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Social comparison nudges: What actually happens when we are told what *others* do?

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ABSTRACT

Social comparison nudges, known to bring about behavioral change, rely on providing information to agents about other agents' decisions or expectations regarding specific actions. Although the procedure consists in transmitting true information, it classically implies a reduction of the transmitted reality: the information provided about others is an average, a proportion, a percentile. What would happen if, instead, full information were shared on what all others do (as nudged agents might legitimately expect), and what would this tell us about how nudges actually work? We assume that cognitive biases occur unintentionally when the information provided is incomplete. By mobilizing Akerlof's (1997) model of social distance, accurately describing polarization effects in social decision-making, we show how the nudge-information conveyed can then act as a decoy: effective in triggering behavioral change, but giving rise to renewed ethical considerations. We illustrate our conjectures with a randomized controlled trial in the context of pesticide use in agriculture in which winegrowers receiving full information about their co-workers' performances are compared with growers receiving the more conventional average performance. After showing that the two differ in their understanding of what others do, we show in the field that the latter nudge induces change unmet by the former.

Nudges, popularized by Thaler and Sunstein (2008), are now widely acclaimed as a way to reorient agents' behaviors in a direction decided upon by a libertarian paternalistic principal. Mobilized with the stated aim of improving the well-being of individuals, nudges would notably help them overcome the behavioral blocks and cognitive biases that, in everyday life, prevent them from making a choice consistent with their real interest (Kahneman et al., 1991). Among them, social comparison nudges, developed in line with the seminal works of Schultz et al. (2007) and Goldstein et al. (2008), consist in providing selected information to targeted agents about decisions made by other comparable agents.[1] In their review of the behavioral science literature, Richburg-Hayes et al. (2014) classified this use of social influence as one of the most frequently studied behavioral interventions. For example, informing individuals about their electricity consumption by comparing it to that of their neighbors has led to a decrease in overall consumption, of the same magnitude as if energy prices had been increased by 11–20 % (Allcott, 2011). This use of comparison proves much more effective than providing information, for instance, on how to reduce water consumption (Ferraro and Price, 2013) and, in another context, was found to be equivalent to a \$50–\$68 grant for participation in an in-home energy

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[1] Nudge implementation generally involves two types of intervention. One is when the environment or the presentation of options is altered, whether by the size or positioning of objects (see for example Bucher et al. (2016) on food choice), the addition of visual elements (e.g. Sueoka et al. (2022)), via default options (e.g. Friis et al. (2017)), or through salience and priming (see Wilson et al. (2016)), etc. The other—sometimes combined with the former—relies on providing information, such as pro-social messages (e.g. Kácha and Ruggeri (2019)) or, as discussed here, different kinds of social norm. Allcott (2011), Ferraro et al. (2011), Costa and Kahn (2013), Ferraro and Price (2013), Allcott and Rogers (2014), Banerjee (2017), Bartke et al. (2017), Wallander et al. (2017) have studied a wide range of applications, including charitable giving, consumer credit, environment and energy, health, marketing, nutrition, voting, and workplace productivity. A broader category of "norm-nudging" can encompass the provision of both what people do (or do not do) and what other people approve (or disapprove) of, distinguishing between descriptive and injunctive norms (Cialdini et al., 1991; Cialdini et al., 1990). The intervention in any case assumes that agents' decisions are socially interdependent in some way (see Bicchieri and Dimant (2022)). All these contributions have updated the earlier teachings of social psychology (Festinger 1954), which relied among other things on the notions of social norms and reference groups (Merton et al., 1950, Turner, 1987), and placing these behavioral experiments at the crossroads of economics, sociology and psychology.

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audit program (Holladay et al., 2019).[2] As the performance of a nudge crucially depends on its design and the attention paid to it by agents, one main objective of the literature up to now has been to measure and improve its efficiency, especially from a public policy perspective: how the effect can be enhanced or prolonged, for example by adding injunctive norms (Bonan et al., 2020), getting closer to the real reference group, controlling for a priori beliefs (Bartke et al., 2017), etc.[3] With regard to proper understanding of the tool, numerous experimental studies have sought to probe the modes of operation at work in these kinds of intervention. In particular, they have looked at the cognitive mechanisms behind convergence reactions triggered by learning what others are doing, including mimetic reflexes, anchoring effects, preferences for conformity and strategic responses to the revelation of third-party positioning.[4]

However, to the best of our knowledge, there are no studies looking further upstream, in particular at the role of mechanisms that can intervene at the moment when information is received (usually read) and interpreted by the agent, although this could provide possible new explanations of how nudges work. Indeed, nudge implementations frequently rely on reduced and simplified information when comparing to peers, such as providing a group average or median behavior[5] or—for binary outputs—a proportion.[6] Following Roels and Su (2014) and Dimant et al. (2024), we argue that this process is far from neutral, but our point will be more about the cognitive mechanisms involved, since it may give rise to a different understanding than if full information were provided.[7] Thus, by deliberately starting from the point of view of the *nudgees* rather than that of the *nudger*, we propose a possible explanation for how social comparison nudges work, based on a form of biased interpretation of the information transmitted.

To formally support our hypothesis of difference in agent behavior depending on the information given, we refer to a model by Akerlof (1997), which formalizes social interactions based on a gravitational principle. This model predates the literature on nudges, but provides a simple explanation for the transition from *individual* decisions to *social* decisions of economic agents. By integrating the "social distance" that each individual maintains in relation to "others", and the resulting externalities, Akerlof explains situations of polarization, in which individuals are locked into suboptimal decisions. We show that this integration of social relations into the utility perceived by economic agents provides an appropriate theoretical understanding of the way nudges may work, allowing us to answer the question of how to improve the efficiency of nudges while at the same time addressing the regulatory ethics vis-à-vis the "nudged" agent. Nevertheless, while social comparison nudges are now brandished with the explicit aim of unlocking suboptimal situations, Akerlof showed how this kind of social influence could, in fact, further jam up the system. The underlying mechanism of his model is based on the existence of localized social classes that reinforce an economic agent's own position (no longer "attracted" to individuals too socially distant from them). Resolving this apparent contradiction in the repercussions of other people's behaviors—generating either standardization or polarization—leads us to see that the efficiency of nudges may depend on the completeness of the information delivered, and thus on the more or less reliable interpretation of this information. As the efficiency of nudges may then be partly due to a misunderstanding of the conveyed information, even with no intention to mislead, it could represent a major point of attention regarding ethical issues.[8]

We propose an experimental protocol to test empirically the relevance of this conjecture by comparing two different schemes of intervention. The context of our study is the reduction of pesticide use in agriculture, a well-known deadlock situation in the productive sector. Agriculture has been an experimental field for nudges in recent years, aiming either at productivity growth (Duflo et al., 2011) or more frequently at shifting to pro-environmental practices (Czap et al., 2015; Kuhfuss et al., 2015; Wallander et al., 2017; Peth et al., 2018; Chabé-Ferret et al., 2019; Hrozencik et al., 2023). However, field experiments are scarce, due to the complexity of interfering with farms' strategies and outcomes, and to the limited number of agents in any uniform reference group. In collaboration with one of the largest Bordeaux cooperative wineries in France, we propose and set up a field experiment in order to highlight behavioral routines that might be modified without any specific financial incentive. We present the results of a randomized controlled trial (RCT),[9] comparing two forms of nudge that differ in terms of the amount of information provided to winegrowers regarding the use of pesticides by their peers: both receive the average level classically used in social comparison nudges, and one of the two groups additionally receives the full distribution of individual levels within the cooperative. In parallel, both nudges are subjected to a comprehension test using an external population, demonstrating that the classic nudge (average information) is more likely to induce these heavy users to think that they use more pesticides than others do.

[2] From a social welfare perspective, however, not detailed here, the moral costs borne by nudge recipients may often be minimized as shown, for example, by Allcott Hunt and Judd (2019).

[3] The use of descriptive norms as nudges is not always crowned with success, as Neckermann et al. (2022), among others, have shown in recent work, and particular attention must be paid to the effects of publication bias on the overall evaluation of these tools.

[4] See for example te Velde and Louis (2022) recently, or Jacobsen (2015) on mimicry, and McFerran et al. (2009) on the degree to which it is conscious; also Duffy and Lafky (2021) and Klick and Parisi (2008) on the strategic aspects of conformism.

[5] e.g. neighborhood average level of energy consumption in Schultz et al. (2007), Holladay et al. (2019) or Kim and Kaemingk (2021), sometimes added to a comparison with a given percentile, as in Myers and Souza (2020) or Ferraro et al. (2011) and Bhanot (2021) for water consumption.

[6] Share of hotel guests reusing towels in Goldstein et al. (2008), of charity donors in Bartke et al. (2017) or of people paying their tax on time in Hallsworth et al. (2017).

[7] Technically speaking, agents can be provided with a full reference distribution of others' choices or behaviors, such as the consumption level of every individual in the reference group. More simply, they can be provided with aggregate reference points, such as a group average. In reality, and even if divergent outcomes are to be expected from each of the two procedures (Roels and Su, 2014), all the examples from the literature mentioned above refer to the second category.

[8] Various ethical issues have been explored in the literature, notably concerning the infringement of individual liberties, institutional transparency, the possible technocratic and political abuses of these instruments or the lack of consideration of the consent of the targeted individuals (see for example Bovens (2009), Hausman and Welch (2010), Grüne-Yanoff (2012), Hansen and Jespersen (2013), Barton and Grüne-Yanoff (2015)Thomas and Jona (2017), Lin et al. (2017)). Most of these concern *heuristics-triggering nudges*; to our knowledge, the basic workings of *informing nudges* and the concomitant ethical concerns have met with fewer challenges.

[9] There is now a vast literature on randomized controlled trials, both in terms of their methodological positioning within experimental methods and their contextualization in empirical cases, across a large number of scientific disciplines. This type of protocol is used to measure the effect of a specific treatment on a group of individuals relative to a control group. Randomization legitimizes the interpretation of differences between groups with respect to the treatment applied (Kapur, 2017). Randomized controlled trials are often mentioned as a reference among experimental methods, particularly because of their relevance in determining causality and the external validity of the results obtained (Banerjee and Duflo, 2017; Roe and Just, 2009). Originating in the medical sciences, this methodology has progressively imposed itself in a large number of scientific fields, including economics and particularly development economics, bringing about an "RCT 'revolution'" (Banerjee and Duflo, 2017), although to varying degrees depending on the discipline (Cameron et al., 2016). In a recent article, DellaVigna and Linos (2022) analyzed 126 RCTs run by two Nudge Units in the United States involving 241 nudges and over 23 million participants in the space of less than 10 years.

In the RCT, while the latter group subsequently shows no difference from the control group in terms of pesticide use, the group exposed to the more conventional nudge does show differences: the largest drops in pesticide use are significantly more frequent, and the heaviest users reduced their pesticide use more than the control group, as evidenced by difference-in-difference tests. However, the effect does not persist over time, being no longer visible or even observable after the first year of observation, due to the contingency of the chosen field of application, and in particular its dependence on weather conditions.

The article is structured as follows. The first section presents the literature and the theoretical foundations of our debate based on the Akerlof's model of social distance. The second section presents the empirical framework chosen for our experiment, and the indicator chosen as the variable of interest. The third section presents the details of the protocol, the results of which are presented in section 4. The fifth section presents a general discussion of the results, with particular reference to their ethical aspects. The article concludes with a sixth and final section.

1. Theoretical background

The agricultural sector has long experienced significant socio-technical deadlocks in the use of fertilizers or phytosanitary products (notably illustrated by the work of Cowan and Gunby (1996)). It has also provided numerous testing grounds for behavioral methods to change these practices, including in the form of nudges. Duflo et al. (2011), for example, test nudge solutions to counter the under-utilization of fertilizers that is the root cause of farmers' lack of productivity. Conversely, in many developed countries where plant protection products are often overused, the main aim is rather to reduce the use of these products in order to protect the health of users and the environment and to meet the new health requirements of populations (consumers of food products or people living near agricultural areas that are highly exposed to spraying).

Numerous public policies have been implemented to limit the use of agricultural inputs in Europe, particularly in France, over the last twenty years, but their effectiveness is highly disputed.[10] The lack of encouraging results highlights both errors in the design of these public policies and a lack of alternatives to effectively reduce current pesticide use.

1.1. Nudges and non-monetary incentives for farmers

Ferraro et al. (2022) recently observed that experimental research in behavioral economics was less focused on profit-maximizing producers than on consumers. Experimenting with producers and measuring effects on observed behaviors rather than on hypothetical choices has indeed consequences in terms of interference with companies' strategies and outcomes, involves difficulties related to data access, and presents the risk that the impact in terms of behavioral change will be limited. Focusing on suitable reference groups (in terms of geographic location, crop orientation, distribution channels, etc.) also limits the number of observations, making impact significance difficult to determine. Nevertheless, we can now report on numerous academic efforts to identify new forms of non-monetary incentive to change farmers' behavior and direct them towards reducing pesticides, or reducing water use, or generally towards environmentally-friendly practices, including via the use of nudges: among others Czap et al. (2015), Kuhfuss et al. (2015), Wallander et al. (2017), Peth et al. (2018), Chabé-Ferret et al. (2019), Hrozencik et al. (2023). In recent years, numerous field or laboratory experiments have been carried out with farmers. The aim is often to study the impact of informational nudges or social norms on the adoption of best management practices schemes, notably in the USA or the EU (Czap et al., 2019; Thomas et al., 2019; Chabé-Ferret et al., 2023; Wallander et al., 2023). Some works focus on the particular importance of information framing (e.g., Davidson and Goodrich (2023), or the comparative effects of different types of network (Boun My et al. (2022) show, for example, that social comparison is more effective in a circle network than in a star network), or on how these interventions can be reinforced by combing them (Howley and Ocean, 2021) or by combining non-monetary and monetary incentives (Boun My and Ouvrard, 2019; Ouvrard et al., 2023). Finally, it is interesting to see that many works report the unintended effects or failures that these interventions can induce (Pellegrin et al., 2018; Okello et al., 2023; Chabé-Ferret et al., 2024).

1.2. Akerlof's model of social distance applied to social comparison nudges

Akerlof (1997) uses a fairly simple model to show how the externalities generated by social influences lead to permanent positional heterogeneity between economic agents in different subgroups located at suboptimal levels. The utility function of economic agents is based on a principle of gravity whereby individuals in a group are all the more attracted to each other when they are already close in their initial choices (their initial or inherited positions). By giving a sufficiently high value to this social dimension, and by integrating this value into the maximization of their utility, agents' decisions can be locked out of a socially beneficial equilibrium, even over the long term.

The utility function used by Akerlof consists of two components (for the sake of brevity, appendix A.1 details the mathematical formalization of the model, as well as the developments and demonstration described below).

$$U_i = \sum\nolimits_{j\neq i} e/\left[\left(f+\left|x_{0i}-x_{0j}\right|\right)\left(g+\left|x_{1i}-x_{0j}\right|\right)\right] + \left[-ax_{1i}^2+bx_{1i}+c\right] \quad (1)$$

While the second quadratic component is an "intrinsic" utility linked to the individual decision to use the resource, showing an intrinsic optimum at $b/2a$, the first component is a utility related to the social decision regarding this level of resource use (expressed through a gravity principle). Indeed, this decision has consequences for the individual's social positioning in the group. More precisely, the positive externalities linked to social influences will be all the stronger the closer the individual's decision is to that of others, especially those who were already close (the gravity principle).

Akerlof shows with a three-agent example that, depending on the value of the parameters of the equation, maximizing this form of utility can lead two agents 1 and 2, distant from the intrinsic optimum but close to each other in inherited, to simply swap places in period 1, without getting any closer the intrinsic optimum.

Now, what happens with nudges, in a situation where the position of others is initially unknown? With this model, transmitting an average behavior should not provide any information on the diversity of others' behaviors, in particular the behavior of those to whom each agent seeks to relate (i.e. the second part of the utility function). Then, the nudge

[10] In France, the Cour des Comptes (Court of Auditors) ruled in 2019 that despite a decade of actions mobilizing significant public funds, the State's plans to reduce the use and effects of plant protection products had not achieved their objectives. In particular, the 50 % reduction in the use of pesticides targeted between 2008 and 2018, postponed from 2016 to 2025, was offset by a 12 % increase between 2009 and 2016 (Cour des Comptes, 2019 – ref. S2019–2659 of November 27, 2019, "Le bilan des plans Écophyto"). A few months later, the European Court of Auditors ruled that despite the EU's commitment to halt biodiversity loss by 2020 with, to this end, a planned allocation of 66 billion euros by the Commission under the Common Agricultural Policy (CAP) between 2014 and 2020, the contribution provided by the CAP had not stopped the decline (European Court of Auditors - Special Report 13/2020). These successive failures have led some regions to redirect public policies towards more local actions, notably with the development of living lab methodologies to better identify winegrowers' behavioral barriers. This is notably the case for the VitiREV program, estimated at €45 m over 2020–2017, for the wine regions of Nouvelle-Aquitaine (Bordeaux, Cognac, Bergerac, Armagnac, etc.).

should not operate. However, let us imagine that the transmission of an average is accompanied by an interpretation bias, and that it is assimilated as information about the behavior of others as a whole. In particular, if it leads them to assimilate the *behavior of others* to *average behavior*, then eq. (1) becomes eq. (2) and it is easily demonstrated then that the nudge should operate in the way that is expected (see appendix A.1).

$$U_i = [n.e/(f+|x_{0i}-\mu_{0i}|)] \times [1/(g+|x_{1i}-\mu_{0i}|)] + [-ax_{1i}^2+bx_{1i}+c] \tag{2}$$

Thus, considering this model, we can see that nudges may owe their functioning to the fact that the information conveyed acts as a *decoy*, giving a false view of reality regarding the decisions of others. It also shows how "class solidarity" phenomena can explain why revealing the positions of others does not always produce the expected effect of incentives to social comparison. If the exact positioning of each of the other individuals were given, the bias would no longer be present and the nudge would no longer have any effect.

These are the hypotheses we propose to test experimentally in this article.

2. Experimental setting: The use of pesticides in agriculture

2.1. A monitoring indicator to measure pesticide use

In the literature, different methodological approaches have been used to measure the environmental impacts of agriculture, and more specifically to quantify pesticide use: risk mapping, life cycle analysis, development of agri-environmental indicators (Payraudeau and van der Werf, 2005). Nevertheless, in view of the difficulty of ascribing credibility to composite toxicity indicators in relation to different living species (Bockstaller et al., 1997; van der Werf, 1996; Levitan et al., 1995), it is often more objective to simply account for the doses of pesticides, whatever they may be, applied by farmers. In this framework, the Treatment Frequency Indicator (TFI) for plant protection products is defined as the number of reference doses (a level subject to regulatory validation when a marketing authorization is awarded) applied on a cultivated plot during one growing season (Pingault et al., 2009). It was originally based on Danish research (Gravesen, 2003), which was later adapted in different countries (see Champeaux (2006) and Aubertot et al. (2005) for France). This indicator is more precise than a raw "headcount" of treatments carried out, since it takes into account the dosages chosen and the areas actually treated, and is also easily understood by farmers.[11]

Formally, the TFI corresponds to the ratio between the dose of commercial product actually applied at each pass and a reference or standard dose, taking into account the surface area treated. The calculation method is as follows:

$$TFI = \sum \frac{\textit{applied dose}}{\textit{standard dose}} \times \frac{\textit{treated area}}{\textit{total area}} \tag{4}$$

The TFI thus calculated corresponds to an annual value, always positive, giving a measure of the phytosanitary pressure exerted on the environment during an agricultural season and aggregating all the different phytosanitary products used by the farmer. Finally, it should be noted that different classes of pesticides can be included in the calculation of the TFI. Their doses can thus be added together and grouped into categories: "TFI Fungicides", "TFI Herbicides", etc.

We will limit ourselves to insecticides and fungicides, which account for almost all treatments in viticulture (Ambiaud, 2016).

[11] See Pingault et al. (2009) or Fuentes Espinoza et al. (2018) for a more detailed presentation of this indicator.

2.2. Arbitration by winegrowers regarding the use of pesticides

To formalize the choice of the quantity of pesticides used by a winegrower in a given year, it can be considered that the winegrower derives a utility U from a quantity x of pesticides used (the TFI being the indicator of this quantity). There is then an individual trade-off made by each winegrower between the costs of purchasing and using these pesticides and the benefits provided by their use, generating an inverted U-curve for U, corresponding in fact to Akerlof's intrinsic utility (see Fig. 1).

The increasing part of this curve expresses the need to increase production yields and at the same time protect crops to ensure a minimum yield. The decreasing part expresses the idea that the use of pesticides (treatment dates, doses used on plots, etc.) cannot, however, develop infinitely.[12] Several reasons can be put forward to explain this formalization and the concavity of utility. First of all, the inefficiency and toxicity of excessive plant protection. Second, the cost of treatment, which in some cases can be significant, particularly if the cost of labor or energy is taken into account. Moreover, there are currently several factors that are difficult to measure concerning the health risk linked to spraying, environmental protection and societal pressure to reduce pesticides. The influence of health risk on farmers' reluctance to overuse pesticides has been studied by Liu and Huang (2013). These intangible factors have become prominent in agriculture, raising awareness in the productive sector and leading to a deep questioning of production methods.[13]

All these arguments explain why there is an "individual optimal level", TFI*, for each winegrower. Looking solely at the profit of the winegrowers, with a level of use below TFI*, the marginal increase in profit is greater than the cost of marginal units of additional pesticides, and beyond TFI*, the profit decreases due to the cost of over- or underused pesticides. Nevertheless, especially under Protected Designation of Origin (PDO) wine sector, we can easily assume that the vast majority of winegrowers are initially above TFI*, to a greater or lesser extent depending, among other things, on farmers' risk aversion and work organizations (Gent et al., 2011; Delière et al., 2015). Indeed, under PDO, their yield is limited by regular specifications, to a level well below the vine's productive potential (limiting yield improves the quality of the end product). Winegrowers therefore set themselves the goal of reaching this maximum authorized yield (especially in a cooperative where winegrowers are financially incentivized to reach the yield defined in the chosen contract), and secure it through the extensive use of pesticides, (i) because their cost is low: based on Bordeaux benchmarks, the cost linked to pesticide protection was recently estimated at less than 4 % of the cost price of a bottle, or a few cents (Davy, 2020), and (ii) because their effectiveness is very high (in ideal technical and climatic conditions, certain products approach zero sanitary risk). Given that the means of knowing the level of local parasite risk in real time, which could help curb the use of pesticides, are currently highly imperfect (Chen et al., 2018; Aubert et al., 2022), and that failure to carry out a single treatment during a period of high fungal pressure can lead to substantial losses, an effective, risk-minimizing strategy is to

[12] It should be noted here that we are considering a function of utility in relation to the quantity of pesticides used, and not a function of utility in relation to earnings, which is more classically debated in the literature on agricultural economics (see, for example, Tanaka et al. (2010) or Bocquého et al. (2014)). The arguments given here are based mainly on technical rather than economic elements, to do with the increasingly marginal effect of pesticides on yield: beyond a certain threshold, the cost of their use predominates over the expected increase in yield, as the yield biologically reaches an impassable plateau.

[13] In France, the "Phyto-Victimes" association was created in 2011 by the farmers themselves to support their peers in preventing the dangerousness of plant protection products and to promote alternatives that no longer endanger the health of professionals and their families.

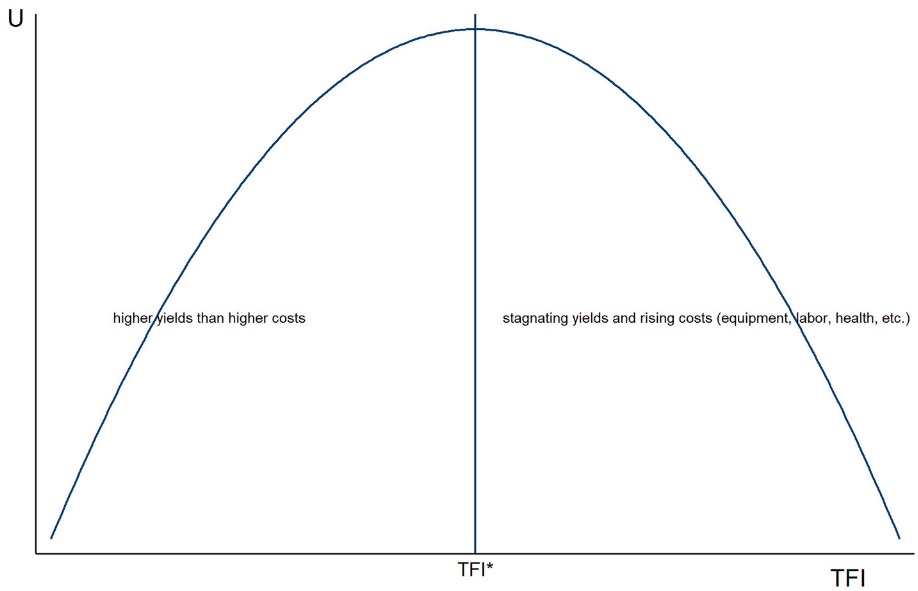

Fig. 1. Winegrower's utility expressed as a function of their Treatment Frequency Index.

protect the vineyard constantly during the vegetative period, regardless of the level of risk, i.e. above the theoretical necessary and sufficient level (TFI*), which is unknown to growers. This strategy mechanically leads to unnecessary treatments, but not identified as such at the time of the decision. Arguments in support of the widespread adoption of this strategy among winegrowers include the following:

- Compared with other crops, large quantities of pesticides are applied to vineyards; for example in France, the average TFI was 13.5 in 2016 versus 4.9 in 2017 for wheat (Fouillet et al., 2022). French viticulture (mostly under PDO) accounts for around 13 % of national pesticide expenditure for only 3–4 % of French agricultural land (Aubertot et al., 2005; Butault et al., 2010);
- Numerous studies have shown that there is considerable scope for reduction without lowering yields, notably through the use of decision-support systems (Kuflik et al., 2009; Gil et al., 2011; Delière et al., 2015). Recently, a pesticide decision-support tool tested in the Bordeaux region, making it possible to reduce treatments as much as possible while preserving the yield objective of conventional (i.e., non-organic) winegrowers (by modeling pathogen development and integrating weather data) showed that the level of TFI achieved on the experimental site was at the 2nd percentile of winegrowers in the region (Lefebvre et al., 2023).

Consistent with Akerlof's model, we propose to go beyond this initial technical approach, with its parabolic characterization of utility, by integrating the social influence of pesticide use. In what follows, we will assume that (i) winegrowers integrate the relative position of their peers into their utility, at least because the position of others may reveal strategic information about pest monitoring[14]; and (ii) they are more influenced by those whose practices are close to their own, for example in accordance with a confirmation heuristic (on which, see Wason (1960) and Jones and Sugden (2001)).

3. Protocol

In this section, we test our hypothesis of an interpretation bias induced by the transmission of a group average, and detail the implementation of a randomized controlled trial. To set up the experiment, access was granted to data from one of the largest wine cooperatives in France. The choice of a cooperative winery rather than a population of independent farmers provided a sample with relatively similar technical and economic constraints, as each winegrower within the cooperative shared the same processing and marketing circuit (little heterogeneity due to potentially differentiated behavior).[15] A cooperative also guarantees a certain geographical proximity and stabilized internal social relations. Moreover, the information provided by the cooperative concerning individual pesticide-use levels is highly credible (reduced risk of manipulation) since the winegrowers have every interest in sharing their actual treatment data with the cooperative's technicians who, in return, advise them on the practices to adopt to ensure the targeted yield is achieved. The intervention was designed with the full agreement of the cooperative's president and its director.

We first present the design of a protocol (sub-section 3.1) and test the interpretation bias induced by the information conveyed (sub-section 3.2). The randomized controlled trial set up (sub-section 3.3) will then compare the effects of (i) providing each winegrower with complete information on the position of the other winegrowers and (ii) providing each winegrower with a single value, namely the group average.

The observation period of the groups is spread over a full crop year, in order to observe the global quantity of pesticides used by winegrowers in 2016 and the following years, compared to that calculated

[14] In the case of agriculture, analyses based on a spatial approach have been conducted on European countries (Schmidtner et al., 2012; Allaire et al., 2015) to understand the drivers for the diffusion of organic agriculture. Alongside economic factors, a certain degree of spatial dependence is observed, with agglomeration and "contagion" effects between farmers.

[15] The winegrowing industry is characterized by a very wide diversity of valuation methods, depending on whether producers are valuing a volume of grapes, a degree of alcohol, a volume of must, bottled wine, bulk wine, etc., and by products (PDO or non-PDO wine, liqueur wine, brandy, etc.). The choice to focus the treatments on winegrowers who were suppliers to the same PDO wine cooperative enabled us to control this aspect, to give greater weight to the notion of a reference group and thus to the social norm transmitted.

before the experiment in 2015. Pesticide uses were monitored up to 2019.[16]

3.1. Treatment design

The cooperative selected 247 winegrowers likely to digitally provide the elements (type of phytosanitary products and quantity used, with the reference dose of the molecules used) that would enable us to calculate an individualized TFI level. The descriptive statistics on the 247 TFIs calculated for the year 2015 are given in Table 1. Fig. 2 shows the graphical distribution of the values. It is thus verified that there is a certain heterogeneity of behavior as regards the use of phytosanitary products in the group of winegrowers (TFIs range from 6.18 to 28.43).

Regarding potential selection bias, a reading of the TFIs in our sample shows that they are fairly representative of the diversity of TFIs in the reference wine-growing area (Bordeaux). The authors obtained permission to access the results of the "Cultivation practices in viticulture" survey carried out by the French Ministry of Agriculture. These surveys are carried out only every three years. The distribution of TFIs from the 546 Bordeaux plots observed in these surveys, over the nearest survey year, i.e. 2016 (Ministère de l''Agriculture SSP, 2016), shows a mean of 16.47 and a standard deviation of 4.29, compared with 17.17 and 4.55 for our control group in the same year (a group unaffected by our treatment), or 16.41 and 3.81 for our total sample over the year 2015. With regard to surface area, the Agricultural General Censuses carried out by the administration (every 10 years) indicate that our sample was made up of slightly smaller farms than those in the reference basin: an average of just over 11 ha for our sample, compared with references of between 13 ha in 2000 and 19 ha in 2020 for all Bordeaux winegrowing farms (Agreste Nouvelle-Aquitaine Etudes, 2020). However, the latter averages include all Bordeaux winegrowing farms, not just cooperative farms, which are often smaller (on average, the "Cultivation practices in viticulture" survey cited above shows a ratio of 0.6 between the two).

Two different types of information letters, noted "Full info" and "Average info" below, were designed (see appendices A.3 and A.4). In the two letters, information is provided about the recipient's TFI, initially unknown, plus the average TFI of all winegrowers (247 winegrowers), i.e. 16.36. To test our hypothesis, letter "Full info" included an addition: a histogram showing the complete distribution of TFIs (analogous to the one in Fig. 2), thereby canceling out any potential ambiguity of interpretation of the average. As providing this histogram could also modify the salience of the initial information provided, the histogram was placed after the information—common to Groups "Full_info" and "Average info" —about their own positions and the average position. Equally, it should be noted that, at the time of the experiment, calculation of TFIs was rare, as tools were not yet developed for the purpose. Although growers might have had beliefs about their own intensity of pesticide use (as discussed later in section 4), we assumed that they did not have any particular TFI standards in mind, and that simply providing their TFI level was not instructive per se, in particular in terms of prior beliefs, except when compared to the average TFI level, making the difference between the two figures the one real piece of information,

Table 1
Descriptive statistics of the TFIs of the 247 winegrowers in 2015.

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
TFI 2015	247	16.36	3.81	6.18	28.43

[16] The data collected and exchanged between the cooperative winery and the authors is subject to confidentiality. Access to raw but anonymized data can nevertheless be requested from the authors, and will in any case be the subject of an agreement.

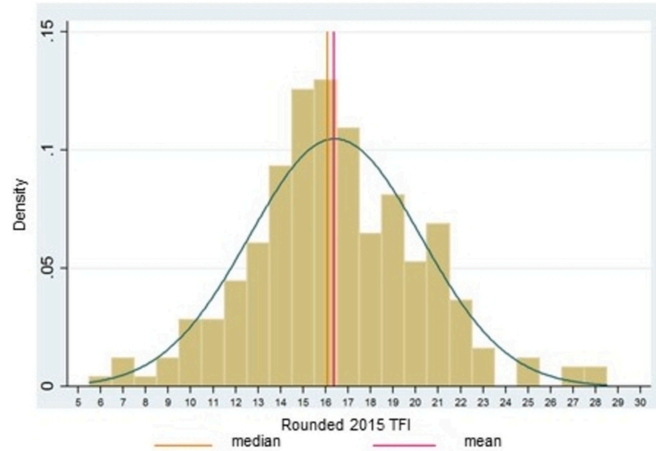

Fig. 2. Distribution of TFIs of the 247 winegrowers in 2015.

which was evenly provided to Groups "Full info" and "Average info".

It should also be noted that, in order to create an overall effect on the average TFI by nudging the heavy users but not the light ones, a difference was introduced (symmetrically applied to both Groups, "Full info" and "Average info") between the letters destined for winegrowers initially located below the average pesticide use (the "virtuous" group) and those located above, in order to curb the "boomerang effect". This perverse collateral effect, well illustrated in the article by Schultz et al. (2007), consists in virtuous individuals also moving towards the group average, diluting the overall effect of the intervention when its effects on the entire group are considered. One way to avoid this is to convey, in addition to the *descriptive* social norm, an *injunctive* norm, that is, a message of a moral nature that praises the already virtuous agents (Schultz et al., 2007). In our case, in addition to applying a red color gradient to the histogram, we opted to replace, for virtuous agents, the sentence "*You have thus performed about* X *fewer treatments than the average member*" by "*You therefore*<u>managed to perform</u>*about* X *fewer treatments than the average member*".[17]

The letters were drafted on the model of the cooperative's internal mail, with its own illustrations and dedicated header. Sample letters were first tested with a population of 21 winemakers who were not part of our study sample. This test led us to simplify the histogram in particular and to add a short paragraph to enable understanding at the top of the figure (see Appendix A.3). It was indeed crucial that the histogram be easily understood by readers, it being the differentiating feature between the two letters, so that possible differences between Groups "Full info" and "Average info" could not be imputed to difficulties of understanding.

3.2. Confirming the activation of an interpretation bias

Using the two sample letters now drafted, we first started by testing our hypothesis of a different interpretation of the information given, through an online questionnaire submitted to a population outside our study sample (online survey via a polling company). Two classes of Internet users were formed: Class A, which received the standard "Full info" letter from the randomized controlled trial, i.e. the letter revealing all the individual positions (101 subjects interviewed), and Class B, which received the standard "Average info" letter, i.e. the letter revealing only the average position (108 subjects interviewed). These 209 Internet users were invited to put themselves in the position of winegrowers receiving a letter informing them about their level of

[17] The emphasis here on the terms "managed to perform" is added for clarity and was obviously not used in the letter.

Table 2
Highlighting the interpretation bias induced by incomplete provision of information.

"You use more pesticides than the other winegrowers in the cooperative"	Class A	Class B
Yes	48.5 %	62.0 %
No	51.5 %	38.0 %

pesticide use by means of a TFI. For this test, we set the individual TFI level at value 19 for all. According to this letter, all 209 subjects were therefore in a situation of above-average processing intensity (TFI = 19), that is, above 16.36.

After the letter was read, a comprehension test was put to the Internet users, proposing four non-mutually-exclusive options, listed below. The option of interest for testing our hypothesis is the third one:

"Among the following suggestions, check the boxes corresponding to the actual information learned in the situation you have just read (several check boxes are possible):

- *The cooperative has 247 winegrowers.*
- *You produce wine under a Protected Designation of Origin (PDO).*
- *You use more pesticides than the other winegrowers in the cooperative.*
- *The director of the cooperative would like the winegrowers to increase their use of pesticides to better protect their vines."*

According to our hypothesis that bias is induced by providing the mean as the only available information, the third proposition, ambiguous in its framing, should be more frequently checked in Class B.[18] The results are presented in Table 2.

We can see that the answer "yes" is more frequent in Class B ("yes" / "no" ratio of almost 2/3) than in Class A ("yes" / "no" ratio of a little less than 1/2). A statistical test (probit) shows that the statement does have a significant effect ($p = 0.049$) on the answer to this question: the statement received by Class B, corresponding to the letter received by Group "Average info" in the randomized controlled trial, makes the answer "yes" more likely. The very design of Letter "Average info", equivalent to Letter "Full info" save for the histogram, makes them more likely to perceive themselves as being in a more unfavorable situation than that of other members.

An exploration could be carried out of the real heuristic at work in this situation, between representativeness, availability and anchoring, with the scopes of these three heuristics overlapping in part (Gigerenzer, 1996). We opt here for an availability heuristic insofar as individuals will deduce a frequency from a number of isolated observations that are immediately cognitively available. Here, this frequency is deduced from the sole knowledge of the mean observation. Although it may be debatable, this choice does not modify our reasoning. Indeed, the essence of our argument rests on the optical effect induced by the transmission of such information and the interpretation that individuals make of it. The next question, addressed by the following section, is the robustness of this effect when transposed to a real-life situation, and the impact on winegrowers' choices.

3.3. Treatment set-up

The protocol then involved sending Letters "Full info" and "Average info" to two equivalent and randomly constituted groups of growers, called Group "Full info" and "Average info" respectively. To control for cyclical effects due to natural changes in TFI between 2015 and 2016, a third equivalent group, called Group "Control", was also created. The pressure of fungal diseases varies from year to year, leading to an equivalent variability in plant protection efforts, and thus in TFIs (Ministère de l'Agriculture et de l'Alimentation, 2021).

Our initial set of 247 winegrowers was then divided into three groups:

- A group of 82 winegrowers receiving Nudge Letter "Full info", called Group "Full info"
- A group of 83 winegrowers receiving Nudge Letter "Average info", called Group "Average info"
- A group of 82 winegrowers not receiving a letter, called Group "Control".

Under this arrangement, as presented later in the results, Group "Control" serves as a control group for Groups "Full info" and "Average info" (up to the letter), just as Group "Average info" serves as a control group for Group "Full info".

Given the dispersion of TFIs (3.81), we felt it was reasonable to consider a decrease of 1.636 (or 10 %) in the average TFI in the treated groups compared to the control group. Using Stata's power command, we determined that 87 growers per group were needed for this effect to be significant at the 5 % level (68 at the 10 % level), for a testing power of 80 %.[19] With 82 growers per group, we are not far off: the power of the test is 78 % at the 5 % significance level.[20] Randomization was then ensured by a stratification scheme according to the observed variable, the TFI. We adopted the principle of pairwise matching, presented notably by Duflo et al. (2007). In our case, because we have three groups and not two (two action groups and a control group), we performed matching in trios rather than in pairs. After being ordered by the value of their TFI in 2015, trios were formed and, within these trios, each winemaker was randomly assigned to one of groups "Full info", "Average info" or "Control". A rereading was then carried out with the cooperative's agents to take into account potential proximity between agents, to avoid spillover effects between groups, and the balancing of the sub-sample receiving the cooperative environmental diagnostic questionnaire (which will be presented later in the Discussion section), leading to a few one-to-one swaps. An analysis of variance shows that the heterogeneity of the initial TFIs between groups is quite negligible (F = 0.02 and Prob>F = 0.982), making them comparable for the TFI in 2015.[21]

The cooperative itself sent out the letters in order to make the transmission of this information credible and unsuspicious. The 165 letters were sent on Friday, April 8, 2016, for reception by the winegrowers on Monday, April 11, 2016 (just before the start of the treatment season). The winegrowers were subsequently neither influenced nor even contacted during the experiment.

The pesticide treatment data from the cooperative's membership for 2016 was made available on January 16, 2017. Only 230 observations could be collected, as some winegrowers did not submit their treatment

[18] As the question was expressly ambiguous, there was no right or wrong answer. Nevertheless, the answers given by Class A were based on a higher level of available information, and therefore serve as a baseline against which we can measure the difference in interpretation with Class B.

[19] The power of a test is the probability of rejecting the null hypothesis when the null hypothesis is false. The default in Stata is 80 %.

[20] Increasing the number of growers would have meant going outside the cooperative, which would have posed other control problems. We therefore decided to keep it this way.

[21] We also show that the three groups formed do not show significant differences in two possible covariates, namely (micro)geographical positioning—local pathogen attacks, soil quality or weather conditions that might partly explain some treatment heterogeneities—and the size of the area cultivated per farm, another possible factor of heterogeneity in terms of phytosanitary strategy (Diederen et al., 2003; Whittaker et al., 1995).

data to the cooperative in time.[22] Group "Control" in particular lost 10 observations (compared to 3 and 4 respectively for Groups "Full info" and "Average info"). A new variance analysis of the TFIs ensured that the three groups remained insignificantly different in terms of initial TFI, location and area.

4. Results

We adopt two empirical strategies to statistically identify the impact of the treatments, by successively computing (i) a "difference-in-difference" estimation and (ii) an analysis of the magnitudes of the year-to-year variations in TFI.

With Strategy (i), we will see that the asymmetrical effects of the two nudges are particularly visible for the subgroup of most heavy users who reduced more their TFIs in Group "Average info". Strategy (ii) will provide further insight into the differing effects of the two nudges, showing that the largest TFI drops were more frequent in Group "Average info".

4.1. Descriptive results

The overall changes in TFIs between 2015 and 2016 are shown in Table 3. The two lower panels of Table 3 display the same statistics for growers who had the highest and lowest TFIs in 2015, i.e. 0, 1 and 2 points above and below the global average (16.36) respectively. In each case, they are almost evenly distributed among the three groups (no statistical difference between groups, see Table A.1 in appendix A.5).

We complete this first descriptive approach of the results with a comparison of the distribution of TFI changes from 2015 to 2016, between groups. Table 4 shows the comparative variations in TFI by decile, and Fig. 3 compares the shape of the distributions of this evolution by group in pairs. Taken together, these elements suggest that the Full info group has behaved more closely to the Control group than the Average info group to the Control group. The next two sub-sections analyze these differences statistically.

4.2. Difference-in-difference estimation

Starting with Strategy (i), we first perform a "before-after" (BA) estimation that compares the 2016 average TFI to that of 2015. The following equation is estimated for each of our three groups, where each observation is the TFI for Farm i in Group G observed in Year t.[23]

$$lnTFI_{it}^{G} = \alpha_G + \beta_G Post_t + \delta_i + u_{it}^{G} \quad (5)$$

where δ_i is a farm-fixed effect. In this equation, the before-after estimate of the effect of the treatment, as a percentage, is given by β_G. The equation compares the average TFI for 2016 (after: $Post_t$ is an indicator variable which equals 1 for $t = 2016$ and 0 for $t = 2015$), with that of 2015 (before).[24]

We then perform a "difference-in-difference" (DiD) estimation, first taking Group "Control" as the control for treated groups "Full info" and "Average info" ($T = 1$ or 2 and $C = 3$), then Group "Average info" as the control for Group "Full info" ($T = 1$ and $C = 2$). In the first case, we assume that Group "Control" shows what Groups "Full info" and "Average info" would have shown in the absence of intervention.

Table 3
Changes in TFIs between 2015 and 2016 – Mean (Std. Dev.) and mean comparison tests.

	Total	Group "Full info"	Group "Average info"	Group "Control"
All growers				
N	230	79	79	72
TFI:				
2015	16.406	16.275	16.476	16.474
	(3.812)	(3.994)	(3.896)	(3.557)
2016	16.807	16.920	16.365	17.170
	(4.418)	(4.126)	(4.996)	(4.546)
Diff.	0.401	0.645	−0.111	0.696
P-value	(0.172)	(0.166)	(0.838)	(0.179)
Heavy users				
TFI 2015 > 16.36				
N	110	35	41	34
Diff.	−1.077	−1.178	−1.439	−0.537
P-value	(0.026)	(0.092)	(0.090)	(0.583)
TFI 2015 > 17.36				
N	83	26	28	29
Diff.	−1.635	−1.255	−2.913	−0.741
P-value	(0.004)	(0.154)	(0.001)	(0.509)
TFI 2015 > 18.36				
N	67	20	24	23
Diff.	−2.253	−2.218	−3.749	−0.722
P-value	(0.001)	(0.029)	(0.000)	(0.602)
Light users				
TFI 2015 < 16.36				
N	120	44	38	38
Diff.	1.756	2.095	1.321	1.799
P-value	(0.000)	(0.000)	(0.043)	(0.000)
TFI 2015 < 15.36				
N	93	34	31	28
Diff.	2.080	2.375	1.880	1.943
P-value	(0.000)	(0.001)	(0.001)	(0.000)
TFI 2015 < 14.36				
N	62	24	21	17
Diff.	2.545	2.427	2.548	2.706
P-value	(0.000)	(0.007)	(0.000)	(0.000)

Note: Mean comparison tests for no difference in means estimated from two paired samples (ttest Stata command).

Table 4
year-to-year variation: distribution by group.

	Group "Full info"	Group "Average info"	Group "Control"
Q(10)	−5.050	−5.745	−4.000
Q(20)	−2.229	−3.259	−2.020
Q(30)	−0.672	−2.300	−1.025
Q(40)	0.000	−1.309	−0.310
Q(50)	0.692	0.293	0.818
Q(60)	1.322	1.000	1.420
Q(70)	2.344	1.726	2.030
Q(80)	3.584	3.188	3.161
Q(90)	6.090	5.330	5.103

Notes: Percentiles of year-to-year variation of TFI.

[22] The monitoring of phytosanitary treatments by the cooperative winery was still a recent activity in 2016. The setting up of a computerized database dates from 2014. By law, treatment records must be kept and must be available for inspection by the State phytosanitary services. However, this information remains private data that the winegrower is entitled not to disclose to other third parties, including the cooperative winery. In 2015–2016, the data collection system was still being tested and the cooperative winery preferred not to use coercion against the few members who did not transmit their data in time. The loss of these 17 datasets is nevertheless small in relation to the size of the overall group and it is likely that their inclusion would have only marginally altered the results obtained and presented below.

[23] The randomization process ensures that α_G is almost the same in all three groups. Indeed, it is 16.27, 16.48 and 16.47 in groups "Full info", "Average info" and "Control" respectively.

[24] The TFI is thereafter expressed in logarithm in order to attenuate the impact of a few extreme values, but parallel tests are carried out with the TFI in level (and presented in appendix: Table A.3) and give similar results.

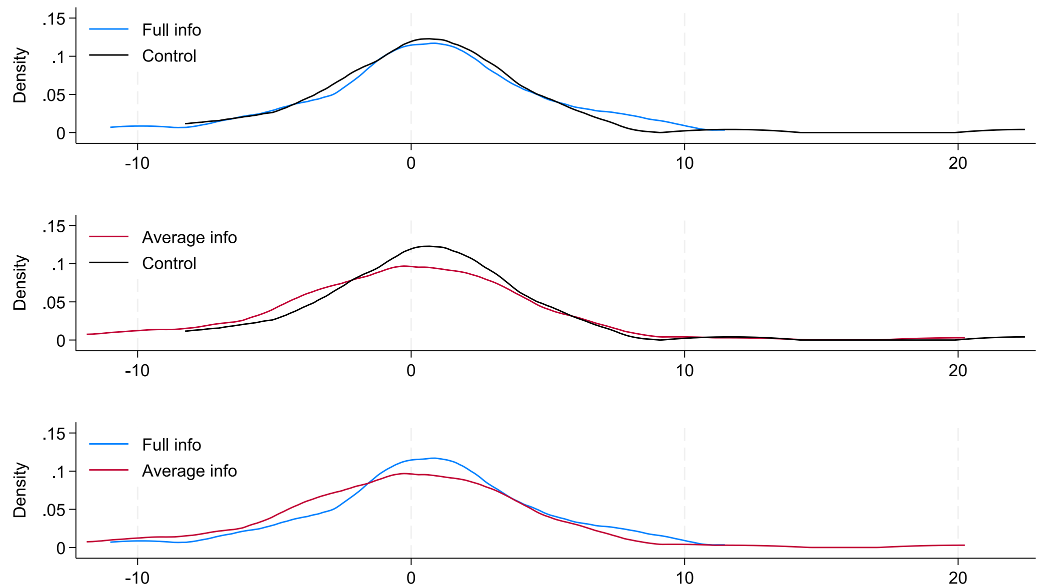

Fig. 3. Two-way comparison of TFI evolution distributions between 2015 and 2016.

Similarly, in the second case, Group "Average info" is assumed to show what Group "Full info" would have shown had it only been informed of its position relative to the mean (i.e. no histogram). We estimate the following model:

$$lnTFI_{it}^{G_{T,C}} = \alpha_{G_{T,C}} + \beta_{G_T} D_{G_T} \times Post_t + \gamma_{G_{T,C}} Post_t + \delta_i + u_{it}^{G_{T,C}} \quad (6)$$

where $G_{T,C} = \{\text{treated group} + \text{control group}\}$ and $G_T = \{\text{treated group}\}$, and D_{G_T} equals 1 for the treated group and 0 for the control group. The average impact of the treatment on the TFIs of the treated groups, as a percentage, is given by the coefficient β_{G_T} associated with the interaction term $D_{G_T} \times Post_t$.

Table 5 presents the results.

The upper panel reports the estimates obtained for the entire sample of growers ($N = 230$). On average, Group "Control" growers increased their TFI by almost 4 %. This increase reflects the less favorable conditions encountered in 2016 than in 2015, as relayed in the winegrowers technical bulletin (Laveau, 2016). Those in Group "Full info" did the same (+4 %), while those in Group "Average info" reduced their TFI by 1.5 % on average. In the DiD specification, the estimates show that on average the treatment had no effect on Group "Full info" and decreased the TFIs in Group "Average info" by more than 5 %, as compared to Group "Control"; it increased the TFIs of Group "Full info" by more than 5 % as compared to Group "Average info". None of these estimates is significant though, indicating a large heterogeneity within each group (note the relatively large standard errors for the control group BA estimates).

The three lower panels display the results obtained for the growers with the highest TFIs in 2015. This time, many of the BA estimates are large and strongly significant, especially in Group "Average info" (e.g. -17.5 % as compared to -7 % for the two others for growers 1 point above the average in 2015). The DiD estimates are insignificant except for growers 2 points above the average in 2015, who significantly ($p = 0.058$) reduced more their TFI as compared to Group "Control" ($\beta_{G_T} = -15.027$). The parallel results obtained for growers with the lowest TFIs in 2015 are not reported here for brevity but in appendix A.5, Tables A.2 (lnTFI) and A.4 (TFI). They show less asymmetry between groups (overall, the mean TFI of all groups increases, although this increase seems to be somewhat contained for the group of winegrowers below 16.36 in 2015, without this trend being confirmed for the sub-groups still below) and no significant DiD estimates, whatever the situation.

4.3. *Magnitudes of the year-to-year variations in TFI*

Following with Strategy (ii), we compute the year-to-year variation in TFI for each grower, $\Delta TFI_i^G = lnTFI_{i,2016}^G - lnTFI_{i,2015}^G$, and define two binary variables indicating whether a grower belongs to the first quartile of the resulting distribution (those who reduced their TFI the most), or to the fourth quartile (those who increased their TFI the most). We then regress these two variables onto two indicator variables for Groups "Full info" and "Average info".

Table 6 reports the results. 19.4 % of growers in Group "Control" (the constant term in the regression) belong to those who reduced their TFI the most; they are only 0.8 percentage points (pp) more in Group "Full info" (insignificant) but 16.0 pp. more in Group "Average info" ($p = 0.027$).

Again, the coefficient is particularly strong for the subgroup of growers 2 points above average in 2015 (coeff = 0.275, $p = 0.059$ for Group "Average info" compared with an insignificant coeff = 0.009 for Group "Full info") but the trend also holds when considering light users (coeff = 0.211, $p = 0.011$ for Group "Average info" compared with an insignificant coeff = 0.061 for Group "Full info", considering growers below average in 2015). Conversely, there is no significant difference across groups for those who increased their TFI the most. Table A.5 (see appendices) reports the same results as Table 6, but defining $\Delta TFI_i^G = TFI_{i,2016}^G - TFI_{i,2015}^G$.

This confirms the existence of a specific effect for Group "Average info" that is not found for Group "Full info". "Average info" nudge overall prompted more growers to sharply reduce their TFI between 2015 and 2016, and comparatively reduced the TFIs of the growers who were most above average in 2015.

5. Discussion

In this section, we discuss the results presented in the previous section from a temporal zoom-out perspective, looking first at the initial, pre-intervention state about the initial beliefs of the agents targeted by the nudges (sub-section 5.1), and then at the consequences of these interventions in the years that followed 2016 (sub-section 5.2).

5.1. *Prior beliefs about relative positions*

In Akerlof's model, agent information is complete and perfect and

Table 5
Impact of the treatments on TFIs – Percent.

			Total	Group "Full info"	Group "Average info"	Group "Control"
All growers						
	BA		1.948 (1.708)	3.745 (2.807)	−1.531 (3.334)	3.794 (2.646)
	DiD, control:					
		Group "Control"	–	−0.049 (3.844)	−5.326 (4.242)	–
		Group "Average info"	–	5.277 (4.344)	–	–
TFI 2015 > 16.36						
	BA		−7.693*** (2.380)	−7.194* (3.607)	−9.905** (4.380)	−5.538 (4.346)
	DiD, control:					
		Group "Control"	–	−1.657 (5.606)	−4.368 (6.127)	–
		Group "Average info"	–	2.711 (5.637)	–	–
TFI 2015 > 17.36						
	BA		−10.515*** (2.763)	−7.050 (4.318)	−17.490*** (5.035)	−6.888 (4.866)
	DiD, control:					
		Group "Control"	–	−0.162 (6.445)	−10.601 (6.938)	–
		Group "Average info"	–	10.440 (6.570)	–	–
TFI 2015 > 18.36						
	BA		−13.943*** (3.117)	−11.983** (4.774)	−22.131*** (5.183)	−7.103 (5.851)
	DiD, control					
		Group "Control"	–	−4.880 (7.463)	−15.027* (7.729)	–
		Group "Average info"	–	10.148 (6.963)	–	–

Notes: The dependent variable is the logarithm of TFI; These estimates are obtained from 28 separate regressions; They represent the changes in the TFI, in % points, between 2015 and 2016 (BA rows: β_G in Eq. (5)) and the difference in the changes between treated and control groups, with treated = Group "Full info" or Group "Average info" when control = Group "Control", and treated = Group "Full info" when control = Group "Average info" (DiD rows: β_{G_T} in Eq. (6)); Standard errors in parentheses; ***, ** and * Significant at the 1 %, 5 % and 10 % levels.

Table 6
Year-to-year variation: Proportion by group.

	Group "Full info"	Group "Average info"	Constant
$\Delta TFI_i^G \leq Q(25)$	0.008 (0.065)	0.160** (0.072)	0.194*** (0.047)
$\Delta TFI_i^G \geq Q(75)$	0.041 (0.073)	−0.035 (0.069)	0.250*** (0.051)

Notes: The dependent variable is a binary variable indicating whether the year-to-year variation in the logarithm of TFI is lower (higher) than or equal to the first (fourth) quartile of its distribution; Standard errors in parentheses; ***, ** and * Significant at the 1 %, 5 % and 10 % levels.

the choice of each individual is at all times known to everyone else. While individuals cannot know the decision of the other individuals in the subsequent sequence, they can measure at each stage the distance that separates their strategic decision from that of the other individuals. In this way, individuals can synthesize the two components of their utility: the individual component, linked to the a priori optimal level of resource use; and the social component, linked to positive social interactions, which increase with proximity.

Concerning our empirical scope, the question arises about the knowledge of relative position in the initial situation: were individuals aware to some extent of their relative position in terms of pesticide use prior to the experiment? It seems that this question is not frequently formalized in the literature on nudging experiments, implicitly assuming an absence of common knowledge about the position of each agent beforehand (notably when the information concerns private data, such as energy use), or incorrect prior beliefs. But part of the success or failure of nudges may be due to the width of the gap between these prior beliefs and the information provided. Bartke et al. (2017) show for example that guessing the norm before it is communicated reinforces the effect of the communication. In our case, we know that the information conveyed by Letter "Average info" was prone to misinterpretation and it is highly probable that the particular effect identified in Group "Average info" stems from a significant gap between prior beliefs and the misleading information that *other* growers were on the whole more virtuous. But what about Group "Full info"? Was the lack of impact in their case due to the nudge being inefficiently well framed, or was it because the information provided did not contradict their prior beliefs?

Answering these questions would be a topic for new experiments to be held; nevertheless, we had the opportunity to measure these *ex ante* beliefs by means of a questionnaire issued several weeks prior to the intervention, within a subgroup of 66 winegrowers from our study sample. The question was in fact included in a wide-ranging environmental diagnostic questionnaire that was independently being conducted by the cooperative's wine technicians (a study conducted as part of the environmental audit associated with the ISO 14001 standard).

Table 7
Breakdown of the 66 winegrowers surveyed on their relative position in three categories.

	Category 1	Category 2	Category 3
Real mean TFI of winegrowers by category	14.20	15.59	17.23

Technicians enjoy relationships of trust and frequent contact with the winegrowers, enabling this information on beliefs about relative positions to be collected by trusted intermediaries as part of a quality control exercise, which for us represented a sufficient guarantee that it would not skew our field study. An equivalent number of winegrowers from future Groups "Full info" and "Average info" were interviewed: 32 winegrowers from future Group "Full info" and 34 from future Group "Average info". By means of the question included, the 66 winegrowers were asked to estimate their relative position in terms of pesticide use (without using TFI terminology) compared to the others by positioning themselves within increasing categories of treatment intensity (Category 1 corresponding to the lowest intensity). The results, compared to the actual 2015 TFIs of the winegrowers in each category, calculated in parallel, are presented in Table 7 below.

We observe that the average real TFIs of the winegrowers in each category are different from each other, and especially that they are classified in ascending order from Category 1 to Category 3. An analysis of variance shows that the difference in TFIs between the three groups is significant at 10 % ($p = 0.073$). The 66 winegrowers thus managed, on their own, to collectively order themselves satisfactorily in relation to the actual situation.

This survey would of course gain from having more winegrowers interviewed. But at the very least, it allows us to verify that the hypothesis of the winegrowers' correct perception of their own positions cannot be rejected. It is therefore reasonable to consider that the initial situation from which we started was relatively close to that envisaged by Akerlof, where individuals knew how to compare their choices with those of other individuals, thereby reinforcing themselves in their initial positions. Subsequently, information received by Group "Full info" did not contradict their prior beliefs, whereas Group "Average info" may have shifted from a correct perception of the situation to an erroneous vision where the other individuals were more clustered around the average value, generating different behaviors.

5.2. Persistence of the effects of the nudge

Is our nudge likely to be effective over time? And will this depend on whether it is repeated over time or suspended? These questions refer to two elements of the debate on the long-term effect of nudges. The first concerns the risk of trivialization of the nudge, involving a dilution of its impact when it is maintained or repeated, as agents become accustomed to the nudge and/or it loses its salience, or even perverse effects when people become accustomed to being manipulated by nudges, as for example in the case of default options (Thomas and Jona, 2017). The second is that of its potential for transforming the long-term preferences of the targeted agents: has the nudge brought lasting lessons, persisting even after the nudge has disappeared? In our case, there may be the pedagogical potential for a shift, following the nudge, towards practices that prove to be more efficient, and thus likely to be maintained over the long term. To address these questions, we agreed with the cooperative on a protocol including two years of nudge treatment (to measure the effect of nudging in Year 2) and three years of observation (to measure the long-term learning effect post-treatment). The experiment was therefore renewed the following year, in 2016, and then stopped. The winegrowers' phytosanitary practices were observed until 2019.

Unfortunately, due to the need for experimentation in real conditions, the two years 2017 and 2018, which were marked in Bordeaux by bad weather, skewed the phytosanitary practices of the cooperative's members, rendering any nudge effect illegible. In 2017, frost caused a lot of localized damage, including the destruction of vegetation and crop losses in the North Aquitaine vineyards; this damage was highly variable at every levels, both inter- and intra-plot. The frost also caused a significant phenological shift that complicated the entire management of the vineyard, particularly vine protection with phytosanitary products.[25] TFI reduced by a third on average for the winegrowers observed, since it became pointless to use fungicides on damaged and non-productive plant material that year (average TFI of 9.45 in 2017 for our set of winegrowers, compared to 16.41 and 16.81 in 2015 and 2016 respectively). The variability within each group between those who were affected by the frost (who therefore had low TFIs) and those who were spared (and who maintained the same order of magnitude of TFIs) makes it impossible to interpret intergroup differences. In 2018, the spring-summer period was this time marked by big hailstorms that severely impacted a number of wine regions. The May 26 storm hit the area particularly hard, destroying up to 80–100 % of vines.[26] The winegrowers affected by these incidents saw their future harvests destroyed and stopped all phytosanitary protection. However, as these incidents were very localized, in hail corridors or frost clusters, they led to a new factor of variability between individuals and between groups. It is thus impossible to interpret any variation in TFIs from the letters sent.

Consequently, the first year comparable to 2015 and 2016, and which can be used to measure the effect of the nudge over time, is 2019, the latest year for data collection. In that year, low-humidity conditions facilitated the harvest and favored good crop health, even better than in 2015 and 2016, and the percentage of plots affected by powdery mildew in the public observation network, for example, was—at 18 %—very close to that observed in 2015 and 2016, i.e. 17 % (Martigne, 2019).

The data collected that year were analyzed in the same way as the data for 2015 and 2016. First of all, a loss of members was observed. A total of 57 winegrowers retired between 2016 and 2019, which is consistent with the demographic situation in the area.[27] In 2019, of the three initial groups, there were still 60 individuals in Group "Full info", 60 individuals in Group "Average info" and 53 individuals in Group "Control" (already the smallest group in 2016), i.e. 173 individuals in all. After calculation of the TFIs, Table 8 shows that there was no longer any significant difference between the three groups in terms of their TFIs. Only 0.014 TFI point separated the group with the highest average TFI (Group "Control") from the group with the lowest average TFI (Group "Average info"), a negligible difference compared to that which existed between the groups in 2016. The change in behavior observed in 2016 did not translate into a sustainable transformation of practices.

6. Conclusion

As the starting point of our reflection, Akerlof's model is based on the social dynamics of a group of individuals whose utility includes a component related to the relative position of their decision with respect to the decisions of the other members of the group. Being locked into suboptimal positions then results from externalities linked to interactions between economic agents who are relatively close from the point of view of their predisposition to use a resource. The proximity of others, and the resulting social interactions, jointly keep individuals in a trap, far away from the individual economic optimum. We sought to mobilize this formalism to explain how social comparison-based nudges work, illustrated by a field experiment, to better understand the sources of their efficiency. In this experiment, a treatment group receiving full information on the behavior of others showed no difference from a control group, while a group exposed to a more conventional nudge (receiving only average information) did show differences from the

[25] Nouvelle-Aquitaine Chamber of Agriculture. 2017. Review of the 2017 campaign, Edition Nord-Aquitaine. In Bulletin de Santé du Végétal, Nouvelle-Aquitaine, Vigne. N°20–05/12/2017.

[26] Nouvelle-Aquitaine Chamber of Agriculture. 2018. Review of the 2018 campaign, Edition Nord-Aquitaine. In Bulletin de Santé du Végétal, Nouvelle-Aquitaine, Vigne. N°19–18/12/2018.

[27] 32 % of Gironde farms in 2017 were to undergo a transfer of ownership within five years (Agreste Aquitaine-Limousin-Poitou-Charentes, 2016).

Table 8
TFIs by group in 2019.

	Total		Group "Full info"		Group "Average info"		Group "Control"	
Number of observations	173		60		60		53	
TFI 2019. Mean (Std. Dev.)	13.457	(3.38)	13.455	(3.65)	13.448	(3.49)	13.462	(2.99)

control group, albeit not persistent or visible over time. This can now either extend their reach, or question their ethical legitimacy, since misinterpretation may be part of the recipe for their effectiveness. Of course, this first attempt with a limited number of observations calls for more powered experiments based on similar protocols. Also, the choice of an a priori difficult field of application, as much in terms of its capacity to really influence the choice of profit-maximizing producers as in the observability of results subject to random weather conditions, certainly reduced the chances of obtaining significant effects. Nonetheless, this choice ensured that the results in favor of our hypothesis would be more generally applicable outside our case study, in the event of actual differences between our different groups, even if only over the first year.

The application of the lessons of behavioral economics to the design of public policies has had the effect of reviving debates over the ethical dimension of regulation. As already suggested by Thaler and Sunstein (2008), it is commonly accepted that the use of nudges must be accompanied by a democratic process, or at least by a moral obligation towards economic agents (consumers or companies) who are oriented, or even "manipulated", in their behavior and strategic decisions. It is through this type of control that the line between the acceptable and the unacceptable can be drawn. However, we argue that the analysis of the ethical dimension of such an intervention should not be limited to legal or dogmatic considerations regarding the need to respect the free will of individuals (though fundamental). Based on this research, we defend the idea that a nudge, even of an informational nature, can in reality be based on incorrect interpretations of the information communicated. The behavioral sciences are full of well-characterized examples of bias in the interpretation of information contained in our environment, particularly when subjects are presented with statements: the attraction effect (Huber et al., 1982), or the compromise effect (Simonson, 1989), for example, in the case of jointly presented information. While nudges are supposed to help us overcome our cognitive biases to make the best choices (Sunstein, 2015), we know that they frequently resort to the very same biases to make us act in a way that conforms to the public interest. One obvious example is that of nudges based on status quo bias, whether to increase the number of organ donors (Johnson and Goldstein, 2003) or to promote a more balanced diet (Wisdom et al., 2010). Another is the optical illusions used to reduce traffic speed (Calvi et al., 2019). Why should the same not be true of social comparison nudges, where biases in reading and interpreting the information conveyed could turn out to have more impact than the information itself? This question strikes us as all the more crucial in that, as we have seen, the information on which nudges are based is most often simplified into aggregate reference points, reducing the time it takes for the target audience to analyze it.[28] From a regulatory perspective, this can notably change the way in which different kinds of interventions are categorized. Referring to the intervention types suggested by Hansen and Jespersen (2013), the nudge received by Group "Average info" seems to mobilize the "System 1 thinking" more than the nudge "Full info" does, and proves to have a better effect. The tension between efficiency and ethics is highlighted here, with an unavoidable trade-off between the two. It seems not all information is "*good*" to share, and by "*good*" here we mean *effective*. In the end, we also note the extreme mutability of this type of intervention which, through the simple addition or withdrawal of complementary information on the same informational canvas, causes the nudge to change category, and in so doing gives it all its effectiveness. Without a precise analysis of the mechanisms at work in any given nudge, we cannot correctly frame the debate on the ethics of intervention. Designers of social comparison nudges can integrate these questions about modes of action prior to intervention.

Finally, while this article raises concerns about the way nudges work and the difficulty of using them for public policy purposes, they nonetheless remain very useful as indicators of behavioral room for maneuver. What we have brought to light is that the targeted individuals were able to modify their choices without economic constraint, even though their initial situation seemed frozen. Nudges reveal the technical potential of change, and break down the hypothesis of an impenetrable lock. Used well, they may even help us to measure the potential for this change, which other forms of public policy can then engage with, in order to accompany sustainable change with greater certainty.

CRediT authorship contribution statement

Yann Raineau: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Éric Giraud-Héraud:** Conceptualization, Funding acquisition, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Sébastien Lecocq:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

The authors report that his research was co-funded as part of a European research project (Interreg SUDOE), named VINOVERT, conducted between 2016 and 2019. Otherwise, the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Access to some confidential data, on which is based this work, has been made possible within a secure environment offered by CASD – Centre d'accès sécurisé aux données (Ref. 10.34724/CASD).

[28] Here we echo the link between attention and the effectiveness of nudges, discussed at the theoretical level by Löfgren and Nordblom (2020).

Appendix A. Appendices

1. Formal presentation of Akerlof's model and application to nudges functioning
2. Experiment Design Summary
3. Example of a letter received by Group "Full info" winegrowers, with English translation
4. Example of a letter received by Group "Average info" winegrowers, with English translation
5. Protocol and results – Supplementary material

A.1. Formal presentation of Akerlof's model and application to nudges functioning

The utility function used by Akerlof consists of two components. The first is an "intrinsic" utility linked to the individual decision to use the resource at a level x, formalized in the form of $-ax^2 + bx + c$ (a, b and c being strictly positive reals), which the individual optimizes independently with the quantity $\hat{x} = b/2a$.

The second component of the chosen model is a utility related to the social decision regarding this level of resource use x. Indeed, this decision has consequences for the individual's social positioning in the group. More precisely, the positive externalities linked to social influences will be all the stronger the closer the individual's decision x is to that of others, especially those who were already close (the gravity principle). This second part of the utility function takes the form:

$$\sum\nolimits_{j \neq i} e/\left[\left(f + |x_{0i} - x_{0j}|\right)\left(g + |x_{1i} - x_{0j}|\right)\right] \tag{A.1}$$

where x_{0i} and x_{0j} correspond to the initial or "inherited" positions of agents i and j, respectively, and x_{1i} to the decision on x that agent i chooses in the new period.[29]

Thus, based on these two components, the utility of agent i forming a social group with agents $j \neq i$ is written in the form:

$$U_i = \sum\nolimits_{j \neq i} e/\left[\left(f + |x_{0i} - x_{0j}|\right)\left(g + |x_{1i} - x_{0j}|\right)\right] + \left[-ax_{1i}^2 + bx_{1i} + c\right] \tag{A.2}$$

Akerlof shows with a three-agent example that, depending on the value of the parameters of the equation, maximizing this form of utility can lead two agents 1 and 2, distant from the intrinsic optimum ($b/2a$) but close to each other in inherited positions (x_{01} and x_{02}), to simply swap places in period 1, without getting any closer to $b/2a$, as shown in Fig. A.1.[30]

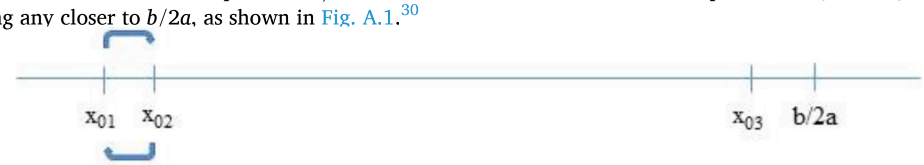


Fig. A.1. Stability of positions in a three-person model.

Now, what happens with nudges, in a situation where the position of others is initially unknown? Instead of being taught the exact position x_{0j} of a number n of agents j ($j \neq i$), imagine agent i is provided only partial, though true, information, namely the average $\mu_{0i} = 1/n\sum_{j \neq i} x_{0j}$.[31] Transmitting this average either contradicts a belief or confirms it. In both cases, it provides no information on the diversity of others' behaviors, in particular the behavior of those to whom each agent seeks to relate (i.e. the second part of the utility function). It may well be possible, for example, that half of the other agents are located around the same value of x as i. Apart from possible behavioral effects, not taken into account in the theoretical model used, such as the salience effect of the information provided, or the generation of emotion, for example fears about the monitoring or possible publication of individual behaviors, the operation should have no effect.

Now let's imagine that the transmission of an average is accompanied by an interpretation bias, and that it is assimilated as information about the behavior of others as a whole. Consider the extreme case where *agentihypothesizes that*$\forall j \neq i\ x_{0j} = \mu_{0i}$, then eq. (A.2) becomes:[32]

[29] In a sequential model, agents must make a choice in each period based on their estimates of the choice that others will make. Akerlof simplifies these conjectures with a static estimation assumption. Thus individual i considers that agents j will maintain, at date $t = 1$, their position at date $t = 0$. Two parameters—strictly positive reals f and g—are introduced to avoid giving this second part of the utility an infinite weight as the distance between individuals diminishes, while a last, strictly positive, parameter e is also introduced to quantify the weight of this social component in the overall function.

[30] In this model, which he uses to explain the permanence of social classes, Akerlof presents exchanges between individuals as vectors of externalities, which can materialize through trade, mutual aid, etc. The decision is thus no longer just an individual decision but a social one, while remaining a rational decision. Indeed, it is not always necessary to mobilize a behavioral bias to explain the inertia of economic agents' behavior. The benefit linked to social exchanges is integrated into the agents' utility function. While Akerlof refers first and foremost to the positive externalities linked to the social proximity of a group, we can also add the potential negative externalities of being *extracted from it,* not only through the loss of the exchanges that the individual has with the group, but also through additional reputational or image-related damage, as soon as the individual moves away from the group.

[31] The same reasoning applies if we instead consider a common average for all $\mu_0 = 1/n\sum_i x_{0i}$.

[32] Still following Akerlof's simplified static estimation assumption. Thus individual i considers that agents j will maintain, at date $t = 1$, the positions they occupied at date $t = 0$ (cf. Footnote 29).

$$U_i = [n.e/(f + |x_{0i} - \mu_{0i}|)] \times [1/(g + |x_{1i} - \mu_{0i}|)] + [-ax_{1i}^2 + bx_{1i} + c] \quad \text{(A.3)}$$

In period 1, still considering our three-agent example, it is easily demonstrated that the optimum (or the possible optima) for each of the agents i is now located in the interval $[\mu_{0i}; b/2a]$ or $[b/2a; \mu_{0i}]$.[33]

We can illustrate this by taking Akerlof's example of three agents as a starting point. For agent 1, the decision will no longer be x_{02} but a value of x between μ_{01} and $b/2a$, depending on the relative weight of the parameters in the equation, as shown in Fig. A.2. This is the expected effect of the nudge. The centers of gravity considered by the agent were previously chosen by the author of the intervention.

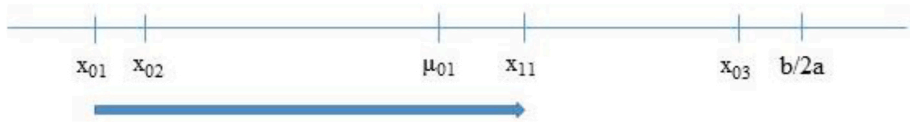


Fig. A.2. Evolution of the position of agent 1 with partial information on the position of other agents

A.2. Experiment design summary

A.2.1. Intervention

Within the framework of this partnership project carried out with a wine cooperative, postal mails were co-designed with the technical service of the cooperative and then sent by this service (in order to ensure the credibility of the information received). 165 letters were sent on April 8, 2015, 82 containing the social comparison nudge modality A (complete information on the distribution of the group), and 83 containing the social comparison nudge modality B (information limited to individual positioning and the group average). No further mail was sent afterwards.

Intervention Date
2016-04-08

A.2.2. Primary outcomes

A.2.2.1. Primary outcomes. Three groups of winemakers were formed in this study: two groups each receiving a type A or B social comparison nudge that compared (in a different way from A to B) the practices of the targeted individual with those of the rest of the group, and a third control group. At the end of the experiment, we find that only one of the two nudges manages to change the group practices: Group B (limited information). This leads us to a better understanding, by comparing the formulation of the two nudges, of the necessary element for their efficiency. This element consists of an incomplete level of information, leaving room for interpretation bias. We also note the disappearance of the nudge effect after a few years (monitoring of practices until 2019).

A.2.3. Experimental design

A.2.3.1. Experimental design. From 2015 to 2019, we collected data on the phytosanitary practices of a group of winegrowers belonging to the same cooperative in the Bordeaux region, randomly divided into three subgroups A, B and C. Before chemical protection began in spring 2016, each individual in Groups A and B received a letter informing them of their intensity of use of phytosanitary products for the previous year 2015, expressed through a new synthetic indicator, compared to the average intensity of the whole group A + B + C. The letters addressed to group B also presented the complete distribution of all the different levels of intensity. No further action was taken afterwards. The results were obtained at the end of each crop year, with a follow-up from 2016 to 2019.

A.2.3.2. Randomization method. To ensure randomization, individuals' assignment to of the three groups was conducted according to a stratification scheme by the observed variable, the treatment frequency indicator (TFI). We adopted the principle of pairwise matching, presented by Duflo et al. (2007). In our case, because we wanted three groups instead of two (two action groups and a control group), we performed an assortment by trios and not by pairs. Thus, once ordered by the value of their TFI in 2015, trios were formed and, within these trios, each winemaker was randomly assigned to one of Groups "Full info", "Average info" or "Control". A few one-to-one swaps were then carried out to take account of personal relationships between agents and constraints linked to the administration of a pre-questionnaire.

A.2.4. Experiment characteristics

Sample size
247 individuals.
Sample size by treatment arm
82, 82 and 83.

[33] We see that $k = [n.e/(f + |x_{0i} - \mu_{0i}|)] > 0$ and $\forall x_{1I} \in \mathbb{R}\, g + |x_{1i} - \mu_{0i}| \geq g > 0$. The 1st part of U_i, $k.[1/(g + |x_{1i} - \mu_{0i}|)]$ as a function of x_{1i} is thus continuous on $\mathbb{R}$, increasing on $]-\infty; \mu_{0i}[$ and decreasing on $]\mu_{0i}; +\infty[$. The 2nd part $[-ax_{1i}^2 + bx_{1i} + c]$ is increasing on $]-\infty; b/2a[$ and decreasing on $]b/2a; +\infty[$. When $\mu_{0i} < b/2a$, U_i is increasing on $]-\infty; \mu_{0i}[$ (where both parts are increasing) and decreasing on $]b/2a; +\infty[$ (where both parts are decreasing). U_i thus admits a maximum, possibly local maxima, in the interval $[\mu_{0i}; b/2a]$. When $b/2a < \mu_{0i}$, the optimum lies in $[b/2a; \mu_{0i}]$.

A.3. Example of a letter received by group "full info" winegrowers, with English translation

LES VIGNERONS DE

[redacted]

BORDEAUX

M. [redacted]
18. [redacted]
[redacted]
Code adhérent : [redacted]

Monsieur,

La coopérative des Vignerons d[redacted]a mis en place en 2014 un outil de traçabilité phytosanitaire informatique. Vous avez commencé à le renseigner et nous vous en remercions sincèrement car cet outil est un élément essentiel de la démarche de développement durable et de la réputation globale de notre coopérative.

Sur la base de ces informations, la coopérative peut désormais vous communiquer votre **Indice de Fréquence de Traitement (IFT)**, qui mesure la quantité de produits phytosanitaires utilisée sur votre vignoble.
Vous aurez ainsi, pour l'année 2015, connaissance de cet indicateur parmi vos autres éléments de gestion vous permettant d'avoir une vision globale de votre exploitation.
Les données de ce courrier vous sont communiquées à titre informationnel et pour votre usage privé.

Dans ce courrier, nous nous concentrons sur les valeurs d'IFT *hors herbicides* (l' « IFT hors herbicides » est ainsi surtout marqué par les fongicides) des 247 adhérents ayant renseigné l'outil.
Cet IFT hors herbicides mesure la quantité globale de produits phytosanitaires employée sur vos parcelles rapportée aux doses homologuées des produits (pour les cibles visées) et à l'ensemble de vos surfaces.
Ainsi rapporté, l'IFT est un indicateur du nombre global de doses homologuées de produits phytosanitaires que votre vignoble a reçu au cours de la campagne 2015, ces produits pouvant être différents.

L'IFT est un indicateur simple qui permet des **comparaisons** entre différents itinéraires techniques :

- Un IFT par exemple deux fois supérieur au vôtre pour une autre personne indique que celle-ci, à surface égale, a employé deux fois plus de produits phytosanitaires, tous produits confondus. Cette personne peut par exemple être passée deux fois plus souvent sur ses parcelles, ou alors avoir employé des doses deux fois plus importantes à chaque passage.

- Un IFT deux fois inférieur indiquerait en revanche qu'une quantité de produits deux fois moindre a été employée par hectare, soit par le fait d'une réduction de la dose employée à chaque passage, soit par une réduction de nombre de passages, soit encore par la réduction de la surface traitée à chaque passage (traitements localisés).

L'IFT est donc un des indicateurs importants mesurant la performance environnementale et économique de votre exploitation.
Réduire ses traitements, et ainsi son IFT, permet de préserver l'environnement et sa santé, ainsi que celle de son entourage.

Vous trouverez en page suivante les informations concernant votre IFT.
N'hésitez pas à contacter votre technicien viticole si vous avez des questions ou remarques sur ce courrier.

[redacted]

1/2

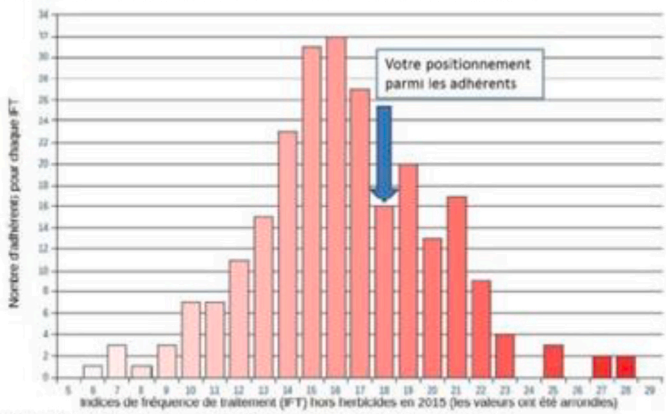
La valeur moyenne de l'IFT des adhérents pour l'année 2015 est de : **16,36.**
Pour information, elle était de 17,00 en 2014, ***les traitements ont donc baissé*** *entre ces deux années.*

Votre valeur d'IFT pour l'année 2015 est de : **18,00.**
Vous avez donc effectué environ **2 traitements de plus que la moyenne** des adhérents.

Le graphique suivant présente la répartition des IFT hors herbicides des adhérents.
Quelques éléments pour faciliter sa lecture :

- L'IFT se lit sur l'axe horizontal, en bas du graphique, au pied de chaque barre. À gauche se situent les adhérents avec les IFT les plus faibles. **Plus on va vers la droite, plus l'IFT est élevé.**
- La hauteur des barres indique le nombre d'adhérents pour chaque valeur d'IFT. Le nombre d'adhérents pour une valeur donnée d'IFT se lit donc sur l'axe vertical, à gauche du graphique, à la même hauteur que la barre.
- Les barres plus hautes indiquent que les valeurs d'IFT associées sont partagées par un plus grand nombre d'adhérents et les barres plus basses indiquent des valeurs d'IFT plus rares.

Votre positionnement dans le graphique est donné par la flèche bleue.
Elle vous indique la valeur arrondie de votre IFT hors herbicides (lisible au pied de la barre indiquée par la flèche) et le nombre d'adhérents qui ont le même IFT que vous (lisible sur l'axe vertical à gauche, à la hauteur de la barre).
À gauche apparaissent donc ceux qui traitent moins et à droite, ceux qui traitent plus.



Vous continuerez à être informé les prochaines années sur la valeur de votre IFT.

Réduire son IFT, comment ?
On peut réduire son IFT de plusieurs manières :

- par une **baisse de nombre de traitements**, en s'assurant que chacun d'entre eux est nécessaire,
- par une **réduction de la dose à chaque passage**, beaucoup de traitements nécessitant des doses bien inférieures aux doses homologuées,
- en **limitant les mélanges de produits** (par exemple combinant anti-mildiou et anti-oïdium) quand une seule cible est visée (par exemple le mildiou uniquement),
- par la réalisation de **traitements plus localisés**, sur les ilots visés uniquement,
- en associant les traitements à d'autres pratiques qui préviennent les maladies : **travaux en vert, biocontrôle.**

N'hésitez pas à contacter votre technicien viticole pour vous aider à mettre en place une stratégie de réduction de votre IFT.

Dear Sir,

The XXX Winegrowers' Cooperative set up a computerized phytosanitary traceability tool in 2014. You have started to provide it with information and we sincerely thank you, because it is essential to the sustainable development approach and the global reputation of our cooperative.

Based on this information, the cooperative can now provide you with your **Treatment Frequency Index (TFI)**, which measures the quantity of phytosanitary products used on your vineyard.

You will thus have, for the year 2015, knowledge of this indicator among the other management tools allowing you to have a global vision of your operation.

The data in this letter are communicated to you for information purposes and for your private use.

In this letter, we focus on the values of TFI excluding herbicides (thus mainly fungicides) of the 247 members who filled in the information.

This non-herbicide TFI measures the overall quantity of phytosanitary products used on your plots in relation to the registered doses of the products (for the targeted targets) and to all your surfaces.

Thus reported, the TFI is an indicator of the overall number of registered doses of phytosanitary products that your vineyard received during the 2015 campaign; these products may be different.

The TFI is a simple indicator that offers **comparisons** between different technical routes:

- Another person's TFI, for example, which is twice as high as yours indicates that this person, for the same surface area, has used twice as many phytosanitary products, all products combined. For example, this person may have treated their plots twice as often, or used twice as much each time.

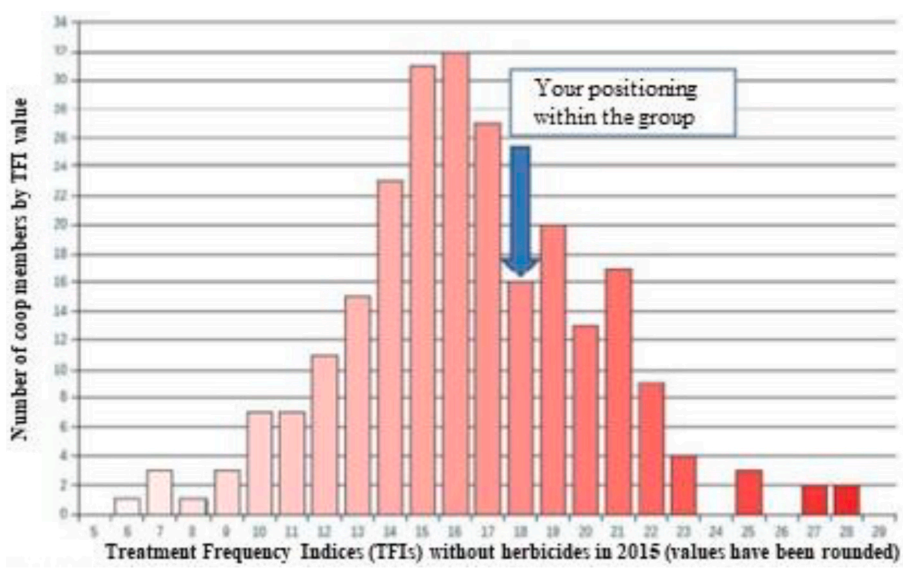
- A TFI which is half yours would indicate that half the amount of product was used per hectare, either by reducing the rate used in each treatment, by reducing the number of treatments, or by reducing the area treated (spot treatments).

The TFI is therefore one of the important indicators measuring the environmental and economic performance of your operation.
Reducing your treatments, and thus your TFI, helps preserve the environment and your health, as well as that of your entourage.

On the following page you will find information about your TFI.
Do not hesitate to contact your wine technician if you have any questions or remarks about this letter.
The average TFI value of members for the year 2015 is: **16.36**.
*For information, it was 17.00 in 2014, **so values have decreased** between these two years.*
Your TFI value for the year 2015 is: **18.00**.
You have thus performed about **2 more treatments** than the average member.
The following graph shows the distribution of members'TFIs excluding herbicides.
To help you understand it:

- The TFI can be read on the horizontal axis, at the bottom of the graph, at the foot of each bar. On the left are the members with the lowest TFIs. **The further to the right, the higher the TFI.**
- The height of the bars indicates the number of members for each TFI value. The number of members for a given TFI value can be read on the vertical axis, on the left side of the graph, at the same height as the bar.
- Higher bars indicate that the associated TFI values are shared by a larger number of members and lower bars indicate rarer TFI values.

Your position in the graph is given by the blue arrow.
It shows you the rounded value of your TFI excluding herbicides (readable at the foot of the bar indicated by the arrow) and the number of members who have the same TFI as you (readable on the vertical axis on the left, at the height of the bar).
On the left are those who treat less and on the right those who treat more.



You will continue to be informed over the next few years about the value of your TFI.

How to reduce your TFI?
You can reduce your TFI in several ways:

- By reducing the number of treatments, ensuring that each one is necessary,
- By reducing the dose with each treatment, as many treatments require much lower doses than those approved,
- By limiting mixtures of products (e.g. combining anti-powdery mildew and anti-downy mildew) when only one disease is targeted (e.g. downy mildew only),
- By carrying out more localized treatments, on the targeted plots only,
- By combining treatments with other practices that prevent disease: green work, biocontrol

Do not hesitate to contact your wine technician to help you set up a strategy to reduce your TFI.

A.4. Example of a letter received by group "average info" winegrowers, with English translation

[redacted]

BORDEAUX

Mme [redacted]

Code adhérent : [redacted]

Madame,

La coopérative des Vignerons d[redacted]a mis en place en 2014 un outil de traçabilité phytosanitaire informatique. Vous avez commencé à le renseigner et nous vous en remercions sincèrement car cet outil est un élément essentiel de la démarche de développement durable et de la réputation globale de notre coopérative.

Sur la base de ces informations, la coopérative peut désormais vous communiquer votre **Indice de Fréquence de Traitement (IFT)**, qui mesure la quantité de produits phytosanitaires utilisée sur votre vignoble.
Vous aurez ainsi, pour l'année 2015, connaissance de cet indicateur parmi vos autres éléments de gestion vous permettant d'avoir une vision globale de votre exploitation.
Les données de ce courrier vous sont communiquées à titre informationnel et pour votre usage privé.

Dans ce courrier, nous nous concentrons sur les valeurs d'IFT *hors herbicides* (l'« IFT hors herbicides » est ainsi surtout marqué par les fongicides) des 247 adhérents ayant renseigné l'outil.
Cet IFT hors herbicides mesure la quantité globale de produits phytosanitaires employée sur vos parcelles rapportée aux doses homologuées des produits (pour les cibles visées) et à l'ensemble de vos surfaces.
Ainsi rapporté, l'IFT est un indicateur du nombre global de doses homologuées de produits phytosanitaires que votre vignoble a reçu au cours de la campagne 2015, ces produits pouvant être différents.

L'IFT est un indicateur simple qui permet des **comparaisons** entre différents itinéraires techniques :

- Un IFT par exemple deux fois supérieur au vôtre pour une autre personne indique que celle-ci, à surface égale, a employé deux fois plus de produits phytosanitaires, tous produits confondus. Cette personne peut par exemple être passée deux fois plus souvent sur ses parcelles, ou alors avoir employé des doses deux fois plus importantes à chaque passage.

- Un IFT deux fois inférieur indiquerait en revanche qu'une quantité de produits deux fois moindre a été employée par hectare, soit par le fait d'une réduction de la dose employée à chaque passage, soit par une réduction de nombre de passages, soit encore par la réduction de la surface traitée à chaque passage (traitements localisés).

L'IFT est donc un des indicateurs importants mesurant la performance environnementale et économique de votre exploitation.
Réduire ses traitements, et ainsi son IFT, permet de préserver l'environnement et sa santé, ainsi que celle de son entourage.

Vous trouverez en page suivante les informations concernant votre IFT.
N'hésitez pas à contacter votre technicien viticole si vous avez des questions ou remarques sur ce courrier.

[redacted]

1/2

La valeur moyenne de l'IFT des adhérents pour l'année 2015 est de **: 16,36.**
Pour information, elle était de 17,00 en 2014, ***les traitements ont donc baissé*** *entre ces deux années.*

Votre valeur d'IFT pour l'année 2015 est de **: 18,02.**
Vous avez donc effectué environ **2 traitements de plus que la moyenne** des adhérents.

Vous continuerez à être informée les prochaines années sur la valeur de votre IFT.

Réduire son IFT, comment ?

On peut réduire son IFT de plusieurs manières :

- par une **baisse de nombre de traitements**, en s'assurant que chacun d'entre eux est nécessaire,
- par une **réduction de la dose à chaque passage**, beaucoup de traitements nécessitant des doses bien inférieures aux doses homologuées,
- en **limitant les mélanges de produits** (par exemple combinant anti-mildiou et anti-oïdium) quand une seule cible est visée (par exemple le mildiou uniquement),
- par la réalisation de **traitements plus localisés**, sur les îlots visés uniquement,
- en associant les traitements à d'autres pratiques qui préviennent les maladies **: travaux en vert, biocontrôle.**

N'hésitez pas à contacter votre technicien viticole pour vous aider à mettre en place une stratégie de réduction de votre IFT.

Dear Madam,

The XXX Winegrowers' Cooperative set up a computerized phytosanitary traceability tool in 2014. You have started to provide it with information and we sincerely thank you, because it is essential to the sustainable development approach and the global reputation of our cooperative.

Based on this information, the cooperative can now provide you with your **Treatment Frequency Index (TFI)**, which measures the quantity of phytosanitary products used on your vineyard.

You will thus have, for the year 2015, knowledge of this indicator among the other management tools allowing you to have a global vision of your operation.

The data in this letter are communicated to you for information purposes and for your private use.

In this letter, we focus on the values of TFI excluding herbicides (thus mainly fungicides) of the 247 members who filled in the information.

This non-herbicide TFI measures the overall quantity of phytosanitary products used on your plots in relation to the registered doses of the products (for the targeted targets) and to all your surfaces.

Thus reported, the TFI is an indicator of the overall number of registered doses of phytosanitary products that your vineyard received during the 2015 campaign; these products may be different.

The TFI is a simple indicator that offers **comparisons** between different technical routes:

- Another person's TFI, for example, which is twice as high as yours indicates that this person, <u>for the same surface area</u>, has used twice as many phytosanitary products, all products combined. For example, this person may have treated their plots twice as often, or used twice as much each time.
- A TFI which is half yours would indicate that half the amount of product was used per hectare, either by reducing the rate used in each treatment, by reducing the number of treatments, or by reducing the area treated (spot treatments).

The TFI is therefore one of the important indicators measuring the environmental and economic performance of your operation.
Reducing your treatments, and thus your TFI, helps preserve the environment and your health, as well as that of your entourage.

On the following page you will find information about your TFI.

Do not hesitate to contact your wine technician if you have any questions or remarks about this letter.

The average TFI value of members for the year 2015 is: **16.36**.

For information, it was 17.00 in 2014, ***so values have decreased*** *between these two years.*

Your TFI value for the year 2015 is: **18.02**.

You have thus performed about **2 more treatments** than the average member.

You will continue to be informed over the next few years about the value of your TFI.

How to reduce your TFI?

You can reduce your TFI in several ways:

- By reducing the number of treatments, ensuring that each one is necessary,
- By reducing the dose with each treatment, as many treatments require much lower doses than those approved,

(*continued on next page*)

(*continued*)

• By limiting mixtures of products (e.g. combining anti-powdery mildew and anti-downy mildew) when only one disease is targeted (e.g. downy mildew only),
• By carrying out more localized treatments, on the targeted plots only,
• By combining treatments with other practices that prevent disease: green work, biocontrol
Do not hesitate to contact your wine technician to help you set up a strategy to reduce your TFI.

A.5. Protocol and results - Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108436.

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