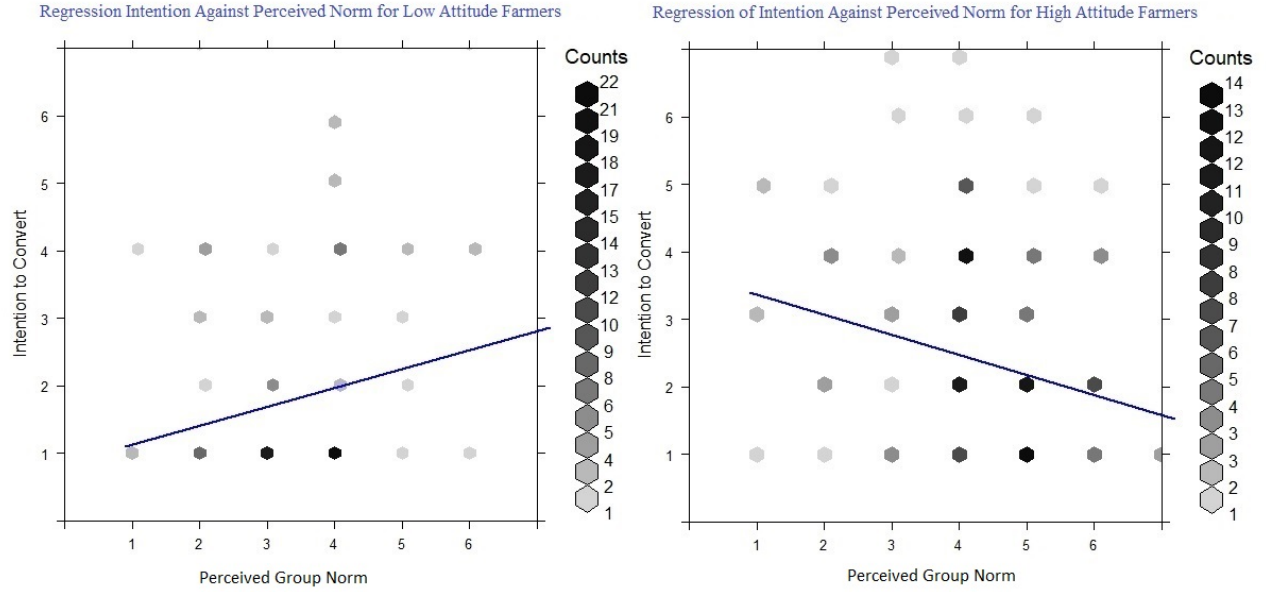


Figure 2. Regression of intention to convert against perceived group norm for both low and high attitudes Eastern European farmers

	Estimate	Std. Error	t value	Pr(> t)
(Intercept) Low attitudes	1.1342	0.4826	2.350	0.0208 *
11[, 4] Low attitudes	0.4002	0.1633	2.451	0.0161 *
(Intercept) High attitudes	6.2702	0.4816	13.019	< 2e-16 ***
12[, 4] High attitudes	-0.7100	0.1510	-4.702	8.82e-06 ***

Table 2. Details of the regressions of intention by perceived group norm for students in French Agricultural College with attitudes lower than average (top lines) and higher than average (bottom lines).

The 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 among which a smaller set represents her close or important others. The subjective and perceived group norms are average of the perceived attitudes of respectively the acquaintances and the close others. The intention is the average of the attitude and the subjective norm. Hence, we can compute regressions and correlations of the intention with the perceived group norm.

Attitudes and biased perception of attitudes

The model includes n virtual agents and each agent i is then characterised 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 $[-1, 1]$. Therefore, attitude -1 is the most against the issue while 1 is the most in favour. Attitude 0 is indifferent. Only the values which 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 .

In accordance with the Social Judgement Theory, we introduce biases in the agents' perception of attitudes.

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

- 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;
- 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 depends on the extremity of attitude a_i . It is assumed to increase linearly for a_i between -1 and 0 and to

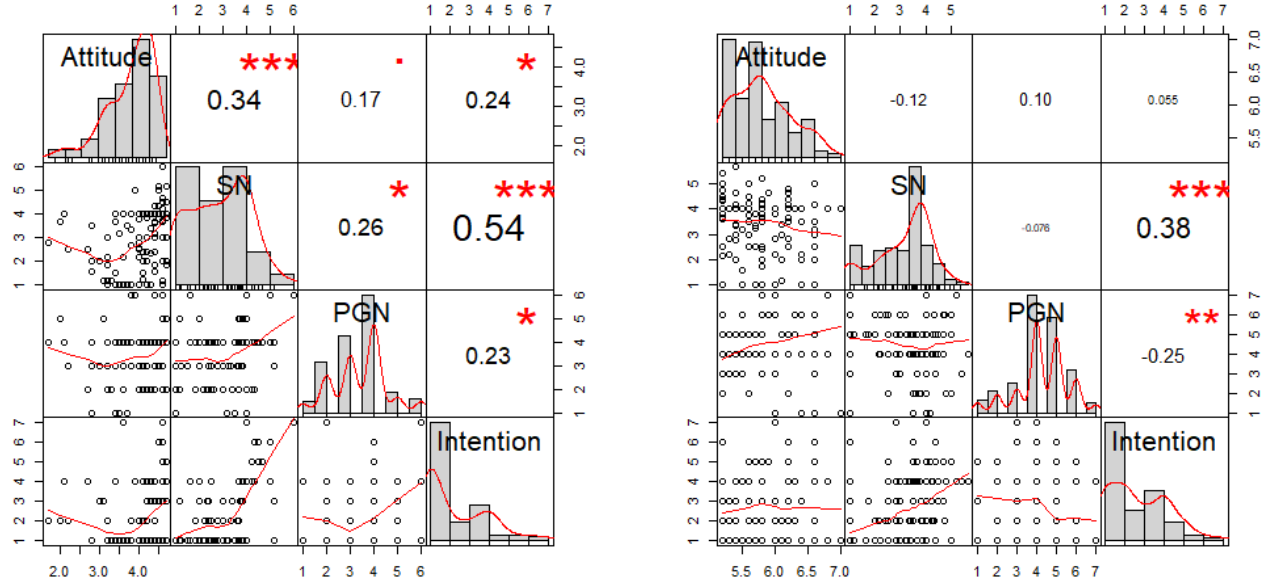


Figure 3. Correlation between personal attitude (Attitude), subjective norm (SN), intention to convert (Intention), and perceived group norm (PGN) for Eastern European farmers for low attitudes (on the left), high attitudes on the right.

decrease linearly for a_i between 0 and 1. More precisely (β and τ_M being parameters of the model), we have:

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

Figure 7 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):

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

To be compatible with the extreme ends of attitude's scale, $p^i(a_j)$ is blocked in the range $[-1, 1]$. Indeed, this equation ensures that, if $\tau_i - |a_i - a_j| > 0$, then $|p^i(a_j) - a_i| < |a_j - a_i|$ and if $\tau_i - |a_i - a_j| < 0$, then $|p^i(a_j) - a_i| > |a_j - a_i|$.

Figure 8 shows how one agent with a high attitude (attitude = 0.9, on the left), and a neutral attitude (attitude = 0, on the right) perceive (red triangles) the attitude of others (black squares). We observe on the left that the agent having an attitude 0.9 views the attitudes closer than its threshold as even closer, while the attitudes further than the threshold are perceived even further. On the right, the agent with an attitude 0 sees all other attitudes closer than they are.

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 agents in interaction with agent i and gives the agent an idea of the attitude of the whole group. The size s_g of this set is assumed the same for all the agents. The perceived group norm N_g^i of agent i is modelled as the average of the attitudes in the set R_g^i as they are perceived by agent i :

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

A subset R_c^i of R_g^i that represents the important others (close to the considered agent) who are the base for the computation of the subjective norm. 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 difference between a_i and a_j :

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

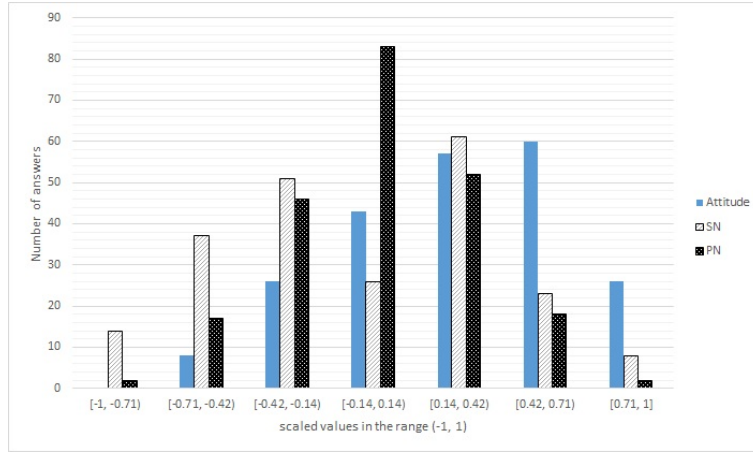


Figure 4. Distribution of attitudes, subjective norms, and perceived group norms of French Agricultural College students.

The subjective norm 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 N_c^i :

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

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 subjective norm:

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

Table 3 breaks down the parameter definitions.

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 of others representing group R_g^i
α	Coefficient ruling probability to be in close agent 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 modification made by the perceived attitude

Table 3. Break-down of model parameters.

Method for studying the model

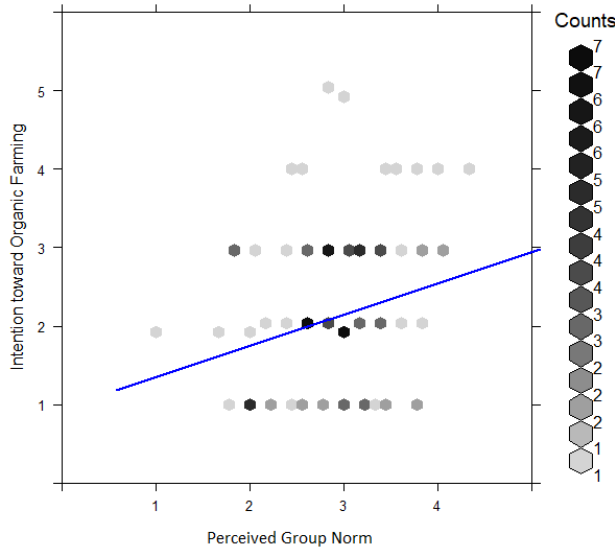
Parameter selection by Approximate Bayesian Computing (ABC)

Approximate Bayesian Computing (ABC)^{14–17} 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.

More precisely, Figure 9 describes the items of the ABC process:

- 1) We have chosen to investigate parameter settings: $p = (\sigma, \delta, \beta, \tau_M, \rho, \alpha)$ (table 3 recalls the meaning of each parameter symbol). Using the Latine Hypercube Sampling (LHS) package in R we generate $N = 25,000,000$ parameter

Regression of Intention Against Perceived Norm For Low Attitude Respondents



Regression of Intention Against Perceived Norm For High Attitude Respondents

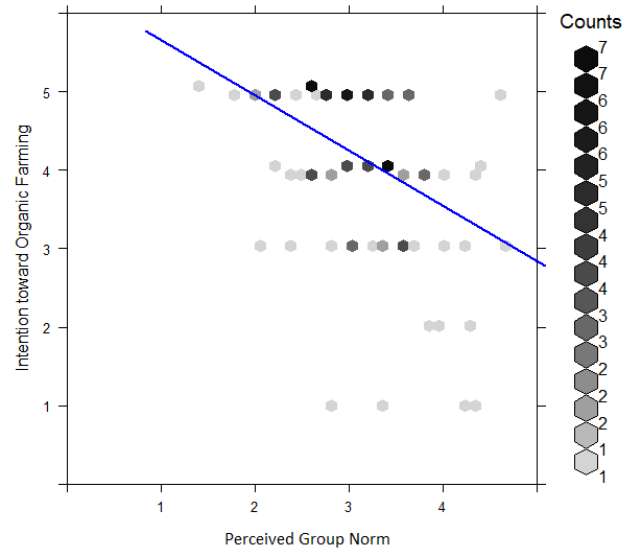


Figure 5. Regression of intention to become organic farmer against perceived group norm for both low and high attitude of French Agricultural College students

settings p . We use the uniform method with step 0.0001. The parameters related to the population and agent connections are set to the following values:

$$n = 1000, s_c = 5, s_g = 30. \quad (7)$$

- 2) For each parameter setting p , the model is run and the results are stored in a csv file.
- 3) The regression coefficients $c_l(p)$ and $c_h(p)$ are computed.
- 4) The acceptance of a parameter setting p is based on the regression coefficients $c_l(p)$ and $c_h(p)$ of the intentions as a function of the perceived group norm for respectively the low and the high attitudes, derived from the simulation run with parameter set p . These coefficients are compared to the averages $\bar{c}_l = 0.36225$ and $\bar{c}_h = -0.499$ of these coefficients obtained from our two case studies (see tables 1 and 2). The acceptance criterion involves the average of standard errors $\bar{e}_l = 0.15195$ and $\bar{e}_h = 0.12438$ of the regressions of intention by perceived group norm for low and high attitudes of the two case studies. More precisely, a parameter set p is accepted if:

$$|c_l(p) - \bar{c}_l| < 2\bar{e}_l \text{ and} \quad (8)$$

$$|c_h(p) - \bar{c}_h| < 2\bar{e}_h. \quad (9)$$

- 5 and 6) If the conditions 8 and 9 are satisfied, then p is accepted (stage 5), otherwise it is rejected (stage 6).
- 7) The simulation is repeated for N times.

The approximate posterior distribution provides the conditions on the parameters for which the features found in the case studies are reproduced by the simulations. This posterior distribution can be visualised by projecting it on 2D spaces defined by pairs of parameters.

Selecting a single parameter setting.

In the 6-dimensional parameter space $(\sigma, \delta, \beta, \tau_M, \rho, \alpha)$, we define $10^4 = 10,000$ 6-dimensional boxes as follows:

- 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. It is the range of the prior distribution of this parameter divided by 10:

$$s_\omega = (\omega_h - \omega_l)/10, \quad (10)$$

where ω_h and ω_l are respectively the maximum and minimum of the interval of the prior distribution for parameter ω ;

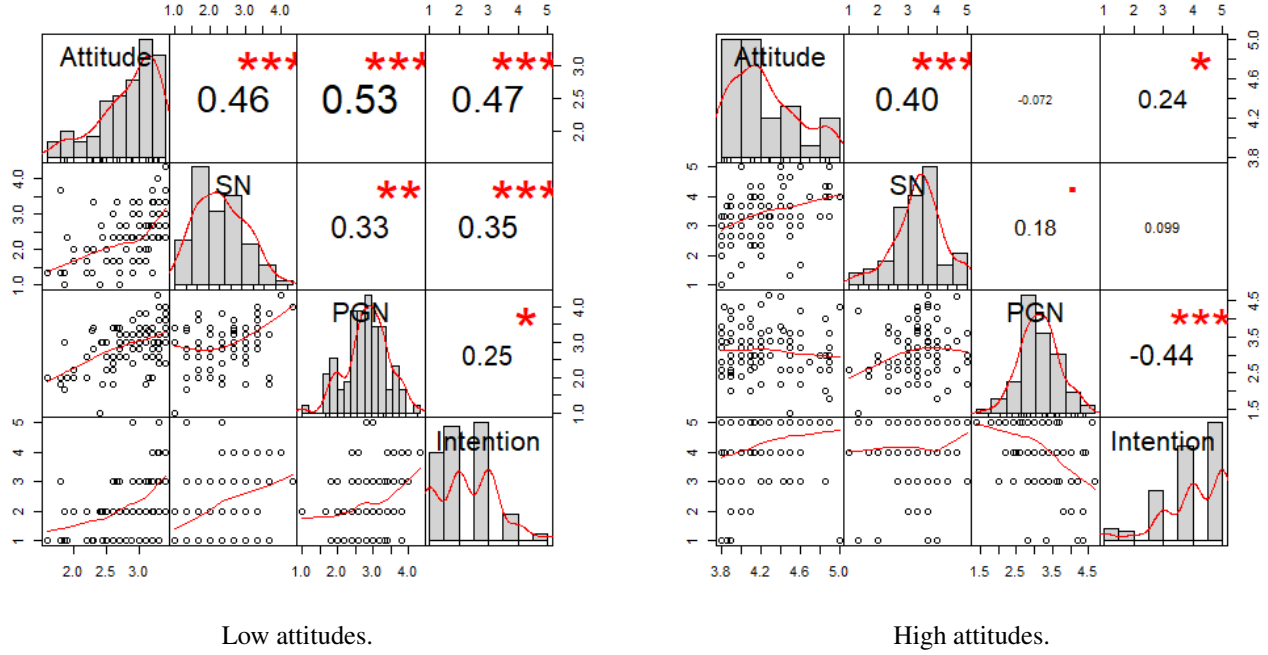


Figure 6. Correlations between personal attitude (Attitude), subjective norm (SN), intention to become organic farmer (Intention), and perceived group norm (PGN) for French Agricultural College students.

- Let δ_0 and σ_0 , be the average of the means and standard deviations of attitudes distributions in our two case studies: $\delta_0 = \frac{1}{2}(\bar{a}_1 + \bar{a}_2)$ and $\sigma_0 = \frac{1}{2}(\sigma_1 + \sigma_2)$. All the boxes are such that:

$$\sigma \in [\sigma_0 - \frac{s\sigma}{2}, \sigma_0 + \frac{s\sigma}{2}], \quad (11)$$

$$\delta \in [\delta_0 - \frac{s\delta}{2}, \delta_0 + \frac{s\delta}{2}]; \quad (12)$$

- Then each box is defined by four integers $k_\omega \in \{1, \dots, 10\}$, for $\omega \in \{\beta, \tau_M, \rho, \alpha\}$ and is such that :

$$\omega \in [\omega_l + (k_\omega - 1)s_\omega, \omega_l + k_\omega s_\omega], \text{ for } \omega \in \{\beta, \tau_M, \rho, \alpha\}. \quad (13)$$

Among the $10^4 = 10,000$ boxes, we selected the ones which include a proportion of accepted parameter settings that is higher than 0.95. Then, among the selected boxes, we selected the one for which the parameter setting at the center of the box provides regression coefficients that are the closest to the average ones of the data.

Explaining the anti-conformist tendency on simulations with the selected parameter setting.

In order to analyse the correlations between the attitudes and the norms generated with the selected parameter setting, we repeat the computation of the norms with many different draws of the attitudes and sets of connected agents. More precisely, the procedure is the following:

- 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;
- Repeat for j from 1 to 1000 (j is the index of the replica):
 - Draw at random from the Gaussian distribution a set of 1000 attitudes: $(a_i^j), i \in \{1, 1000\}$;
 - for i from 1 to 1000, for attitude (a_i^j) we compute the perceived group N_g^{ij} norm and the subjective norm N_e^{ij} from the set of attitudes (a_i^j) .

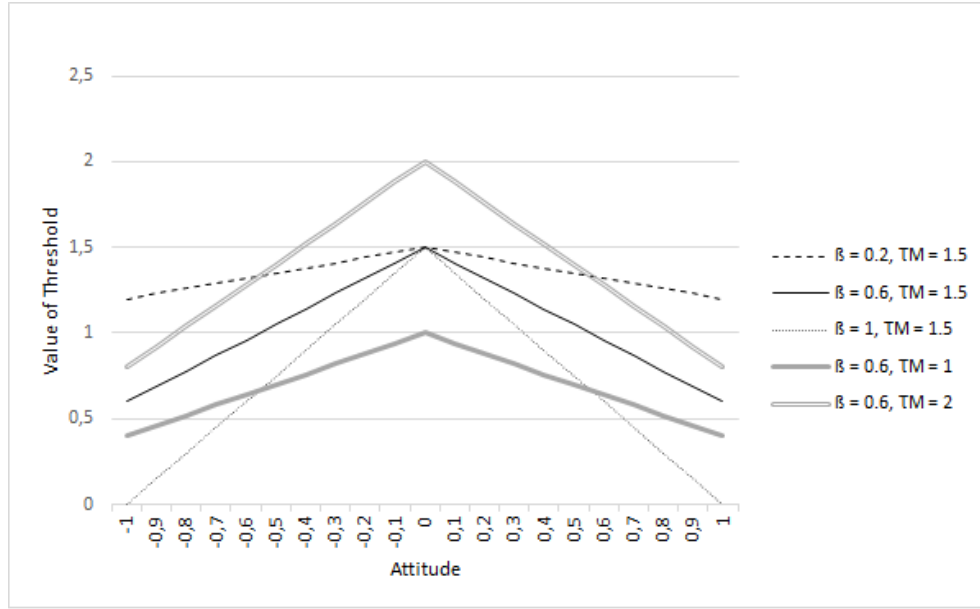


Figure 7. Example of function determining the perception threshold τ_i defined by parameters $\beta = 0.2, 0.6$, and 1 , and $\tau_M = 1, 1.5$, and 2 .

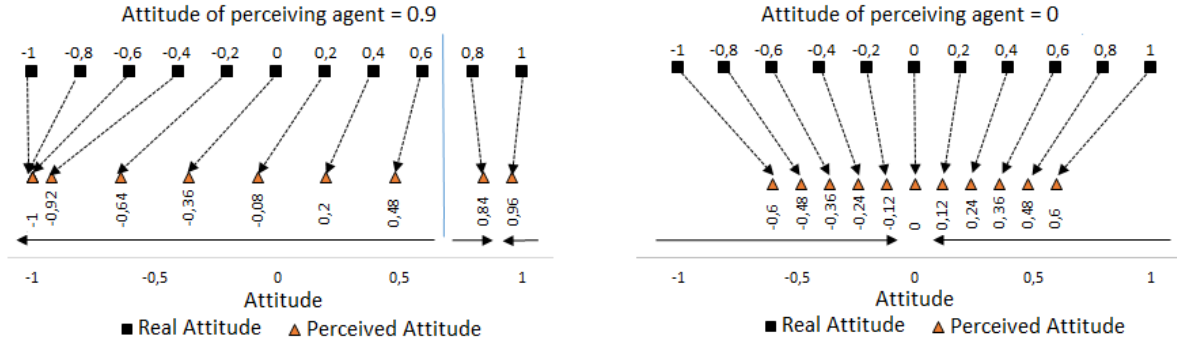


Figure 8. Examples of how real attitude is perceived. Left: attitude of perceiving agent = 0.9 . Right: attitude of perceiving agent = 0 .

- Compute the average perceived group norm \bar{N}_g^i and average subjective norm \bar{N}_c^i over the 1000 populations.

$$\bar{N}_g^i = \frac{1}{1000} \sum_{j=1}^{1000} N_g^{ij} \text{ and } \bar{N}_c^i = \frac{1}{1000} \sum_{j=1}^{1000} N_c^{ij} \quad (14)$$

This procedure allows us to reduce the variability of the norms for a given agent and their distributions look almost like curves. Hence we can easily identify parts of them which are almost linear and the sign of the corresponding slope. Thus we can identify more easily how the perceived group norm correlates with the attitudes and the subjective norm and therefore with the intention.

Results

Distribution of parameters selected by ABC.

948,091 parameter settings have been selected among the 25,000,000 tested in the ABC process. Figures 10 and 11 show the distribution of these selected settings projected on the planes defined by 8 pairs of parameters which include δ or σ . Each panel of figures 10 and 11 shows a $2D$ map of 100×100 cells representing the proportion of accepted parameter settings in the cell.

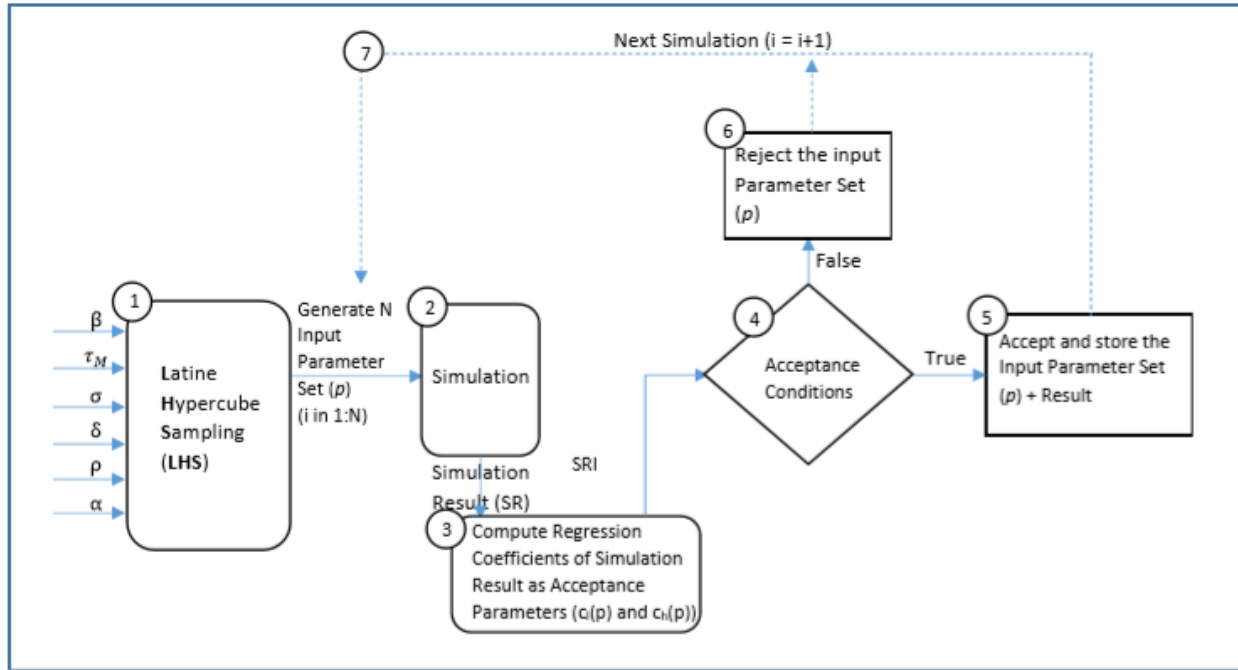


Figure 9. The schema of Approximate Bayesian Computing for accepting/rejecting parameter settings.

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 2D map. The legend indicates this maximum. The line shows the points for which the value of δ or σ is the average of the ones of our case studies ($\delta = \delta_0 = 0.305$ and $\sigma = \sigma_0 = 0.355$).

The figures suggest the following comments (table 3 recalls the definition of each parameter):

- Parameter δ should be larger than approximately 0.05 and parameter σ should be larger than approximately 0.25;
- Parameter β should be larger than approximately 0.3. This indicates that the perception bias should be significantly different at the extremes of the opinion range.
- The graph in the space δ, τ_M does not provide any condition on τ_M . However, τ_M should increase with σ .
- 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.
- 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 .

Selecting a single parameter setting.

The blue points on the lines represented on Figures 10 and 11 are the projections of the middle of the four 4-dimensional boxes (among 10,000) in space $(\beta, \tau_M, \alpha, \rho)$ for which the proportion of accepted sets is the highest.

Box 1 in table 4. It includes 18 accepted parameter sets over 18 tested is the only one with 100% of accepted parameter sets. We also found three boxes that hold higher than 0.95 % of accepted parameter sets (see table 4).

These boxes belong to different regions of the parameter space. In order to select one of them, we pick the center of each box as a parameter setting representing this box and we make the average of coefficients of regression for low and high attitude of 1000 replicas using this parameter setting for each box. Table 5 shows the average of coefficients of regression for low and high attitude for 1000 replicas.

We observe that the centers of boxes 1 and 3 yield regression coefficients that are the closest to the average coefficients derived from the data sets (the average of coefficient for low attitude is 0.36225, and the average of coefficient of regression for

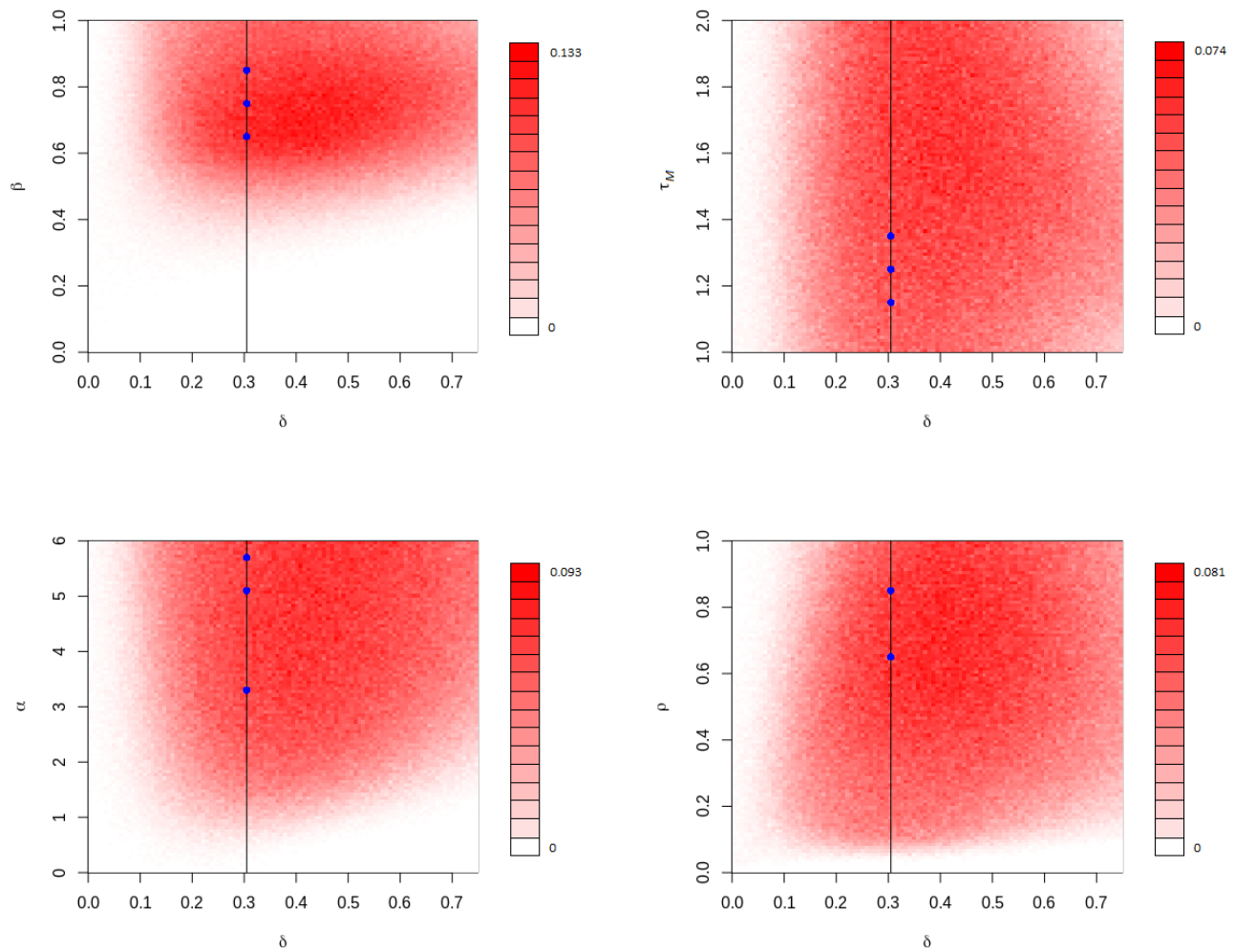


Figure 10. Results of ABC: Proportion of accepted simulations presented on 2D spaces where δ is on the horizontal axis and β , τ_M , α or ρ are on the vertical axis.

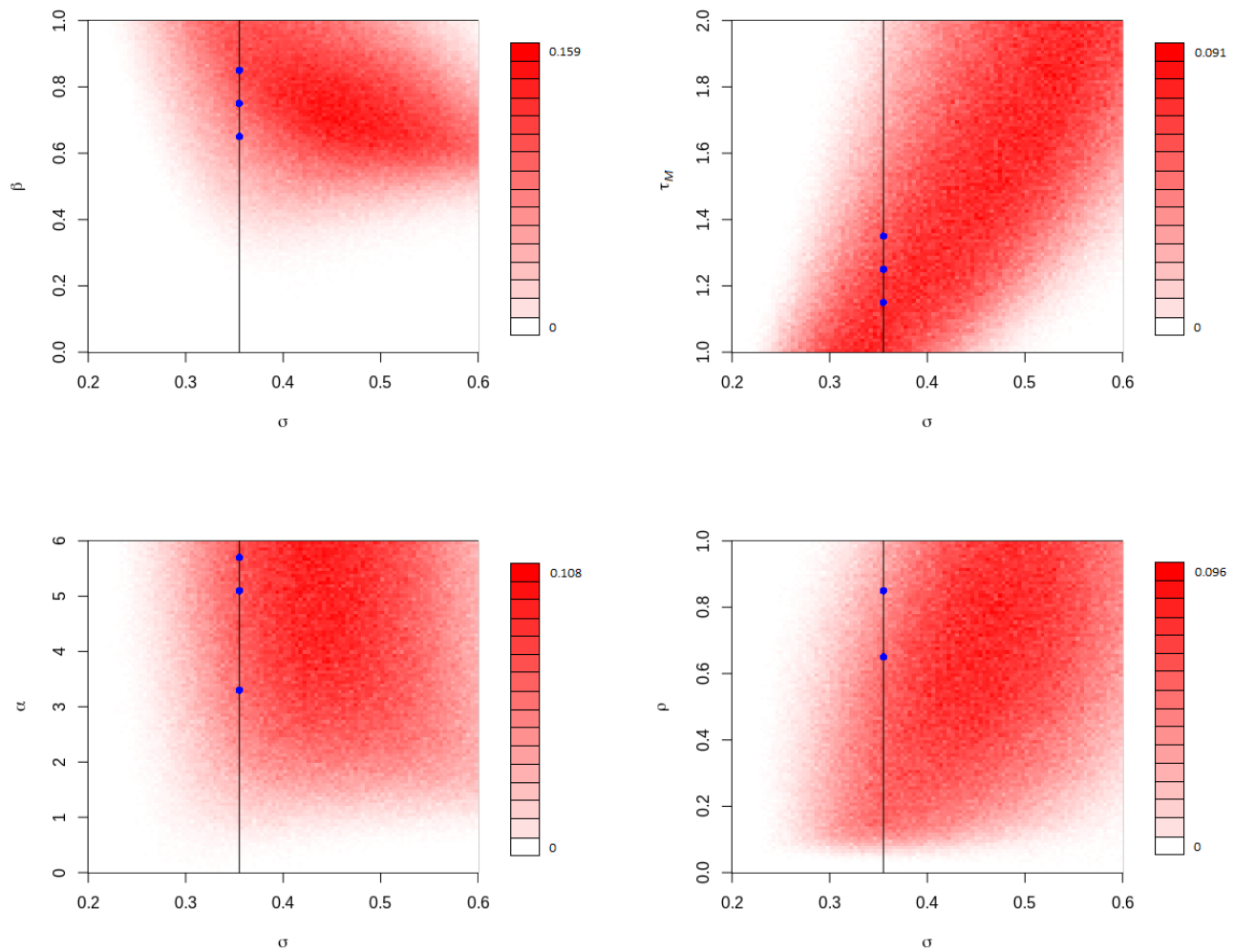


Figure 11. Results of ABC: Proportion of accepted simulations presented on 2D spaces where σ is on the horizontal axis and β , τ_M , α or ρ are on the vertical axis (see comments in text).

Box	% Accepted	Accepted	Tested	β	τ_M	α	ρ
1	100	18	18	(0.8, 0.9)	(1.3, 1.4)	(4.8, 5.4)	(0.6, 0.7)
2	95.8	23	24	(0.7, 0.8)	(1.1, 1.2)	(4.8, 5.4)	(0.8, 0.9)
3	95.5	21	22	(0.7, 0.8)	(1.2, 1.3)	(5.4, 6)	(0.8, 0.9)
4	95.2	20	21	(0.6, 0.7)	(1.1, 1.2)	(3, 3.6)	(0.6, 0.7)

Table 4. The boxes that hold more than 95% of accepted parameter settings.

Box	Avg. coefs. Low	SD of coefs. Low	Avg. coefs. High	SD coefs. High
1	0.329	0.142	-0.468	0.034
2	0.215	0.116	-0.414	0.034
3	0.346	0.136	-0.450	0.034
4	0.284	0.138	-0.450	0.044

Table 5. Average and standard deviation of coefficients of regression of 1000 replicas for low and high attitudes for different parameters that are the center of selected boxes.

high attitude is -0.499005). We select the center of box 1 for further analysis. Table 6 shows these parameter values. Remember that the other parameter values are:

$$n = 1000, s_c = 5, s_g = 30, \delta = 0.305, \sigma = 0.355. \quad (15)$$

Parameter	α	β	τ_M	ρ
Value	5.1	0.85	1.35	0.65

Table 6. Selected parameter values.

Analysing the model for the selected parameter values.

Figure 12 shows the results obtained for the selected parameter values (see table 6) when making the same analysis as the ones done on the case studies. 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). As expected, the regression coefficient of the intention by the perceived group norm is positive for low attitudes and negative for high attitudes and so are the correlation coefficients between intention and perceived group norm. The very high positive correlations between intention and both attitudes and subjective norm for both low and high attitudes were also expected because the intention is modelled as the average of the attitude and the subjective norm.

Moreover, the following observations are noticeable:

- For the low attitudes, there is a small positive correlation (0.18) between attitudes and perceived group norm and a stronger positive correlation between subjective norm and perceived group norm (0.51) ;
- For the high attitudes, there is a strong negative correlation (-0.80) between attitudes and perceived group norm and a weaker negative correlation between subjective norm and perceived group norm (-0.11).

These observations can be related to Figure 13 which shows the average over 1000 replicas of the whole population and averaging the perceived group norm and subjective norm over the 1000 populations (\bar{N}_g^i and \bar{N}_c^i in the procedure described in).

Let us first comment the shape of the perceived group norm (red curve). Without perception bias, this curve would be flat at the value of the average attitude. Instead, because of the perception biases, it starts at its highest value for the lowest attitudes, 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 a very its lowest value for the highest attitudes. Indeed, when an agent's attitude is very low, this agent tends to perceive most other attitudes as higher than they are, and hence her perceived group norm is higher than the actual average attitude. When her attitude increases, the proportion of others' attitudes that are perceived higher than they are decreases, hence the perceived group norm decreases. It decreases until reaching a point where most others' attitudes are seen closer than they are, and from this point, the perceived group norm increases with the attitudes. It increases until reaching a point close enough to the high extreme in which most others' attitudes are seen lower than they are, and this is more and more so when approaching the extreme of the attitude axis. In this last part, the perceived group norm decreases.

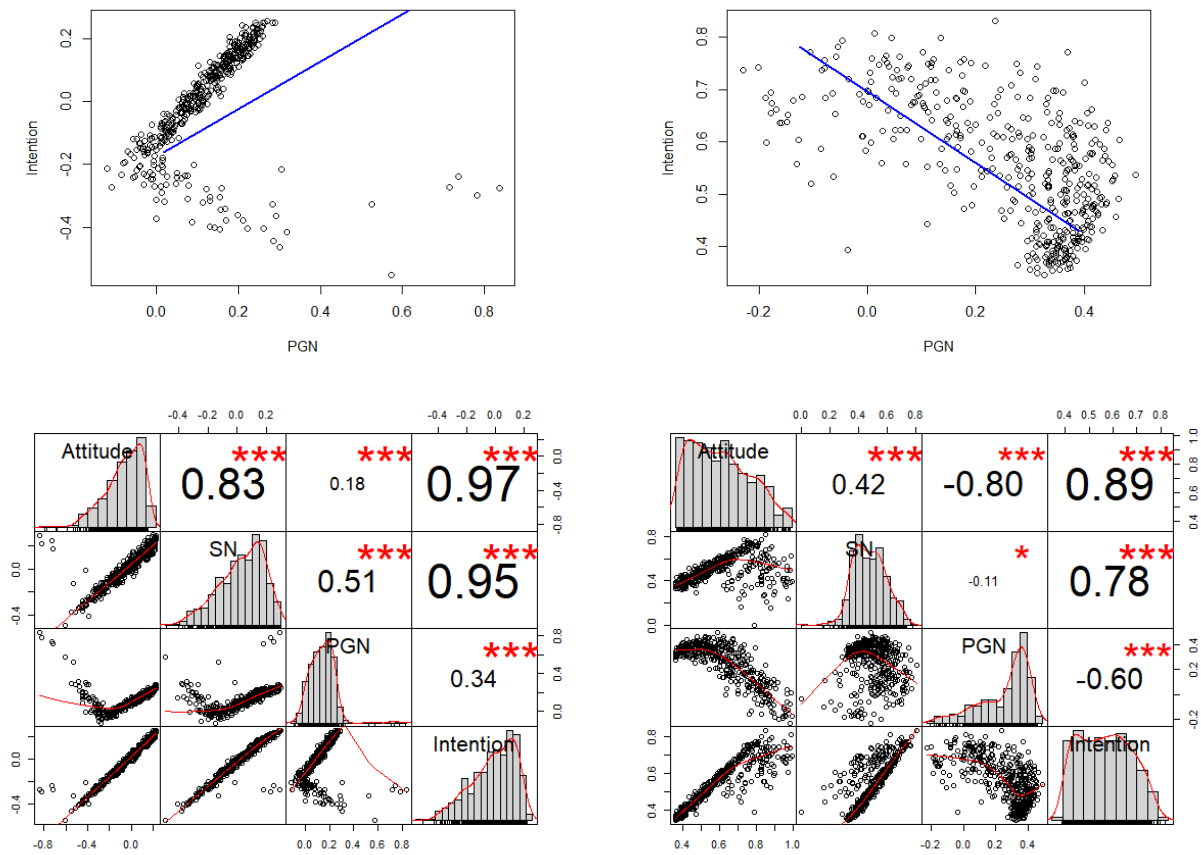


Figure 12. Example of results the selected parameter setting. Top line: regressions of intention (y-axis) as a function of the perceived group norm (x-axis) for low attitudes (on the left), high attitudes (on the right); bottom line: correlations for low attitudes (on the left), high attitudes (on the right).

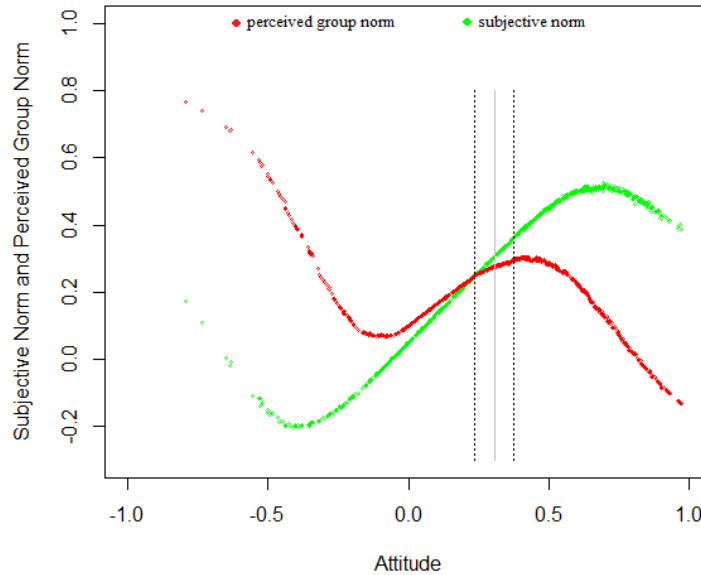


Figure 13. Subjective norm (in green) and perceived group norm (in red) as a function of attitude averaged over 1000 replicas of 1000 agents drawn from the Gaussian distribution. The two dotted black verticals lines indicate the thresholds for low (on the left) and high (on the right) attitudes with, in the middle the grey plain line indicating the average of the attitude distribution.

Without perception bias, the subjective norm (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, with the perception bias, like the perceived group norm, the curve initially decreases until a minimum, then increases until a maximum and finally decreases again. The local minimum 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. The effect of the bias is smaller on the subjective norm than on the PGN because the attitudes taken into account for computing the subjective norm are closer on average to the considered agent's attitude.

These features of the curves can be related to the correlations shown on Figure 13:

- In the low attitudes (below the left dotted vertical line), the perceived group norm decreases and then increases, explaining a low correlation between attitudes and perceived group norm (0.18). Moreover, both norms first decrease and then increase, which explains a positive correlation (0.51);
- On the contrary in the high attitudes (above the right dotted vertical line), the perceived group norm is significantly decreasing, explaining a negative correlation (-0.80) with the attitudes. Moreover, the subjective norm first increases and then decreases, thus there is a low correlation between the norms (-0.11).

This analysis suggests that:

- the positive correlation between intention and perceived group norm within low attitudes is mainly driven by the positive correlation between perceived group norm and subjective norm;
- the negative correlation between intention and perceived group norm within high attitudes is mainly due to the negative correlation between perceived group norm and attitudes;

This analysis can be qualitatively summarized as follows. The bias on the perception of attitudes creates a border effect for both norms: in the vicinity of the extremes of the attitude range, the norms tend to decrease when the attitude increases. This border effect is weaker for the subjective norm, because the attitude of the close others is less likely to be very different from the considered agent's attitude. When the distribution of attitudes is not centred (say $\delta > 0$), in the low attitudes, both norms decrease and then increase together for a significant segment of attitudes. Hence, they are positively correlated. This explains

the positive correlation between the perceived group norm and the intention for low attitudes. On the contrary, in the high attitudes, because its border effect is stronger, the perceived group norm is mostly decreasing and is thus negatively correlated with the attitudes. This explains the negative correlation between the perceived group norm and the intention. These qualitative explanations hold for the parameter settings determined by the 3 other boxes of table 4.

Discussion

For a large set of parameter values, the model reproduces the main features observed in the case studies, namely a positive correlation between perceived group norm and intention in the low attitudes and a negative correlation in the high attitudes. For the selected parameter setting, in the low attitudes, the model also displays a positive correlation between the perceived group norm and the subjective norm, in accordance with the data.

However, for the same setting, in the high attitudes, the model shows a negative correlation between attitudes and perceived group norm which is not observed in the data. Nevertheless, this discrepancy between the case studies and the model might not be statistically relevant because the attitudes have been cut into low and high values, and in each set the variability is thus significantly diminished.

Overall, the approach therefore suggests that the anti-conformist intentions observed in the case studies might be due to biases in the perception of attitudes. This explanation is very different from other possible explanations related to the feeling of some kind of moral superiority. The idea behind this alternative explanation is that people with a high attitude perceive themselves as more advanced than the rest of the group and this reinforces their intention to increase their superiority hence their intention to act against the group norm. It can be related to the willingness to increase the rewarding feeling of being a pioneer. Therefore, this explanation postulates that for these people, a low perceived group norm has some causal effect on reinforcing the anti-conformist intention. On the contrary, in the explanation based on the perception biases, the anti-conformist intention is an accidental correlation, without any causality.

This paper only establishes the possibility of the explanation based on perception biases. It does not give any evidence for privileging it over the other explanation. Moreover, it is important to underline the following limitations of our work:

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

The relevance of the explanation of anti-conformist intention on perception biases can be further assessed by checking the model predictions on new case studies. For instance if the average of the distribution of attitudes is located close to the centre of the attitude scale ($\delta \approx 0$), then the features observed in the case studies presented in this paper should not be found (see figure 10). The model also predicts that if the average of attitudes is negative ($\delta < 0$) and is sufficiently large, then the anti-conformist intention should be expected in the low attitudes.

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Author contributions statement

G.D. designed the model and the experimental protocol for studying the simulations from the selected parameter settings, O.R. implemented the model and the ABC method and conducted the simulation experiments, K.K. and S.G. designed the questionnaire of the second case study and K.K. participated in the data collection, S.H., K.K., A.N. and S.G. identified the anti-conformist intentions in the case studies, discussed the model and its results. All authors reviewed the manuscript.

Additional information

To include, access to R code ? (Omid).

The authors declare no competing interests.