# Diversion Research

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**Abstract**

Industrial lobbies often fund scientific studies strategically aimed at diverting public attention from their culpability in health or environmental issues, perpetuating doubt, and delaying regulatory measures. We call this strategy "diversion research". To understand what determines its use, we propose a new model to study firms' special interests in funding academic research. The harmfulness of industrial activity is uncertain, but the government can regulate it to maximize the expected social welfare perceived by scientists. Firms, coordinating as a lobby, offer money to influence what scientists study. We find that this lobby is interested in funding diversion research when the current science does not indicate a need for regulation. Surprisingly, when the science indicates that regulation is required, firms might even fund research on their own harmfulness. This article highlights the importance of preserving academic freedom to prevent first-order welfare losses due to the strategic use of diversion research. One possibility is to allow private funding, with allocation overseen by an independent committee.

**Keywords:** Research funding, research agenda setting, scientific uncertainty.

**JEL codes:** D01, D72, D83, I18, Q58

# 1 Introduction

Scientists play a crucial role in providing the information required to adopt efficient regulatory measures in uncertain environments. To delay, weaken, or avoid regulations, it is therefore in the interests of firms to intervene in the scientific process. The forced release of confidential corporate documents,[1] revealed that industrial lobbies were spending large sums of money to manipulate public opinion through science. This practice, known as *"manufacturing doubt"*, yields huge welfare losses.[2] Through historical and investigative documentation, we identified a particular manufacturing doubt strategy that deserves attention, here called "diversion research". Diversion research is legitimate scientific research that diverts public attention from the implications of industrial activity for a health or environmental issue. This is done by studying how other factors impact the same issue. One key aspect of this *manufacturing doubt* strategy is that it does not involve dishonesty: diversion research is legitimate. Proctor (2011) shows that the tobacco industry invested more than 300 million dollars from 1950 to 1990 through the Council for Tobacco Research (CTR) to divert attention from cigarette side effects.[3] Foucart (2014) also found a wealth of studies involving diversion research about the effect of pesticides on bees in the very decades when neonicotinoids, a new type of pesticide known to be detrimental to pollinators, were introduced. The sugar lobby funded diversion research on cardiovascular diseases and obesity, and the alcohol industry on breast cancer.[4] Special interest groups also funded diversion research to downplay the anthropogenic origins of climate change or the impact of the hole in the ozone layer on skin cancer.[5] Yet, to the best of our knowledge, the economics literature has never studied diversion research.

This paper proposes a new approach to examine how industry's special interests are

[1] All these documents are available at `https://www.industrydocuments.ucsf.edu/`.

[2] Proctor (2011) contends that the tobacco industry's doubt-manufacturing regarding the harmful effects of tobacco led to the production and consumption of over 8000 billion cigarettes, resulting in 8 million untimely fatalities.

[3] The CTR focused on six areas of research: inherited genetic diseases, infection, nutrition, hormones, nervous exhaustion or nervous tension, and environmental factors.

[4] See Fabbri et al. (2018), Goldberg and Vandenberg (2019), Michaels (2020) and Wood et al. (2020).

[5] See Oreskes and Conway (2011) and Foucart et al. (2020)

served by investing in academic research. In our model, public health or the environment can be threatened by two factors: industrial activity and an alternative factor unrelated to industry. However, it is uncertain whether these factors are harmful or not, and scientists can reduce this doubt. We consider a deep-pocketed industrial lobby that will provide monetary funding to scientists who agree to study one selected factor. Using scientific results, the government regulates the industry by setting a particular limit on industrial production.

We analyze a sequential game with two periods. In the first period, the industrial lobby can influence scientists' choice of research topic by offering funds. In the second period, scientific studies are performed, and the government regulates the industry. We proceed by backward induction, first characterizing the optimal regulation. Then, we analyze the benefits to the industrial lobby from funding academic research and its optimal scientists' reallocations.

Considering a medium-run horizon, we assume the government's actions are limited to controlling industrial externalities, disregarding potential interventions against alternative threats. Since it is the only way to ensure the most effective regulatory decision, research on the harm caused by the industry is always socially beneficial. In this framework, we consider that the number of available scientists is exogenous. Therefore, funding some scientists to perform diversion research is equivalent to avoiding useful scientific progress that would lead to effective regulatory measures. Perpetuating doubt about the externalities of firms leads to indirect but significant welfare losses.

Our analysis yields novel insights. Firms always stand to gain from funding diversion research when, initially, their activity is not likely to be harmful enough to require expensive regulation. By preserving doubt about their harmfulness, they also preserve governmental concern about the cost of regulating. Unexpectedly, we also found that it may be in firms' best interests to fund research on their own harmfulness. This is a way to support scientific advancement that could rid them of a current regulatory decision. Funding such research will always be in firms' interests when, initially, industrial activity is perceived as harmful enough to warrant prohibition, which is relatively inexpensive. In this situation, firms prefer to turn government attention toward scientific results and away from the low cost of regulation. The industrial lobby's funding preferences can also differ with the level of research planned on its externalities. When the industrial activity appears harmful enough to require expensive regulation, the industry may prefer to have some research on its harmfulness and to fund other scientists to conduct diversion research. In this way, the regulatory decision may be affected, but doubt is preserved. Finally, if the industrial activity appears harmless enough not to be regulated, although regulation is arbitrarily inexpensive, two opposite strategies may be deployed; the first best is to promote only diversion research to maintain the situation, and the second best is to promote only research on the industrial activity's harmfulness, which will probably exonerate the industry.

Next, we explore some examples of the industry's optimal funding. First, we observe that greater scientific accuracy systematically improves expected social welfare and compensates for losses due to the increased funding for diversion research. Furthermore, when regulation is both expensive and not immediately required, funds for diversion research may escalate in proportion to the perceived likelihood of the industry's harmfulness. This trend could continue until every available scientist is diverted, especially if convincing them to shift their research focus is not too costly. Finally, when regulation is both inexpensive and required from the start, private funding for research on the industry's harmfulness initially rises with the belief in its harmful nature and subsequently decreases with the same belief.

The article sheds light on the importance of preserving academic freedom to prevent first-order welfare losses due to the use of diversion research. One possibility is to allow private funding, with its allocation overseen by an independent committee. In this way, interest groups might still support research, but influencing scientists' research agenda to perpetuate doubt would no longer be feasible.

This study contributes to several strands of literature. First, it addresses the under-explored topic of *manufacturing doubt* strategies. Bramoullé and Orset (2018) analyze the misinformation strategy, when firms produce pseudo-scientific biased information. They consider that citizens do not distinguish legitimate scientific studies from non-legitimate ones. In our model, the industry can only manipulate the advancement of scientific knowledge, which does not require such an assumption. This allows us to consider fully Bayesian-rational agents. In Chiroleu-Assouline and Lyon (2020), industrial lobbies are not credible information providers for the regulator, due to their vested interest in escaping regulation.

To sow doubt, firms therefore undermine the credibility of NGO scientists and deploy think-tanks to distort reality, using Bayesian persuasion. In our model, we do not have to deal with the credibility issue either. Yet, instead of considering a direct intervention by firms through information provision, we focus on their indirect influence through the manipulation of scientific progress.

Second, our paper adds to a more extended literature on indirect lobbying and public persuasion, where special interest groups try to affect voter's beliefs; see, e.g., Laussel and van Ypersele (2012), Petrova (2012) and Cheikbossian and Hafidi (2022). In Yu (2005), an industrial and environmental lobby competes for political influence directly and through communication campaigns. Scientific progress does not play a role in his analysis. Baron (2005) and Shapiro (2016) consider special interests that seek political influence through the news media, modeling scientific information very simply as either informative or not. In our model, one lobby seeks to influence political decisions by interacting with a richer scientific process. Evidence can accumulate and scientists converge on the truth. This shows how seeking political influence has shaped private interests in academic research funding.

Finally, our model adds to the literature on strategic information provision, see e.g. Lipnowski et al. (2020) and Kirneva (2023). Persson (2018) analyzes the strategic interaction between a decision maker with limited attention and an expert affected by the decision. In one case, the expert prefers that the decision maker stay uninformed but has to provide everything he knows about the state of the world. In such cases, the expert may overload the decision maker with a mass of irrelevant information, which might capture one specific use of diversion research. In our model, diversion research is only related to scientific advancement, and we consider Bayesian rational and clear-sighted agents.

The paper is organized as follows. We introduce the model and describe scientific progress with the formation of opinions in Section 2. Section 3 provides the optimal regulation in the last period. In Section 4, we derive the interests that society and industry have in academic research and characterize the industry's optimal reallocations with some simulations. Section 5 concludes.

# 2 The model

In this section, we model an unknown environmental stock and the factors that may impact its level. We then develop a Bayesian approach to scientific advancement.

## 2.1 Framework

We consider a society composed of four groups of agents: firms, citizens, scientists, and the government. There is an environmental stock that is initially equal to $y_0$. This stock is subject to two independent potential threats: industrial activity (denoted $j = 1$) and an unrelated factor (denoted $j = 2$). The harmfulness of the factor $j$, denoted by $\tilde{\alpha}_j$, is uncertain. For simplicity, we assume that this uncertainty takes a binary form with $\alpha_j = 1$ if $j$ is harmful; otherwise, $\alpha_j = 0$. Therefore, the current level of the environmental stock $\tilde{y} \in [0, y_0]$ depends on the harmfulness of these factors and is also unknown. From now on, to simplify the reading, we will illustrate our model by considering the case of bees, where $\tilde{y}$ represents the current stock of healthy colonies, $j = 1$ corresponds to pesticides and $j = 2$ to Asian hornets.[6] Still, we can apply our analysis to any public health or environmental problem involving industrial lobbies.[7] An amount $x \in [0, x_0]$ of pesticides is sold by the industry, with $x_0$ the business-as-usual amount i.e. the amount sold without regulations. If pesticides are indeed harmful to bees, their overall damages are equal to $H(x) = y_0 hx$ with $hx$ the share of initial bee colonies that die with $x$ sold pesticides and $h > 0$. Similarly, if Asian hornets harm bees, their overall damages are exogenous and given by $y_0 a$ with $a > 0$ the share of bee colonies that disappear because of them. The stock of healthy bee colonies is then given by

$$\begin{aligned} \tilde{y} =& y_0 \left(1 - \tilde{\alpha}_1 hx - \tilde{\alpha}_2 a\right), \\ &\text{s.t. } hx_0 + a \leq 1. \end{aligned} \tag{1}$$

Note that $\tilde{y} = y_0$ if $\alpha_1 = \alpha_2 = 0$ and $\tilde{y} < y_0$ if $\alpha_1 = 1$ or $\alpha_2 = 1$, meaning that if pesticides and Asian hornets are harmless, bees do not decline; otherwise they do.

[6] In his work, Foucart (2014) identifies many factors used in producing diversion research on the decline of bees, such as invasive species, parasites, mushrooms, and disease.

[7] For example, $\tilde{y}$ the number of healthy individuals, $j = 1$ cigarettes and $j = 2$ the genetic inheritances.

To reduce uncertainties about $\tilde{\alpha}_j$, an exogenous number of scientists $N \in \mathbb{N}$ are studying it. We are on a medium-run horizon, i.e. Ph.D. students do not become researchers, and researchers do not retire. Each scientist performs one experiment to learn about $\tilde{\alpha}_1$ or $\tilde{\alpha}_2$. Let $n_1$ and $n_2$ represent the number of experiments on the harmfulness of pesticides and Asian hornets, respectively. The total number of experiments is given by $n_1 + n_2 = N$. We will see below how these studies are translated into scientific progress.

The game involves two stages:

1. The industrial lobby provides funds to reallocate scientists among research questions.

2. Scientific experiments are performed and the government regulates the industry to maximize social welfare.

## 2.2 Scientific beliefs

Building on this framework, we consider the following model of scientific progress. Scientists have prior beliefs $p_{0j} \in (0, 1)$ that $j$ is harmful. Each scientific experiment on $\tilde{\alpha}_j$ generates an unbiased signal $s_{ij}$ with $i \in \{1, 2, .., n_j\}$ and $n_j \leq N$, which is normally distributed $s_{ij} \sim \mathcal{N}(\tilde{\alpha}_j, \sigma^2)$. For technical convenience, we assume that the precision of experiments $\frac{1}{\sigma^2}$ is fixed, known, and identical for both factors $j$. Having an identical precision for both types of experiments does not affect our results. We are interested in the empirical mean of the set of $n_j$ signals, which is equal to

$$\mu_j = \frac{1}{n_j} \sum_{i=1}^{n_j} s_{ij} \sim \mathcal{N}\left(\alpha_j, \frac{\sigma^2}{n_j}\right).$$

Note that the mean of signals about the factor $j$'s harmfulness converge to the true state of the world as $n_j$ increases or $\sigma$ decreases. When this statistic is closer to zero, that is, $\mu_j > \frac{1}{2}$, the signals indicate that the factor $j$ is likely harmful. Otherwise, if $\mu_j < \frac{1}{2}$, it indicates that the factor is likely harmless.

Using the Bayes rule, we can derive the posterior belief expression resulting from experiments that is equal to

$$p_j(p_{0j}, \mu_j, n_j) = \frac{1}{1 + \left(\frac{1-p_{0j}}{p_{0j}}\right) \exp\left[\frac{n_j}{\sigma^2}\left(\frac{1}{2} - \mu_j\right)\right]}. \tag{2}$$

The steps for deriving this expression are provided in Section B in the appendix. Note that the posterior is higher than the prior belief if and only if the signals' empirical mean tends to indicate that $j$ is harmful, i.e. $p_{0j} \leq p_j \Leftrightarrow \frac{1}{2} \leq \mu_j$. Furthermore, when $n_1 \to \infty$, then $p_j = 1$ if $\mu_j = \alpha_j > \frac{1}{2}$ and $p_j = 0$ otherwise.[8] As the number of experiments on pesticides increases, scientists gain confidence in their beliefs, which converge toward the truth. More generally, this formula embodies key features of Bayesian updating. For example, if experiments are run in several stages, the final belief does not depend on their ordering. Formally, $p_j(p_j(p_{0j}, \mu_j, n_j), \mu'_j, n'_j) = p_j(p_{0j}, \mu_j + \mu'_j, n_j + n'_j)$ for any $\mu_j, \mu'_j$ and $n_j < n'_j$.

From an *ex-ante* perspective, i.e. before that experiments are run, the posterior belief is a continuous stochastic variable $\tilde{p}_j$, with a probability density function equal to

$$f_{\tilde{p}}(p_j) = \frac{f_{\tilde{\mu}}(\mu_j)\sigma^2}{n_j p_j(1-p_j)}.$$

As $n_j \to \infty$, we show in Section B in the appendix that $\tilde{p}_j$ converge in probability toward the distribution $p_\infty = 0$ with probability $1 - p_{0j}$ and $p_\infty = 1$ with probability $p_{0j}$. As the number of scientific studies in $j$ increases, the knowledge of scientists converges to the truth.

# 3 Optimal regulation

Using backward induction, we first solve the last period of the game. Experiments are conducted on the harmfulness of pesticides and Asian hornets. Scientists believe that pesticides are harmful to bees with probability $p_1(p_{01}, \mu_1, n_1)$, and that Asian hornets are so with probability $p_2(p_{02}, \mu_2, n_2)$.

With a command and control policy, the government imposes a maximum amount of pesticides $x \in [0, x_0]$ that can be commercialized. This induces an abatement of $x_0 - x$ pesticides sold, involving an abatement cost for firms equal to $C(x_0 - x) = c(x_0 - x)$, where $c > 0$.

We assume that the government is unable to address Asian hornet damage promptly due to constraints in its current agenda. In the short term, the government's actions are limited

[8] We also observe that when $\mu_j \to \infty$, then $p_j = 1$ and when $\mu_j \to -\infty$, then $p_j = 0$.

to controlling pesticides, overlooking potential interventions against Asian hornets in the future.

Bees are beneficial to society.[9] Formally, the social benefit function of bees is expressed as $B(\tilde{y}) = b\tilde{y} - B_0$ with $b, B_0 > 0$. In the absence of bee colonies, social benefits are at their lowest level, denoted by $-B_0$. This negative balance represents the negative spillovers that could result from the extinction of pollinators.

We assume that the government is *technocratic*, i.e. it maximizes the expected social welfare computed with up-to-date scientific knowledge. To set the optimal amount of pesticides allow $x^*$, the government then maximizes the *ex-post* expected social welfare function, equal to

$$\hat{W}(p_1, p_2, x) = by_0(1 - p_1hx - p_2a) - B_0 - c(x_0 - x).$$

The expected social welfare function is linear, leading to a corner solution for $x^*$ that is equal to

$$x^* = \begin{cases} x_0 & \text{if } c > by_0p_1h, \\ [0, x_0] & \text{if } c = by_0p_1h, \\ 0 & \text{if } c < by_0p_1h. \end{cases} \tag{3}$$

If the marginal cost exceeds the marginal benefits of regulation, the government does not regulate the industry, i.e. $x^* = x_0$. If the marginal cost equals the marginal benefits, the government is indifferent, that is, $x^* \in [0, x_0]$. Otherwise, the government completely bans pesticides, i.e., $x^* = 0$.

From equation (3), we can isolate the posterior belief at which the government is indifferent to regulate that we define as $\bar{p} \equiv \frac{c}{by_0h}$. This threshold is the social cost-benefit ratio of regulation beyond which pesticides are banned. If $p_1 > \bar{p}$, pesticides are prohibited. As the cost of regulation increases, the government becomes less inclined to ban pesticides.

When regulation is more socially expensive than beneficial, the regulator will never ban pesticides, i.e. $c > by_0h \Leftrightarrow \bar{p} > 1$. If the prohibition of pesticides is costless $c = 0$, then the regulator will never allow pesticides, that is, $\bar{p} = 0$. In both cases, scientific studies do not

[9] Gallai et al. (2009) found that insect pollinators played an important economic role in global agriculture. The study estimated that their contribution was €153 billion in 2005, equivalent to approximately 9.5% of the total value of agricultural production worldwide that is used for human consumption.

affect the regulatory decision. For the remainder of the paper, we consider $0 < c < by_0h$ to ensure $\bar{p} \in (0, 1)$. It means that if scientists know that pesticides harm bees, the government forbids their sale. This guarantees that the industry has an interest in funding academic research, as we will show in the next section.

Next, we are interested in the empirical mean of signals $\bar{\mu}$ at which the government bans pesticides, that is, such that $p_1(p_{01}, \bar{\mu}, n_1) = \bar{p}$. Using equation (2), we obtain:

$$\bar{\mu} = \frac{1}{2} + \frac{\sigma^2}{n_1}\left[\ln\left(\frac{\bar{p}}{1-\bar{p}}\right) - \ln\left(\frac{p_{01}}{1-p_{01}}\right)\right].$$

Let $\Delta \equiv \ln\left(\frac{\bar{p}}{1-\bar{p}}\right) - \ln\left(\frac{p_{01}}{1-p_{01}}\right)$ denote the logarithmic odd ratio of the regulation threshold with the prior. We can interpret it as the relative importance of the social cost of regulation. This yields:

$$\bar{\mu} = \frac{1}{2} + \frac{\sigma^2}{n_1}\Delta. \tag{4}$$

Note that when $n_1 \to \infty$, then $\bar{\mu} = \frac{1}{2}$, and so pesticides are banned if the empirical mean of the experiments indicates that pesticides are likely harmful. In other words, as the number of pesticide studies increases, the government becomes less concerned with the cost of regulation to make its decision. This is also true when scientific studies are very accurate (low $\sigma$) or when the prior belief $p_{01}$ is close to the threshold belief $\bar{p}$. However, if there is no experiment on pesticide harm, the regulation is entirely determined by the importance of the relative cost of regulation. Formally, at $n_1 = 0$, if $p_{01} < \bar{p}$ then $\bar{\mu} = +\infty$, that is, no empirical mean can lead to regulation and if $p_{01} > \bar{p}$ then $\bar{\mu} = -\infty$, which means that any empirical mean is high enough to require regulation.

# 4 Scientists allocation

We first show how research impacts social welfare and then derive our key results regarding the interests of the industrial lobby. Finally, we explore the main forces affecting the lobby's optimal scientists' reallocation and their social implications.

## 4.1 Social implication of research

We are in the first period of the game, occurring before the experiments are conducted. The prior belief that $j$ harms bees is $p_{0j}$, and the maximum amount of pesticides that will be allowed $\tilde{x}$ is unknown. Formally, the *ex-ante* expected social welfare function is equal to

$$W(p_{01}, p_{02}, n_1) = by_0(1 - p_{01}h\tilde{x} - p_{02}a) - B_0 - c(x_0 - \tilde{x}). \tag{5}$$

Let $\delta(n_1) \equiv P(\bar{\mu} < \mu_1)$ define the probability of regulation. Pesticides are prohibited and $C(x_0 - \tilde{x}) = cx_0$ with probability $\delta(n_1)$, or are allowed and $C(x_0 - \tilde{x}) = 0$ with probability $1 - \delta(n_1)$. The expected cost of the regulation is then equal to $\delta(n_1)cx_0$. A bit of algebra shows the following lemma:

**Lemma 1.** *The ex-ante expected social welfare function ex-ante is equal to*

$$W(p_{01}, p_{02}, n_1) = by_0 \left[1 - p_{01}hx_0\Phi\left((\bar{\mu} - 1)\frac{n_1^{1/2}}{\sigma}\right) - p_{02}a\right] - B_0 - \delta(n_1)cx_0, \tag{6}$$

*where* $\Phi(z)$ *is the cumulative distribution function of a standard normal distribution at* $z$*.*

*Proof.* See Section C in the appendix.

**Proposition 1.** *The expected social welfare function ex-ante is always increasing with the number of experiments on the harmfulness of industrial activity.*

*Proof.* See Section D in the appendix.

To see why Proposition 1 holds, note first that $\tilde{\alpha}_1$ and $\tilde{\alpha}_2$ entered linearly into the expected social benefits of healthy bee colonies $E[B(\tilde{y})]$. Therefore, expected social welfare is as much affected by the probability that pesticides harm bees when Asian hornets are certainly harmful as when they are not. Additionally, the regulatory decision does not depend on the harmfulness of Asian hornets, since $\tilde{\alpha}_1$ and $\tilde{\alpha}_2$ are independent. Finally, the government can control only the damages caused by pesticides, not those caused by Asian hornets. Therefore, by learning about the harmfulness of pesticides, the government can adopt a more efficient regulation. This is not true when learning about Asian hornets.

## 4.2 Industrial lobby's interests

In the first period, the lobby aims to minimize the expected cost of the regulation, which is equal to $\delta(n_1)cx_0$. Since $c$ and $x_0$ are constants, the industry's interest in academic research hinges entirely on how it influences the probability of being regulated $\delta(n_1)$. If studies on pesticides' harmfulness increase the probability of having a regulation, firms have an interest in funding diversion research. Since $N$ is fixed, funding $n_2$ diversion research studies is equivalent to having $n_2$ scientists who do not study pesticides. On the contrary, if research on pesticides' harmfulness reduces the probability of having a regulation, firms are interested in funding it.

Define $\hat{n} \equiv \frac{\Delta\sigma^2}{\frac{1}{2}-\bar{p}}$ such that $\delta'(\hat{n}) = 0$. We explicit every possible industry's interest in academic research below.

**Theorem 1.**
*Firms have an interest in funding diversion research if:*

- $p_{01} < \bar{p}$ *or* $p_{01} = \bar{p}$ *and* $\bar{p} > \frac{1}{2}$, $\forall n_1 < \hat{n}$.

- $\bar{p} > \frac{1}{2}$ *or* $\bar{p} = \frac{1}{2}$ *and* $p_{01} < \frac{1}{2}$, $\forall n_1 > \hat{n}$.

*Firms have an interest in funding research on the harmfulness of their activities if:*

- $p_{01} > \bar{p}$ *or* $p_{01} = \bar{p}$ *and* $\bar{p} < \frac{1}{2}$, $\forall n_1 < \hat{n}$.

- $\bar{p} < \frac{1}{2}$ *or* $\bar{p} = \frac{1}{2}$ *and* $p_{01} > \frac{1}{2}$, $\forall n_1 > \hat{n}$.

*Firms have no interest in funding any kind of research when* $n_1 = \hat{n}$ *or* $p_{01} = \bar{p} = \frac{1}{2}$.

*Proof.* See Section E in the appendix.

Theorem 1 is illustrated for the different ranges of $n_1$ in Figure 1. With a small number of pesticide experiments $n_1 < \hat{n}$, firms are interested in funding diversion research if the prior belief that pesticides harm bees is not high enough to require their prohibition, that is, $p_{01} < \bar{p}$. Yet, if it is high enough, i.e. $p_{01} > \bar{p}$, then the lobby always has an interest in funding research on pesticides' harms. When the government is initially indifferent to regulate, i.e. $p_{01} = \bar{p}$, firms have an interest in diversion research if regulation is relatively

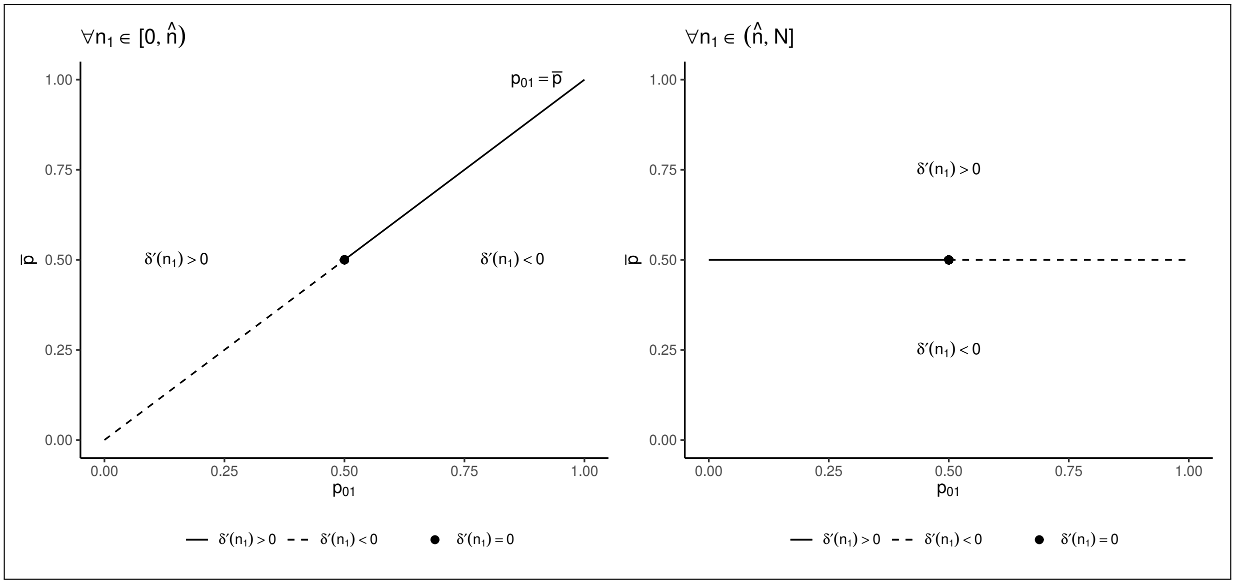


Figure 1: Characterization of industrial interest, for a low (on the left) and a high amount (on the right) of pesticides research.

expensive ($\bar{p} > \frac{1}{2}$) or in pesticide research if it is relatively inexpensive ($\bar{p} < \frac{1}{2}$). With a relatively large number of pesticide experiments $n_1 > \hat{n}$, the industrial lobby is always interested in having diversion research when regulation is relatively expensive. If not, the lobby prefers to fund pesticide research. In the case where the regulation is adopted only if pesticides are likely harmful ($\bar{p} = \frac{1}{2}$), then firms are interested in the diversion research if pesticides are likely harmless and in the pesticide research if they are likely harmful.

Note that depending on $p_{01}$ and $\bar{p}$, the lobby's interest can be monotonic or non monotonic with $n_1 \in [0, N]$. Figure 5 provides a map of cases where the interests are monotonic (upper left and lower right area, including lines) or non monotonic (upper right and lower left area, excluding lines) with $n_1$.

Let us first interpret and provide intuitions for the lobby's interest that are monotonic with $n_1$. We saw with equation (4) that as the number of experiments on pesticides' harms increases, the government increasingly relies on their results to decide the regulation. Another way to see it is that $\tilde{p}_1$ converges in probability to $p_\infty = 0$ and 1 with $n_1$. Therefore, if regulation is not initially required and relatively expensive, the industrial lobby will always prefer to have a government that is more concerned with the cost of regulation by perpetuating doubt. That is exactly what he can do by funding diversion research. Without scientific

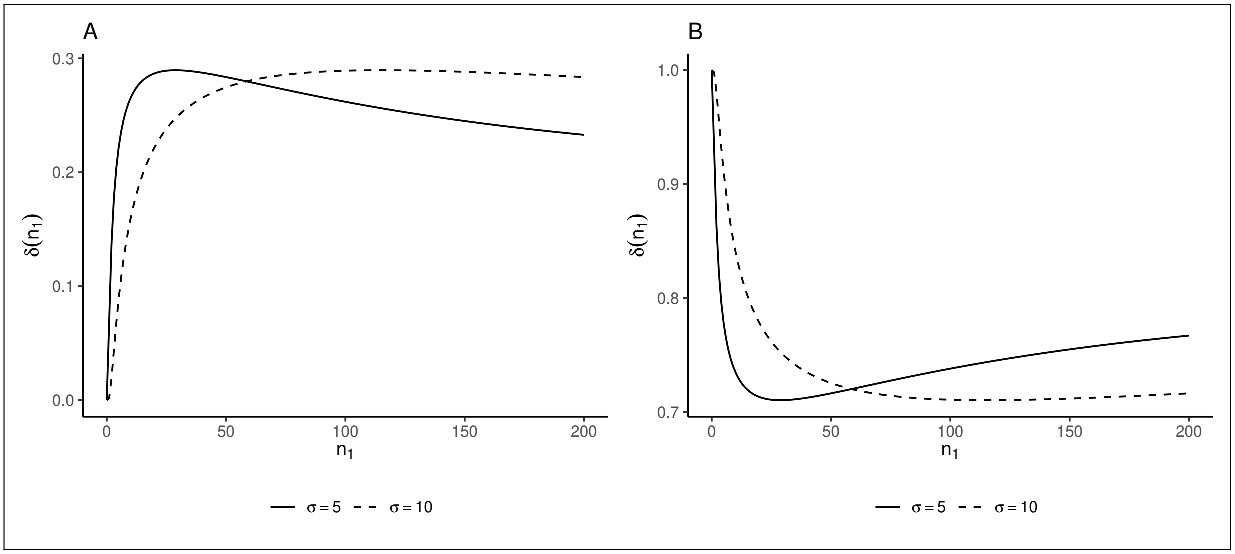


Figure 2: Non-monotonic regulation probability, when regulation is relatively inexpensive (on the left) or relatively expensive (on the right).

progress on the issue of pesticides, the government remains reticent to regulate because of the cost.

If regulation is initially required and relatively inexpensive, the industrial lobby will always be interested in funding research on pesticides' harms. In this way, the regulator is more concerned with scientific results that may change the initial regulatory requirement.

Lobby's interest can also be non monotonic in $n_1$, and we illustrate two representative cases in Figure 2. In graph A, the parameters are $N = 200$, $p_{01} = 0.2$, and $\bar{p} = 0.25$. For graph B, the parameters are $N = 200$, $p_{01} = 0.8$, and $\bar{p} = 0.75$.

In both cases, the prior belief is close to the threshold at which the regulation is determined, leading to a rapid convergence of $\bar{\mu}$ to $\frac{1}{2}$. The government is then very sensitive to the results of the first experiments in its decision, while scientists will not get much closer to the truth. This convergence is strengthened by the accuracy of scientific studies $\frac{1}{\sigma^2}$.

Let us first consider $p_{01} < \bar{p} < \frac{1}{2}$, as illustrated in graph A. The probability of regulation is lowest when there are no pesticide experiments since it does not involve any change in beliefs. Therefore, the industry's first-best situation is when there is full diversion research. However, with some planned pesticide experiments, the probability of regulation may be reduced by funding more of them. Indeed, with a small number of studies, the regulator's decision is highly affected, while scientists are not much closer to the truth that is likely to clear pesticides ($p_{01} < \frac{1}{2}$).

On the other hand, when $\bar{p} < p_{01} < \frac{1}{2}$, as illustrated in graph B, the lowest probability of regulation is reached when there is little research on pesticides, $n_1 = \hat{n}$. Given that they are likely harmful, the industry prefers to have just enough research on them to change the initial government's decision while avoiding scientists to get closer to the truth, which is likely to incriminate the industry ($p_{01} > \frac{1}{2}$).

A shock on the prior belief about the harms of pesticides may change the interest of the lobby. When there is a relatively small number of pesticide studies ($n_1 < \hat{n}$), this is true if such a shock reverses the regulatory requirement. At such a level of research, the government is still concerned with the cost of regulation, so the lobby's preference depends on whether or not it wants to perpetuate the doubt. For example, if the status quo changes and cancels the initial regulation requirement of the previous one, the lobby's interest shifts from funding pesticide research to diversion research. Second, with a relatively large number of studies on pesticides ($n_1 > \hat{n}$) such a shock changes the industry's interest when the government does not consider the cost of regulation ($\bar{p} = \frac{1}{2}$), and the shock reverses the likelihood of pesticides' harmfulness.

With a high enough level of pesticide research ($n_1 > \hat{n}$), if the government considers the cost of regulation to take its decision, i.e. $\bar{p} \neq \frac{1}{2}$, then the lobby's interest cannot be affected by a change in the status quo. First, consider a relatively expensive regulation. If the status quo does not require prohibition, we saw that diversion research is always profitable for firms. Now, if it does require prohibition, pesticides are necessarily harmful ($\frac{1}{2} < \bar{p} < p_{01}$), and the level of research required to effectively affect the regulatory decision is exceeded, so firms prefer to have all remaining scientists involved in diversion research. Next, consider a relatively inexpensive regulation. If prohibition is initially required, we know that firms prefer scientific advancement on the question of pesticides' harmfulness. Otherwise, it means that pesticides are likely harmless ($p_{01} < \bar{p} < \frac{1}{2}$), and knowing that some studies will affect the government's decision, the lobby prefers to have scientists well acknowledged on that issue.

A variation in the relative cost of regulation can always affect the lobby's interest. With a small number of pesticide studies ($n_1 < \hat{n}$), this shock must reverse the initial regulatory requirement to change the funding interest of firms. If the number of studies is large ($n_1 > \hat{n}$), this shock must change the consideration of the regulation cost by the government, i.e. the new $\bar{p}$ reaches $\frac{1}{2}$.

## 4.3 Optimal scientists' reallocation

Now, we analyze the optimal reallocation of scientists by firms in the initial period. This optimization problem involves non-convexities and discrete jumps, so we cannot provide any closed-form solutions. Our objective is then to explore the main forces affecting funding decisions by illustrating a variety of potential outcomes in different settings.

Initially, $N$ scientists decide whether to study the harmfulness of pesticides or Asian hornets in bees according to their preferences. We assume that these preferences are heterogeneous. Some may strongly prefer one topic over the other. We denote the number of scientists who initially chose to study the harmfulness of factor $j$ by $n_{0j}$, with $n_{01} + n_{02} = N$. Each scientist can change his research topic in exchange for additional monetary funds. The final allocation of research on pesticides and Asian hornets is denoted by $n_1$ and $n_2$, with $n_1 + n_2 = N$. Given that $N$ is fixed, the number of scientists re-allocated to another research topic is equal to $|n_{01} - n_1|$.

In the first period, the industrial lobby can influence the allocation of scientists by offering them additional funds. We assume that firms know every scientist's preference and their willingness to accept changes in their research topic. Therefore, to re-allocate $|n_{01} - n_1|$ scientists, the lobby chooses the less demanding ones. Convincing an additional scientist requires a higher additional fund. Formally, we express this reallocation cost as $\frac{\gamma}{2}(n_{01} - n_1)^2$, where $\gamma > 0$. Thus, the industrial lobby chooses the $n_1^*$ that minimizes its expected costs, which are equal to

$$c x_0 \delta(n_1) + \frac{\gamma}{2}(n_{01} - n_1)^2. \tag{7}$$

We illustrate a variety of optimal $n_1^*$ chosen by the lobby and the corresponding expected social welfare *ex-ante* in Figure 3 and 4. These figures have in common the following setting: $N = 200,\ x_0 = 9,\ B_0 = 0,\ p_{02} = 0.1,\ b = 50,\ h = 0.1,\ y_0 = 2$ and $\sigma = 10$. We fix $c = 7.5$

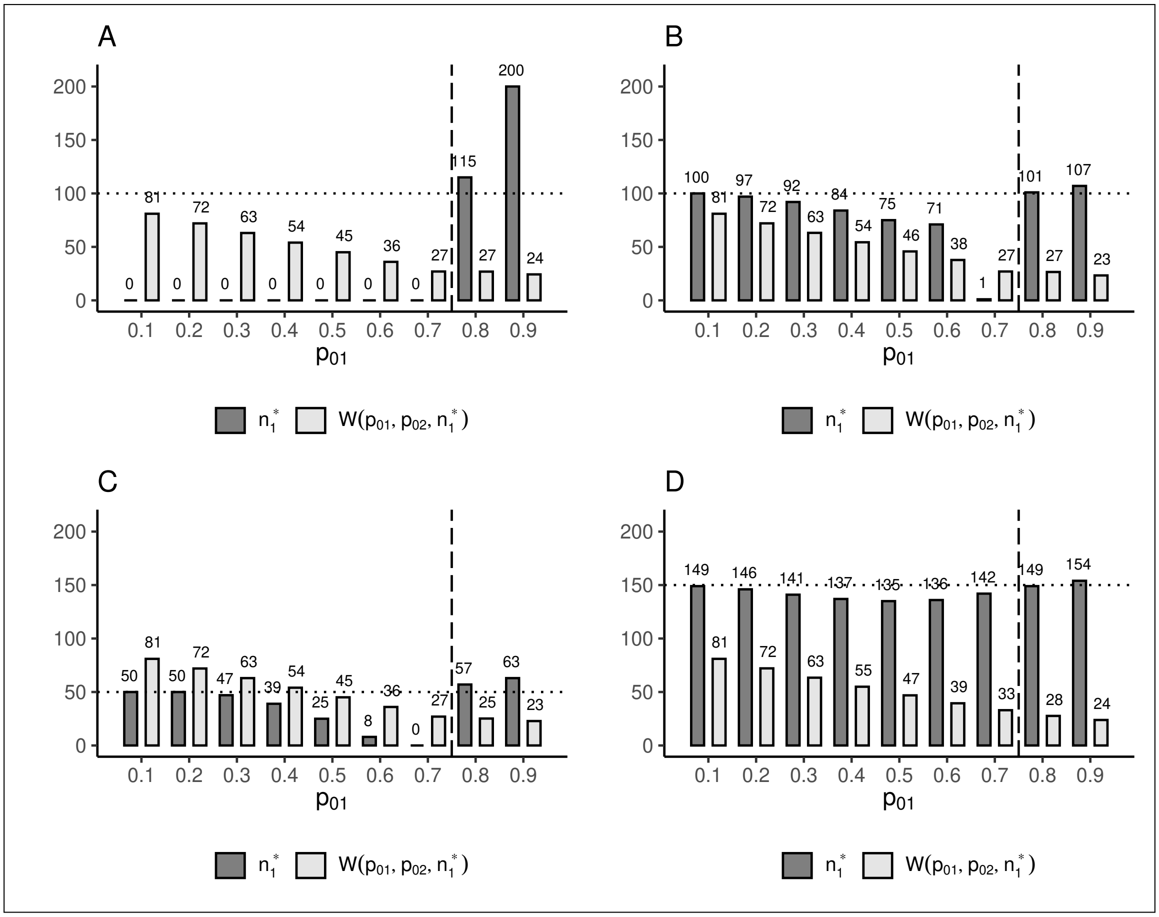


Figure 3: Optimal research allocation examples, with $\bar{p} = 0.75$ (Dashed line) and different initial allocations of scientists (Dotted line).

implying $\bar{p} = 0.75$ for graphs A and C, and $c = 2.5$ implying $\bar{p} = 0.25$ for graphs B and D. Reallocating scientists is free in Graph A, i.e. $\gamma = 0$, so it displays the lobby's first-best allocation, denoted $n_1^{opt}$. The reallocation is costly in graphs B, C, and D, with $\gamma = \frac{1}{200}$, so they show optimal scientist allocations $n_1^*$ that can differ from $n_1^{opt}$. Finally, we rounded the values of $W(p_{01}, p_{02}, n_1^*)$.

Figures 3 and 4 are reproduced with a higher precision of experiments, that is, $\sigma = 5$, in Section A in the appendix with Figures 6 and 7. A variation in scientific accuracy can reverse the lobby's interest. When $\bar{p} = 0.75$ and $\sigma = 10$, the lobby's first-best situation at $p_{01} = 0.8$ would be to reallocate 15 scientists to study pesticides' harmfulness (see Figure 3, graph A). Now, if we fix $\sigma = 5$, the lobby prefers to reallocate 71 scientists to produce diversion research in the same scenario (see Figure 6, graph A). Yet, even when it increases diversion research funds, a higher experiment's accuracy always yields at least similar or improved social welfare.

We now focus on cases where regulation is relatively expensive, as illustrated in Figure 3, but is not initially required. The industry's first best scientists' allocation is always $n_1^{opt} = 0$, as shown in graph A. We know that as scientists get confident in their beliefs, the government becomes less concerned with the cost of regulation. When prior belief approaches the belief threshold of regulation, the scientists' confidence required to effectively influence the government's decision is lower. At $n_{01}$, there is a range of prior beliefs under which the government is still sufficiently concerned with the cost of regulation. In this range, an increase in the status quo about pesticide harms decreases this concern. Therefore, the marginal benefit of diversion research increases with the status quo in the neighborhood of $n_{01}$. For example, diversion research funds continuously increase with $p_{01} \in [0.1, 0.6]$ when $n_{01} = 50$ or 100. With a higher range of prior beliefs, the government is almost not concerned with the cost of regulation, and an increase in the status quo strengthens this. In this situation, the marginal benefit of diversion research decreases with the status quo. This is why the funding for diversion research decreases with $p_{01} \in [0.5, 0.7]$ when $n_{01} = 150$. However, it is sometimes beneficial for the lobby to jump from the initial allocation by funding an aggressive campaign of diversion research. Typically, when the prior belief about pesticides' harmfulness is close to the threshold, $n_{01} \neq 0$ becomes high enough to ensure that the government is strongly concerned with scientific results. Moreover, a higher status quo yields a higher probability of regulation when the government is not concerned with the cost of regulation. Therefore, when $p_{01}$ is high and close to $\bar{p}$, aggressive funding for diversion research becomes more interesting. This is why at $n_{01} = 100$ we go from $n_1^* = 71$ with $p_{01} = 0.6$ to $n_1^* = 1$ with $p_{01} = 0.7$. This strategy may be too expensive if there are too many scientists to convince, which explains why we do not observe such a jump when $n_{01} = 150$. Generally, when regulation is relatively expensive and not initially required, diversion research funds are increasing with the prior probability that pesticides harm bees, except if there are too many scientists who originally planned to study pesticides.

Now, if regulation is initially required but is still relatively expensive, firms have an interest in funding diversion research if $n_{01} > n_1^{opt}$, or pesticide research if $n_{01} < n_1^{opt}$. This

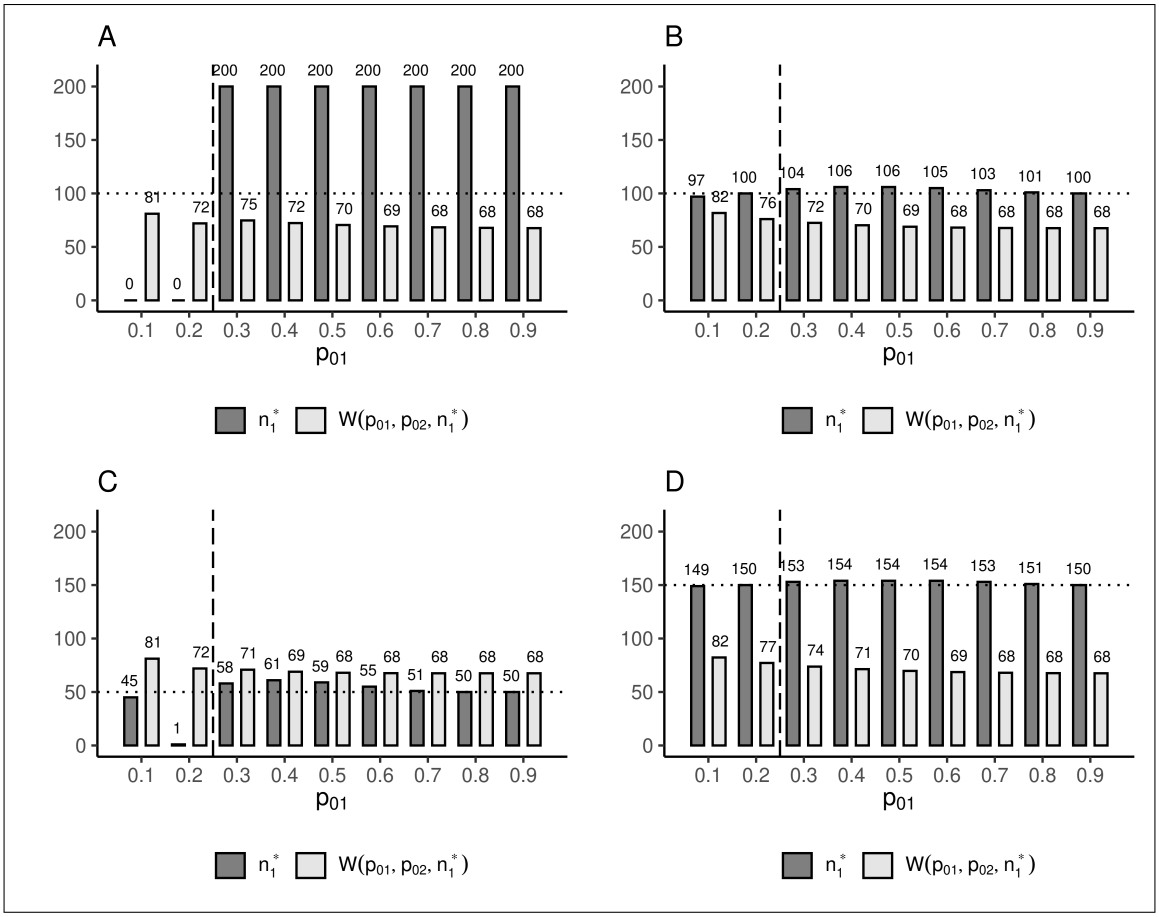


Figure 4: Optimal research allocation examples, with $\bar{p} = 0.25$ (Dashed line) and different initial allocations of scientists (Dotted line).

follows the lobby's interest illustrated in Figure 2, graph B. As the status quo increases, scientists become even more confident that pesticides harm bees, and so firms need additional pesticide research to maximize their influence on the initial regulatory decision. In Figure 3, we see it with $n_1^{opt} < N$ when $p_{01} = 0.8$ and $n_1^{opt} = N$ with $p_{01} = 0.9$.

Next, we focus on scenarios where regulation is relatively inexpensive, but not required, as illustrated in Figure 4. Firms end up with the lowest expected cost if there is no pesticide research, i.e. $n_1^{opt} = 0$. However, if there are too many, the second best would be to have a maximum of pesticide research. This is shown in the graph B of Figure 2. The number of pesticide experiments beyond which firms have an interest in funding pesticide research is lower as the prior increases since it gets closer to the threshold. Here, when $p_{01} = 0.1$ firms always have an interest in funding diversion research since $\hat{n} > N$. When $p_{01} = 0.2$, then $\hat{n} \in [0, N]$, and firms either can fund many scientists to produce diversion research to obtain a quasi-null probability of regulation, or to support pesticide research so that beliefs converge to the likely truth; pesticides are harmless. If there are not too many scientists who want to study pesticides, as with $n_{01} = 50$ here, it is more profitable to opt for the first strategy. If there are too many, as with $n_{01} = 100$ and 150, the lobby prefers to support this research. In this case, higher scientific accuracy increases the marginal benefit of any kind of fund. We can see it by comparing Figures 4 and 7. At $p = 0.2$, with $\sigma = 10$, firms do not fund any research, while they support pesticide research when $\sigma = 5$ for $n_{01} = 100$ and $n_{01} = 150$.

Finally, let us explore cases where the regulation is relatively inexpensive but still required initially. In this case, two opposite forces act when the status quo increases. First, since $p_{01}$ deviates from $\bar{p}$, the number of pesticide studies needed to effectively affect the government's decision is greater. This increases the marginal benefit of pesticide research. Second, a higher probability that pesticides harm bees reduces the chance that science clears pesticides. This deteriorates the marginal benefit of pesticide research. The first effect dominates the second one in a lower range of $p_{01}$, and funds increase with it. In a higher range of $p_{01}$, the second effect is the strongest, and the funds decrease. For example, when $n_{01} = 100$, pesticide research funds increase with $p_{01} \in [0.3, 0.5]$ and decrease with $p_{01} \in [0.6, 0.9]$.

# 5 Conclusion

We identify a *manufacturing doubt* strategy systematically used by industrial lobbies and special interest groups, and we provide the first analyses of it. We show that diversion research prevents scientific advancement that could trigger regulatory requirements. Surprisingly, we also find that the industry may benefit from research on the harmfulness of its activities. This is true when additional knowledge may lead to the withdrawal of an initial regulatory decision.

While banning private research funding is a drastic solution to prevent first-order welfare losses due to the use of diversion research, it would bar access to private funds. A more fruitful approach could involve permitting private funding overseen by an independent committee. In this way, special interest groups would no longer be able to perpetuate doubt by manipulating scientific agendas. However, in cases where science can help to get a regulatory requirement withdrawn, the industry would still be motivated to offer funds, which may contribute to the progress of the desired research, aligning with societal interests.

Moreover, our analysis relies on several simplifying assumptions. Relaxing them could provide valuable future research directions.

Since the agents are Bayesian rational, they treat all information optimally. Diversion research then affects regulation only through the scientists' availability. If non-Bayesian agents are considered, diversion research may have other advantages. For example, the regulator might be unaware of the existence of a harmful factor until he reads one study on it. Assuming that he also has limited attention, diversion research may drown out studies on the industry's harmfulness in a mass of studies on other factors, as discussed by Persson (2018).

We considered a benevolent government, but the former could pursue the maximization of a combination of welfare and transfers, as seen in the framework proposed by Grossman and Helpman (1994). In this scenario, firms would seek to influence regulation directly through transfers, and if they face credibility issues, they could do so indirectly through scientific opinion.

Furthermore, we know that an industrial lobby often employs multiple *manufacturing doubt* strategies. For example, firms might produce doubt using misinformation strategies, as in Bramoullé and Orset (2018), to get rid of an initial regulation, and then use diversion research to perpetuate this doubt. The simultaneous use of multiple *manufacturing doubt* strategies constitutes an intriguing area for further investigation.

Finally, the biased presentation of debates in the media warrants study. Although one side has overwhelming scientific evidence, both sides may receive equal weight.[10] Diversion research may exacerbate this problem by offering a lengthy list of potential factors for one social issue, which can diminish the clearness of the industry's responsibility.

[10] See Boykoff and Boykoff (2004); Shapiro (2016); Bartoš et al. (2022)

# Appendices

## A Figures

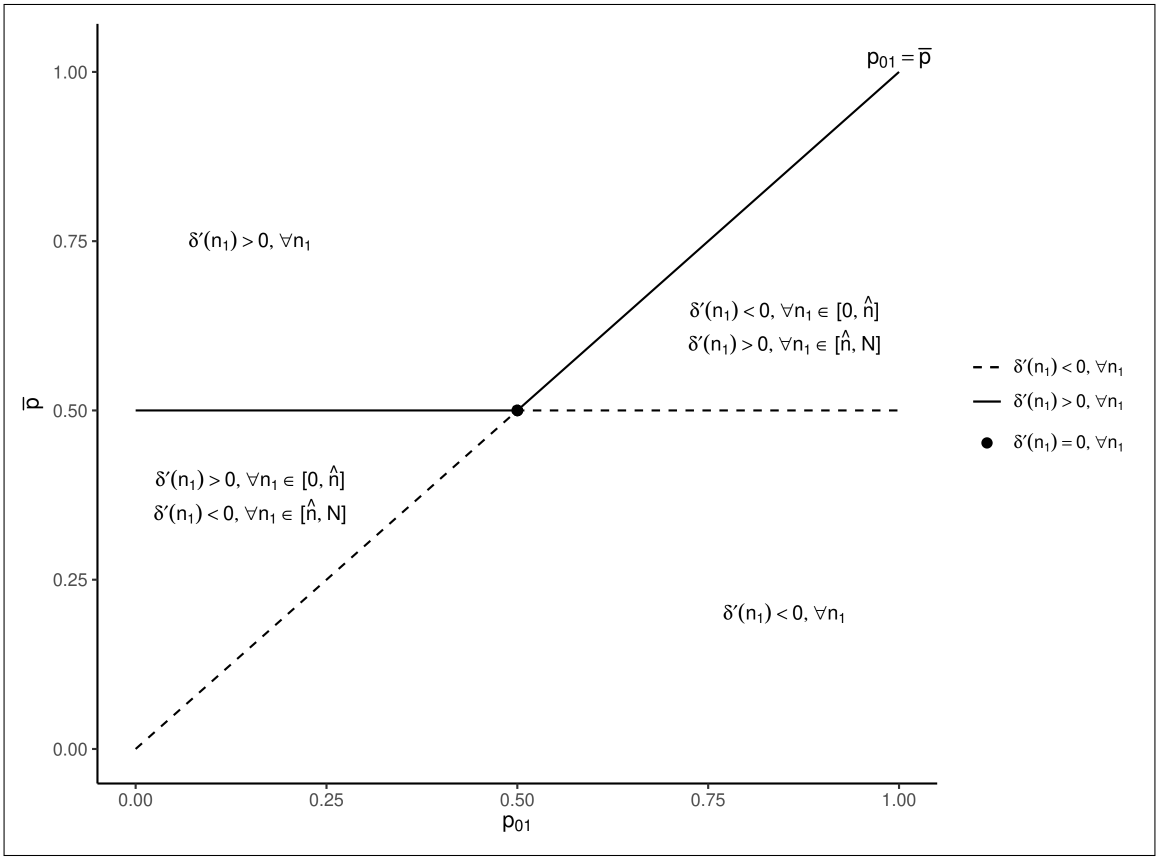


Figure 5: Characterization of industrial interest for any $n_1 \in [0, N]$.

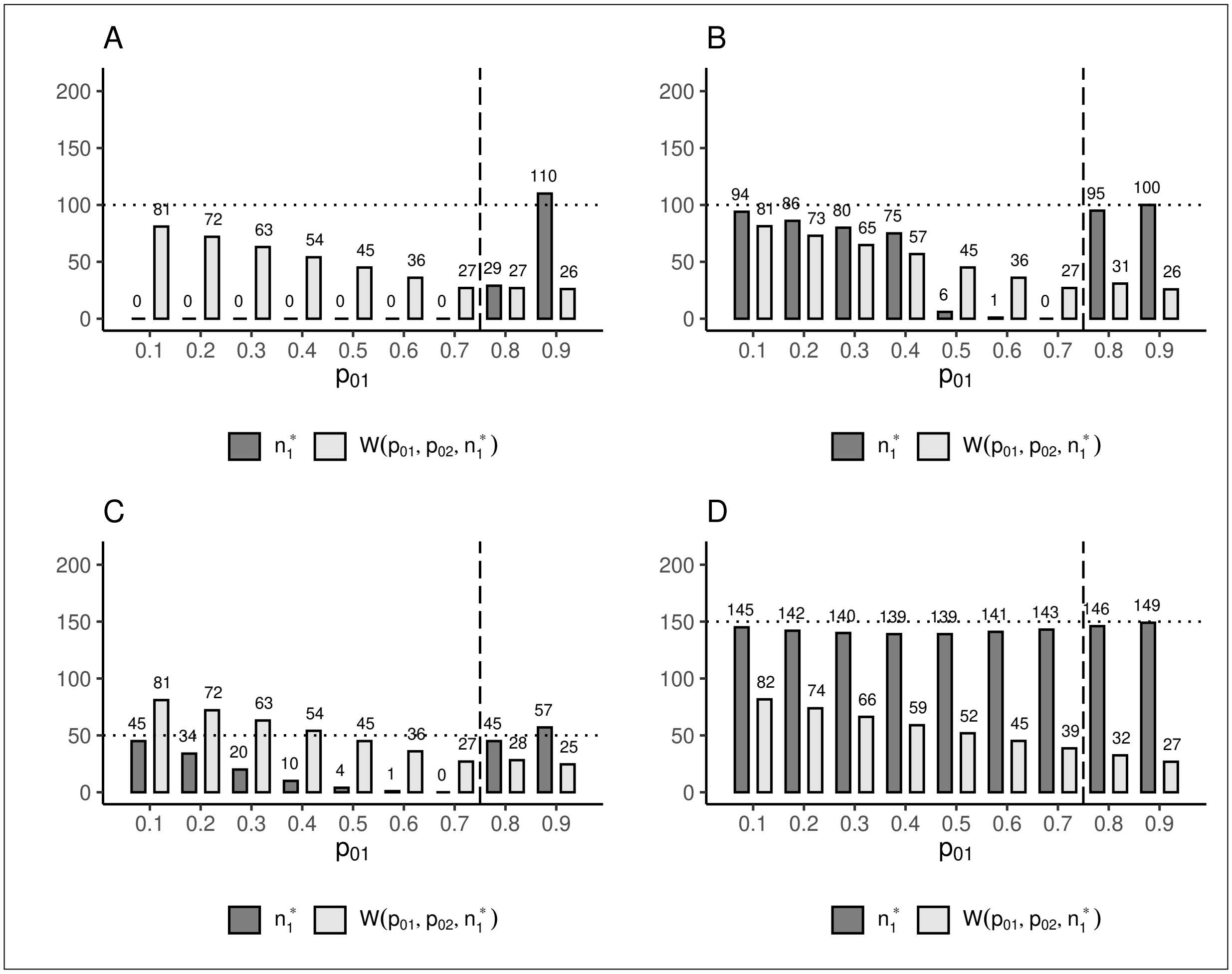


Figure 6: Optimal research allocation examples, with $\bar{p} = 0.75$ (Dashed line) and different initial allocations of scientists (Dotted line).

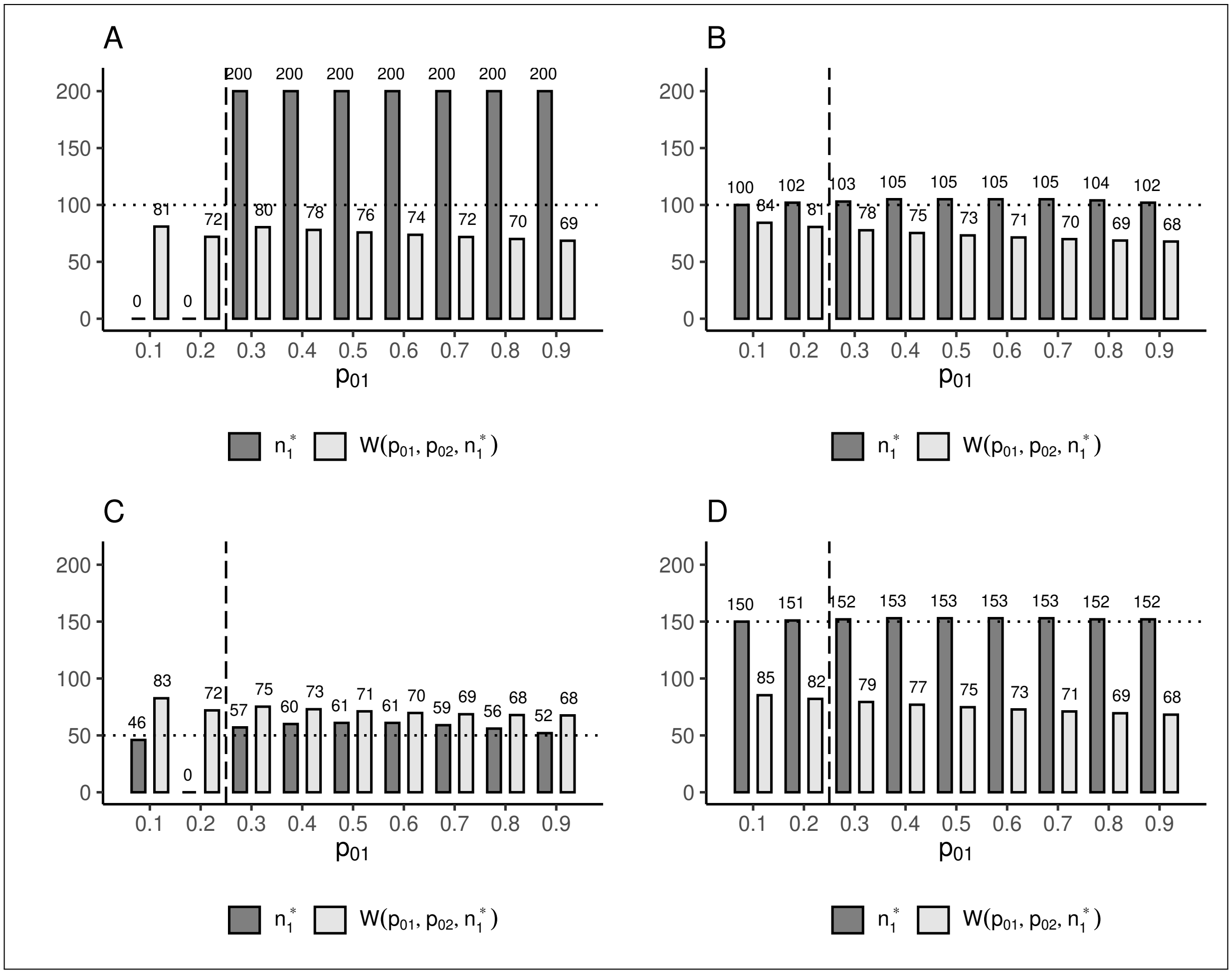


Figure 7: Optimal research allocation examples, with $\bar{p} = 0.25$ (Dashed line) and different initial allocations of scientists (Dotted line).

# B Proof of section 2.2 statements

In this section, the formulas are identical for both factors $j$. For clarity, we then omit this subscript.

Let us first detail the algebra to obtain equation (2). The posterior belief $p(p_0, \mu, n)$ is defined as the *ex-post* probability that the factor is harmful, conditional on the $n$ experiments' results i.e., $P(\alpha = 1|\mu)$. Using the Bayes formula, we derive the posterior, which yields:

$$p(p_0, \mu, n) = \frac{P(\alpha = 1)f(\mu|\alpha = 1)}{P(\alpha = 1)f(\mu|\alpha = 1) + P(\alpha = 0)f(\mu|\alpha = 0)}$$

$$= \frac{p_0 \cdot \exp\left(-\frac{n}{2\sigma^2}(\mu - 1)^2\right)}{p_0 \cdot \exp\left(-\frac{n}{2\sigma^2}(\mu - 1)^2\right) + (1 - p_0) \cdot \exp\left(-\frac{n}{2\sigma^2}\mu^2\right)}$$

$$= \frac{1}{1 + \left(\frac{1-p_0}{p_0}\right) \cdot \frac{\exp(-n\mu^2/2\sigma^2)}{\exp(-n(\mu-1)^2/2\sigma^2)}}$$

$$= \frac{1}{1 + \left(\frac{1-p_0}{p_0}\right) \exp\left[\frac{n}{\sigma^2}(\frac{1}{2} - \mu)\right]}.$$

QED.

We now derive the probability density function of $\tilde{p}$ and its asymptotic convergence. The cumulative distribution function of $\tilde{p}$ at $p(p_0, \mu, n) = p$ is equal to

$$F_{\tilde{p}}(p) = P(\tilde{p} < p) = P\left(\frac{1}{1 + \frac{1-p_0}{p_0}\exp\left(\frac{n}{\sigma^2}\left(\frac{1}{2} - \tilde{\mu}\right)\right)} < p\right)$$

$$= P\left(1 + \frac{1-p_0}{p_0}\exp\left(\frac{n}{\sigma^2}\left(\frac{1}{2} - \tilde{\mu}\right)\right) > \frac{1}{p}\right)$$

$$= P\left(\frac{n}{\sigma^2}\left(\frac{1}{2} - \tilde{\mu}\right) > \ln\left(\frac{1-p}{p}\frac{p_0}{1-p_0}\right)\right)$$

$$= P\left(\tilde{\mu} < \frac{1}{2} + \frac{\sigma^2}{n}\left[\ln\left(\frac{p}{1-p}\right) - \ln\left(\frac{p_0}{1-p_0}\right)\right]\right)$$

$$= F_{\tilde{\mu}}(\mu),$$

where $F_X(x)$ is the cumulative distribution function of the normal stochastic variable $X$ at point $x$. We know that the probability density function $f_X(x)$ is equal to $\frac{\partial F_X(x)}{\partial x}$. Therefore, we can derive the probability density function of $\tilde{p}$, which yields:

$$f_{\tilde{p}}(p) = \frac{\partial F_{\tilde{p}}(p)}{\partial p} = \frac{\partial F_{\tilde{\mu}}(\mu)}{\partial p} = \frac{\partial F_{\tilde{\mu}}(\mu)}{\partial \mu}\frac{\partial \mu}{\partial p} = f_{\tilde{\mu}}(\mu)\frac{\sigma^2}{np(1-p)}.$$

Next, we can derive the convergence in probability for $\tilde{p}$. We know that when $n \to \infty$, then $p(p_0, \mu, n) = 1$ if $\mu > \frac{1}{2}$ or 0 if $\mu < \frac{1}{2}$. Thus $\lim\limits_{n\to\infty} f_{\tilde{p}}(p)$ is equal to $f_{\tilde{p}}(p = 1) = f_{\tilde{p}}(p = 0) = \infty$. Let us show that for all the others $p$, the distribution of $\tilde{p}$ is null. Using the expression of $f_{\tilde{\mu}}(\mu)$ knowing that $\mu$ is normally distributed, the posterior probability density function is equal to

$$\frac{\sigma}{(2\pi n)^{1/2}} \exp\left(-\frac{1}{2}(\mu-\alpha)^2\frac{n}{\sigma^2}\right)\frac{1}{p(1-p)},$$

and we see that this expression tends to 0 as $n \to \infty$. Therefore, the posterior converges in probability to 0 and 1. Note that due to this convergence, the probability of having $p_\infty = 0$ is given by $\lim\limits_{n\to\infty} F_{\tilde{p}}(p)$ for any $p \in (0, 1)$, which is equal to $\lim\limits_{n\to\infty} F_{\tilde{\mu}}(\mu) = F_{\tilde{\mu}}(\frac{1}{2})$. Also, we know that $F_{\tilde{\mu}}(\mu) = F_{\tilde{\mu}}(\mu|\alpha = 1)p_0 + F_{\tilde{\mu}}(\mu|\alpha = 0)(1 - p_0)$, which yields $F_{\tilde{\mu}}(\frac{1}{2}) = 1 - p_0$. Therefore, the probability of having $p_\infty = 1$ is equal to $1 - \lim\limits_{n\to\infty} F_{\tilde{p}}(p) = p_0$. QED.

# C Proof of Lemma 1

First, note that with regulation, the expected *ex-ante* social welfare function is equal to $by_0(1 - p_{02}a) - B_0 - cx_0$, and without regulation we have $by_0(1 - p_{01}hx_0 - p_{02}a) - B_0$. Therefore, we integrate equation (5) over $\mu_1$ and separate the expression for cases where there is and there is no regulation. This yields:

$$\begin{aligned} W(p_{01}, p_{02}, \tilde{x}) = &\int_{-\infty}^{\bar{\mu}} \left[by_0(1 - p_1(p_{01}, \mu_1, n_1)hx_0 - p_{02}a) - B_0\right] f(\mu_1|n_1)d\mu_1 \\ &+ \int_{\bar{\mu}}^{+\infty} \left[by_0(1 - p_{02}a) - B_0 - cx_0\right] f(\mu_1|n_1)d\mu_1, \end{aligned}$$

Knowing that $\int_{\bar{\mu}}^{+\infty} f(\mu_1|n_1)d\mu_1 \equiv \delta(n_1)$, we obtain:

$$
\begin{aligned}
W(p_{01}, p_{02}, \tilde{x}) =& (1-\delta(n_1))\left[by_0(1-p_{02}a) - B_0\right] - \int_{-\infty}^{\bar{\mu}} hx_0by_0p_1(p_{01}, \mu_1, n_1)f(\mu_1|n_1)d\mu_1 \\
&+ \delta(n_1)\left[by_0(1-p_{02}a) - B_0 - cx_0\right] \\
=& by_0(1-p_{02}a) - B_0 - \int_{-\infty}^{\bar{\mu}} dx_0by_0p_1(p_{01}, \mu_1, n_1)f(\mu_1|n_1)d\mu_1 - \delta(n_1)cx_0.
\end{aligned}
$$

By writting the posterior belief as follows:

$$
p_1(p_{01}, \mu_1, n_1) = \frac{p_{01} \cdot f(\mu_1|n_1, \alpha_1 = 1)}{f(\mu_1|n_1)},
$$

we can the simplify the term under the integral, which yields:

$$
\begin{aligned}
\int_{-\infty}^{\bar{\mu}} p_1(p_{01}, \mu_1, n_1)f(\mu_1|n_1)d\mu_1 &= p_{01}F(\bar{\mu}|n_1, \alpha_1 = 1) \\
&= p_{01}\Phi\left((\bar{\mu}-1)\frac{n_1^{1/2}}{\sigma}\right).
\end{aligned}
$$

where $\Phi(z)$ is the cumulative distribution function of a standard normal distribution at $z$. We then substituting it within the expected social welfare function, and we obtain the final expression. QED.

# D Proof Proposition 1

For clarity, we ignore the subscripts for $n_1$, $\mu_1$ and $p_{01}$ since we never use $n_2$,$\mu_2$ and $p_{02}$. First, note that the probability of regulation is equal to

$$
\begin{aligned}
\delta(n) &= 1 - F(\bar{\mu}|n) \\
&= p_0\left[1 - F(\bar{\mu}|n, \alpha = 1\right] + (1-p_0)\left[1 - F(\bar{\mu}|n, \alpha = 0\right] \\
&= p_0\left[1 - \Phi\left((\bar{\mu}-1)\frac{n^{1/2}}{\sigma}\right)\right] + (1-p_0)\left[1 - \Phi\left(\bar{\mu}\frac{n^{1/2}}{\sigma}\right)\right].
\end{aligned}
$$

Substituting $\bar{\mu}$ by its expression from equation (4), we can write

$$
(\bar{\mu}-1) \cdot \frac{n^{1/2}}{\sigma} = \left(\frac{\Delta\sigma^2}{n} - \frac{1}{2}\right)\frac{n^{1/2}}{\sigma} = \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma},
$$

$$\bar{\mu} \cdot \frac{n^{1/2}}{\sigma} = \left( \frac{\Delta\sigma^2}{n} + \frac{1}{2} \right) \frac{n^{1/2}}{\sigma} = \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma}.$$

We then substitute it for the term into the cumulative distribution functions, and we can write the condition at which the expected social welfare function is increasing with $n$ as follows:

$$\frac{\partial W(p_{01}, p_{02}, \tilde{x})}{\partial n} > 0$$

$$\Leftrightarrow \quad - by_0 hx_0 p_{01} \cdot \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \right\} - \delta'(n) cx_0 > 0$$

$$\Leftrightarrow \quad \left[ p_0 \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \right\} + (1 - p_0) \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right) \right\} \right] cx_0$$
$$- by_0 hx_0 p_{01} \cdot \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \right\} > 0$$

$$\Leftrightarrow \quad \frac{p_0}{1 - p_0} \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \right\} (c - by_0 d) + \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right) \right\} c > 0.$$

We know that $\bar{p} = \frac{c}{by_0 d}$, so we can divide both sides of the equation by $c$ to obtain:

$$\frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right) \right\} > \left( \frac{p_0}{1 - p_0} \right) \left( \frac{1 - \bar{p}}{\bar{p}} \right) \frac{\partial}{\partial n} \left\{ \Phi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \right\}$$

$$\Leftrightarrow \quad \varphi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right) \left( -\frac{1}{2} \frac{\Delta\sigma}{n^{3/2}} + \frac{1}{2} \frac{n^{-1/2}}{2\sigma} \right)$$
$$> \left( \frac{p_0}{1 - p_0} \right) \left( \frac{1 - \bar{p}}{\bar{p}} \right) \varphi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \left( -\frac{1}{2} \frac{\Delta\sigma}{n^{3/2}} - \frac{1}{2} \frac{n^{-1/2}}{2\sigma} \right)$$

$$\Leftrightarrow \quad \left( \frac{p_0}{1 - p_0} \right) \left( \frac{1 - \bar{p}}{\bar{p}} \right) \varphi \left( \frac{\Delta\sigma}{n^{1/2}} - \frac{n^{1/2}}{2\sigma} \right) \left( \frac{\Delta\sigma}{n} + \frac{1}{2\sigma} \right) > \varphi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right) \left( \frac{\Delta\sigma}{n} - \frac{1}{2\sigma} \right),$$

where $\varphi(x)$ is the probability density function of the standard normal distribution at $x$. Next, we can simplify the inequality by dividing both sides by $\varphi \left( \frac{\Delta\sigma}{n^{1/2}} + \frac{n^{1/2}}{2\sigma} \right)$, since it provide us with:

$$\frac{\varphi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)}{\varphi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)}=\exp\left[-\frac{1}{2}\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)^2+\frac{1}{2}\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)^2\right]$$

$$=\exp(\Delta)$$

$$=\frac{\bar{p}}{1-\bar{p}}\frac{1-p_0}{p_0}.$$

Therefore, we can rewrite the condition as follows:

$$\frac{\partial E(W|n)}{\partial n}>0$$

$$\Leftrightarrow\quad \frac{\Delta\sigma}{n}+\frac{1}{2\sigma}>\frac{\Delta\sigma}{n}-\frac{1}{2\sigma}.$$

Since $\sigma>0$, this condition is always true. QED.

# E Proof Theorem 1

By clarity, we forget the subscript for $p_{01},\ n_1,\ \mu_1$ since we will not use it for $j=2$. First, note that:

$$(\bar{\mu}-1)\cdot\frac{n^{1/2}}{\sigma}=\left(\frac{\Delta\sigma^2}{n}-\frac{1}{2}\right)\frac{n^{1/2}}{\sigma}=\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma},$$

$$\bar{\mu}\cdot\frac{n^{1/2}}{\sigma}=\left(\frac{\Delta\sigma^2}{n}+\frac{1}{2}\right)\frac{n^{1/2}}{\sigma}=\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}.$$

We can then substitute these terms into the equation (**??**) to obtain

$$\delta(n)=p_0\left[1-\Phi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)\right]+(1-p_0)\left[1-\Phi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)\right].$$

Next, we study the necessary and sufficient condition for having a positive partial derivative of $\delta(n)$ with respect to $n$, which is equal to:

$$-p_0\varphi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)\cdot\left(-\frac{1}{2}\frac{\Delta\sigma}{n^{3/2}}-\frac{1}{2}\frac{n^{-1/2}}{2\sigma}\right)$$
$$-(1-p_0)\varphi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)\cdot\left(-\frac{1}{2}\frac{\Delta\sigma}{n^{3/2}}+\frac{1}{2}\frac{n^{-1/2}}{2\sigma}\right)>0$$

$$
\begin{aligned}
\Leftrightarrow \quad & -p_0\varphi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)\cdot\left(-\frac{\Delta\sigma}{n}-\frac{1}{2\sigma}\right) \\
& -(1-p_0)\varphi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)\cdot\left(-\frac{\Delta\sigma}{n}+\frac{1}{2\sigma}\right)>0
\end{aligned}
$$

$$
\begin{aligned}
\Leftrightarrow \quad & \frac{\Delta\sigma}{n}\left[p_0\varphi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)+(1-p_0)\varphi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)\right] \\
& +\frac{1}{2\sigma}\left[p_0\varphi\left(\frac{\Delta\sigma}{n^{1/2}}-\frac{n^{1/2}}{2\sigma}\right)-(1-p_0)\varphi\left(\frac{\Delta\sigma}{n^{1/2}}+\frac{n^{1/2}}{2\sigma}\right)\right]>0
\end{aligned}
$$

$$
\Leftrightarrow \quad \frac{\Delta\sigma^2}{n}\left[\frac{p_0}{1-p_0}\exp(\Delta)+1\right]+\frac{1}{2}\left[\frac{p_0}{1-p_0}\exp(\Delta)-1\right]>0
$$

$$
\Leftrightarrow \quad \frac{\Delta\sigma^2}{n}\left[\frac{\bar{p}}{1-\bar{p}}+1\right]+\frac{1}{2}\left[\frac{\bar{p}}{1-\bar{p}}-1\right]\gtrless 0.
$$

First, note that when $p_{01}=\bar{p}=\frac{1}{2}$, then $\delta'(n)=0$. Consider that this cannot happen for what follows. If $\Delta \geq 0 \Leftrightarrow p_0 \leq \bar{p}$, a sufficient condition for this inequality to hold would be $\bar{p} \geq \frac{1}{2}$. Thus, $\delta'(n)>0$ when $p_0<\bar{p}$ and $\frac{1}{2}<\bar{p}$. By symmetry, we can then affirm that $\delta'(n)<0$ if $\bar{p}\leq p_0$ and $\bar{p}\leq\frac{1}{2}$.

Next, let us analyze the non-monotonic variations outside of these domains. We denote $\hat{n}$ the amount of experiment in which the direction of the variation of $\delta$ changes, which can be expressed as follows:

$$
\begin{aligned}
& \hat{n}:\delta'(\hat{n})=0 \\
\Leftrightarrow \quad & \hat{n}=\frac{\Delta\sigma^2}{\frac{1}{2}-\bar{p}}.
\end{aligned}
$$

Thus, if $\frac{1}{2}<\bar{p}<p_0$, we have:

- $\delta'(n)<0$ when $n<\hat{n}$.

- $\delta'(n)>0$ when $n>\hat{n}$.

Symmetrically, if $p_0<\bar{p}<\frac{1}{2}$, we have:

- $\delta'(n) > 0$ when $n < \hat{n}$.

- $\delta'(n) < 0$ when $n > \hat{n}$.

QED.

# References


David P Baron. Competing for the Public Through the News Media. *Journal of Economics & Management Strategy*, 14(2):339–376, 2005.

Vojtěch Bartoš, Michal Bauer, Jana Cahlíková, and Julie Chytilová. Communicating Doctors' Consensus Persistently Increases COVID-19 Vaccinations. *Nature*, 606(7914):542–549, 2022.

Maxwell T Boykoff and Jules M Boykoff. Balance as Bias: Global Warming and the US Prestige Press. *Global Environmental Change*, 14(2):125–136, 2004.

Yann Bramoullé and Caroline Orset. Manufacturing doubt. *Journal of Environmental Economics and Management*, 90:119–133, 2018.

Guillaume Cheikbossian and Houda Hafidi. Lobbying, Public Persuasion, and Environmental Policy under Imperfect Competition. *Annals of Economics and Statistics*, (145):91–116, 2022.

Mireille Chiroleu-Assouline and Thomas P Lyon. Merchants of Doubt: Corporate Political Action when NGO Credibility is Uncertain. *Journal of Economics & Management Strategy*, 29(2):439–461, 2020.

Alice Fabbri, Alexandra Lai, Quinn Grundy, and Lisa Anne Bero. The Influence of Industry Sponsorship on the Research Agenda: a Scoping Review. *American Journal of Public Health*, 108(11):e9–e16, 2018.

Stéphane Foucart. *La Fabrique du Mensonge. Comment les Industriels Manipulent la Science et nous mettent en Danger*. Editions Gallimard, 2014.

Stéphane Foucart, Stéphane Horel, and Sylvain Laurens. *Les Gardiens de la Raison: Enquête sur la Désinformation Scientifique*. la Découverte, 2020.

Nicola Gallai, Jean-Michel Salles, Josef Settele, and Bernard E Vaissière. Economic Valuation of the Vulnerability of World Agriculture Confronted with Pollinator Decline. *Ecological Economics*, 68(3):810–821, 2009.

Rebecca F Goldberg and Laura N Vandenberg. Distract, Delay, Disrupt: Examples of Manufactured Doubt from five Industries. *Reviews on Environmental health*, 34(4):349–363, 2019.

Gene M Grossman and Elhanan Helpman. Protection for Sale. *American Economic Review*, 833, 1994.

Margarita Kirneva. Informing to Divert Attention. 2023.

Didier Laussel and Tanguy van Ypersele. When the Squeakiest Wheel gets the Most Oil: Exploiting one's Nuisance Power. *European Economic Review*, 56(8):1593–1606, 2012.

Elliot Lipnowski, Laurent Mathevet, and Dong Wei. Attention Management. *American Economic Review: Insights*, 2(1):17–32, 2020.

David Michaels. *The Triumph of Doubt: Dark Money and the Science of Deception.* Oxford University Press, 2020.

Naomi Oreskes and Erik M Conway. *Merchants of Doubt: How a Handful of Scientists Obscured the Truth on Issues from Tobacco Smoke to Global Warming.* Bloomsbury Publishing USA, 2011.

Petra Persson. Attention Manipulation and Information Overload. *Behavioural Public Policy*, 2(1):78–106, 2018.

Maria Petrova. Mass Media and Special Interest Groups. *Journal of Economic Behavior & Organization*, 84(1):17–38, 2012.

Robert Proctor. *Golden Holocaust: Origins of the Cigarette Catastrophe and the Case for Abolition.* Univ of California Press, 2011.

Jesse M Shapiro. Special Interests and the Media: Theory and an Application to Climate Change. *Journal of Public Economics*, 144:91–108, 2016.

Benjamin Wood, Gary Ruskin, and Gary Sacks. How Coca-Cola Shaped the International Congress on Physical Activity and Public Health: an Analysis of Email Exchanges Between

2012 and 2014. *International Journal of Environmental Research and Public Health*, 17 (23):8996, 2020.

Zhihao Yu. Environmental Protection: A Theory of Direct and Indirect Competition for Political Influence. *The Review of Economic Studies*, 72(1):269–286, 2005.