Strategic Ignorance and Perceived Control

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Abstract

When useful information provokes negative emotion, it may deliberately be ignored. We experimentally investigate whether increasing perceived control can mitigate such strategic ignorance. Participants from India were presented with a choice to receive information about the average loss of life expectancy due to air pollution in their district and were later asked to recall it. We find that an increase in perceived control substantially improves information recall, an effect driven by individuals with optimistic prior beliefs. We conduct the same experiment in the US and confirm this latter result. A theoretical framework rationalizes our findings.

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Keywords: Information avoidance; Information recall; Perceived control; Life expectancy loss.

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From online platforms to newspapers and social interactions, we are exposed to a vast amount of information. The decision to attend to information depends on whether it is useful (Stigler, 1961) but also on the emotional response it provokes (Kőszegi, 2003). Most of us dislike distressing information related to our environment or personal well-being such as a looming economic recession, reports of a violent conflict in our vicinity, the outbreak of a pandemic, or the threat of climate change. Because interacting with such unsettling information can leave us feeling uneasy or anxious, we might find ourselves deliberately ignoring it, thereby forgoing valuable insights. Such strategic ignorance can occur in two distinct forms. First, one can actively avoid information before being exposed to it, see Golman, Hagmann and Loewenstein (2017) for a comprehensive review. Second, once the information is voluntarily or involuntarily acquired, one may deliberately not recall it, see the review by Amelio and Zimmermann (2023).[1]

In this paper, we propose *perceived control* – the belief that one's actions can influence a specific outcome – as a mechanism to limit strategic ignorance, both in the form of deliberately avoiding and not recalling information. In fact, information is often ignored in situations where individuals have limited or no control over the outcome. Examples include foregoing medical tests for untreatable diseases or genetic conditions (Thornton, 2008; Oster, Shoulson and Dorsey, 2013), and the avoidance of information on past events, such as yesterday's financial portfolio returns during a market decline (Sicherman et al., 2016). Information may also be ignored in situations where actions to avoid adverse outcomes are available but awareness of these actions or their effectiveness is limited. Prime examples come from the health domain, where numerous diseases can be prevented or treated, if detected early. Due to poor awareness of preventive actions and treatments or an insufficient understanding of their effectiveness, individuals are often reluctant to take action, incurring significant personal and societal costs.

Evidence on the effectiveness of perceived control as a tool to reduce strategic ignorance is scarce. Theoretical contributions indirectly support a negative correlation between perceived control and information avoidance by predicting that the avoidance of medical diagnoses decreases in the extent to which a disease can be treated (Kőszegi, 2003; Schward-

[1] Not recalling information can result from *inattention* to information (*e.g.,* Sims, 2003; Caplin and Dean, 2015; Amasino, Pace and van der Weele, 2021), *biased processing* of information (*e.g.,* Eil and Rao, 2011; Glaeser and Sunstein, 2013; Peysakhovich and Karmarkar, 2016; Sunstein et al., 2016; Möbius et al., 2022) and the deliberate *forgetting* of information (*e.g.,* Zimmermann, 2020; Huffman, Raymond and Shvets, 2022). In our study, we only measure whether information is recalled and do not make any claim about the specific path through which the information may not be recalled.

mann, 2019). These theories are empirically supported by Ganguly and Tasoff (2017) and Li et al. (2021) who show that the avoidance of medical tests increases with the severity of the disease, but neither study can provide direct causal evidence on the effectiveness of perceived control in reducing information avoidance.[2] We are only aware of one study by Trope, Gervey and Bolger (2003) where they experimentally shift perceived control over one's social abilities. They find that participants exhibit a greater demand for feedback when social abilities are depicted as controllable traits. However, to the best of our knowledge, there is no direct evidence on the effect of perceived control on information avoidance with respect to health-related risks and no theoretical or empirical contribution on the effectiveness of perceived control in reducing the selective recall of information, neither in the health domain, nor beyond.

We first present a simple theoretical framework to illustrate how perceived control affects two key decisions: (i) whether to acquire or avoid new information, and (ii) whether to recall it or not. In this framework, individuals hold a prior belief about the realization of an event that generates disutility. While there is a costly action to reduce the impact of the negative event, individuals have different levels of perceived control over the impact of this action. Building on previous work (Kőszegi, 2003; Oster, Shoulson and Dorsey, 2013; Schwardmann, 2019), we assume that individuals experience anticipatory utility based on their beliefs about the event's impact on their future utility. Once the event occurs, they experience realized utility. By comparing total expected utilities, individuals decide whether to acquire or avoid the information. As perceived control increases, the protective action is perceived as more effective, leading to a rise in the total expected utility of acquiring information and consequently decreasing information avoidance. After acquiring the information, individuals re-evaluate the total utilities to make a decision whether to recall the information or not. We show that this decision hinges on an indifference point in the distribution of prior beliefs about the event's severity. Individuals with a prior belief below this point are better off not recalling the information and instead reverting to their optimistic belief. Increasing perceived control reduces the indifference point, reducing the

[2]Without a focus on information acquisition and processing, the economics literature has largely focused on how an internal locus of control, *i.e.*, the degree to which people believe that they generally have control over the outcome of events in their lives, correlates with different economic behaviors, ranging from applications in labour (Coleman and DeLeire, 2003; Caliendo, Cobb-Clark and Uhlendorff, 2015; Caliendo et al., 2022), health (Kesavayuth et al., 2020; Churchill et al., 2020), development (Buddelmeyer and Powdthavee, 2016; Abay, Blalock and Berhane, 2017; Churchill and Smyth, 2021), and risk-taking and financial decisions (Pinger, Schäfer and Schumacher, 2018; Fehr and Reichlin, 2022).

share of individuals that decide not to recall the information.

In an extension to our framework, we propose that the value of acquiring information is increased if individuals account for the possibility to not recall information that disadvantageously contradicts their prior beliefs. This can result in less information avoidance, but at the cost of lower recall rates. Our theoretical insights thus challenge approaches that solely rely on information acquisition as a measure of strategic ignorance and emphasize the importance of recall as a more comprehensive outcome measure.

We conduct a pre-registered experiment with an Indian sample from 33 different states and union territories (N=2,031) to study the influence of perceived control on the decisions to avoid and recall information about the loss of life expectancy due to air pollution. First, we provide all participants with detailed information on air pollution including its main sources, associated illnesses, and how excessive exposure can be converted into an average loss of life expectancy. In the treatment group, we then increase participants' perceived control by listing various simple yet effective measures to protect one's health against outdoor and indoor air pollution. Subsequently, we measure information avoidance by eliciting participants' preference to receive information about the average loss of life expectancy due to air pollution in their home district. Their preference is implemented with a 60% probability to ensure that the information is also shown to a share of participants that indicates a preference not to receive it. After participants complete an unrelated effort task, we measure information recall by asking participants who were randomly assigned to receive the information to recall it.

We focus on information related to loss of life expectancy for several reasons. First, the information is expected to be particularly useful. For example, it can aid in making informed decisions about retirement planning, investments, and healthcare. Second, due to its inherent association with mortality and uncertainty, the information can be notably distressing. In fact, there is extensive evidence on the avoidance of health-related information (Kőszegi, 2003; Thornton, 2008; Oster, Shoulson and Dorsey, 2013; Ganguly and Tasoff, 2017; Schwardmann, 2019; Li et al., 2021). Additionally, the loss of life expectancy due to air pollution is a highly policy relevant area of research. According to the World Health Organization (WHO) in 2021, about 6.7 million deaths worldwide are attributable to ambient and household air pollution every year, a quarter of which occur in India alone (Pandey et al., 2021). Importantly, the associated level of perceived control is typically low, presenting opportunities for intervention. Despite various effective and relatively affordable methods to shield against the adverse health impact of air pollution — such as face masks, air purifiers, or adequate indoor ventilation — awareness of and demand for these measures remain consistently low, particularly in developing countries (Greenstone and Jack, 2015; Pattanayak, Pakhtigian and Litzow, 2018; Greenstone, Lee and Sahai, 2021).

In our experiment, we observe that 8% of participants in the control group prefer to avoid the information and about 27% of participants who receive the information do not recall it. The treatment – which effectively increases perceived control – does not affect information avoidance but significantly decreases the share of participants that do not recall the information to 20%, reflecting a 25% reduction.

To demonstrate that not recalling is strategic, we first exploit the heterogeneity in prior beliefs about air quality.[3] We find that in the control group, participants categorized as optimists – those who have a prior belief to experience particularly good air quality – exhibit significantly lower recall rates than all other participants. Moreover, we show striking treatment effect heterogeneity, with optimists primarily driving the treatment effect on recall in the overall sample. Importantly, the treatment-induced improvement in recall stems from a decrease in the proportion of optimists who recall overly optimistic values. Such patterns of strategic recall are in line with the assumption in our theoretical framework that individuals derive anticipatory utility from their prior beliefs. Also, they are consistent with related models of deliberate information recall (Bénabou and Tirole, 2002; Chew, Huang and Zhao, 2020), where individuals are less likely to recall information that disadvantageously contradicts their prior beliefs. Importantly, our results are not predicted by a model that only considers realized utilities.

To further argue for strategic recall, we leverage the randomization into receiving the information to compare recall rates between participants who prefer to avoid and those who prefer to receive the information. We show that recall is significantly lower when participants prefer to avoid the information. Yet, the treatment significantly improves recall, suggesting that low recall rates in the control group are strategic. Moreover, among participants that prefer to receive the information, recall is notably lower when the information conflicts with optimistic prior beliefs. A possible explanation for the behavior observed in our experiment is provided by the extension of our theoretical framework. A share of participants appears to acquire the information while being aware that it does not need to be recalled. This results in an overall low rate of information avoidance and, in the absence

[3] In the context of information recall, the term *strategic* does not refer to considerations with respect to the actions and reactions of other agents. Rather, the term refers to the deliberate manipulation of behavior and beliefs (also referred to as "motivated beliefs", see Zimmermann, 2020) to maximize own utility.

of the treatment, a comparatively high rate of not recalling. Lastly, we argue that the observed treatment effect on recall cannot be explained by a salience effect or differences in general cognitive abilities.

The findings from the Indian sample highlight that increasing perceived control can encourage people to engage with distressing information in settings of severe health consequences due to air pollution. To test for external validity, we conduct the same experiment with participants from the US (N = 2,272). This allows us to examine the prevalence of strategic ignorance and assess the role of perceived control when the information is objectively less distressing, as air pollution levels are comparatively lower in the US, but nonetheless above official recommendations and significantly detrimental to health (see Deryugina et al., 2019, on the sizable mortality effects of air pollution in the US).

In the US sample, we find that 17% of participants avoid the information, a share that is unaffected by the treatment. Among participants randomized to receive information on life expectancy loss, 16% are unable to recall it. While the treatment does not affect information recall in the aggregate, the results of the heterogeneity analysis by prior belief mirror the patterns observed in the Indian sample: recall rates are lowest among optimists and the treatment significantly improves recall only in this subgroup. We interpret the robustness of this result as further evidence that an increase in perceived control is an effective tool to improve recall among optimists. With these results, we join the ongoing debate on the importance of self-deception to maintain optimistic beliefs about one's future (see Engelmann et al., 2024, for a review of the literature and experimental evidence).

This paper contributes to the literature threefold. Our main contribution is to present direct evidence on perceived control as an effective tool to mitigate the strategic recall of distressing but useful information. Given the adverse consequences of strategic recall (Cordes, Friedrichsen and Schudy, 2023; Gödker, Jiao and Smeets, 2024), there is a growing interest in understanding how and why individuals recall information selectively. Yet, little progress has been made in understanding how to curb it (Amelio and Zimmermann, 2023). Theoretical and empirical contributions on motivated beliefs suggest that increasing monetary incentives improves recall to the extent that information is suppressed, rather than forgotten (Bénabou and Tirole, 2002; Zimmermann, 2020). However, providing monetary incentives is costly and so far, non-monetary incentives such as providing feedback (Huffman, Raymond and Shvets, 2022) appear to be ineffective. To the best of our knowledge, this study provides the first successful non-monetary alternative to mitigate strategic recall of distressing information.

Second, this paper studies information avoidance and recall jointly. The approach facilitates a test on whether deliberately not recalling information is used as a complement or a substitute for information avoidance. The literature typically considers memory distortions as a last resort when information cannot be avoided (see Golman, Hagmann and Loewenstein, 2017, and references therein). We find support for such complementarity as recall rates are lower among participants who state a preference against receiving the information but are randomly assigned to see it. Still, we find substantial rates of unsuccessful recall among those who want to receive the information, especially when it contradicts prior beliefs. This suggests that not recalling can also serve as a substitute for information avoidance, consistent with the assumption that participants consider the possibility of not recalling during the decision to acquire information. Therefore, studying information avoidance in isolation may lead researchers to critically underestimate the extent of strategic ignorance.

Third, we demonstrate that information avoidance and the lack of recall are a relevant concern also with respect to aggregate-level information. The related literature has been primarily concerned with information that is directly applicable to the individual that consumes it. In particular, negative feedback on personal intelligence or beauty, teacher evaluations, own financial outcomes, and medical test results are prominent instances of information that is often ignored (Karlsson, Loewenstein and Seppi, 2009; Eil and Rao, 2011; Ganguly and Tasoff, 2017). With our experiment on information about the average loss of life expectancy due to air pollution exposure, we contribute to an expanding body of literature that examines attitudes towards aggregate-level information, where accurate individual estimates are not accessible (Carrillo and Mariotti, 2000; Loewenstein and O'Donoghue, 2006; Kahan et al., 2012).

Our findings carry important policy implications for tackling strategic ignorance about health-related risks. When information is ignored, the insufficient use of preventive actions can have detrimental social and economic consequences. Those include not only premature mortality (Lelieveld et al., 2015; Pandey et al., 2021) but also the loss of economic productivity (Fu, Viard and Zhang, 2021) and an increased burden on the health care system (Deryugina et al., 2019). Another recent and prominent example in the health domain is the outbreak of the COVID-19 pandemic which highlighted how low perceived control over infectious diseases can lead to widespread fear, uncertainty, and difficulties in implementing effective public health measures such as vaccination campaigns (Fetzer et al., 2021; Kaplan and Milstein, 2021). Our study suggests that policymakers should complement health risk information with actionable advice on coping strategies. By doing so, they can mitigate strategic ignorance of the underlying problem, thus clearing an initial hurdle towards lasting behavioral change.

I. Theoretical Framework

We propose a simple model to illustrate the role of perceived control on the acquisition and recall of distressing information, highlighting differences between the two decision types. Consider an individual whose utility is negatively impacted by an exogenous event Z. The individual cannot directly influence the realization of Z but she can undertake action a to reduce the impact of Z on her utility.[4] The utility function is given by:

$$U(a, \gamma, Z) = -(1 - \gamma a)Z - C(a). \tag{1}$$

Taking action a is costly, as represented by a convex cost function.[5] The level of perceived control is denoted by γ, it represents the belief about the extent to which action a can mitigate the impact of Z. The individual chooses action a to maximize her utility, conditional on event Z and her perceived control γ, with $a^*_Z = \arg\max_a U(a, \gamma, Z)$.

In the following, we examine the optimal decisions for the acquisition and recall of information about the realization of the distressing event Z. Consider a horizon with two time periods, as illustrated in Figure 1. While event Z has already occurred prior to $t = 0$, its impact on utility will only be experienced in $t = 1$. The individual decides whether to acquire or avoid information about the true level of Z, and whether to recall or not recall the information if acquired. Both decisions occur at $t = 0$ and determine the level of action a to implement. At time $t = 1$, contingent on the selected decision path, the impacts of event Z materialize.

Our framework builds on Caplin and Leahy (2001), Kőszegi (2003), Oster, Shoulson and Dorsey (2013), and Schwardmann (2019) by assuming that individuals experience

[4] Examples for action a include wearing a face mask to protect oneself against air pollution exposure, doing physical exercise to reduce the incidence of illnesses, and seeking medical care to prevent a disease (*e.g.*, a vaccination), among many other.

[5] The convexity corresponds to a setting where reducing the effects of Z becomes more costly at an increasing rate as a increases, typical in settings of pollution reduction, climate change mitigation, medical treatments, etc.

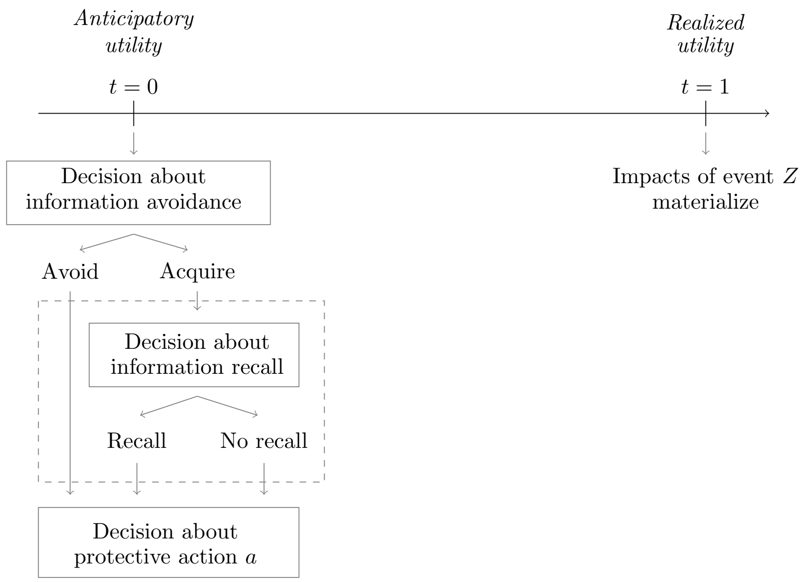

FIGURE 1 – TIMELINE AND DECISION TREE.

Notes: The figure depicts the timeline for experiencing anticipatory ($t = 0$) and realized utility ($t = 1$) as well as the information avoidance and recall decisions at $t = 0$. The dashed box illustrates that the individual is not aware of the opportunity to not recall when deciding whether to acquire or avoid information. This assumption is relaxed in Section I.C.

anticipatory utility.[6] That is, individuals faced with uncertainty derive direct utility from holding certain expectations about their future utility levels, which is experienced at time $t = 0$. At time $t = 1$, when the impact of event Z materializes, the individual experiences *realized utility*.

A. Information Avoidance

First, we consider the decision to acquire or avoid information about the true level of Z at time $t = 0$. Initially, the individual does not know the realized value of the event, but holds a belief about Z, where π and σ are the subjective expected value and variance,

[6] Li et al. (2021) identify three main models of information avoidance relying on the assumption of anticipatory utility: (i) models of optimal expectations (Brunnermeier and Parker, 2005; Oster, Shoulson and Dorsey, 2013), (ii) curvature models (Caplin and Leahy, 2001; Kőszegi, 2003), and (iii) attention models (Ganguly and Tasoff, 2017; Golman, Hagmann and Loewenstein, 2017; Golman et al., 2022).

respectively.[7] Acquiring information imposes an opportunity cost $\kappa \geq 0$.[8] For now, we assume that the individual is not aware of the option to not recall the information when deciding whether to acquire or avoid information; see by the dashed box in Figure 1. We relax this assumption in Section I.C.

Conditional on the acquisition decision, the individual chooses the optimal preventive action a^* at time $t = 0$. If the individual chooses to learn the true value of Z, she will implement action $a^*_Z = \arg\max_a U(a, \gamma, Z)$. In contrast, if the individual chooses not to learn the true value of Z, she will base her decision on her prior belief π and set $a^*_\pi = \arg\max_a U(a, \gamma, \pi)$. At time $t = 1$, the impact of event Z on the individual's utility is realized. Table 1 illustrates the timeline of decision making and the respective utility levels.

TABLE 1 – INFORMATION ACQUISITION AND INCURRED UTILITY.

Timeline:	$t = 0$	$t = 1$
Decision type:	Info acquisition and action a	
Incurred utility:	Anticipatory utility	Realized utility
Information acquisition	$U(a^*_Z, \gamma, Z) - \kappa$	$U(a^*_Z, \gamma, Z)$
Information avoidance	$U(a^*_\pi, \gamma, \pi)$	$U(a^*_\pi, \gamma, Z)$

The decision of whether to acquire or avoid information about the true value of Z will be taken to maximize the total expected utility, as given by the sum of expected anticipatory and realized utilities. Namely, the individual will choose to acquire information if her total expected utility from doing so is higher than her total expected utility from maintaining belief π. Let Δ^{IA} denote the difference in total expected utilities between acquiring and

[7] Our model comes close to Kőszegi (2003), with a notable distinction that we assume individuals to differ in their subjective beliefs about the event Z. In contrast, Kőszegi (2003) assumes variations among individuals in terms of the curvature of their utility function, while maintaining identical expectations regarding the negative event. Furthermore, our framework has similarities with that of Brunnermeier and Parker (2005) and Oster, Shoulson and Dorsey (2013), albeit with a notable difference. Unlike their assumption that the belief is formed concurrently with the decision on action a, we assume that the individual holds her belief before deciding on the acquisition of information about Z. Namely, we treat the belief about Z as exogenous and do not make specific assumptions about how it is formed.

[8] We consider κ to primarily be non-monetary costs such as the time spent on acquiring information, and cognitive efforts to comprehend new information. When information is not freely available, κ may also be monetary expenses of purchasing information. We view κ as a perceived cost as the individual might not be fully aware of the actual cost until the moment she decides to engage with the information.

avoiding information. Δ^{IA} is given by:

$$\Delta^{\text{IA}} = \Big(\mathbb{E}[U(a_Z^*, \gamma, Z)] - \kappa + \mathbb{E}[U(a_Z^*, \gamma, Z)]\Big) - \Big(U(a_\pi^*, \gamma, \pi) + \mathbb{E}[U(a_\pi^*, \gamma, Z)]\Big) \tag{2}$$

We assume that individuals vary with respect to their prior beliefs π and σ, as well as their level of perceived control γ, and the perceived opportunity cost of acquiring information κ. Accordingly, some individuals will be better off acquiring the information ($\Delta^{\text{IA}} > 0$), while others will prefer to avoid the information ($\Delta^{\text{IA}} < 0$).

The role of perceived control. To study the role of perceived control on the decision to avoid or acquire information, we derive the general condition from Equation (2) accounting for the functional form of the utility function assumed in Equation (1). For illustrative purposes, we define the cost function as $C(a) = a^2$. Δ^{IA} is then given by:

$$\Delta^{\text{IA}} = \frac{\gamma^2}{2}\sigma - \kappa. \tag{3}$$

Equation (3) shows that the expected utility gain from information acquisition relative to information avoidance is an increasing function of γ – individual's level of perceived control. Moreover, there is a unique value of γ for which the individual will be indifferent between acquiring and avoiding the information. Let $\gamma_{ind} = \sqrt{\frac{2\kappa}{\sigma}}$ denote the indifference point. Individuals with perceived control γ below γ_{ind} are better off avoiding the information, while individuals with perceived control γ above γ_{ind} are better off acquiring the information.

Assuming that in a given population, perceived control levels are distributed according to function v, an exogenous increase in perceived control will move more individuals above the indifference point γ_{ind}, thereby decreasing the share of individuals that are better off avoiding the information, defined as $s^{IA} = \int_0^{\gamma_{ind}} v(\gamma)\, d\gamma$. Accordingly, we formulate the following prediction:

Prediction 1 *All other things equal, an exogenous increase in perceived control decreases the share of individuals that prefer to avoid the information in a given population.*

Prediction 1 warrants further discussion. Information avoidance is only expected when the perceived opportunity cost of information acquisition exceeds its benefits, see Equation (3). When κ is low such that $\kappa < \frac{\gamma^2}{2}\sigma$, information acquisition is always optimal. Then, higher perceived control leads to higher utility levels but it does not affect the decision to acquire information as, in this case, individuals are always better off doing so.

B. Information Recall

We now study the recall of information in the general case in which the individual has received information about the true level of Z regardless of her own choice. We thereby acknowledge that, at times, individuals are inadvertently exposed to information, such as unsolicited advertisements during online browsing, unexpected news updates on social media feeds, or overheard conversations in public.

Upon receiving the information, the individual takes the decision to recall or not at time $t = 0$, directly influencing her choice of action a and consequently her anticipatory utility. If the individual recalls the true level of Z, she implements the optimal action a_Z^* and experiences a level of anticipatory utility denoted by $U(a_Z^*, \gamma, Z)$. Conversely, if the individual opts not to recall the true value of Z, she instead implements action a_π^* consistent with her prior belief π, resulting in the anticipatory utility given by $U(a_\pi^*, \gamma, \pi) - K$. Following Bénabou and Tirole (2002), we assume that self-deception is costly such that utility decreases by $K > 0$ when the true value of Z is forgotten. Conditional on the selected action a, the individual then experiences realized utility from the impact of Z at $t = 1$. Table 2 illustrates the timeline and the anticipatory and realized utilities experienced in each of the two situations.

Table 2 – Information recall and incurred utility.

Timeline:	$t = 0$	$t = 1$
Decision type:	Info recall and action a	
Incurred utility:	Anticipatory utility	Realized utility
Information recall	$U(a_Z^*, \gamma, Z)$	$U(a_Z^*, \gamma, Z)$
Lack of information recall	$U(a_\pi^*, \gamma, \pi) - K$	$U(a_\pi^*, \gamma, Z)$

By comparing total utility levels, the individual decides whether to recall the information or not. The difference in total utilities between recalling or not is denoted by Δ^{IR} and is given by:

$$\Delta^{\text{IR}} = \Big[U(a_Z^*, \gamma, Z) + U(a_Z^*, \gamma, Z)\Big] - \Big[U(a_\pi^*, \gamma, \pi) - K + U(a_\pi^*, \gamma, Z)\Big]. \tag{4}$$

Given heterogeneity in prior beliefs π, the level of perceived control γ, and the self-deception cost K, individuals for whom $\Delta^{\text{IR}} > 0$ will be better off recalling the information, while individuals for whom $\Delta^{\text{IR}} < 0$ will prefer to not recall it.

The role of perceived control. To study the role of perceived control on the decision to recall the information, we employ the assumed functional form of the utility function and derive Δ^{IR}:

$$\Delta^{\text{IR}} = \left(1 - \tfrac{\gamma^2}{2} Z\right) \pi - \left(Z - \tfrac{\gamma^2}{2} Z^2 - K\right). \tag{5}$$

Equation (5) is linear and increasing in the prior belief π.[9] Hence, for a given Z, there is a unique belief about Z – henceforth denoted $\pi_{ind} = Z - K/\left(1-\frac{\gamma^2}{2}Z\right)$ – at which the individual is indifferent between recalling and not recalling the information. Individuals with prior beliefs below the indifference point π_{ind} are better off not recalling the true Z, as $\Delta^{\text{IR}} < 0$, $\forall \pi < \pi_{ind}$. In contrast, individuals with prior beliefs above the indifference point π_{ind} are better off recalling the true Z, as $\Delta^{\text{IR}} > 0$, $\forall \pi > \pi_{ind}$. A straightforward implication is that more optimistic individuals who believe Z to be relatively low are less likely to recall the information compared to individuals with more pessimistic beliefs. We formulate the following auxiliary prediction:

Auxiliary Prediction 1 *All other things equal, the share of individuals that do not recall the information will be larger among individuals with more optimistic beliefs compared to individuals with less optimistic beliefs.*

We note that Auxiliary Prediction 1 hinges on the assumption of anticipatory utilities and does not hold in a model where individuals solely act based on realized utilities, as discussed in Section I.C.

Increasing perceived control affects the indifference point π_{ind} such that:

$$\frac{\partial \pi_{ind}}{\partial \gamma} = \frac{-\gamma Z K}{\left(1 - \frac{\gamma^2}{2} Z\right)^2} \leq 0. \tag{6}$$

[9] Unlike Δ_{IA}, Δ_{IR} is not necessarily an increasing function of perceived control γ. To illustrate this, we rearrange the terms as $\Delta_{IR} = \frac{\gamma^2}{2} Z(Z - \pi) - (Z - \pi) + K$. In essence, the impact of an increase in perceived control on Δ_{IR} relies on the interplay between the actual level of event Z and the prior belief π. Therefore, our analysis regarding the influence of perceived control on information recall requires the investigation of heterogeneous treatment effects by prior beliefs π.

Equation (6) shows that an increase in perceived control decreases the indifference point above which recalling the true Z is optimal. For a given population, where prior beliefs π are distributed according to function f, an exogenous increase in perceived control will decrease the share of individuals that are better off by not recalling the information, defined as $s^{IR} = \int_0^{\pi_{ind}} f(\pi)\, d\pi$.

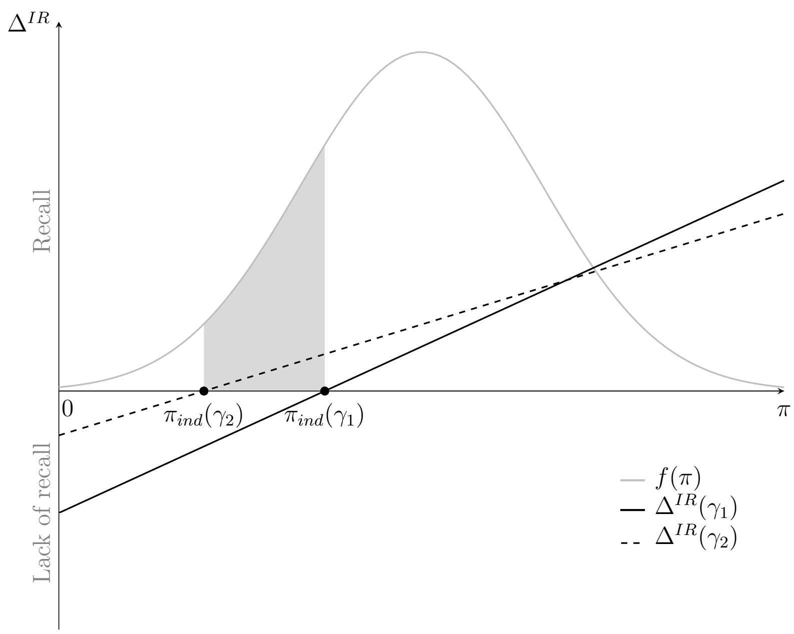

Figure 2 – Utility difference between information recall and lack of recall.

Notes: The figure illustrates the difference in utility between recalling and not recalling the information, following Equation (5). We present two cases. First, the black solid line depicts a case of low perceived control (γ_1). $\Delta^{\text{IR}}(\gamma_1)$ intersects the x-axis at the indifference point $\pi_{ind}(\gamma_1)$. Second, the dashed line depicts the case of high perceived control (γ_2). $\Delta^{\text{IR}}(\gamma_2)$ intersects the x-axis at the indifference point $\pi_{ind}(\gamma_2)$, which lies to the left of the indifference point in the case of low perceived control, *i.e.* $\pi_{ind}(\gamma_2) < \pi_{ind}(\gamma_2)$, where $\gamma_2 > \gamma_1$. The bell-shaped curve depicts the distribution of prior beliefs in the population, following function $f(\pi)$. As perceived control increases from γ_1 to γ_2, a larger share of the population (illustrated by the gray area) will be better off by recalling the true value of Z rather than not recalling it.

Figure 2 illustrates Δ^{IR}, the difference in utilities between recalling and not recalling, by prior belief π. All else being equal, we consider two distinct levels of perceived control, with $\gamma_2 > \gamma_1$. As γ increases, the slope of Δ^{IR} decreases, and the indifference point π_{ind} shifts to the left. The bell-shaped curve depicts a distribution of prior beliefs in the population. As perceived control increases and the indifference point moves to the left, an additional share of individuals (illustrated by the gray area under the curve) experiences a positive Δ^{IR} and consequently prefers to recall the information. We formulate the following prediction:

Prediction 2 *All other things equal, an exogenous increase in perceived control decreases the share of individuals that do not recall the information in a given population.*

Empirically, the effect of an exogenous increase in perceived control is expected to be population-specific. First, it will depend on the distribution of prior beliefs in the sample. Second, in line with Equation (6), it will depend on the baseline level of perceived control, the magnitude of the negative event, as well as the cost of self-deception.

C. Additional Considerations

Anticipatory utility. To emphasize the role of anticipatory utility in the decision to acquire and recall information, we now revisit our model assuming only realized utilities and compare its predictions against the ones we derived in the previous section.

First, let $\Delta^{\text{IAr}} = \mathbb{E}[U(a_Z^*, \gamma, Z)] - \kappa - U(a_\pi^*, \gamma, \pi)$ be the expected difference in realized utilities between information acquisition and information avoidance, *i.e.*, the case without anticipatory utilities. With the assumed functional form of the utility function, we obtain that $\Delta^{\text{IAr}} = \frac{\gamma^2}{4}\sigma - \kappa$, which has the same properties as Δ^{IA}.[10] Accordingly, Prediction 1 on the effect of perceived control to decrease information avoidance are expected to hold.

Second, let $\Delta^{\text{IRr}} = U(a_Z^*, \gamma, Z) - U(a_\pi^*, \gamma, \pi) + K$ be the difference in total utilities between recalling and not recalling when only realized utilities are considered. Then, $\Delta^{\text{IRr}} = \frac{\gamma^2}{4}(\pi - Z)^2 + K \geq 0$, such that it is always optimal to recall the information. In contrast to the case where both anticipatory and realized utilities are taken into account, we expect no heterogeneity in information recall based on prior beliefs. Moreover, an increase in perceived control is not expected to influence the individual's decision to recall information. Consequently, neither Auxiliary Prediction 1 nor Prediction 2 are expected to hold.[11]

In the context of our paper, these considerations are important as the predictions will be tested against the observed patterns in the data. In particular, the presence of

[10] Note that an increase in perceived control has a lower impact on information avoidance when only realized utilities are considered, relative to the case when both anticipatory and realized utilities enter the objective function as $\frac{\partial \Delta^{\text{IAr}}}{\partial \gamma} < \frac{\partial \Delta^{\text{IA}}}{\partial \gamma}$.

[11] In our model, one could also consider a cost associated with recalling new information. In our framework, the predictions remain unchanged even when factoring in a positive cost of recall, provided that such costs remain below the costs associated with self-deception K.

heterogeneity in recall rates and treatment effects by prior beliefs will serve as evidence supporting the presence of anticipatory utility, thereby suggesting strategic recall behavior.

Awareness of the option to not recall. So far, we have assumed that the individual is unaware of the possibility to not recall the information when making the decision to avoid or acquire it. We now relax this assumption to study information avoidance when individuals are aware that information, once acquired, does not necessarily need to be recalled, see the dashed box in Figure 1.

As recall is optional, it will only be exercised when it generates higher utility than not recalling. Accounting for this option changes the objective function of an individual that decides whether to acquire the information or not, such that:

$$\Delta^{\text{IAnR}} = \Delta^{\text{IA}} + \mathbf{E}[\Delta^{\text{InR+}}] \geq \Delta^{\text{IA}}, \tag{7}$$

where Δ^{IAnR} is the difference in total expected utilities between acquiring and avoiding information about the true level of Z when the individual accounts for the option to not recall the information. $\mathbf{E}[\Delta^{\text{InR+}}]$ is the subjective expected value of the option to not recall, with $\Delta^{\text{InR}} = -\Delta^{\text{IR}}$. We denote $\Delta^{\text{InR+}}$ the difference in utility between not recalling the information and recalling it when not recalling is preferred: $\Delta^{\text{InR+}} = \mathbf{1}_{\Delta^{\text{InR}}>0} \cdot \Delta^{\text{InR}} > 0$.

In summary, the option to not recall increases the value of acquiring information relative to the case when information is recalled with certainty. This decreases the rate of information avoidance within the population.[12] As information acquisition can be undone through not recalling, we argue that a lack of recall serves as a more comprehensive measure for determining whether information is ignored.

II. Materials and Methods

A. Experimental Design

To empirically investigate the role of perceived control on decisions to acquire and recall distressing information, we present a large-scale online experiment in the context of information about the average loss in life expectancy due to air pollution in one's home region.

[12]The option to not recall is similar to an *exit* option in the real options literature, where the value of an investment is higher when the option to exit the market in case of unfavorable conditions is accounted for, see Trigeorgis (1996) for an overview.

Treatment. The treatment is designed to increase perceived control over the adverse health effect of air pollution exposure. After all participants were provided with detailed information on air pollution and were tested for comprehension, participants in the treatment group received information about private measures they can implement to protect themselves against air pollution, see Figure 3. The treatment was randomly assigned at the individual level. To ensure that participants engaged with the information, they were asked to provide a short summary of these protective measures and were only allowed to proceed after correctly answering a comprehension question. Participants in the control group did not receive information about these protective measures. To test whether the treatment successfully increased perceived control, we measured participants' perceived control both via the general perceived control questionnaire (Pearlin and Schooler, 1978) adapted to the context of air pollution, and via the one-item measure by Trope, Gervey and Bolger (2003). Both measures were elicited at the end of the experiment.

FIGURE 3 – TREATMENT: PROTECTION MEASURES AGAINST AIR POLLUTION.

Notes: Information presented to participants in the treatment group. The selection of protective measures follows Carlsten et al. (2020). The source of the information was presented to participants below the information box, including a link to the original article.

Information structure. At the core of the experiment, participants were given the opportunity to receive information about the average life expectancy loss due to constant exposure to the level of air pollution in their home district. Figure 4 illustrates an example of this information page for a participant from the Kolkata district in the state of West Bengal. Those who received the information were informed about how the level of air pollution in their home district compares to the WHO recommendation and how the exposure translates into an average life expectancy loss.[13]

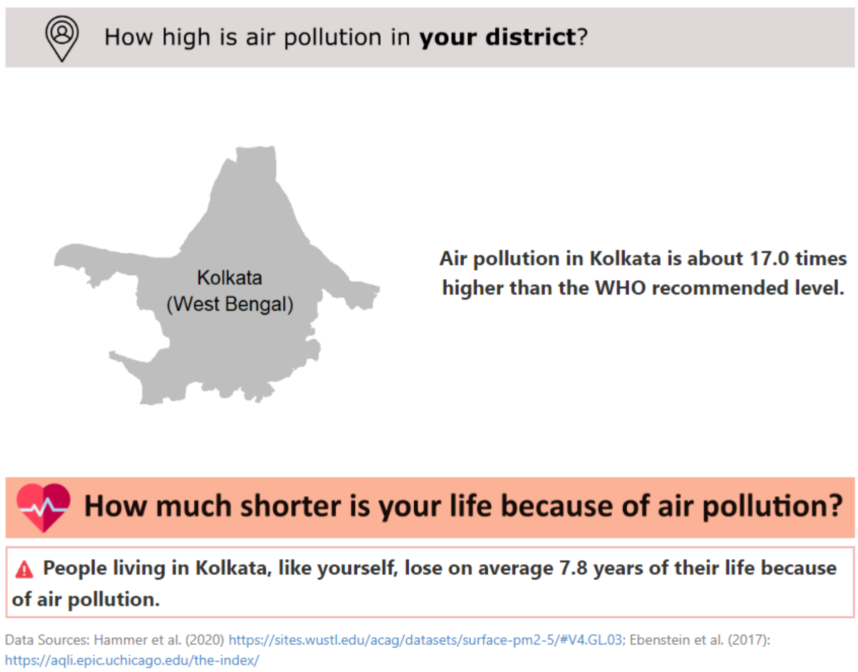

Figure 4 – Example of personalized information screen.

Notes: The figure illustrates an example of an information page that was displayed to experiment participants from the Kolkata district in West Bengal (India). The information presented on this page was personalized to reflect district-level information including (i) a map of the participant's home district, (ii) a comparison of air pollution levels in the participant's home district with the WHO recommendation, and (iii) information about the associated average loss of life expectancy. Our sample covers 269 Indian districts over 33 states and union territories.

We chose to communicate the information about the aggregate health risk in the form of a loss of life expectancy for two main reasons. First, air pollution tends to be communicated in terms of the concentration of pollutants in the air which – assuming a layperson's understanding – is not quantifiable into the associated health risk in a straightforward manner. In contrast, a conversion to the expected loss of life expectancy provides a tan-

[13]The information is based on population-weighted yearly average $PM_{2.5}$ estimates in the raster data by Hammer et al. (2020). We then follow Ebenstein et al. (2017) for a conversion to a loss of life expectancy.

gible interpretation. Second, the information is not only highly relevant but also notably distressing. That is, although information about a loss of life expectancy can serve as a compelling motivation for behavioral change, it may also trigger emotional discomfort and lead individuals to ignore it. Customizing the information to the participant's home district aims to further increase relevance.

Information avoidance. To measure information avoidance, participants were asked to indicate whether they prefer to receive information about the average loss of life expectancy in their home district due to air pollution (as described above and illustrated in Figure 4) or not. Following a similar approach to the one of Saccardo and Serra-Garcia (2023), participants were informed that their choice would be implemented with a 60% chance. This feature of the design ensures that the information was also shown to a share of participants that indicated a preference not to receive it. Thereby, we prevent self-selection issues for the recall task (see below) that could arise from the fact that the choice of acquiring information is endogenous.

Information recall. To measure information recall, we asked participants who received the information about the average loss of life expectancy in their home district to recall it. The recall task was incentivized by rewarding participants for recalling this number to the first decimal place with 40 Indian Rupees (INR), *i.e.*, about USD 0.50. Recall within an error margin of ±0.5 years was rewarded with INR 20. If participants were off by more than 0.5 years, they did not receive a reward in this task.

B. Procedures and Implementation

Procedures. An overview of the experimental procedure is displayed in Table 3.[14] After obtaining participants' informed consent, the online experiment started with an entry questionnaire on demographics, including age, gender, self-reported income, household size, education level as well as the district of residence. The participant's residence is particularly important for personalizing the information on the average loss of life expectancy later in the experiment.

Afterwards, all participants received general information on air pollution, including a list of its main sources, associated illnesses, how air pollution is measured, the WHO recommendation of $5\mu g/m^3$ $PM_{2.5}$, how excessive exposure can generally be converted into

[14] For full experimental instructions, see `https://osf.io/h3xat`.

Table 3 – Experimental procedure.

Step	Description	Control	Treatment
1.	Entry questionnaire	X	X
2.	General information on air pollution	X	X
3.	Belief elicitation (prior on air quality and worry about air pollution)	X	X
4.	Treatment		X
5.	Information acquisition decision	X	X
6.	Information on loss of life expectancy (cond. on randomization and 5.)	X	X
7.	Real effort task	X	X
8.	Information recall (cond. on 6.)	X	X
9.	Perceived control questionnaire	X	X
10.	Visual memory task	X	X

Notes: The table describes the experimental procedure in chronological order. The information acquisition decision in step 5 was implemented with a 60% probability.

an average loss of life expectancy, and that there are approximately 1.7 million pre-mature deaths per year due to air pollution in India, as estimated by Pandey et al. (2021). To encourage attention, participants were asked to answer comprehension questions throughout. Moreover, we elicited their prior belief about air quality in their home district (on a scale from 1 – "best air quality" to 10 – "worst air quality") as well as how worried they are about air pollution in general (on a scale from 1 – "not worried at all" to 7 – "very worried").

Next, we introduced the treatment variation and then elicited participants' preference to receive information about the loss of life expectancy due to air pollution. Participants who received the information were then tasked to recall it after undertaking an incentivized real effort coin-counting task for two minutes.[15] Participants who did not receive the information moved straight to the coin-counting task. At the end of the study, we measured participants' perceived control over the health impacts of air pollution as well as their general memorization ability. For the latter, we used an incentivized item recognition task: Participants were instructed to memorize 30 items, each displayed for one second. Their memory ability was then tested by showing 15 items and asking the participant whether each of them was part of the previous list. Of those 15 items, eight were previously shown while seven were not. For each correct answer, participants received a reward of INR 5. After the experiment concluded, participants in the control group who received the personalized information on the expected loss of life expectancy additionally saw a research disclaimer that included the list of private protection measures.

[15]In this task, participants earned a fixed piece-rate of INR 2 for correctly counting the number of coins in a randomly generated image.

Implementation. The experiment was implemented with Dynata, a survey company commonly used for economic research (Stantcheva, 2022). Completion was rewarded by the survey company in the form of panel points that can be redeemed in various forms, including cash payments. In addition, participants received a bonus incentive payment depending on their performance in the incentivized recall task, the effort task, and the visual memory task. Exclusion criteria that either prevented participants from completing the experiment or excludes them from the analysis were pre-registered.[16] The experiment was programmed in nodeGame (Balietti, 2017) and conducted in November 2022. All screens were displayed in English. A total of 2,357 participants completed the experiment of which 2,031 observations are retained after applying exclusion criteria.[17]

III. Aggregate Results

A. Perceived Control

We begin by examining participants' perceived control over the negative health effects of air pollution exposure.[18] Table 4 shows estimates of perceived control at baseline. We estimate two models, distinguishing between participants who were randomized to see the personalized information on the average life expectancy loss due to air pollution in their home district (column 1) and those who were not (column 2).

We document two noteworthy findings. First, conditional on being informed, a higher life expectancy loss is correlated with significantly lower perceived control ($p < 0.001$). Crucially, the correlation is weaker and not significant when participants do not receive the info. It appears thus that receiving information about a loss of life expectancy due to

[16]We took several steps to ensure good data quality. First, we included a question designed to detect straight-lining, *i.e.*, choosing the same response option multiple times in a row. Second, we checked for consistency with respect to the participant's reported age by including a question with a free numerical input as well as a question with pre-defined age bins. Third, we excluded participants that gave unambiguously automated or otherwise entirely nonsensical responses to the free text input feedback questions. Fourth, participants were excluded if they needed more than five attempts to correctly answer any of the comprehension questions during the general information on air pollution. And lastly, we excluded participants that completed the full experiment in less than five minutes. For the pre-analysis plan, see AEARCTR-0010083.

[17]2,645 participants were initially recruited, *i.e.*, we observe an attrition rate of just over 10%. Refer to Appendix A-1 for summary statistics of participants' characteristics and balance tests. The sample is typical for online recruitment in developing countries (Dechezleprêtre et al., 2022).

[18]As detailed in Section II.A, we collected two measures of perceived control. Throughout our analysis, we primarily focus on an index measure computed based on a seven-item questionnaire from Pearlin and Schooler (1978) that is adapted to the context of air pollution. In the appendix, we also analyze a one-item measure adapted from Trope, Gervey and Bolger (2003) to show robustness. Both measures are standardized following Kling, Liebman and Katz (2007).

Table 4 – Predictors and estimated treatment effects on the main outcomes.

	Perceived control			Information avoidance		Lack of recall	
	Control		Control & Treatment	Control	Control & Treatment	Control	Control & Treatment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perceived control				0.016		-0.075**	
				(0.017)		(0.036)	
Treatment			0.186***		0.004		-0.068***
			(0.023)		(0.012)		(0.023)
Information avoidance	0.077	0.043	-0.012			0.218***	0.141***
	(0.089)	(0.078)	(0.043)			(0.077)	(0.053)
Prior belief	0.013	-0.004	0.009*	-0.003	-0.001	-0.024***	-0.022***
	(0.008)	(0.011)	(0.005)	(0.004)	(0.003)	(0.007)	(0.005)
Confidence	-0.073***	0.018	-0.031**	-0.048***	-0.051***	-0.004	-0.005
	(0.027)	(0.032)	(0.015)	(0.011)	(0.008)	(0.023)	(0.016)
Life expectancy loss	-0.028***	-0.011	-0.016***	-0.007**	-0.004*	0.011	0.009*
	(0.008)	(0.009)	(0.004)	(0.003)	(0.002)	(0.007)	(0.005)
Visual memory	0.298*	0.805***	0.634***	-0.195***	-0.098**	-0.627***	-0.610***
	(0.153)	(0.178)	(0.087)	(0.063)	(0.045)	(0.134)	(0.087)
Observations	581	419	2,031	1,000	2,031	581	1,196
Control mean	-0.007	0.010	0.000	0.079	0.079	0.265	0.265
Rand. to info	Yes	No	Yes+No	Yes+No	Yes+No	Yes	Yes

Notes: This table presents results of ordinary least squares regression analyses on the perceived control index, information avoidance, and lack of recall in the Indian sample. Columns 1, 2, 4 and 6 only rely on the control group sample. Columns 3, 5, and 7 rely on both the treatment and control samples and test for average treatment effects. Prior beliefs are coded such that lower values correspond to more optimistic beliefs about the experienced air quality. Confidence refers to participants' confidence in their prior beliefs. Standard errors are reported in parentheses. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

air pollution is notably distressing and reduces perceived control over the adverse health effects of air pollution. Second, among those who receive the information, perceived control is significantly lower ($p < 0.001$) when participants have higher confidence in their prior belief about air quality. Among those that do not receive the info, confidence in the prior belief is not correlated with perceived control. Overall, results suggest that participants were not aware of and underestimated the extent to which the level of air pollution in their home district affects their life expectancy.

Next, we test whether the treatment successfully increases perceived control. Figure 5 plots the distribution of the standardized index of perceived control for participants in the control (in light gray) and treatment group (in dark gray). The distribution in the treatment group is shifted to the right, indicating that the treatment successfully increases

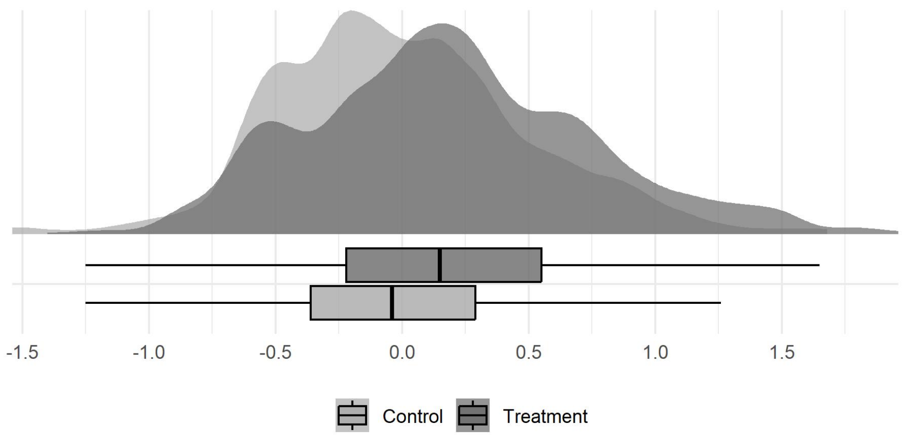

Figure 5 – Distribution of the perceived control index.

Notes: The figure presents the kernel densities of the distributions of perceived control, as measured by the standardized index of participants' answers to the 7-item questionnaire from Pearlin and Schooler (1978) adapted to the context of air pollution. Two distributions are presented, where light gray corresponds to the control group and dark gray corresponds to the treatment group. Perceived control was elicited after the main outcomes of interest, see Table 3 for the experimental procedure. The figure uses all observations in the Indian sample (N = 2,031).

perceived control. The effect size corresponds to 0.19 standard deviations with $p < 0.001$ in a Mann-Whitney U two-sample test, hereafter MW test, combined N=2,031.

The treatment effect on perceived control is further supported by a regression analysis in which we control for the actual average life expectancy loss due to air pollution in the participant's home district, the prior belief about air quality, the confidence in this prior belief, the preference to avoid or receive information, and the performance in the visual memory task (Table 4, column 3).[19] The estimated average treatment effect on the perceived control index is 0.19 standard deviations ($p < 0.001$). Overall, we find evidence that the treatment manipulation significantly increased perceived control.

B. Information Avoidance

Our main research question is to study the effect of perceived control on whether the information is ignored. We first investigate the effect of our treatment on information avoidance. We measure information avoidance as the share of participants who state that they prefer to not receive the information about the loss of life expectancy due to air pollution in their home district. 7.90% of participants in the control group indicate that they prefer to not

[19] Robustness to including different sets of control variables is presented in Appendix Table A-2.

receive the information. The share is comparable to studies on the willingness to acquire health-related information, such as getting tested for medical conditions (*e.g.*, Sullivan et al., 2004; Ganguly and Tasoff, 2017; Li et al., 2021).

Table 4 illustrates the determinants of information avoidance at baseline (column 4). We note that there is no apparent correlation between information avoidance and perceived control in the control group, suggesting that a treatment that exogenously increases perceived control might have limited ability to affect the decision to acquire or avoid information. Indeed, we observe no treatment effect on information avoidance. Figure 6 displays the share of participants who prefer to avoid the information in the control and treatment groups (Panel A). In the treatment group, the proportion of participants who prefer to avoid the information is 8.24%, which is not significantly different from the 7.90% share in the control group (Fischer exact test: $p = 0.807$, combined N=2,031). The absence of a treatment effect is confirmed with a linear probability model, where we additionally control for participants' prior belief about air quality, their confidence in this prior belief, the actual average life expectancy loss in their home district, and their performance in the visual memory task (column 5 in Table 4).[20]

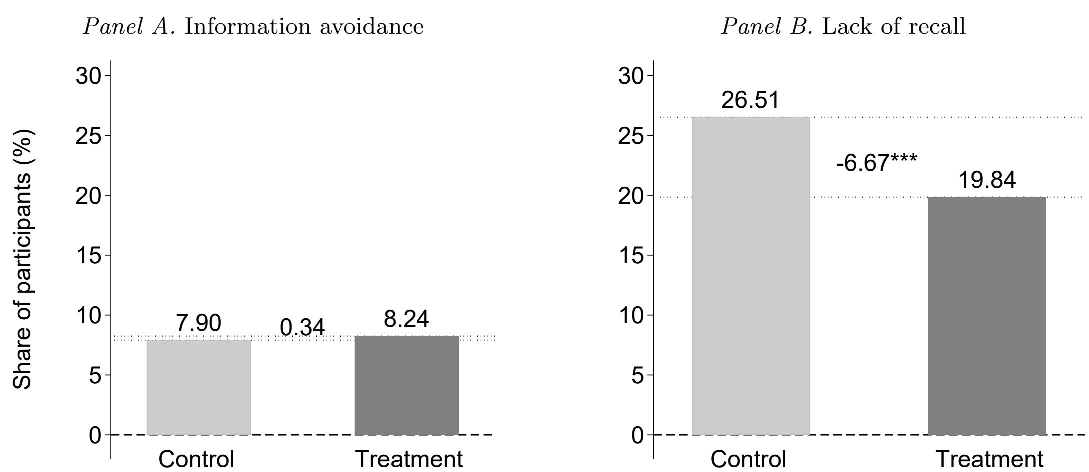

Figure 6 – Information avoidance and lack of recall.

Notes: The figure plots the share of participants that prefer to avoid the information (Panel A) and the share of participants that do not recall the information (Panel B) in the control (light gray) and treatment (dark gray) groups. The Panel A relies on the full sample (N = 2,031) while Panel B uses only participants that have been randomized to receiving the information (N = 1,196).

[20]Results are robust to using a nonlinear regression models, see Appendix Table A-3.

Result 1 *We find no evidence that the treatment significantly affects the share of participants who prefer to receive the information, in the aggregate.*

Our findings on information avoidance are again consistent with participants not being aware and underestimating what the information would reveal about the life expectancy loss due to air pollution in their home district. Linking back to the theoretical model in Section I, this suggests a low perceived opportunity cost of information acquisition κ and corresponds to the case where participants prefer to acquire rather than avoid the information, independent of the level of perceived control. An alternative explanation for a low share of information avoidance is provided by the extension of our theoretical framework which suggests that individuals acquire information while accounting for the option to not recall it later on. Section IV discusses this mechanism further.

C. Information Recall

We turn now to the effect of the treatment on information recall. Our primary measure of information recall is the share of participants who are able to recall the correct average loss of life expectancy in their home district within a ± 0.5 year error margin. For the subsequent analysis, we only consider participants that were randomized into receiving the information.

We find that 26.51% of participants in the control group do not recall the information. Table 4 illustrates the baseline determinants for the lack of recall (column 6). Importantly, lower perceived control is associated with a lower rate of recall. As a result, we anticipate that the treatment, which effectively enhances perceived control, will lead to an improvement in recall.

Indeed, we find that the lack of recall is significantly less pronounced in the treatment group (see Figure 6). 19.84% of participants do not recall the information in the treatment group compared to 26.51% in the control group. Hence, we observe a 25% decrease in the proportion of participants who do not recall the information (Fisher exact test: $p = 0.007$, combined N=1,196). The result is confirmed by a regression analysis where the average treatment effect is estimated conditional on participants' preference to avoid information, their prior belief about the air quality in their home district, their confidence in the prior belief, the actual average life expectancy loss in their home district, and their general memory ability. We find that the treatment reduces the likelihood to not recall the information by 6.8 percentage points ($p = 0.004$, Table 4 column 6).

Result 2 *The treatment significantly decreases the share of participants that do not recall the information, in the aggregate.*

Our regression analysis on information recall provides additional noteworthy insights. First, not recalling is negatively correlated with the performance in the visual memory task: as intuitively expected, those with a better general memory are also better at recalling the information on the average loss of life expectancy ($p < 0.001$). Second, participants who would have preferred to not receive the information are also less likely to recall it ($p = 0.008$). We further discuss the implication of this result in Section IV.B. Finally, holding more optimistic prior beliefs about the air quality in one's home district increases the likelihood to not recall the information ($p < 0.001$). This is in line with the theoretical framework outlined in Section I. We explore the role of prior beliefs in more detail in Section IV.A.[21]

IV. Strategic Ignorance

In this section, we present evidence that the observed ignorance of information in the experiment is strategic, as proposed in our theoretical framework. Our argumentation follows three steps. In Section IV.A, we leverage the heterogeneity in prior beliefs about air quality to examine Auxiliary Prediction 1, which posits that individuals who anticipate a lower health risk are less likely to recall the information. Furthermore, we investigate whether the treatment effectively improves recall within this group by reducing the tendency to recall overly optimistic values. The analysis serves as a test for the presence of anticipatory utility and, consequently, of strategic recall. If optimistic priors are associated with higher anticipatory utility, then information is strategically ignored to retain it. In Section IV.B, we investigate the relationship between information avoidance and recall. Our analysis reveals that participants seem to deliberately utilize recall as either a substitute or a complement to information avoidance. Finally, Section IV.C argues against potential alternative mechanisms.[22]

[21] With the intent of investigating the effect of the treatment on perceived control and information recall over time, we invited participants that received the information on the average life expectancy loss during the experiment to a follow-up experiment two weeks later (as per the pre-registration plan). However, participation in this follow-up study appears to be conditional on the main variables of interest from the first experiment. This prevents us from conducting unbiased tests of the treatment effect over time. For transparency, we provide details on the design of the follow-up, recruitment procedure, and estimated treatment effects on the main outcomes in Appendix D.

[22] Note that our analyses in Sections IV.A and IV.B were not pre-registered.

A. Heterogeneity by Prior Beliefs

When information is useful but distressing, the deliberate decision to recall it or not involves a trade-off between the anticipatory and realized utilities it generates. This trade-off fundamentally varies with one's prior belief. Individuals with a more optimistic belief stand to gain more by not recalling particularly distressing information than those who are less optimistic. As shown in the theoretical framework in Section I, strategically attending to information implies that optimists will be (i) less likely to recall the information at baseline, and (ii) more responsive to an increase in perceived control, compared to less optimistic participants. In this section, we investigate whether these predictions are observed in the experiment, thereby testing for strategic behavior.

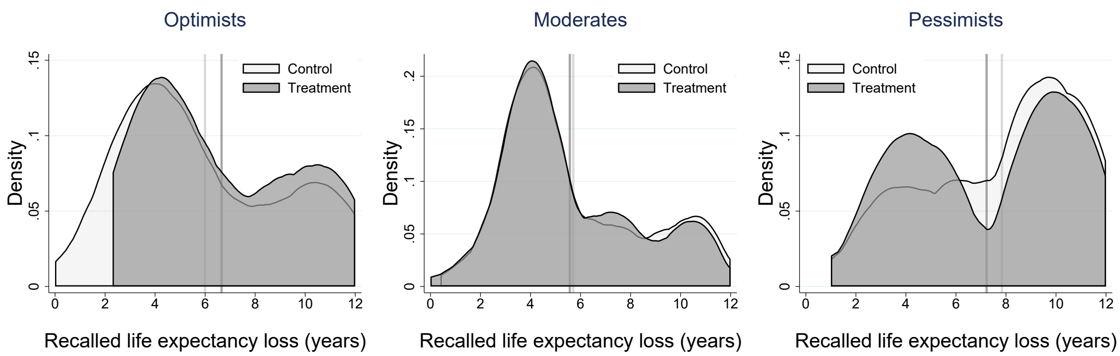

Figure 7 – Distribution of recalled life expectancy loss by prior beliefs.

Notes: The figure plots the distribution of recalled values for the life expectancy loss in the Indian sample. The graph uses responses only from participants randomized to receive the information (N = 1,196). We categorize participants with a prior of 1 or 2 as "optimists", participants with a prior between 3 and 8 as "moderates", and participants with a prior of 9 or 10 as "pessimists". The vertical lines indicate average values for the control (light gray) and the treatment group (dark gray).

We begin by studying the distribution of the value that participants recall in the control and treatment groups, split by whether participants have a particularly optimistic (a prior of 1 or 2 on the 10 point Likert scale, *i.e.*, good air quality), moderate (a prior between 3 and 8), or particularly pessimistic (a prior of 9 or 10) prior belief, see Figure 7.[23] The treatment group distribution for optimists is shifted to the right as the treatment reduces the share of optimists recalling a particularly low value. These patterns are suggestive of

[23]Recall that the prior belief was elicited at the beginning of the experiment as a qualitative response about the air quality in the participant's home district, from 1 – "best air quality" to 10 – "worst air quality".

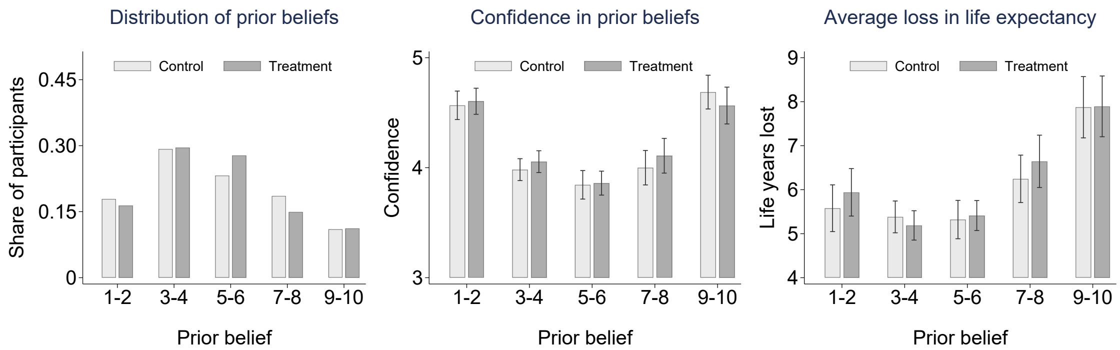

Figure 8 – Prior beliefs, average confidence, and average loss of life expectancy.

Notes: The figure presents the distribution of prior beliefs (left panel), the average confidence by prior belief (middle panel), and the associated average loss of life expectancy by prior belief (right panel) in the control and treatment group of the Indian sample. The graph uses responses only from participants randomized to receive the information (N = 1,196). Prior beliefs are re-scaled to a 5 point from a 10 point scale from 1 – "best air quality" to 10 – "worst air quality". Whiskers indicate the 95% confidence interval.

strategic ignorance among optimists in the control group: when perceived control is lower, participants tend to revert to their priors beliefs instead of recalling the information.

To study prior beliefs in more detail, Figure 8 gives an overview of participants' prior beliefs and the confidence with which they are stated, contrasted to the actual loss of life expectancy.[24] The left panel captures the distribution of prior beliefs in the control and treatment group and documents substantial variation. About 15 to 20% of participants believe that the air quality in their respective district is extremely good (a prior of 1 or 2), while only about 10% believe it to be extremely bad (a prior of 9 or 10). Interestingly, the average confidence with which participants state their prior belief follows a U-shape in both the control and treatment group, see the middle panel. While all participants appear to be generally confident in their prior belief (the lowest average is around 4 on a 5 point Likert scale), participants with more neutral priors are less confident than those who are optimistic or pessimistic.

Figure 8 also displays the average loss of life expectancy by prior belief (right panel). While participants with more pessimistic priors are generally subject to worse air quality, the level of air quality is strikingly similar for participants with priors between 1 and 6. Participants who believe that they are experiencing excellent air quality (a prior of 1 or

[24]In the following, we transform the belief measure into a variable with five categories to balance groups and retain statistical power, effectively grouping value pairs from the original 10 point scale.

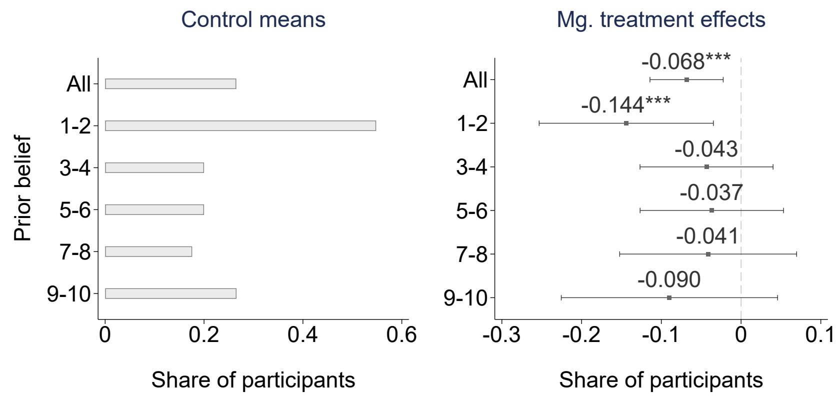

FIGURE 9 – CONTROL GROUP MEANS AND TREATMENT EFFECTS ON LACK OF INFORMATION RECALL BY PRIOR BELIEF.

Notes: The figure presents control group means and marginal treatment effects on the lack of information recall in the Indian sample. The graph uses responses only from participants randomized to receive the information (N = 1,196). The marginal treatment effects are estimated from linear probability models where we include an interaction between the treatment and the prior belief about the air quality in the home district. All models control for the confidence in the prior belief, the actual average life expectancy loss in the home district, the preference to avoid the information, and the performance in the visual memory task. The error bars in the right panel correspond to the 95% confidence interval. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1. Appendix Table B-1 presents the marginal treatment effects together with q-values computed using the Benjamini-Hochberg procedure (Anderson, 2008) to adjust for multiple hypothesis testing and reports all covariate coefficients.

2) are considerably more optimistic than participants with more neutral priors (a prior of 3 to 6) although their respective losses of life expectancy are comparable at around five to six years. Importantly, we document no significant differences between the control and treatment group.

Next, we focus on our main outcome of interest and study the rate of unsuccessful recall by prior beliefs in the control group. Figure 9 illustrates a striking pattern: in the control group, participants with optimistic priors are notably less likely to recall the information on the loss of life expectancy than any other subgroup (left panel). About 57% of participants with a very optimistic prior do not recall the information, compared to 26.5% in the control group average and as little as 20% among participants with more pessimistic priors. The result aligns with Auxiliary Prediction 1 of our theoretical model and with insights from the related literature, indicating that a lack of recall is most likely to occur when the information disadvantageously contradicts prior beliefs (Bénabou and Tirole, 2002; Brunnermeier and Parker, 2005).

To study heterogeneous treatment effects on recall, we estimate a linear probability model that interacts the treatment with participants' prior belief, while controlling for the confidence in the prior belief, the actual average loss of life expectancy, the preference to avoid the information, and the performance in the visual memory task. Marginal treatment effects are plotted in the right panel of Figure 9. We find that the treatment is particularly effective for participants with the most optimistic priors. For this subgroup, the share of participants that do not recall the information decreases by about 14 percentage points ($p = 0.001$). The effect remains significant after adjusting for multiple hypothesis testing using the Benjamini-Hochberg procedure described in Anderson (2008), see Appendix Table B-1.

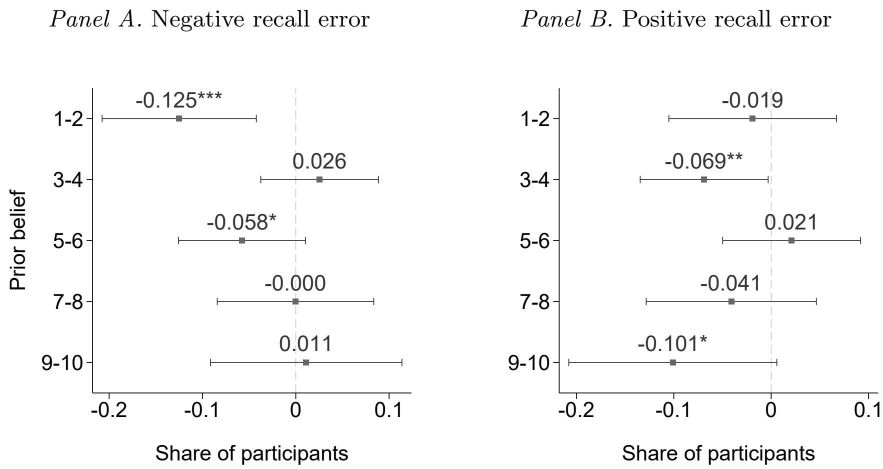

FIGURE 10 – TREATMENT EFFECTS ON THE SHARE OF PARTICIPANTS THAT HAVE A NEGATIVE OR POSITIVE RECALL ERROR BY PRIOR BELIEF.

Notes: The figure presents marginal treatment effects on the share of participants that have a negative (Panel A) and positive recall error (Panel B) in the Indian sample. The graph uses responses only from participants randomized to receive the information on life expectancy loss (N = 1,196). Effects are estimated from linear probability models where we include an interaction between the treatment and the prior belief about the air quality in the home district. All models control for the confidence in the prior belief, the actual average life expectancy loss in the home district, the preference to avoid the information, and the performance in the visual memory task. The error bars correspond to the 95% confidence interval. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

We further decompose the heterogeneous treatment effect into whether it reduces a positive or a negative recall error to gather more support for our theory that predicts optimists to revert back to their optimistic prior after strategically ignoring the information. We indeed find that the treatment limits a reversion to beliefs among optimists. In panels A and B of Figure 10, we study an indicator variable for whether participants have a negative or positive recall error[25] as the dependent variable and again plot marginal treatments

[25] In line with our incentive structure, we consider recall error to appear when the recalled life expectancy loss is more than 0.5 years below or above the correct value.

effects from a linear probability model that interacts the treatment with prior beliefs. The treatment significantly reduces the share of optimistic participants that have a negative recall error (a 12.5 percentage point reduction with $p = 0.003$), *i.e.*, an error that indicates a reversion to an optimistic belief. In contrast, the treatment does not affect the share of optimistic participants that have a positive recall error.

B. Complementarity and Substitutability

To further investigate whether the observed lack of recall is strategic, we leverage the randomization into receiving information about the life expectancy loss and examine differences in recall between those who prefer and those who do not prefer to receive the information.

In the related literature, information avoidance and recall are generally studied separately. This implies that not recalling is typically considered as a complement to information avoidance, *i.e.*, it is only necessary if information cannot be avoided. To test for complementarity, we investigate whether the information is less likely to be recalled among those that express a preference to avoid it, but are randomized to receive it. Moreover, in the extension to our theoretical framework we argue that not recalling will also be used as a substitute for information avoidance. In particular, participants might hold overly optimistic beliefs about the life expectancy loss and only acquire the information because they are aware of the option to forget in case it disadvantageously contradicts prior beliefs. To test for such substitutability, we examine whether not recalling is common among those that prefer to receive the information, and particularly so among participants with optimistic prior beliefs.

We estimate a model in which the treatment is interacted with an indicator variable for whether the participant prefers to avoid the information, see column 1 in Table 5. First, we find that in the control group, participants who indicate that they prefer not to receive the information are about 21 percentage points less likely to recall the information than those who prefer to receive it ($p = 0.005$). This is the complementary effect: when participants prefer to avoid information but are not able to, they are less likely to recall it. Importantly, we find that the treatment significantly decreases the likelihood to not recall the information independent of the preference to receive or avoid it ($p = 0.010$). Given the significant treatment effect, not recalling the information at baseline appears strategic, rather than driven by a lack of interest.

Table 5 – Estimated effects on information recall and performance in unrelated tasks, by preference to receive or to avoid information.

	Lack of recall (1)	Performance coin counting (2)	Performance visual memory (3)
Treatment	-0.061**	0.126	-0.007
	(0.024)	(0.106)	(0.008)
Information avoidance	0.207***	-0.151	-0.019
	(0.073)	(0.272)	(0.024)
Treatment × Information avoidance	-0.137	0.490	-0.001
	(0.105)	(0.375)	(0.035)
Observations	1,196	2,031	1,196
Control mean, prefer to receive	0.25	5.45	0.87

Notes: The table displays the estimated coefficients derived from ordinary least squares regression models utilized for the Indian sample. The treatment variable is interacted with an indicator for information avoidance. Each column corresponds to a different outcome variable. All models control for the participant's prior belief about air quality in the home district, confidence in the prior belief, and the actual life expectancy loss. Models (1) and (2) additionally control for the performance in the visual memory task. Model (3) controls for participant's lack of recall. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Second, we observe a substitutability effect: among participants in the control group who express a preference for receiving the information, 25% are not able to recall it. Also here, not recalling is most prevalent among optimists, see Appendix Figure B-1. In other words, participants who initially prefer to receive the information are more likely to not recall it when it conflicts with their optimistic prior beliefs. Furthermore, the treatment effect on optimists drives the aggregate effect on the sample of participants that prefer to receive the information, similar to the pattern discussed in Section IV.A.

Overall, our findings suggest that not recalling distressing information can serve as both a complement to and a substitute for information avoidance. A possible explanation for this result is that a share of participants is indeed aware of the option to not recall the information when deciding to acquire it. Thereby, we challenge the prevailing notion in the related literature, which assumes information avoidance and not recalling as strictly complementary strategies, thus potentially underestimating how often information is ignored. Furthermore, the presence of both complementarity and substitutability inherently strengthens our argument that the observed ignorance of information is strategic.

C. Alternative Treatment Mechanisms

We now explore two alternative channels through which our treatment could affect information avoidance and recall.

Salience and Associativeness. The treatment presents participants with a list of measures to reduce exposure to air pollution, *i.e.*, the screen shown in Figure 3. The additional information could increase the salience of the air pollution threat or the general association to the topic of air quality for participants in the treatment group relative to the control, which may influence whether participants ignore the information (see Golman et al., 2022), beyond any effect of actually increasing perceived control. We present several arguments to refute the concern.

First, note that the information about a loss of life expectancy appears to be distressful as evident from the negative correlation between perceived control and life expectancy loss levels observed at baseline, see Section III.A. We argue that it is precisely this negative emotional impact that induces strategic ignorance, which is in turn mitigated by the treatment. If the treatment was to impact outcomes through a pure salience effect, one would expect the negative emotion to be amplified rather than mitigated. This would not only suggest that the treatment should decrease perceived control, it should also increase strategic ignorance. However, we observe the opposite.

Second, we find that the treatment effect on information recall is primarily driven by optimists who have a significantly lower rate of recall than any other subgroup to begin with. Had the treatment only increased salience or the general association to the topic, one would expect treatment effects across the distribution of prior beliefs, in contradiction to our results.

Finally, one would expect that a pure salience or association effect induces participants to devote more attention to the experiment. We argue that a good proxy for an attention measure is the time that participants spent on the experiment, in particular in key moments. We examine three specific instances of the experiment: the decision to receive or avoid information, the information on the loss of life expectancy itself, and the task to recall the information. Figure 11 presents marginal effects of regression analyses by prior beliefs that test for treatment effects on the time spent in each of these three instances. For each of the three cases, treatment effects are not significant, neither in the aggregate sample, nor when distinguishing by prior beliefs.

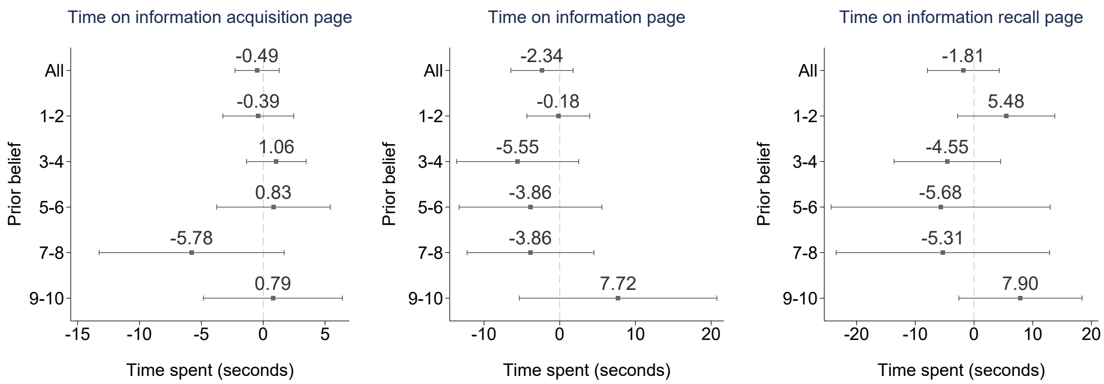

FIGURE 11 – TREATMENT EFFECTS ON THE TIME SPENT IN KEY INSTANCES.

Notes: The figure presents the average (all priors) and the marginal treatment effects (by prior) on the number of seconds participants spend on the key decision pages in the experiment, in the Indian sample. Observations from all participants are used in the left panel (N = 2,031), while only observations from participants randomized to receive information are used in the middle and right panels (N = 1,196 each). The marginal treatment effects are estimated with ordinary least squares regression models where we include an interaction between the treatment and the participants' prior beliefs about the air quality in their home district. All models control for the participants' confidence in the prior belief, the actual average number of life expectancy loss in their home district, their preference to avoid the information, and their performance in the general memory task. The error bars correspond to the 95% confidence interval. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

General cognitive abilities. A different mechanism could be that the treatment impacts information recall by influencing participants' overall cognitive abilities beyond those specifically linked to processing information about a life expectancy loss due to air pollution. Such an effect would be independent of strategic considerations. We examine this alternative explanation by analyzing participants' performance in the coin counting task that is undertaken immediately after the information is received and in the visual memory task at the end of the experiment, see columns 2 and 3 in Table 5. In both tasks, we find no evidence of a treatment effect, as well as no interaction with participants' preference to avoid the information.[26] These results suggest that the observed treatment effects on information recall are not explained by a change in participants' general cognitive abilities. Rather, the treatment appears to have only affected the cognition that is strictly related to the processing of information about the life expectancy loss.

[26]For robust results concerning the aggregate treatment effects or heterogeneous treatment effects by prior beliefs, see the Appendices C-1 and C-2.

V. Lowering the Threat? Evidence From the USA

The results from the experiment with an Indian sample show that increasing perceived control can be an effective strategy to reduce strategic ignorance, particularly among optimists. The experiment was purposefully conducted against the backdrop of a severe and persistent air pollution crisis. Given the severity of the context, information about a life expectancy loss can be particularly distressing, making it more susceptible to dismissal and especially sensitive to perceived control. Indeed, the theoretical framework presented in Section I posits that the decision to ignore information depends on how distressing the information is or is expected to be. This raises questions on the prevalence of strategic ignorance and on the role of perceived control in a setting where the threat is considerably lower.

To address these questions, we implemented the same experiment with a sample from the USA, where the level of air pollution is significantly lower than in India but still imposes substantial health risks in terms of mortality and morbidity (Deryugina et al., 2019). We recruited 2,518 participants via Amazon Mechanical Turk of which 2,340 completed the experiment. We retain 2,264 observations after applying the same exclusion criteria as in the experiment with the Indian sample. Experimental procedures between the US and Indian sample were, barring minor adaptations, identical, see Section II.[27] We primarily sampled participants from states with the highest average air pollution in the raster data by Hammer et al. (2020). Those include California, Illinois, Missouri, Mississippi, Tennessee, Iowa, Nebraska, Kansas, Louisiana, Alabama, Georgia, and Arkansas. The average loss of life expectancy in the US sample was about 0.5 years (with values ranging between 0.1 and 1.5 years), which is substantially lower than the average loss of life expectancy in the Indian sample (average of 5.85 with values between 1.0 and 11.8 years). Information on the expected average loss of life expectancy was provided at the county level.[28]

The treatment successfully increases perceived control in the US sample by around

[27] The following was adjusted for the experiment in the US. First, we referred to the participant's home county instead of district. Second, we introduced a slight variation in the leaflet used for the treatment with the US sample. As the choice of cooking and heating fuels in developed countries is less of a health concern than in developing countries, we substituted the action "use clean cooking and heating fuels" under the "at home" category as shown in Figure 3 with the action "avoid smoke from open fires and waste burning". Participants in the US received a fixed reward of USD 3.00 for completing the experiment. Together with the variable incentives (USD 0.50 for a perfect recall of the information, USD 0.20 for recalling the information within a ± 0.5 year error margin, USD 0.02 for each correctly solved exercise in the effort task, and USD 0.05 for each correct response in the visual memory task), participants earned an average of USD 3.85.

[28] For sample characteristics (incl. balance tests), see Table A-4.

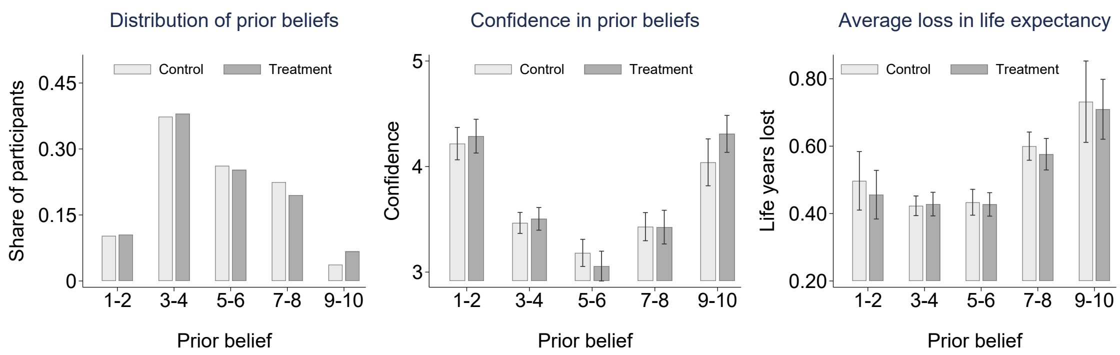

FIGURE 12 – PRIOR BELIEFS, AVERAGE CONFIDENCE, AND ACTUAL AVERAGE LOSS OF LIFE EXPECTANCY (US SAMPLE).

Notes: The figure presents the distribution of prior beliefs in the US sample (left panel), the average confidence by prior belief (middle panel), and the associated average loss of life expectancy by prior belief (right panel) in the US sample. The graph uses responses only from participants randomized to receive the information (N = 1,298). Prior beliefs are re-scaled from a 10 point to a 5 point scale. Whiskers indicate the 95% confidence interval.

0.50 standard deviations for the index adapted from Pearlin and Schooler (1978), significant with $p < 0.001$ in a MW test.[29] The observed rates of information avoidance are 16.5% and 17.7% in the control and treatment group, respectively ($p = 0.469$ in a Fisher exact test, combined N=2,264). Among participants in the control group who received the information, about 16.7% cannot recall it. The share of unsuccessful recall is 15.3% in the treatment group. The difference is not significant ($p = 0.545$ in a Fisher exact test, combined N=1,298), see Appendix Figure A-2 for an illustration.

We repeat the heterogeneity analysis of the treatment effect on information recall with respect to participants' prior beliefs about air quality in their home county, see Figure 12. We find the same overall pattern as in the Indian sample. Independent of the assignment to control or treatment group, about 10% of the US participants are very optimistic (a prior belief of 1 or 2 on the 10 point Likert scale), a prior of 3 or 4 is the modal response, and confidence follows a U-shape in which participants with a more neutral belief are significantly less confident than those who believe to experience particularly good or bad air quality. Yet, just like in the Indian sample, participants with an optimistic prior (a prior of 1 or 2) do not reside in counties with lower average losses of life expectancy than participants with more neutral beliefs (a prior of 3 to 6).

Figure 13 plots marginal treatment effects by prior beliefs on the lack of recall in the

[29] For an illustration, see Figure A-1. The estimated effect is an increase by 0.53 standard deviations for the one-item measure adapted from Trope, Gervey and Bolger (2003), with $p < 0.001$ in a MW test.

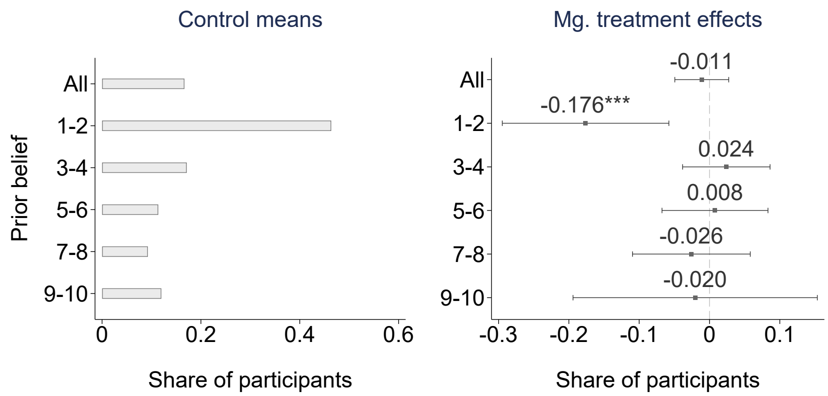

Figure 13 – Control group means and treatment effects on the lack of information recall by prior belief (US sample).

Notes: The figure presents control group means and marginal treatment effects on the lack of information recall in the US sample. The estimation is based on responses only from participants randomized to receive the information (N = 1,298). The marginal treatment effects are based on an interaction between the treatment and the prior beliefs about the air quality in the home district. All models include controls for the confidence in the prior belief, the actual average life expectancy loss in the home district, the preference to avoid the information, and the performance in the visual memory task. The error bars in the right panel correspond to the 95% confidence interval. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1. Appendix Table B-1 presents the marginal treatment effects together with q-values computed using the Benjamini-Hochberg procedure (Anderson, 2008) to adjust for multiple hypothesis testing and reports all covariate coefficients.

US sample. We replicate our previous finding that the treatment significantly reduces the share of optimists that do not recall the distressing information. As in the Indian sample, optimists are the least likely to recall the information in the control group but are most responsive to the treatment. For this subgroup, the treatment reduces the share of participants who do not recall the information by almost 18 percentage points ($p = 0.004$). Moreover, the treatment has no effect on recall in any other subgroup.[30]

The result of the heterogeneity analysis on information recall is robust to an adjustment for multiple hypothesis testing, see Appendix Table B-1. Identifying the same pattern across independent samples from two different countries serves as additional, compelling evidence for the external validity of our finding.[31] In summary, increasing perceived control appears to be an effective tool to improve recall among those most prone to forgetting, even

[30]Similar to the patterns in the Indian sample, the heterogeneity of the treatment effect persists when restricting the US sample to participants that have a preference to acquire the information, see Appendix Figure B-2.

[31]At the 5% level of significance, the probability to observe a false positive for the same specific sub-group (among a total of 5 groups) in two independent populations is below one percent, and can be computed as $P = B(5, 1, p = 0.05) \times \left(\frac{1}{5} \times B(5, 1, p = 0.05)\right) = 0.83\%$, where $B(5, 1, p = 0.05) = \binom{5}{1} \times 0.05 \times (1-0.05)^{(5-1)}$ is the probability mass function of the binomial distribution.

in settings where the objective life expectancy loss is less severe.

VI. Conclusion

In this paper, we use an experiment with samples from India and the US to demonstrate that perceived control reduces the strategic ignorance of information about the life expectancy loss due to air pollution exposure. We find that recall rates are notably low among participants that are *ex-ante* oblivious of the underlying threat. Increasing perceived control improves recall in this group by reducing the share of participants that recall overly optimistic values. This is consistent with our theoretical framework which suggests that increasing perceived control shifts the indifference point in the distribution of prior beliefs, below which participants prefer to revert to their optimistic prior instead of recalling the information.

The empirical application in our paper centers on studying how participants attend to information about the life expectancy loss they face due to exposure to local air pollution. Air pollution is an example of a major global health crisis that is often not acknowledged, met with indifference, or easily drowned out by other, seemingly more pressing issues. We show that actionable advice on how to protect oneself against the adverse health effects of air pollution can reduce the extent to which the information is ignored. With a broader interpretation, our results may be informative for other types of distressful information, especially in situations where individuals perceive little control over how to cope with the underlying threat, such as the outbreak of infectious diseases, violent conflicts, and climate change.

With our finding that not recalling is not only used as a complement to but also as a substitute for information avoidance, our study makes an important methodological contribution to research on strategic ignorance. A possible explanation for the substitutability is provided by the extension to our theoretical framework which suggests that individuals acquire information while accounting for the option to not recall it later on. Our results imply that the mere lack of information avoidance is not sufficient to conclude that there is no underlying issue of strategic ignorance, which may also occur through selective recall or other forms of memory distortion. Rather, we believe it to be best practice that information avoidance and recall are studied in a unified framework. Otherwise, the extent to which people forego the instrumental benefits of new information may be crucially underestimated, compromising the accuracy of policy implications.

A promising avenue for future research lies in exploring whether and to what extent an increase in the recall of useful but distressing information will translate into behavioral changes, including the adoption of private actions and changes in the demand for public policies. The effect on the latter is particularly difficult to predict. On the one hand, less ignorance should lead to more support for public action. On the other hand, if perceived control is increased through raising awareness about private coping mechanisms, demand for public action might stall.

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Appendix – For Online Publication

A. Additional Results from the Main Experiment

A-1. The Indian Sample

In the following, we present additional results from the main experiment with the Indian sample.

Participant Characteristics and Balance Tests

In Table A-1, we present sample characteristics by control (C) and treatment (T) group in the Indian sample, including mean comparison t-tests to examine balance.

TABLE A-1 – SAMPLE CHARACTERISTICS AND BALANCE TESTS FOR THE INDIA SAMPLE.

	Control		Treatment		T - C
	N	Mean	N	Mean	
Age	1,000	34.11	1,031	34.15	0.05
		(10.94)		(11.12)	(0.49)
Female	1,000	0.34	1,031	0.34	0.00
		(0.47)		(0.47)	(0.02)
Household size	1,000	4.33	1,030	4.34	0.01
		(2.38)		(1.57)	(0.09)
Urban	1,000	0.90	1,031	0.89	-0.01
		(0.31)		(0.31)	(0.01)
Income group	1,000	8.03	1,031	7.92	-0.11
		(2.58)		(2.69)	(0.12)
Education	1,000	2.31	1,031	2.29	-0.02
		(0.64)		(0.64)	(0.03)
Life expectancy loss	1,000	5.81	1,031	5.89	0.08
		(2.72)		(2.66)	(0.12)
Prior belief about air quality	1,000	4.90	1,031	4.99	0.09
		(2.56)		(2.47)	(0.11)
Confidence in prior	1,000	4.13	1,031	4.13	-0.00
		(0.78)		(0.78)	(0.03)
Worried about air pollution	1,000	5.61	1,031	5.66	0.05
		(1.56)		(1.49)	(0.07)
Joint orthogonality F-stat					0.28
					(0.99)

Notes: Pre-treatment participant characteristics and mean comparison t-tests between control and treatment groups in the main experiment for a total sample of $N = 2,031$ participants from India after data cleaning according to the pre-registered exclusion criteria. The calculation of number of life years lost follows (Ebenstein et al., 2017) and is based on the annual average population-weighted $PM_{2.5}$ concentration in the participant's district of residence (Hammer et al., 2020). Standard deviations are reported in parentheses. The right-most column reports the difference in means between treatment and control, with the estimated standard errors in parentheses. C = control, T = perceived control treatment. Significant t-test results are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Participants are, on average, 34 years old, predominantly male (66%), live in urban areas (89%), are rich (median household income between the 80th and 90th percentile of the national distribution), and well educated (40% with a Masters degree or higher). The average loss of life expectancy in the sample is about 6 years (with values ranging between 1 and 12 years). This appears aligned with the average prior beliefs of participants. When asked to rate the air quality in their district, the average response rate is a value of 5 on a 10-point Likert scale, which is given rather confidently (median response of 4 on a 5-point Likert scale). Moreover, participants are rather worried about air pollution (average of 5.6 on a 7 point Likert scale). The sample is balanced across control and treatment group with respect to all observable characteristics.

Perceived Control

In Table A-2, we present regression results in the Indian sample for perceived control as measured by the 7 item index adapted from Pearlin and Schooler (1978) (columns 1 to 3) and the 1 item measure adapted from Trope, Gervey and Bolger (2003) (columns 4 to 6). We find that the treatment effect on perceived control is robust to the inclusion of control variables (including the participant's prior belief about air quality, the confidence in this prior, and the life expectancy loss due to air pollution in the participant's home district, denoted by average life expectancy loss) as well as the inclusion of state fixed effects.

TABLE A-2 – ESTIMATED TREATMENT EFFECTS ON PERCEIVED CONTROL IN THE INDIAN SAMPLE.

	7-item Index (Pearlin and Schooler, 1978)			1-item Measure (Trope, Gervey and Bolger, 2003)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.188***	0.186***	0.190***	0.179***	0.191***	0.187***
	(0.024)	(0.023)	(0.023)	(0.043)	(0.040)	(0.041)
Prior belief about air quality		0.009*	0.014***		-0.104***	-0.108***
		(0.005)	(0.005)		(0.009)	(0.009)
Confidence in prior belief		-0.030**	-0.025		0.196***	0.193***
		(0.015)	(0.015)		(0.026)	(0.027)
Life expectacy loss		-0.016***	0.009		-0.015*	0.041
		(0.004)	(0.022)		(0.008)	(0.039)
Visual memory		0.635***	0.632***		-0.627***	-0.619***
		(0.086)	(0.087)		(0.151)	(0.154)
State FE	No	No	Yes	No	No	Yes
Observations	2,031	2,031	2,028	2,031	2,031	2,028
Control mean	0	0	0	0	0	0

Notes: This table presents OLS estimations of two standardized measures of perceived control adapted to the context of air pollution from Pearlin and Schooler (1978) and Trope, Gervey and Bolger (2003). Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Information Avoidance

In Table A-3, we present regression results in the Indian sample for information acquisition, using both a linear probability model (columns 1 to 3) and a non-linear logistic regression (columns 4 to 6). Our finding that information acquisition is not affected by the treatment is robust to the inclusion of control variables (prior belief and confidence in the prior) as well as the inclusion of state fixed effects.

Table A-3 – Estimated treatment effects on information acquisition in the Indian sample.

	Information acquisition					
	LPM			Logistic		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.003	-0.004	-0.003	-0.004	-0.004	-0.000
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.002)
Prior beliefs about air quality		0.001	0.000		0.002	0.000
		(0.003)	(0.003)		(0.003)	(0.001)
Confidence in prior		0.051***	0.052***		0.045***	0.008
		(0.008)	(0.008)		(0.007)	(0.008)
Life expectancy loss		0.004*	0.007		0.005**	0.001
		(0.002)	(0.012)		(0.003)	(0.001)
Visual memory		0.098**	0.109**		0.084**	0.017
		(0.045)	(0.046)		(0.042)	(0.015)
State FE	No	No	Yes	No	No	Yes
Observations	2,031	2,031	2,028	2,031	2,031	1,980
Control mean	0.92	0.92	0.92	0.92	0.92	0.92

Notes: This table presents estimates from linear probability models and logistic models on information acquisition in the Indian sample. Coefficients of the logistic models are marginal effects. We use a conditional logit model for the fixed effect model in column 6. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

A-2. The US Sample

In the following, we present additional results from the main experiment with the US sample.

Participant Characteristics and Balance Tests

In Table A-4, we present sample characteristics by control (C) and treatment (T) group in the US sample, including mean comparison t-tests to examine balance.

Table A-4 – Sample characteristics and balance tests for the US sample.

	Control		Treatment		T - C
	N	Mean	N	Mean	
Age	1,124	39.19	1,140	38.62	-0.56
		(11.69)		(11.85)	(0.49)
Female	1,124	0.50	1,140	0.51	0.01
		(0.50)		(0.50)	(0.02)
Household size	1,118	3.12	1,136	3.06	-0.06
		(2.21)		(1.45)	(0.08)
Urban	1,124	0.74	1,140	0.74	-0.00
		(0.44)		(0.44)	(0.02)
Income group	1,124	5.09	1,140	5.07	-0.02
		(2.33)		(2.31)	(0.10)
Education	1,124	1.97	1,140	1.97	0.00
		(0.67)		(0.66)	(0.03)
Life expectancy loss	1,124	0.49	1,140	0.48	-0.02
		(0.29)		(0.28)	(0.01)
Prior belief about air quality	1,124	4.98	1,140	4.96	-0.02
		(2.12)		(2.20)	(0.09)
Confidence in prior	1,124	3.49	1,140	3.56	0.06*
		(0.88)		(0.90)	(0.04)
Worried about air pollution	1,124	4.45	1,140	4.47	0.03
		(1.72)		(1.73)	(0.07)
Joint orthogonality F-stat					1.02
					(0.42)

Notes: Summary statistics of pre-treatment participant characteristics and balance tests between means values in control and treatment groups for a total sample of $N = 2,264$ participants from the US after data cleaning according to the pre-registered exclusion criteria. The calculation of number of life years lost follows (Ebenstein et al., 2017) and is based on the annual average population-weighted $PM_{2.5}$ concentration in the participant's district of residence (Hammer et al., 2020). Standard deviations are reported in parentheses. The right-most column reports the difference in means between treatment and control, with the estimated standard errors in parentheses. C = control, T = treatment. Significant t-test estimates are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Participants are, on average, 39 years old and equally split by gender. About 75% of participants live in urban areas and the mean income is around the median income of the US national income distribution. The average loss of life expectancy in the sample is about 0.5 years and when asked to rate the air quality in their district, the average response rate is a value of 5 on a 10-point Likert scale, which is given with an average confidence of 3.5 on a 5-point Likert scale. We find that the sample is balanced across control and treatment group with respect to all observable characteristics, except for the confidence with respect to the prior belief about the regional air quality. Here, we observe that participants in the treatment group are marginally more confident.

Perceived Control

Figure A-1 illustrates the positive treatment effect on our 7 item index measure of perceived control in the US sample. The distribution of the index in the treatment group (in dark gray) is shifted to the right when compared to the control group (in light gray).

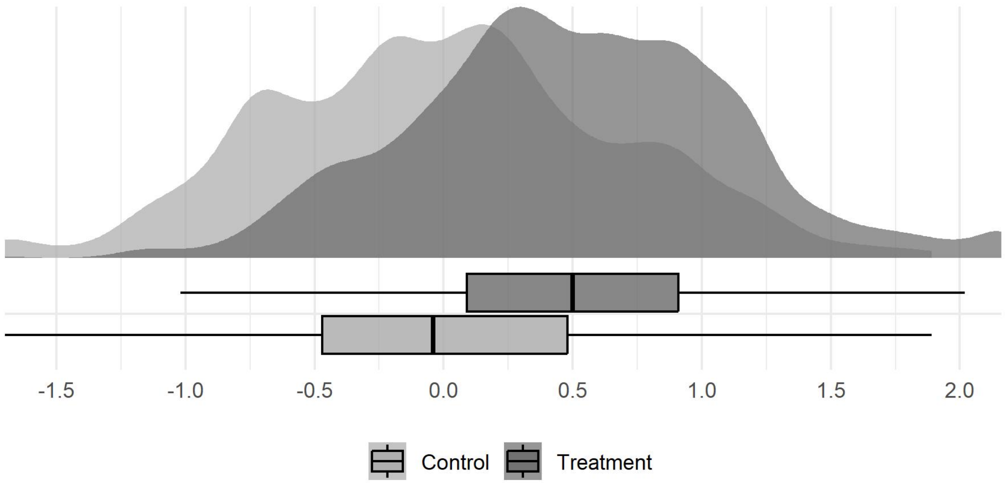


FIGURE A-1 – DISTRIBUTION OF THE PERCEIVED CONTROL INDEX (US SAMPLE).

Notes: This figure presents the kernel densities of the distributions of perceived control, as measured by the standardized index of participants' answers to the 7-item questionnaire, adapted from Pearlin and Schooler (1978) to the context of air pollution. Two distributions are presented: lighter gray corresponds to responses in the control group and darker gray corresponds to responses in the treatment group.

Moreover, Table A-5 reports regression results (both for the 7 item index and the 1 item measure) on perceived control. Results indicate that the positive treatment effect on perceived control is robust, both to the inclusion of covariates (prior belief, confidence, and life expectancy loss) as well as the inclusion of state fixed effects.

Table A-5 – Estimated effects on perceived control (US sample).

	7-item Index (Pearlin and Schooler, 1978)			1-item Measure (Trope, Gervey and Bolger, 2003)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.495***	0.493***	0.494***	0.527***	0.514***	0.514***
	(0.027)	(0.027)	(0.027)	(0.040)	(0.039)	(0.039)
Prior belief about air quality		-0.017**	-0.015**		-0.096***	-0.095***
		(0.007)	(0.007)		(0.009)	(0.009)
Confidence in prior belief		0.014	0.015		0.162***	0.164***
		(0.016)	(0.016)		(0.022)	(0.022)
Life expectancy loss		-0.057	-0.133		-0.040	-0.070
		(0.051)	(0.086)		(0.072)	(0.122)
Visual memory		0.222*	0.219*		-0.272	-0.227
		(0.125)	(0.126)		(0.178)	(0.179)
State FE	No	No	Yes	No	No	Yes
Observations	2,251	2,251	2,251	2,262	2,262	2,262
Control mean	0	0	0	0	0	0

Notes: This table presents OLS estimations of two standardized measures of perceived control adapted to the context of air pollution from Pearlin and Schooler (1978) and Trope, Gervey and Bolger (2003). Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Information Avoidance

Figure A-2 depicts descriptive results for information avoidance and lack of recall for control and treatment group in the US sample. Results suggest that there is no treatment effect on either outcome which is supported by the regression results in Table A-6.

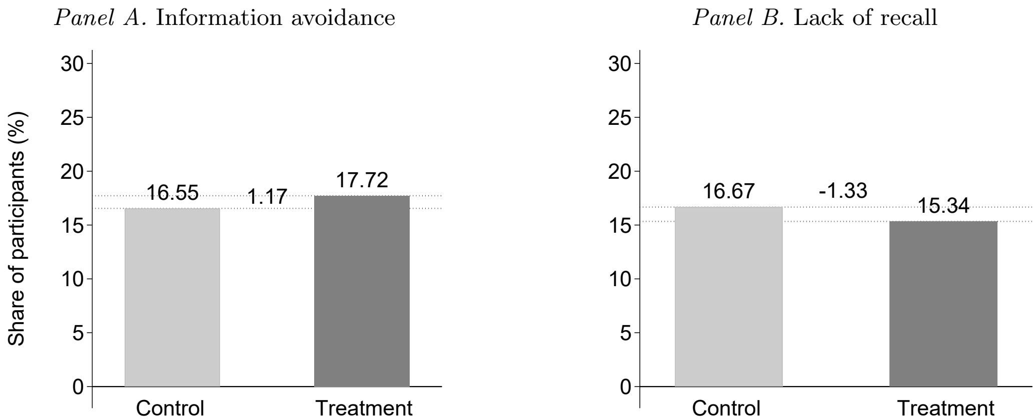


Figure A-2 – Information avoidance and lack of recall (US sample).

Notes: The figure plots the share of participants that prefer to avoid the information (Panel A) and that do not recall the information (Panel B) in the control (light gray) and treatment (dark gray) groups in the US sample.

Table A-6 – Estimated effects on information acquisition in the US sample.

	Information acquisition					
	OLS			Logistic		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.012	-0.012	-0.011	-0.012	-0.012	-0.013
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.018)
Prior beliefs about air quality		-0.006	-0.006		-0.006*	-0.007
		(0.004)	(0.004)		(0.004)	(0.005)
Confidence in prior		-0.000	-0.001		0.000	-0.001
		(0.009)	(0.009)		(0.009)	(0.010)
Life expectancy loss		-0.008	-0.030		-0.008	-0.032
		(0.029)	(0.050)		(0.029)	(0.056)
Visual memory		0.314***	0.317***		0.284***	0.310***
		(0.072)	(0.073)		(0.065)	(0.058)
State FE	No	No	Yes	No	No	Yes
Observations	2,264	2,264	2,264	2,264	2,264	2,264
Control mean	0.83	0.83	0.83	0.83	0.83	0.83

Notes: This table presents estimates from linear probability models and logistic models on information acquisition in the US sample. Coefficients of the logistic models are marginal effects. We use a conditional logit model for the fixed effect model in column 6. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

B. Heterogeneity by Prior Beliefs and Multiple Hypothesis Testing

Our heterogeneity analysis by prior beliefs suggests that it is particularly optimistic participants – those who have a prior belief to experience particularly good air quality – strategically not recall the information. And that is exactly this subsample that drives the positive treatment effect on recall, see Figure 9 and Figure 13 for the result in the Indian and the US sample, respectively.

In Figure B-1 (for the Indian sample) and Figure B-2 (for the US sample), we show that the result patterns of the heterogeneity analysis by prior belief persist when restricting the respective sample to participants that prefer to receive the information in the first place. In both samples, we still observe that optimists are less likely to recall the information on the loss of life expectancy than any other subgroup and that the treatment is particularly effective for participants with the most optimistic priors. Hence, we show that the heterogeneity by prior belief with respect to recall is not driven by participants that wanted to use not recalling as a complement to information avoidance.

In Table B-1, we show that the heterogeneous treatment effect on recall for optimists in the Indian and the US sample is robust to multiple hypothesis testing following the Benjamini-Hochberg method as described in Anderson (2008).

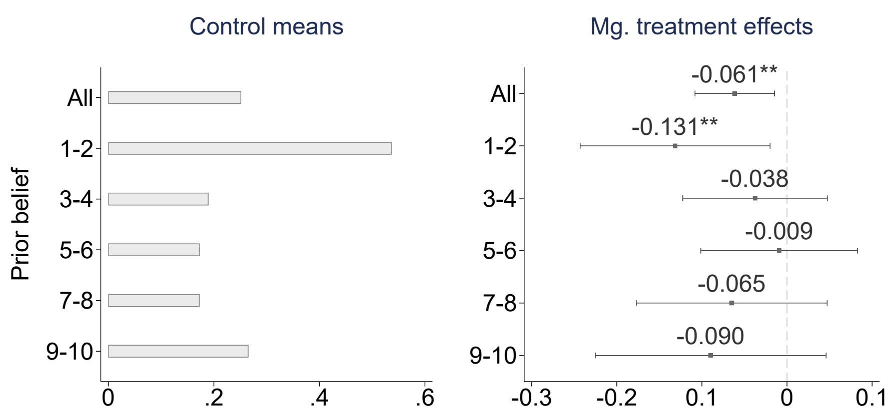


Figure B-1 – Control group means and treatment effects on lack of information recall by prior belief in the Indian sample. Only participants that prefer to receive the information.

Notes: The figure presents control group means and marginal treatment effects on the lack of information recall in the Indian sample. Only participants that stated to prefer to receive the information about life expectancy loss are included. The marginal treatment effects are based on an interaction between the treatment and the prior belief about the air quality in the home district. We include controls for the confidence in the prior belief, the actual average life expectancy loss in the home district, and the performance in the visual memory task. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

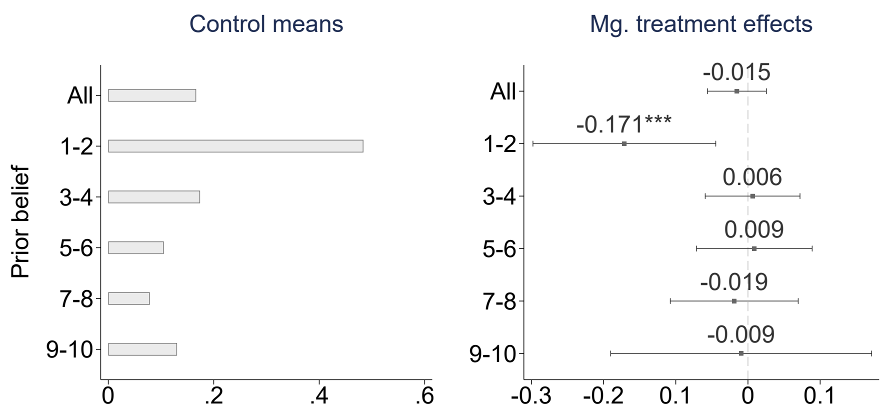


Figure B-2 – Control group means and treatment effects on lack of information recall by prior belief in the US sample. Only participants that prefer to receive the information.

Notes: The figure presents control group means and marginal treatment effects on the lack of information recall in the US sample. Only participants that stated to prefer to receive the information about life expectancy loss are included. The marginal treatment effects are based on an interaction between the treatment and the prior belief about the air quality in the home district. We include controls for the confidence in the prior belief, the actual average life expectancy loss in the home district, and the performance in the visual memory task. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table B-1 – Estimated marginal effects on lack of information recall, by prior belief about air pollution in home district in the Indian and the US sample.

	Lack of recall	
	India sample (1)	US sample (2)
Treatment x Prior 1-2	-0.144***	-0.176***
SE	(0.056)	(0.060)
p-value	0.0098	0.0035
q-value	0.0520	0.0190
Treatment x Prior 3-4	-0.043	0.024
SE	(0.043)	(0.032)
p-value	0.3090	0.4506
q-value	0.5940	1
Treatment x Prior 5-6	-0.037	0.008
SE	(0.046)	(0.038)
p-value	0.4243	0.8392
q-value	0.5940	1
Treatment x Prior 7-8	-0.041	-0.026
SE	(0.057)	(0.043)
p-value	0.4655	0.5468
q-value	0.5940	1
Treatment x Prior 9-10	-0.090	-0.020
SE	(0.069)	(0.089)
p-value	0.1942	0.8181
q-value	0.5940	1
Confidence in prior belief	-0.040**	0.028**
	(0.017)	(0.012)
Life expectancy loss	0.004	0.057
	(0.005)	(0.037)
Visual memory	-0.516***	-0.578***
	(0.087)	(0.092)
Prefer to avoid info	0.122**	0.007
	(0.052)	(0.029)
Observations	1,196	1,298

Notes: The table presents the estimated marginal treatment effects on ithe lack of information recall in the India and US samples. The coefficients presented here correspond to the values displayed in Figure 9 and Figure 13 in the main text. The marginal treatment effects are based on an interaction between the treatment dummy and the participants' prior beliefs about the air quality in their district (India) or county (US) of residence. All models control for the participants' confidence in the prior belief, the actual average number of life years lost in their home district/county, their preference to avoid the information, and their performance in the general memory task. Standard errors are denoted SE and are reported in parentheses below the coefficients. For each estimated marginal treatment effect by prior beliefs, we present both the p-values and the q-values. We compute the q-values using the Benjamini-Hochberg method as described in Anderson (2008). The reported q-values indicate the smallest false discovery rate at which the null hypothesis of a zero effect is rejected. Significance reflects the p-values and is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

C. Performance in unrelated cognitive tasks

C-1. Coin counting

To study whether performance in the coin counting task is affected by the treatment, we first perform a Fligner-Pollicelo test to test for differences in participants' performance in the coin counting test between those that were randomized to see the information about the average loss of life expectancy and those that were not. In the Indian sample, the one-tailed asymptotic p-value is equal to 0.457 according to a two-sample Fligner-Policello robust rank order test. In the US, the p-value is 0.371. We conclude that performance in the coin counting task is not affected by the treatment.

Our conclusion is supported by regression results presented in Table C-1. Results additionally suggest that performance in the coin counting task is positively correlated with performance in the memory task, a pattern that is likely due to overall cognitive ability.

Table C-1 – Estimated effects on performance in the coin counting task in the main experiment.

	USA (1)	India (2)
Treatment	0.058	0.165
	(0.098)	(0.102)
Prior belief about air quality	0.137***	0.110***
	(0.024)	(0.022)
Confidence in prior belief	-0.174***	-0.093
	(0.056)	(0.067)
Life expectancy loss	-0.346*	-0.006
	(0.181)	(0.020)
Prefer to avoid	-0.196	0.103
	(0.131)	(0.190)
Visual memory	4.572***	5.502***
	(0.450)	(0.382)
Observations	2,264	2,031
Control mean	6.96	5.42

Notes: The standard error reported in parantheses are clustered at the county/district level. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Lastly, we study heterogeneous treatment effects on the task performance by prior belief about air quality, see Figure C-1 for results in India and the US. We find no evidence of heterogeneous treatment effects by prior beliefs.

Panel A. India | *Panel B.* USA

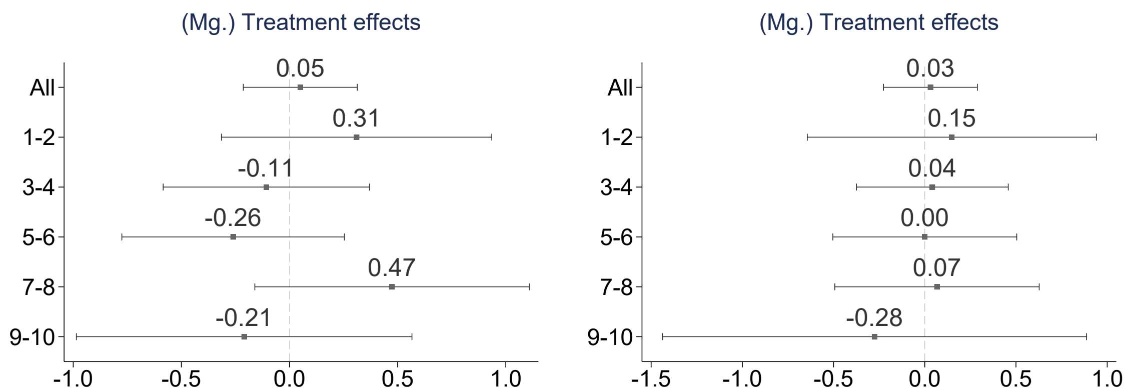
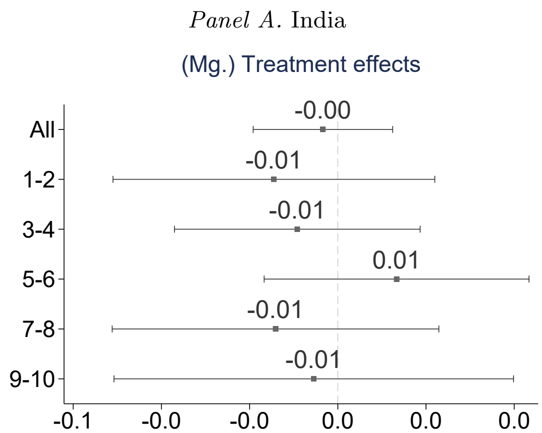


Figure C-1 – participants' performance in the coin counting task by prior belief, by prior beliefs about air quality in home region.

Notes: This figure presents the estimated marginal treatment effects on participants' performance in the coin counting in the Indian and USA samples. The marginal treatment effects are estimated on interaction models between the treatment dummy and participants' prior beliefs about the regional air quality. All models control for the participants' confidence in the prior belief, their performance in the visual memory task, the regional average life expectancy loss in their home district (India) or county (USA), as well as their preference to receive or avoid information. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

C-2. Visual memory

We study heterogeneous treatment effects on the participants' performance in the visual memory task, by prior belief about air quality. Figure C-2 illustrates the estimation results for the Indian and the US samples. We find no evidence of heterogeneous treatment effects by prior beliefs.



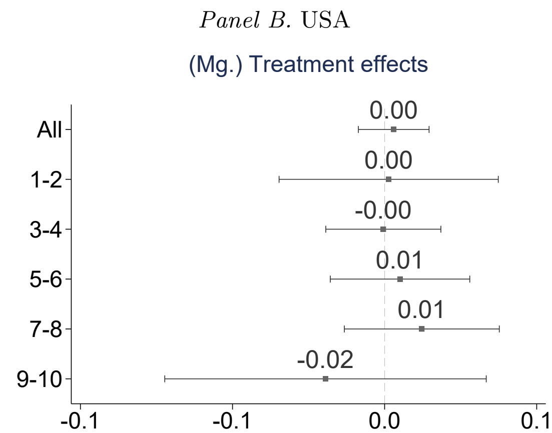


FIGURE C-2 – PARTICIPANTS' PERFORMANCE IN THE VISUAL MEMORY TASK, BY PRIOR BELIEFS ABOUT AIR QUALITY IN HOME REGION.

Notes: This figure presents the estimated marginal treatment effects on participants' performance in the visual memory task in the Indian and USA samples. The marginal treatment effects are estimated on interaction models between the treatment dummy and participants' prior beliefs about the regional air quality. All models control for the participants' confidence in the prior belief, the regional average life expectancy loss in their home district (India) or county (USA), as well as their preference to receive or avoid information. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

D. The Follow-Up Experiment

Design and objectives

We conducted a follow-up for both the Indian and the US sample. All participants who received the information on the average loss of life expectancy in their home region in the main study were invited to take part in the follow-up study two weeks later. First, we again elicited demographic variables to test for inconsistencies with responses in the main experiment. Then, participants were asked to recall the information on the number of life-years lost provided in the main experiment. The incentive scheme used for the recall task in the follow-up was identical to the one used in the main experiment.[32] Participants were neither contacted nor reminded of any information in-between the main and follow-up experiments. The follow-up experiment concluded with two questionnaires: (i) we repeated the measurement of perceived control equivalent to the main experiment, and (ii) we asked participants how often they engage with various protective measures against air pollution exposure.[33]

Sample

In India, a total of 1,198 participants were invited to the follow-up, 626 (52%) were recruited, and 604 completed the follow-up experiment. 494 participants remain for the analysis after addressing inconsistency issues between the location information provided in the main and follow-up experiments. A total of 1,302 participants in the US sample received information on the number of life years lost in their home county in the main experiment and were therefore invited to partake in the follow-up study. 660 (51%) were recruited out of which 649 completed the follow-up experiment. After applying the location consistency criteria, a total of 502 participants remain available for the analysis.

Selection

To test for potential selection issues, we compare participants who selected into the follow-up with participants who selected out of it. We observe substantial differences between both groups in both countries, see Appendix Tables D-4, D-5, D-6, and D-7. Importantly, we find that participation in the follow-up is conditional on our main variables of interest from the main study: in both the US and Indian samples, participants who selected into the follow-up i) scored higher on perceived control, and ii) were significantly better at recalling

[32] As for the main study, Indian participants were rewarded by the survey company in panel points and received an additional average bonus payment of INR 22 (about USD 0.27). US participants received a fixed reward of US $1.00 for completing the follow-up (which took about 3 minutes). Together with the incentives that participants were able to earn, the average reward was US $1.24.

[33] All participants were invited to give open feedback at the end of each experiment. Additionally, we debriefed participants in the control group on the protective measures one can utilize to protect oneself against air pollution exposure. Participants who did not receive information on life years lost were debriefed after the main experiment as they were not re-invited for the follow-up. All others were debriefed after the follow-up experiment.

the number of life-years lost than those that selected out of the follow-up. Consequently, we cannot provide a clean test of the long term effect of perceived control on information retention and leave this question open for future research. For the sake of completeness, we report the results from our pre-registered analyses on our self-selected sample below but remind the reader that these results should be interpreted with care.

Results on Perceived Control

In the US follow-up sample, perceived control is 0.42 points higher in the treatment group than in the control group, a significant positive difference (MW test $p < 0.001$, combined N=501). In the Indian follow-up sample, perceived control is 0.12 points higher in the treatment group than in the control group, a marginally significant difference (MW test $p = 0.052$, combined N=494). We find similar results using our one-item measure: perceived control is 0.51 points higher in the treatment group than in the control group in the USA ($p < 0.001$) and 0.24 points higher in India ($p = 0.008$).

To assess changes in treatment effects over time, we estimate differences-in-differences regressions using data from both the main and follow-up experiments for the sub-sample of participants who took part in both the main and the follow-up study. Appendix Table D-1 presents the estimated treatment effects in interaction with a dummy variable for the follow-up study. First, we find a significant and positive effect of our treatment in the main study in all specifications for our self-selected sample of participants in both countries. In addition, the coefficient of the interaction term is negative and significant for the perceived control index. However, the overall effect of our treatment manipulation on perceived control is still positive and significant in the follow-up in both countries, see the *Treatment* × *Follow-up (margin)* coefficient in Appendix Table D-1. These results suggest that while the treatment effect on perceived control fades over time, it still has a positive and significant impact two weeks after participants' have been exposed to it.

Results on Information Recall

We pre-registered a test on whether participants in the treatment group are more likely to recall the information about the number of life-years lost in their home region two weeks after having been exposed to it. In both countries, the share of participants that is still able to recall the information is about 64%, and this proportion does not differ between the treatment and the control group.[34] To evaluate changes in treatment effects between the main and follow-up studies, we estimate differences-in-differences by interacting the treatment dummy with a follow-up dummy. Results are presented in Appendix Table D-2.

We find no treatment effect in the main experiment for the self-selected sub-sample of participants who completed both experiments in either country. It is therefore not

[34]In the US sample, 63.6% of participants in the control group and 57.9% in the treatment group are able to recall the information within a 0.5 year error margin; the difference is not statistically significant (Fisher exact test: $p = 0.201$, combined N=501). In the Indian sample, 65.4% of participants in the control group and 65.4% of participants in the treatment group are able to recall the information within a 0.5 year error margin; the difference is not significant (Fisher exact test: $p = 1$, combined N=494).

surprising that we find no treatment effect in the follow-up either. Nonetheless, results point to a significant decrease in the recall rate over the two-week period of 24 percentage points in the US sample and 14 percentage points in the Indian sample ($p < 0.001$ in both samples). Yet, the decrease in successful recall over time does not differ between the treatment and control groups. Given that the sample that has selected into the follow-up study appears to be less susceptible to engage in strategic memory distortion, we view the estimated reduction in recall over the two-week period as a lower bound for the true effect.

Results on Protective Measures

We also pre-registered that we would test whether participants in the treatment group report engaging more often with the protective measures than participants in the control group. In the main study, participants in the treatment group were provided with information about a set of private measures to protect themselves against air pollution exposure. To test the effect of exposing participants to information about such measures on their reported preventive behavior, we asked participants to report how often they engage with these measures, offering five response options that range from "never" to "every day".[35] We standardized the responses for all nine activities to z-scores following Kling, Liebman and Katz (2007) and computed an equally-weighted index.

We find that among participants who completed both studies, participants in the treatment group report using the defensive measures more frequently than participants in the control group. This difference is significant (marginally for India) in both samples (MW test: $p = 0.011$, combined N=501 for the US sample and $p = 0.066$, combined N=494 for the Indian sample). In addition, we examine the effect of our treatment on each component of our aggregated measure separately. The regression results are displayed in Appendix Table D-3. We find that a change in commuting habits (in both the US and Indian samples) as well as a higher intention to undertake preventive medical tests (in the US sample) drive the treatment effect on the aggregate measure. These results suggest that providing information about protection measures moderately increases their reported use two weeks after receiving the information.

[35] In particular, we asked about the following activities: wearing a face mask, using an air purifier indoors, checking the air quality in the area, avoiding highly polluted areas when commuting, opening windows to ventilate rooms, removing dust in the household, spending time in nature, burning waste, and handling open fires (*e.g.*, for cooking or heating).

TABLE D-1 – ESTIMATED EFFECTS ON PERCEIVED CONTROL OF AIR POLLUTION IN MAIN VERSUS FOLLOW-UP EXPERIMENTS.

	7-item Index (Pearlin and Schooler, 1978)			1-item Measure (Trope, Gervey and Bolger, 2003)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: India					
Treatment	0.214***	0.224***	0.191***	0.286***	0.271***	0.240***
	(0.049)	(0.048)	(0.047)	(0.086)	(0.083)	(0.084)
Follow-up	-0.060	-0.060	-0.060	0.089	0.089	0.089
	(0.050)	(0.049)	(0.047)	(0.088)	(0.085)	(0.084)
Treatment x Follow-up	-0.097	-0.097	-0.097	-0.044	-0.044	-0.044
	(0.069)	(0.068)	(0.065)	(0.122)	(0.118)	(0.116)
State FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Observations	988	988	988	988	988	988
Control mean Main	0.06	0.06	0.06	-0.09	-0.09	-0.09
Treatment x Follow-up (margin)	0.116**	0.127***	0.094**	0.242***	0.227***	0.196**
	(0.049)	(0.048)	(0.047)	(0.086)	(0.083)	(0.084)
	Panel B: USA					
Treatment	0.567***	0.573***	0.574***	0.640***	0.654***	0.654***
	(0.062)	(0.062)	(0.062)	(0.086)	(0.085)	(0.085)
Follow-up	0.028	0.028	0.028	0.099	0.099	0.099
	(0.061)	(0.060)	(0.060)	(0.085)	(0.083)	(0.083)
Treatment x Follow-up	-0.153*	-0.153*	-0.154*	-0.127	-0.127	-0.127
	(0.088)	(0.087)	(0.087)	(0.122)	(0.119)	(0.119)
State FE	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Observations	994	994	994	1,000	1,000	1,000
Control mean Main	-0.03	-0.03	-0.03	-0.10	-0.10	-0.10
Treatment x Follow-up (margin)	0.414***	0.420***	0.420***	0.513***	0.526***	0.527***
	(0.062)	(0.061)	(0.061)	(0.087)	(0.085)	(0.085)

Notes: This table presents estimated coefficients of difference-in-differences models. Models (2), (3), (5), and (6) control for participants' prior belief about air quality in the home region, their confidence in the prior belief, and the average number of life years lost due to air pollution in the home region. Columns (3) and (6) additionally include state fixed effects. All control variables have been collected in the main experiment. The analysis relies only on answers from participants that took part in both the main and follow-up experiments, *i.e.*, a balanced panel. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table D-2 – Estimated effects on information recall in the main versus follow-up experiments.

	India (1)	USA (2)
Treatment	0.051	-0.003
	(0.039)	(0.037)
Follow-up	-0.141***	-0.242***
	(0.040)	(0.036)
Treatment x Follow-up	-0.044	-0.054
	(0.055)	(0.053)
Observations	988	1,000
Control mean Main	0.79	0.88

Notes: This table presents estimated coefficients of difference-in-differences models, where the treatment indicator is interacted with a dummy indicator for the follow-up study. Each column corresponds to a different outcome variable. All models control for participants' prior belief about air quality in the home region, their confidence in the prior belief, and the average number of life years lost due to air pollution in the home region. All control variables have been collected in the main experiment. The analysis relies only on answers from participants that took part in both the main and follow-up experiments, *i.e.*, a balanced panel. Significance is denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table D-3 – Estimated effects on the adoption of defensive measures against air pollution in the follow-up experiment.

	Index (1)	Face mask (2)	Air purifier (3)	Medical tests (4)	Change in commute (5)	Frequent ventilation (6)	Dust removal (7)	Time in nature (8)	Avoid waste burning (9)	Avoid open fires (10)
Panel A: India										
Treatment	0.069*	0.088	0.048	0.075	0.189**	0.123	0.105	0.107	-0.041	-0.079
	(0.040)	(0.084)	(0.089)	(0.090)	(0.088)	(0.084)	(0.090)	(0.088)	(0.090)	(0.089)
Obs.	494	494	494	494	494	494	494	494	494	494
Panel B: USA										
Treatment	0.104***	0.067	0.083	0.175**	0.238***	0.086	0.105	0.101	0.017	0.067
	(0.038)	(0.090)	(0.086)	(0.089)	(0.090)	(0.084)	(0.085)	(0.084)	(0.084)	(0.085)
Obs.	500	500	500	500	500	500	500	500	500	500

Notes: The table presents estimated treatment effects on the adoption of various defensive measures against air pollution. Each column corresponds to a different defensive measure. All outcome measures have been collected in the follow-up experiment, approximately two weeks after the main experiment. Column (1) presents the estimated treatment effect on an index that equally weights the defensive measures used as outcome variables in Columns (2)-(9). Each component of the index has been standardized following Kling, Liebman and Katz (2007). All outcome variables have a mean value of 0 in the control group. All models control for participants' prior belief about air quality in the home region, their confidence in the prior belief, the average number of life years lost due to air pollution in the home region, and participants' performance in the visual memory task. All control variables have been collected in the main experiment. Significance is denoted as follows: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Balance Tests: Main Versus Follow-Up

Table D-4 – Sample characteristics and balance tests for the India control group in the main *versus* follow-up experiments.

	Selected In		Main		Selected Out		In - Main	In - Out
	N	Mean	N	Mean	N	Mean		
Age	234	34.44	581	34.07	347	33.82	0.37	0.61
		(11.31)		(10.71)		(10.30)	(0.84)	(0.91)
Female	234	0.31	581	0.35	347	0.38	-0.04	-0.07*
		(0.46)		(0.48)		(0.49)	(0.04)	(0.04)
Household size	234	4.40	581	4.43	347	4.45	-0.03	-0.05
		(1.41)		(2.84)		(3.49)	(0.19)	(0.24)
Urban	234	0.90	581	0.90	347	0.90	-0.00	-0.00
		(0.30)		(0.30)		(0.29)	(0.02)	(0.03)
Income group	234	8.18	581	8.07	347	7.99	0.11	0.19
		(2.48)		(2.48)		(2.48)	(0.19)	(0.21)
Education	234	2.28	581	2.32	347	2.34	-0.03	-0.06
		(0.65)		(0.64)		(0.63)	(0.05)	(0.05)
Life expectancy loss	234	5.72	581	5.84	347	5.92	-0.12	-0.20
		(2.70)		(2.73)		(2.75)	(0.21)	(0.23)
Prior belief about air quality	234	5.28	581	4.99	347	4.80	0.28	0.48**
		(2.41)		(2.59)		(2.68)	(0.20)	(0.22)
Confidence in prior belief	234	4.11	581	4.14	347	4.16	-0.03	-0.05
		(0.75)		(0.77)		(0.79)	(0.06)	(0.07)
Worried about air pollution	234	5.57	581	5.61	347	5.64	-0.04	-0.07
		(1.50)		(1.59)		(1.65)	(0.12)	(0.13)
Prefer to not receive info	234	0.05	581	0.06	347	0.06	-0.01	-0.01
		(0.22)		(0.23)		(0.24)	(0.02)	(0.02)
Time on life expectancy loss page (s)	234	25.87	581	23.34	347	21.62	2.54	4.25
		(56.92)		(50.52)		(45.71)	(4.06)	(4.27)
Recall	234	0.79	581	0.73	347	0.69	0.06*	0.10***
		(0.40)		(0.44)		(0.46)	(0.03)	(0.04)
Perceived control (index)	234	0.06	581	-0.01	347	-0.05	0.07*	0.11***
		(0.48)		(0.50)		(0.51)	(0.04)	(0.04)
Perceived control (1 item)	234	-0.09	581	-0.00	347	0.06	-0.09	-0.15*
		(0.90)		(0.98)		(1.02)	(0.07)	(0.08)
Coin counting	234	5.68	581	5.51	347	5.39	0.17	0.28
		(2.37)		(2.49)		(2.57)	(0.19)	(0.21)
Visual memory	234	0.89	581	0.87	347	0.86	0.02*	0.03***
		(0.12)		(0.14)		(0.15)	(0.01)	(0.01)
Joint orthogonality F-stat							0.64	1.46
							(0.87)	(0.09)

Notes: The table presents summary statistics of participant characteristics and balance tests between the samples of participants that took part in the main and follow-up experiments, only in the control group. Selected In refers to participants that took part in both the main and follow-up experiments. Selected Out refers to participants that took part only in the main experiment. All characteristics have been collected in the main experiment. Parentheses underneath mean values are standard deviations of the respective observable characteristic. The two right-most columns report the difference in means between the sample that selected in the follow-up and the and sample in the main experiment or the sample that selected out of the follow-up, with estimated standard error in parentheses. Significant t-test estimates are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table D-5 – Sample characteristics and balance tests for the India treatment group in the main *versus* follow-up experiments.

	Selected In		Main		Selected Out		In - Main	In - Out
	N	Mean	N	Mean	N	Mean		
Age	260	34.15	615	33.85	355	33.63	0.30	0.52
		(11.37)		(11.24)		(11.15)	(0.83)	(0.92)
Female	260	0.28	615	0.31	355	0.34	-0.04	-0.06
		(0.45)		(0.46)		(0.47)	(0.03)	(0.04)
Household size	260	4.46	614	4.45	354	4.45	0.00	0.01
		(1.59)		(1.62)		(1.64)	(0.12)	(0.13)
Urban	260	0.93	615	0.89	355	0.87	0.04*	0.06**
		(0.25)		(0.31)		(0.34)	(0.02)	(0.03)
Income group	260	8.47	615	7.94	355	7.55	0.53***	0.91***
		(2.31)		(2.64)		(2.80)	(0.19)	(0.21)
Education	260	2.34	615	2.33	355	2.32	0.02	0.03
		(0.61)		(0.63)		(0.64)	(0.05)	(0.05)
Life expectancy loss	260	5.77	615	5.90	355	5.99	-0.12	-0.21
		(2.61)		(2.65)		(2.69)	(0.20)	(0.22)
Prior belief about air quality	260	5.04	615	4.99	355	4.95	0.06	0.10
		(2.30)		(2.49)		(2.61)	(0.18)	(0.20)
Confidence in prior belief	260	4.13	615	4.16	355	4.17	-0.02	-0.04
		(0.73)		(0.75)		(0.76)	(0.05)	(0.06)
Worried about air pollution	260	5.68	615	5.69	355	5.69	-0.01	-0.02
		(1.47)		(1.47)		(1.47)	(0.11)	(0.12)
Prefer to not receive info	260	0.03	615	0.05	355	0.06	-0.02	-0.03*
		(0.17)		(0.22)		(0.24)	(0.02)	(0.02)
Time on life expectancy loss page	260	23.94	615	20.98	355	18.80	2.97	5.14***
		(31.45)		(24.14)		(16.62)	(1.96)	(1.96)
Recall	260	0.84	615	0.80	355	0.77	0.04	0.06*
		(0.37)		(0.40)		(0.42)	(0.03)	(0.03)
Perceived control (index)	260	0.27	615	0.21	355	0.16	0.07	0.11**
		(0.57)		(0.56)		(0.55)	(0.04)	(0.05)
Perceived control (1 item)	260	0.20	615	0.21	355	0.22	-0.02	-0.03
		(0.93)		(0.95)		(0.96)	(0.07)	(0.08)
Coin counting	260	5.98	615	5.53	355	5.20	0.45**	0.78***
		(2.21)		(2.45)		(2.56)	(0.18)	(0.20)
Visual memory	260	0.88	615	0.87	355	0.86	0.01	0.02*
		(0.13)		(0.14)		(0.16)	(0.01)	(0.01)
Joint orthogonality F-stat							1.21	3.08
							(0.24)	(0.00)

Notes: The table presents summary statistics of participant characteristics and balance tests between the samples of participants that took part in the main and follow-up experiments, only in the treatment group. Selected In refers to participants that took part in both the main and follow-up experiments. Selected Out refers to participants that took part only in the main experiment. All characteristics have been collected in the main experiment. Parentheses underneath mean values are standard deviations of the respective observable characteristic. The two right-most columns report the difference in means between the sample that selected in the follow-up and the and sample in the main experiment or the sample that selected out of the follow-up, with estimated standard error in parentheses. Significant t-test estimates are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table D-6 – Sample characteristics and balance tests for the USA control group in the main *versus* follow-up experiments.

	Selected In		Main		Selected Out		In - Main	In - Out
	N	Mean	N	Mean	N	Mean		
Age	260	41.35	672	39.22	412	37.87	2.13**	3.48***
		(12.29)		(11.62)		(10.98)	(0.86)	(0.91)
Female	260	0.53	672	0.51	412	0.50	0.02	0.03
		(0.50)		(0.50)		(0.50)	(0.04)	(0.04)
Household size	260	2.96	669	3.21	409	3.37	-0.25	-0.41**
		(2.38)		(2.36)		(2.34)	(0.17)	(0.19)
Urban	260	0.78	672	0.74	412	0.72	0.04	0.06*
		(0.42)		(0.44)		(0.45)	(0.03)	(0.03)
Income group	260	5.09	672	5.22	412	5.31	-0.13	-0.22
		(2.42)		(2.37)		(2.34)	(0.17)	(0.19)
Education	260	1.96	672	1.97	412	1.98	-0.01	-0.02
		(0.63)		(0.65)		(0.67)	(0.05)	(0.05)
Life expectancy loss	260	0.47	672	0.48	412	0.49	-0.02	-0.03
		(0.28)		(0.28)		(0.28)	(0.02)	(0.02)
Prior belief about air quality	260	5.02	672	4.94	412	4.89	0.08	0.13
		(1.93)		(2.06)		(2.14)	(0.15)	(0.16)
Confidence in prior belief	260	3.44	672	3.48	412	3.51	-0.04	-0.06
		(0.82)		(0.85)		(0.88)	(0.06)	(0.07)
Worried about air pollution	260	4.20	672	4.47	412	4.64	-0.27**	-0.44***
		(1.76)		(1.69)		(1.63)	(0.12)	(0.13)
Prefer to not receive info	260	0.15	672	0.13	412	0.11	0.02	0.03
		(0.35)		(0.33)		(0.32)	(0.02)	(0.03)
Time on life expectancy loss page	260	23.39	672	21.18	412	19.78	2.21	3.61*
		(25.50)		(25.76)		(25.86)	(1.88)	(2.04)
Recall	260	0.88	672	0.83	412	0.81	0.04*	0.07**
		(0.33)		(0.37)		(0.40)	(0.03)	(0.03)
Perceived control (index)	256	-0.03	665	0.02	409	0.06	-0.05	-0.08
		(0.71)		(0.67)		(0.64)	(0.05)	(0.05)
Perceived control (1 item)	260	-0.10	671	0.01	411	0.09	-0.11	-0.18**
		(0.95)		(0.99)		(1.00)	(0.07)	(0.08)
Coin counting	260	7.25	672	6.94	412	6.75	0.31*	0.50**
		(2.51)		(2.48)		(2.45)	(0.18)	(0.20)
Visual memory	260	0.91	672	0.91	412	0.90	0.01	0.01
		(0.10)		(0.11)		(0.12)	(0.01)	(0.01)
Joint orthogonality F-stat							1.19	2.78
							(0.26)	(0.00)

Notes: The table presents summary statistics of participant characteristics and balance tests between the samples of participants that took part in the main and follow-up experiments, only in the control group. Selected In refers to participants that took part in both the main and follow-up experiments. Selected Out refers to participants that took part only in the main experiment. All characteristics have been collected in the main experiment. Parentheses underneath mean values are standard deviations of the respective observable characteristic. The two right-most columns report the difference in means between the sample that selected in the follow-up and the sample in the main experiment or the sample that selected out of the follow-up, with estimated standard error in parentheses. Significant t-test estimates are denoted as follows: *** p<0.01, ** p<0.05, and * p<0.1.

Table D-7 – Sample characteristics and balance tests for the USA treatment group in the main *versus* follow-up experiments.

	Selected In		Main		Selected Out		In - Main	In - Out
	N	Mean	N	Mean	N	Mean		
Age	240	40.27	626	38.69	386	37.71	1.57*	2.55**
		(11.92)		(12.39)		(12.59)	(0.93)	(1.01)
Female	240	0.49	626	0.50	386	0.51	-0.01	-0.02
		(0.50)		(0.50)		(0.50)	(0.04)	(0.04)
Household size	239	2.85	625	3.04	386	3.16	-0.19*	-0.31***
		(1.41)		(1.42)		(1.42)	(0.11)	(0.12)
Urban	240	0.78	626	0.75	386	0.73	0.03	0.05
		(0.42)		(0.44)		(0.45)	(0.03)	(0.04)
Income group	240	5.32	626	5.05	386	4.89	0.27	0.43**
		(2.28)		(2.31)		(2.32)	(0.17)	(0.19)
Education	240	1.94	626	1.99	386	2.01	-0.04	-0.07
		(0.63)		(0.66)		(0.68)	(0.05)	(0.05)
Life expectancy loss	240	0.45	626	0.48	386	0.50	-0.03*	-0.05**
		(0.24)		(0.27)		(0.29)	(0.02)	(0.02)
Prior belief about air quality	240	5.14	626	4.99	386	4.89	0.15	0.25
		(2.02)		(2.17)		(2.26)	(0.16)	(0.18)
Confidence in prior belief	240	3.40	626	3.51	386	3.58	-0.11	-0.18**
		(0.94)		(0.92)		(0.90)	(0.07)	(0.08)
Worried about air pollution	240	4.27	626	4.46	386	4.59	-0.19	-0.31**
		(1.69)		(1.72)		(1.73)	(0.13)	(0.14)
Prefer to not receive info	240	0.13	626	0.13	386	0.13	0.00	0.00
		(0.34)		(0.34)		(0.34)	(0.03)	(0.03)
Time on life expectancy loss page	240	20.13	626	19.55	386	19.19	0.58	0.94
		(21.31)		(25.44)		(27.72)	(1.85)	(2.09)
Recall	240	0.88	626	0.85	386	0.83	0.03	0.05
		(0.33)		(0.36)		(0.38)	(0.03)	(0.03)
Perceived control (index)	238	0.54	622	0.47	384	0.43	0.07	0.11**
		(0.63)		(0.62)		(0.61)	(0.05)	(0.05)
Perceived control (1 item)	240	0.54	625	0.53	385	0.53	0.01	0.02
		(0.89)		(0.89)		(0.90)	(0.07)	(0.07)
Coin counting	240	7.34	626	6.98	386	6.76	0.36**	0.58***
		(2.35)		(2.37)		(2.36)	(0.18)	(0.19)
Visual memory	240	0.92	626	0.91	386	0.91	0.01	0.01
		(0.10)		(0.10)		(0.11)	(0.01)	(0.01)
Joint orthogonality F-stat							1.17	2.58
							(0.28)	(0.00)

Notes: The table presents summary statistics of participant characteristics and balance tests between the samples of participants that took part in the main and follow-up experiments, only in the treatment group. Selected In refers to participants that took part in both the main and follow-up experiments. Selected Out refers to participants that took part only in the main experiment. All characteristics have been collected in the main experiment. Parentheses underneath mean values are standard deviations of the respective observable characteristic. The two right-most columns report the difference in means between the sample that selected in the follow-up and the and sample in the main experiment or the sample that selected out of the follow-up, with estimated standard error in parentheses. Significant t-test estimates are denoted as follows: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.