*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


# Who Opts In?

## Composition Effects and Disappointment from Participation Payments

Sandro Ambuehl, Axel Ockenfels, and Colin Stewart*

October 24, 2022

**Abstract**

Participation payments are used in many transactions about which people know little, but can learn more: incentives for medical trial participation, signing bonuses for job applicants, or price rebates on consumer durables. Who opts into the transaction when given such incentives? We theoretically and experimentally identify a composition effect whereby incentives disproportionately increase participation

*Ambuehl: University of Zurich, Department of Economics, sandro.ambuehl@econ.uzh.ch. Ockenfels: University of Cologne, Department of Economics, ockenfels@uni-koeln.de. Stewart: University of Toronto, Department of Economics, colinbstewart@gmail.com. This paper previously circulated under the titles "For They Known Not What They Do: Selection through Incentives when Information is Costly," and "Attention and Selection Effects." We are grateful to Roland Bénabou, Yoram Halevy, Matthew Osborne, Collin Raymond, Jakub Steiner, Roberto Weber, Ronald Wolthoff, and participants at various seminars and conferences for helpful comments and suggestions. This research has been approved by the University of Toronto's REB in protocol 34310. Rami Abou-Seido, Viola S. Ackfeld, Max R.P. Grossmann, En Hua Hu, Ruizhi Zhu, and Jiaqi Zou provided excellent research assistance. Ockenfels gratefully acknowledges support by the German Science Foundation through the DFG Research Unit "Design & Behavior" (FOR 1371) and through Germany's Excellence Strategy (EXC 2126/1 390838866). Ambuehl gratefully acknowledges support through a University of Toronto Connaught New Researcher Award and the Wynne and Bertil Plumptre Fellowship at the University of Toronto Scarborough. This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 741409); the results reflect the authors' view; the ERC is not responsible for any use that may be made of the information it contains. This research was supported by the Social Sciences and Humanities Research Council of Canada.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


among those for whom learning is harder. Moreover, these individuals use less information to decide whether to participate, which makes disappointment more likely. The learning-based composition effect is stronger in settings in which information acquisition is more difficult. *Keywords: Rational inattention, incentives, composition effect, selection, screening, evaluability.*

*JEL codes: C91, D01, D83, D91*

## 1 Introduction

Payments and discounts incentivize participation in many transactions about which people know little, but can learn more by investing time and mental effort: a purchaser of a product may investigate its quality; a job candidate may seek information about whether the firm is a good match for them; a potential participant in a clinical trial may contemplate the risk of an undesired outcome; and a consumer offered a teaser-rate on a credit card may investigate whether the costs of using the card are likely to exceed the initial discount. The size of the participation payment affects how much decision makers invest in information acquisition and what type of information they seek. As some individuals learn more easily than others, they will react differently to monetary incentives. In this paper, we address three questions: Who opts in when given stronger incentives to participate in a transaction, those who find it easier to learn or harder? How does strengthening the incentive change the quality of participation decisions? And how does the strength of such effects vary with the intrinsic difficulty of learning?

Participation decisions depend on several interacting elements, making the effect of monetary incentives on the composition of participants far from obvious. As incentives change, each individual may adjust their information gathering efforts so as to seek not only a different amount of information but also a different kind. The extent of these changes are likely to vary according to how easily the individual acquires and processes information, due both to idiosyncratic factors and the inherent difficulty of the problem.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


Despite the potentially complicated interaction of these elements, we identify general answers to our questions. First, we show that incentives to participate produce a composition effect: they disproportionately increase take-up by individuals for whom learning is hard and thus change the composition of the group of participants. Stronger incentives also change any given individual's information acquisition about the transaction. Both effects increase the likelihood of disappointment (by which we mean a worse-than-expected outcome). Moreover, we find suggestive evidence that the composition effect is stronger for transactions that are more difficult to understand, in the sense that acquiring information about them is more costly. We obtain these findings in an incentivized experiment motivated by novel theoretical predictions derived from the standard rational inattention framework (see Matějka and McKay, 2015).

The mechanisms we identify apply to any transaction in which an individual makes or accepts a payment in exchange for an outcome with uncertain yet learnable consequences. They are of particular relevance if the provider of the incentive cares about the type of agents who participate or about the likelihood of disappointment. For example, consider the decision to participate in a clinical trial. Individuals for whom learning is generally harder, and who are thus disproportionately selected by higher incentives, might respond differently to instructions or differ in other relevant unobservable characteristics. In addition, subjects who experience disappointment may be more inclined to pull out of the trial early, with negative consequences for the study. In the context of teaser rates on consumer financial products with shrouded fees, individuals for whom learning is harder might make systematically different decisions about other products the supplier offers. In the context of finance, if costly learning is necessary to determine whether participation in a risky asset market is in a specific investor's interest, then a decrease in the safe return will, *ceteris paribus*, lead to a disproportionate inflow of less-informed traders into that market, and hence, to a potential decrease in that market's efficiency. In the labor market, an employer offering a higher signing bonus may disproportionately attract

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


less-informed decision makers who are more likely to be disappointed and seek alternative opportunities, thus leading to higher employee turnover. Finally, consider a monopolist selling a good for which each consumer must exert effort to assess whether it is a good match with their preferences. Our results imply that the lower the price, the less informed the consumers, and hence, the more likely they are to be disappointed by their purchase. The monopolist may therefore want to choose a higher price to avoid negative word-of-mouth reports or critical online reviews.

Our model and experiment both concern the following setting. An agent receives a known, fixed payment if and only if she chooses to participate in a transaction. *Ex ante*, the agent lacks information about the consequences of participating; whether participation is optimal depends on an unknown state of the world. She decides how much and what kind of information to obtain—at a cost—before committing to a decision.

Our main composition result—that stronger incentives shift the composition of participants toward individuals for whom learning is more costly—formalizes the idea that individuals with higher information costs arrive at less firm views regarding whether participating is the right action for them, and are thus more susceptible to influences such as participation payments. As the incentive amount increases, each individual adjusts the information she acquires: less certainty is required in order to participate, and more certainty in order to abstain. This adjustment increases the likelihood of participation for each individual regardless of her own cost of information; we show that the effect on behavior is larger for individuals with a higher cost. Consequently, stronger incentives increase the likelihood of disappointment through two compounding effects: the direct effect on each individual's participation choice, and the composition effect that less informed individuals opt in relatively more. Section 2 explains this mechanism, as well our additional results, in detail.

Our theoretical predictions demand empirical investigation for two reasons. First, they rely

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


on sophisticated information choice behavior. In fact, our composition effect does not generally occur if individuals have exogenous information of varying quality. Given people's limited sophistication in other settings (for instance when strategic considerations are involved, see Camerer, 2011), it is far from obvious that the predicted comparative statics will describe actual behavior. Second, empirical evidence on choice with endogenous information acquisition is scarce and does not address composition effects caused by participation payments (Pinkovskiy, 2009; Cheremukhin et al., 2015; Bartoš et al., 2016; Ambuehl, 2022; Dean and Neligh, 2019).

Our data originate from a laboratory experiment. For our purposes, the main virtues of this method are the clean identification and possibility to isolate mechanisms it affords. It also allows us to observe the counterfactual decisions that subjects would make based on perfect information. We can therefore benchmark the quality of partially informed choice and directly measure the incidence of disappointment.

In the main experimental task, subjects each receive a payment of €2, €6, or €10 if they choose to participate in a gamble in which they lose either €0 or €12, with equal prior probability. After learning the payment amount, but before deciding whether to participate in the transaction, subjects can exert effort to learn about whether they will gain or lose money from taking the gamble. Subjects are shown a list of 60 solved addition problems, such as *23 + 45 = 68*. For gambles with a net gain, 35 of the addition problems are solved correctly and 25 are solved incorrectly; for gambles with a net loss, the number of correct and incorrect solutions are reversed. There is no time limit, enabling subjects to determine whether they will gain or lose with whatever degree of accuracy they desire. As in our model, subjects have much freedom in choosing their information; for example, they can demand a higher level of accuracy in order to participate than they require to abstain. Importantly, better information costs more time and effort—and more so for some subjects than for others.

A crucial feature of our experimental design is that we capture information costs in multiple

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


ways, allowing us to explore the robustness of our theoretical predictions. First, relying on Vernon Smith's induced preferences paradigm (Smith, 1976), we induce differences in information costs within subjects by varying the total number of addition problems in the list (keeping the proportion of correct and incorrect calculations approximately constant). Our corresponding within-subjects analysis ensures that factors such as risk preferences that vary on the individual level cannot play a role. Second, since one might worry that induced variation in costs operates differently from heterogeneity in costs across individuals, we measure each individual's reservation price for processing a given amount of information in the experimental task we employ. With these measures, we can directly observe the composition of individuals who opt into the transaction in an across-subjects analysis. Third, we test whether the predicted comparative statics also apply for measures that are frequently available in real-world settings—such as cognitive test scores and educational background—that arguably serve as proxies for individual learning costs.

Empirical behavior confirms our theoretical predictions according to all of our measures. An increase in the participation payment from €2 to €10 increases participation by just under 15 percentage points if the list that informs the subject about the state contains 25 calculations, but by over 45 percentage points if the list contains 100 calculations. We also find that this increase in the payment raises our reservation price measure of information costs by 4.1 percentile points amongst subjects who opt into the transaction, and to a decrease in average cognitive task performance by 3.2 percentile points (averaged across task difficulty levels). Moreover, a subject with the lowest level of cognitive task performance is 7.8 percentage points more likely to be disappointed by the outcome of their decision to participate in the transaction than a subject with the highest level of cognitive task performance, as well as 8.8 percentage points more likely to choose non-participation when participation would have been better. Finally, composition effects on our reservation price measure of information costs are stronger when the list

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


of addition problems is longer, indicating that differences across people become magnified for transactions whose consequences are generally more difficult to comprehend.

Our empirical results are not an artifact of a correlation between our measures of information cost and other sources of individual heterogeneity, such as risk preferences or non-Bayesian updating. To demonstrate this, a control treatment eliminates endogenous information choice but is otherwise identical to our main task. If our results were simply an artifact of a correlation with other factors, composition effects should survive. Instead, we find that eliminating endogenous information acquisition entirely eliminates the composition effects we document.

There are alternative mechanisms that can generate composition effects related to information (detailed in Appendix B.3), but we are not aware of any that yield the pattern of comparative statics effects that we document. For instance, in a population with heterogeneous priors and a transaction that does not allow for information acquisition, raising the payment for participation would lead to a selection of subjects with increasingly pessimistic priors. However, unlike our model, this alternative predicts no selection based on persistent personality characteristics such as cognitive ability.[1] Another alternative mechanism consists of people drawing conclusions from the payment amount *per se*, for instance, by making the transaction appear suspicious (Kamenica, 2008; Cryder et al., 2010). Depending on how a propensity for such inferences correlates with information acquisition costs, it could exacerbate or attenuate the mechanism we document. Because our subjects are informed about the probability with which a good or bad gamble is drawn, our experiment precludes both of these mechanisms by design.

Our paper contributes to three main strands of literature. First, our work documents a fundamental comparative statics result, applicable to many economic transactions, that arises from en-

[1]Moreover, selection in this alternative model relies on the absence of information acquisition. Appendix B.1 examines an extension of our model with heterogeneous priors, and shows that the effect of information acquisition tends to dominate the effect of heterogeneity in the priors.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


dogenous information acquisition. The mechanism is related to that of Ambuehl (2022), which studies how participation payments affect optimal information acquisition. More generally, we add to an emerging literature that explores the informational foundations of individual-level economic choice (Gabaix, 2019), as well as to an experimental literature studying complexity in economic choice (e.g., Abeler and Jäger, 2015; Oprea, 2020). Like our work, Evaluability Theory (Hsee and Zhang, 2010) considers how responsiveness varies according to the difficulty of evaluating an alternative. One can view the payoffs in our model as combining an incentive payment that is easy to evaluate with a state-dependent payment that is not. According to Evaluability Theory, making the low-evaluability attribute more difficult to evaluate leads the decision-maker to place greater weight on the high-evaluability attribute, and therefore to choose the gamble more often. In contrast, we find that increasing the learning cost leads to greater responsiveness to *changes* in the incentive payment, but does not generally increase participation.[2]

Second, by exploring how the effects of participation payments vary with personality characteristics, we contribute to the literature on personality psychology and economics (Almlund et al., 2011), specifically, traits related to motivation and cognitive ability (Borghans et al., 2008; Dohmen et al., 2010; Segal, 2012).

Third, we contribute to the burgeoning literature on the moral constraints on markets (Kahneman et al., 1986; Roth, 2007; Ambuehl et al., 2015; Ambuehl, 2022; Elias et al., 2019). Around the world, the principles of informed consent are fundamental to regulations concerning human research participation, as well as to transactions such as human egg donation, organ donation, and gestational surrogacy (DHEW 1978, The Belmont Report; Faden, Beauchamp, 1986). According to these principles, the decision to participate in a transaction is ethically sound if it is made not only voluntarily, but also in light of all relevant information, properly

[2]Our experiment describes net payments; it does not display the incentive payment separately.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


comprehended.[3] Our results show that payments for participation can be in conflict with participants' understanding about the consequences of participation. They further show that the severity of this conflict grows with respect to both the amount of the payment and the difficulty of acquiring and processing information about the consequences of the transaction.[4]

The remainder of this paper proceeds as follows. Section 2 derives the theoretical predictions. Section 3 introduces the experiment design, and Section 4 presents the empirical findings. Finally, Section 5 suggests policy implications and discusses the scope and generalizability of our findings.

## 2 Theoretical Predictions

We organize our empirical investigation around predictions from a standard model of costly information acquisition, which we employ for its tractability (Matějka and McKay, 2015). We discuss robustness to functional form assumptions, extensions, and alternative models at the end of this section.

**Setting** An agent decides whether or not to participate in a transaction in exchange for a payment $m$. The agent is uncertain about the (utility) consequences of participation, which depend

[3]An obvious issue in the definition of informed consent lies in what constitutes proper comprehension. The literature remains intentionally imprecise, claiming that "[a]ny exact placement of this line risks the criticism that it is 'arbitrary,' ... and controversy over any attempt at precise pinpointing is a certainty" (Faden and Beauchamp, 1986). The literature does maintain, however, that "there must sometimes be an extrasubjective component to the knowledge base necessary for substantial understanding" (*ibid*). Generally, proper comprehension is understood to encompass both objective consequences and subjective well-being, rendering the mere provision of information about typical consequences insufficient.

[4]Our discussions with economists have indicated that many do not subscribe to the principles of informed consent. Because of the strong support for these principles outside economics (Kanbur, 2004; Satz, 2010; Ambuehl and Ockenfels, 2017), an understanding of how incentives affect informed consent is nonetheless instrumental to advancing the policy debate.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


on an unknown state of the world $s \in \{G, B\}$. The state is good ($s = G$) with prior probability $\mu$, and bad ($s = B$) with the remaining probability $1 - \mu$. If the agent participates and the state is $s$, she obtains utility $\pi_s$. If she does not participate, she obtains utility 0. We assume $\pi_G + m > 0 > \pi_B + m$, making the agent's choice problem nontrivial.

Before the agent decides whether or not to participate, she can acquire information about the state. As is typical in the rational inattention literature, we allow the agent to choose *any* information structure to learn about the state, with different structures incurring different costs.[5] For example, structures that provide more precise information have higher costs. These costs can be psychological, physical, or some combination thereof. Modeling information acquisition in this way captures the idea that there are many possible learning strategies, varying not only in their precision but also in exactly how information depends on the state. The agent could, for example, choose to look for information that, if found, would strongly indicate that the state is good, but if not found would leave her quite uncertain; or she could similarly try to ascertain if the state is bad (or both). Thus the agent can choose both the amount and the type of information to acquire.

In the model, there is a fixed set of possible signal realizations (containing at least two elements) and the agent chooses the distribution of signals in each state of the world. As in much of the rational inattention literature, we assume that cost of information is proportional to the expected reduction in the Shannon entropy of the agent's belief about the state from observing the signal. This assumption makes the model analytically tractable and allows us to

[5]That the agent can acquire perfect information does not mean that the model only applies to cases in which the consequences of the transaction can be known for sure. Instead, the states should be interpreted as capturing all there is to know about the consequences: any uncertainty that cannot be reduced by further information acquisition can be incorporated into the states of the world. In this interpretation, $\pi_G$ and $\pi_B$ represent expected utilities from participation conditional on the best available information.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


draw on the characterization of the solution in Matějka and McKay (2015). We have verified numerically that our results also hold for a number of other cost functions; see Appendix B.2 for details.

A strategy for the agent—which combines the information choice with the choice of an action for each signal realization—amounts to choosing the probability of participation in each state (Matějka and McKay, 2015). Under this interpretation, the cost of information depends on the difference in entropy between the prior belief $\mu$ and the posterior belief conditional on the agent's action; this is the cost associated with the least expensive information structure for implementing this strategy. Letting $p_s$ denote the probability of participation in each state $s \in \{B, G\}$, the agent's posterior belief that the state is good is $\gamma_{\text{part}} := \mu p_G / \big(\mu p_G + (1-\mu) p_B\big)$ when she participates and $\gamma_{\text{abst}} := \mu(1-p_G)/\big(\mu(1-p_G)+(1-\mu)(1-p_B)\big)$ when she does not. The information cost associated with the strategy $(p_G, p_B)$ is therefore proportional to

$$c(p_G, p_B) := h(\mu) - p h(\gamma_{\text{part}}) - (1-p) h(\gamma_{\text{abst}}),$$

where $p := \mu p_G + (1-\mu) p_B$ is the *ex ante* probability of participation and $h(\gamma) := -\gamma \log \gamma - (1-\gamma)\log(1-\gamma)$ is the entropy associated with belief $\gamma$.

The agent chooses $(p_G, p_B)$ to maximize her expected utility

$$U(p_G, p_B; m) = \mu p_G(\pi_G + m) + (1-\mu) p_B(\pi_B + m) - \lambda c(p_G, p_B), \tag{1}$$

where $\lambda > 0$ is an information cost parameter that may capture both individual heterogeneity and variation in the difficulty of learning across various decision problems. Let $\big(p_G(m,\lambda), p_B(m,\lambda)\big)$ denote the solution to this problem and let

$$p(m, \lambda) = \mu p_G(m, \lambda) + (1-\mu) p_B(m, \lambda)$$

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


be the corresponding *ex ante* participation probability. We refer to $p(\cdot, \lambda)$ as type $\lambda$'s *participation curve* as it indicates the expected fraction of individuals of this type who participate as a function of the "price" $m$.

Our model, like other rational inattention models, does not explicitly specify the source of the information cost. Costs could be incurred for acquiring, processing, or interpreting information, or some combination thereof; the exact source of this friction is irrelevant for our behavioral predictions. The cost parameter $\lambda$ captures the difficulty of learning both due to idiosyncratic factors and to the transparency of the context in which the choice is made. Similarly, uncertainty about the state of the world has several possible interpretations. In particular, it may capture risk that is idiosyncratic to the agent, including uncertainty about her own preferences.

The assumption that the agent can choose *any* information structure merits discussion. One natural interpretation is that the agent acquires information over time according to a process by which she continuously updates her belief. The choice of $p_G$ and $p_B$ then corresponds to choosing threshold beliefs at which to stop learning and choose an action; thus, for example, a high threshold belief for participation corresponds to a small value of $p_B$. Morris and Strack (2019) identify a behavioral equivalence between optimal sequential learning and optimal choice in a rational inattention problem.

**Analysis** Before we state our formal results, it is instructive to examine an example of the participation curves for different information cost parameters. Figure 1 shows two such curves, for $\lambda = 0.1$ and $\lambda = 0.3$, with parameters $\mu = \frac{1}{2}$, $\pi_G = 0$, and $\pi_B = -1$. The participation probability of the high-cost type becomes positive only once the payment $m$ crosses a lower threshold, which is higher than the corresponding threshold for the low-cost type. As long as the participation probabilities are strictly between 0 and 1, however, observe that the high-cost type's probability responds more strongly to changes in the payment than that of the low-cost type. We also plot the proportion of high-cost types among those who choose to participate

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


under the assumption that each type forms half of the total population. Observe that the proportion of high-cost types steadily increases with the payment amount until the high-cost type participates with probability 1.

The following proposition shows that these observations hold generally.

**Proposition 1.**

*(i) Suppose $\lambda$ is (absolutely) continuously distributed with support on some interval $[\underline{\lambda}, \overline{\lambda}]$ with $0 \leq p(m, \lambda) < 1$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$ and $p(m, \lambda) > 0$ for some $\lambda \in [\underline{\lambda}, \overline{\lambda}]$. Then, for any $m' \leq m$, the distribution of $\lambda$ conditional on participating at $m$ first-order stochastically dominates that at $m'$.*

*(ii) Suppose $\lambda$ and $m$ are such that $0 < p(m, \lambda) < 1$. Then, $\frac{\partial}{\partial \lambda}\left[\frac{\partial p(m,\lambda)}{\partial m}\right] > 0$.*

Proposition 1 captures, in two different ways, the idea that increases in the payment $m$ disproportionately affect those with higher information costs.

Part (i) directly relates to applications, showing that the composition of the pool of participants shifts toward types with higher costs as the payment increases. Part (ii) illuminates the underlying mechanism. It shows that while increasing the payment increases the likelihood of participation for any given type, this effect is stronger for higher cost types. This slope result requires that the agent has an interior participation probability. The composition result is more general: it applies as long as $m$ is not so high that some type participates without acquiring any information, allowing for some types to abstain with certainty.

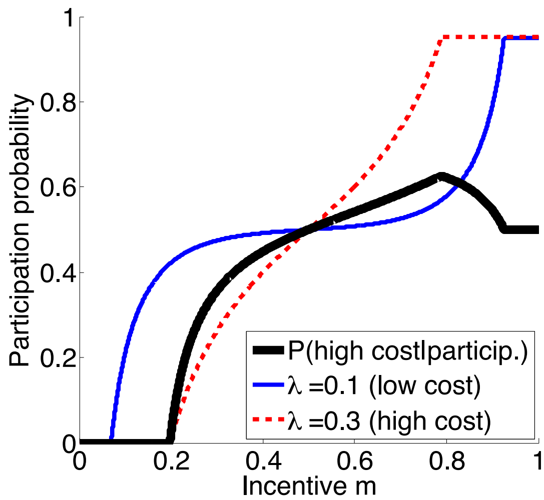
While the two parts of Proposition 1 are related, neither implies the other. Varying the cost parameter not only causes the slope effect identified in part (ii), but also causes a level effect that may countervail the slope effect in terms of the composition of the pool of participants.[6]

To gain some intuition for the result, consider the effect of marginal changes in the payment

[6]The following example clarifies this point. Consider two payment amounts, $m_0$ and $m_1$. Suppose that there are two types of agents, $h$ and $\ell$, that are equally frequent in the population.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Figure 1:** Composition effects and participation curves predicted by the model.




***Notes:*** The simulation uses $\pi_G = 0$, $\pi_B = -1$, and $\mu = 0.5$. It assumes two types with $\lambda = 0.1$ and $\lambda = 0.3$ that are equally frequent in the population.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


$m$ on types that differ in the value of their information cost parameters. Each type optimally chooses a binary signal splitting her prior into two posteriors; she participates at the higher posterior and abstains at the lower one. The probability of participating is therefore equal to the probability of obtaining the higher posterior. By the Law of Iterated Expectations, the expected posterior is equal to the prior, and hence the probability of participating is decreasing in the distance between the higher posterior and the prior, and increasing in the distance between the lower posterior and the prior. As $m$ increases, the gain from participation in the good state increases and the loss in the bad state decreases. Hence, the agent needs to be less convinced that the state is good in order to participate and more convinced that the state is bad in order to abstain. Thus both of the optimal posteriors decrease (see Proposition 3(ii)). Mechanically, the probability of participating therefore increases. For a type that has a low cost of information, the higher posterior almost always occurs when the state is good, as does the lower one when the state is bad. The decrease in posteriors as $m$ increases therefore has only a small effect on her probability of participating. For types with higher costs, the realized posteriors are not as closely tied to the state. Consequently, the decrease in posteriors as $m$ increases has a larger effect on behavior.

The magnitude of the effects identified in Proposition 1 depend on the difficulty of the information acquisition problem. To capture this dependence, we consider the impact of scaling the information cost up by some factor, $a$. Thus as $a$ increases, learning becomes more costly in a uniform way across types. The following result shows that a marginal increase in this scaling factor increases the magnitude of the slope effect. One can interpret this as saying that the slope effect is larger in more opaque contexts (where acquiring information is more difficult for all

Let the participation probability of type $i$ at payment $m_j$ be $p_{ij}$. The condition that high-cost individuals display a larger response is $p_{h1} - p_{h0} > p_{\ell 1} - p_{\ell 0}$. The condition that switching from $m_0$ to $m_1$ increases the proportion of $h$-types among those who participate is $p_{h1}/(p_{h1} + p_{\ell 1}) > p_{h0}/(p_{h0} + p_{\ell 0})$, or, equivalently, $p_{h1}/p_{h0} > p_{\ell 1}/p_{\ell 0}$.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


types).

**Proposition 2.** *Suppose $\lambda$ and $m$ are such that $0 < p(m, \lambda) < 1$. Then, $\frac{\partial}{\partial a}\Big|_{a=1} \left[\frac{\partial}{\partial m}\frac{\partial}{\partial \lambda}\, p(m, a\lambda)\right] >$ 0.*

A restatement of this result illuminates the intuition: individual differences lead to less pronounced variation in responses to payments for transactions for which information costs are lower. If the information costs approach zero, so do all agents' probabilities of making a suboptimal choice. Accordingly, no agent's behavior can respond much to changes in the payment in either state of the world, regardless of her individual-specific information cost parameter. Therefore, the slopes of the participation curves converge across the different types of agents.[7]

The next proposition shows that higher cost types make less-informed decisions, and are thus more likely to experience disappointment. It also shows the direct effect of incentives on disappointment among those individuals who opt in. Let $\gamma_{\text{part}}(\lambda, m)$ and $\gamma_{\text{abst}}(\lambda, m)$ denote, for type $\lambda$ at payment $m$, the posterior beliefs that the state is good when she chooses to participate and to abstain, respectively. Higher cost types make less informed decisions: both posterior beliefs become closer to the prior belief as the cost parameter increases. Since $\gamma_{\text{part}}(\lambda, m)$ is the probability that participating is the correct decision (conditional on type $\lambda$ participating), a lower value of $\gamma_{\text{part}}(\lambda, m)$ corresponds to a higher likelihood of disappointment.

**Proposition 3.** *Suppose $\lambda$ and $m$ are such that $0 < p(m, \lambda) < 1$. Then,*

*(i)* $\frac{\partial}{\partial \lambda}\gamma_{\text{part}}(\lambda, m) < 0$ *and* $\frac{\partial}{\partial \lambda}\gamma_{\text{abst}}(\lambda, m) > 0$*,*

*(ii)* $\frac{\partial}{\partial m}\gamma_{\text{part}}(\lambda, m) < 0$ *and* $\frac{\partial}{\partial m}\gamma_{\text{abst}}(\lambda, m) < 0$*.*

The assumption that costs are proportional to the reduction in entropy is not necessary for this result. Its proof is based on the concavification approach to rational inattention developed in

[7]While agent's choice probabilities also converge as information costs approach infinity, that case violates the assumption in Proposition 2 that choice probabilities are interior.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


Caplin and Dean (2013) and immediately extends to the much larger class of posterior separable cost functions described therein.

The intuition for part (i) is straightforward. Whenever information is more expensive to acquire and process, it is optimal, *ceteris paribus*, to acquire and process less of it. The intuition for part (ii) derives from Ambuehl (2022). If the incentive to participate is low, an individual has little to gain from participation, but possibly much to lose. Hence, she requires high confidence that participation is the right course of action before opting in. As the incentive increases, the costs of mistaken participation shrink so that she requires less confidence before she is willing to opt in.[8]

**Robustness.** Our results are robust to various extensions. First, our results continue to apply in the case of heterogeneous prior beliefs as long as all types have an interior participation probability (Appendix B.1). Second, while we present our model assuming risk neutrality, a careful inspection of the proofs shows that they generalize to the case of risk-nonneutrality, including gain/loss utility with a fixed reference point. Third, within the class of rational inattention models, simulations show that our results also apply for several cost functions other than Shannon entropy (Appendix B.2). Fourth, there are interpretations of our setting other than that of a known participation payment and uncertain utility consequences of participation. Indeed, the main driver of our model is not the assumption that there is one activity with a safe payoff and another with an uncertain payoff. Instead, the relevant feature is that a higher payment raises the payoff of one activity versus that of another in every state of the world. This holds regardless of the riskiness of each option.

[8]Increasing the value of the participation payment in our model is equivalent to reducing the value of the safe outside option. Ke and Villas-Boas (2019) study sequential allocation of attention among multiple alternatives with a known outside option. They obtain comparative statics results that, when specialized to the case of a single uncertain alternative, are analogous to those of Proposition 3.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


At the same time, our results cannot be easily reproduced in alternative models that are ostensibly simpler (Appendix B.3). For instance, if the quality of agents' information is heterogeneous but they cannot tailor their signals to the choice problem, increasing the participation payment does not always lead to disproportionate selection of those with less informative signals.

## 3 Experiment design

Our theory makes strong and testable predictions concerning the composition and disappointment effects of participation payments, which we put to a laboratory test. Because it is the comparative statics of incentives and information costs that are of interest for applications, we focus on those rather than on the primitives of the model.[9]

**Task** Subjects decide whether to take a gamble in which they receive $\pi_G + m$ if the state is good, or $\pi_B + m$ if the state is bad. The prior probabilities of the states are 50/50. Before deciding whether to take the gamble, but after learning the values of $\pi_G + m$ and $\pi_B + m$, subjects obtain information about the state of the world in a way that is perfectly revealing but costly to interpret. Specifically, they see a list of calculations as in panel A of Figure 2. The list comprises $N$ two-digit addition problems with proposed solutions. If the state is good, $k$ are solved correctly and $N - k$ are solved incorrectly. If the state is bad, the numbers of correct and incorrect solutions are reversed. Subjects are aware of this setting, and can examine each such list for as long as they desire.

We choose this task for three reasons. First, it provides subjects considerable flexibility in gathering information and choosing when to stop and make a decision. This is crucial, as the theoretical setting rests on the assumption that subjects can tailor their information acquisition to the specifics of the choice problem.[10] Second, our task allows us to experimentally vary the cost

[9]Moreover, our theoretical predictions appear to be robust to some changes in primitives, as discussed in Section 2.

[10]In particular, subjects can bias their information acquisition. To implement a bias towards

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


of information acquisition. We do so by simultaneously varying the number of calculations in a list and adjusting the ratio of correct to incorrect ones. By increasing the list length and making the ratio closer to $1/2$, we ensure that checking any given calculation reveals less information about the state, thereby making information acquisition more costly. Third, it is plausible that individuals differ both in their ability and their willingness to extract information from a list of calculations. We measure this idiosyncratic variation by eliciting subjects' reservation price for checking a given number of calculations. We also elicit information about subjects' choices and performance in school, and by having them complete a cognitive test.

**Treatments** We set $\pi_G = 0$, $\pi_B = -12$, and vary the payment $m \in \{2, 6, 10\}$ for the *low*, *medium* and *high-incentive* treatments, respectively. (All amounts are denominated in euros.) Hence, in these treatments subjects decide whether to accept a win 2 / lose 10, a win 6 / lose 6, and a win 10 / lose 2 gamble, respectively, and they see the gambles presented this way.[11] Note that for $m \leq 6$, any risk-averse subject who bases her participation decision on the prior alone would reject the gamble.[12]

Our three *Endogenous Information* treatments vary the level of difficulty for information acquisition. The *low-cost* treatment has 25 addition problems, of which 15 are correct (incorrect) in the good (bad) state; the *medium-cost* treatment has 60 addition problems, of which 35 are correct (incorrect) in the good (bad) state; and the *high-cost* treatment has 100 addition

participation, a subject can, for instance, accept the gamble soon after the first signs that the state is good, but continue searching intensely after the first signs that the state is bad, similar to a researcher scrutinizing criticisms of her work but readily accepting praise.

[11] An alternative framing would present the decision as receiving an initial payment followed by a potential loss. Ambuehl (2022) performs experiments using the latter frame. The results do not differ markedly from those in pilot experiments using the former frame.

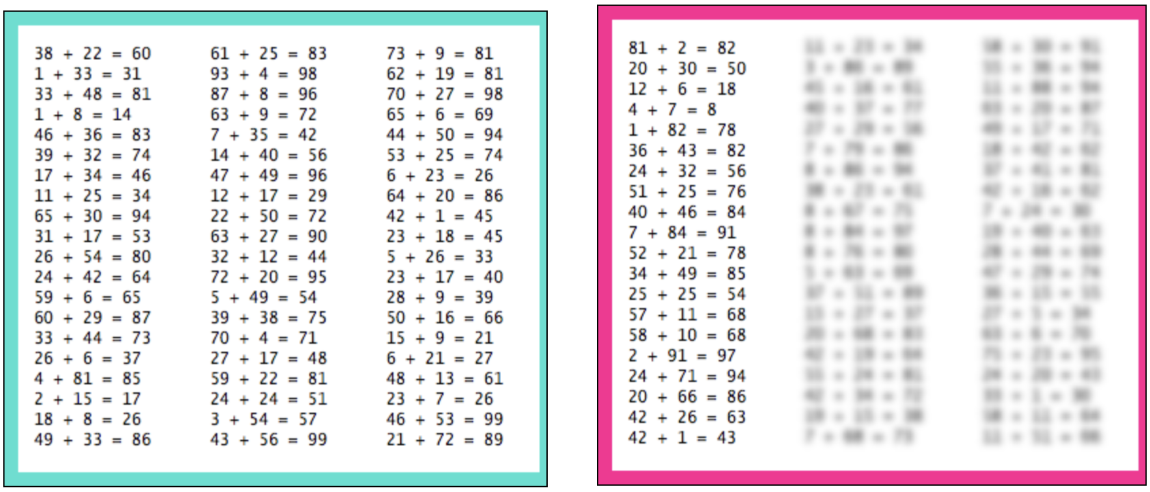
[12] Following List et al. (2011), we select the two relatively extreme incentive amounts €2 and €10 to maximize statistical power. We add the amount €6 to test for our predicted treatment effects without changing the prior-optimal action.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Figure 2:** Presentation of information about the state.

A. Main condition

B. Exogenous information condition




***Notes:*** In the Exogenous Information condition, subjects are explicitly told the number of correct and incorrect calculations in the visible part of the picture.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


problems, of which 55 are correct (incorrect) in the good (bad) state.[13]

The *Exogenous Information* treatment is an important control that effectively eliminates the possibility of endogenous information acquisition. It lets us check whether our results are driven by information choice (in which case they will vanish in the Exogenous Information treatment) or by other factors (in which case they will also occur in the Exogenous Information treatment). Specifically, subjects observe a picture similar to that in the medium cost treatment, but only a portion of it is visible, with the rest heavily blurred, as shown in panel B of Figure 2. Because the state is still determined by the entire list of calculations, the blurring places an upper limit on the amount of information a subject can acquire. A line of text above the picture explicitly informs the subject how many correct and incorrect calculations the visible part contains. For any subject who pays attention to these numbers, this places a lower bound on the information they acquire. We fix the difference between the number of correct and incorrect calculations in the visible portion of the picture such that among the 20 expressions that are not blurred out, either 11 or 13 are correct (incorrect) in the good (bad) state.

Each subject participates in 18 rounds of decision making that cover all treatments in individually randomized order, as summarized in Panel A of Table 1. The state of the world is redrawn in each round. We anticipated that in the low-incentive treatments, subjects would frequently refuse to take the gamble. Hence, to obtain adequate statistical power, we oversample these decisions.[14] Subjects know that their earnings are determined by at most one randomly selected round.

[13] In sessions 2, 3, and 4, the low-cost treatment used 30 calculations per picture, with 60% correct (incorrect) in the good (bad) state, and session 1 had 20, also with 60% correct (incorrect) in the good (bad) state.

[14] We anticipated that subjects would reject the gamble at the €2 payment more often than they would accept it at the €10 payment, due to risk aversion. Therefore, we did not oversample the latter condition.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


After each of the 18 rounds, we elicit the subject's posterior belief that they have seen a good-state picture, incentivized by the mechanism proposed in Karni (2009) and Holt and Smith (2009), in which they may either win or lose €3. Subjects know from the start that there is an 80% chance that they will be paid according to one decision in one of these 18 rounds. They also know that in this case, there is an 80% chance that the selected decision will be a betting decision, and a 20% chance that it will be a belief elicitation decision, and never both. We chose to put the lion's share of the probability mass onto incentivizing the betting decision to ensure that it would be the main driver of information acquisition.[15]

**Individual measures** After subjects complete the first part of the experiment, we elicit four individual-level characteristics that we interpret as measures for idiosyncratic variation in information costs, in the order summarized in Panel A of Table 1.

*Reservation price for checking calculations.* As a direct measure of information acquisition costs, we elicit subjects' reservation price for the opportunity to verify $n$ addition problems for correctness in exchange for an additional payment, for each $n \in \{30, 60, 100, 200\}$. Subjects know that if they agree to check $n$ calculations in exchange for money, and this decision is randomly selected for implementation, then they need to check at least 90% of them correctly. Otherwise, they not only lose the money they would have obtained for completing the task correctly, but also forfeit another €10 from their completion payment. For each value of $n$, a subject sees a separate list, and decides, on each line, whether to check the calculations in exchange for €$p$. In each list, $p$ ranges from 0 to 10 in steps of 0.5, and also includes 0.25 and 0.75. Subjects are informed that one of these decisions will be selected for implementation in addition to the chosen decision from the main stage of the experiment.[16]

[15]The belief elicitation decision does not vary across rounds. Hence, while its presence may affect information acquisition, it does not affect the sign of treatment comparisons.

[16]We chose to disburse this payment in addition to other payments to make the experiment simpler to understand for subjects. While this design choice could in principle lead to income

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Table 1:** Experiment overview

**A. Type and number of decisions taken by each subject.**

| Condition | Endogenous Information | | | Exogenous Information |
|---|---|---|---|---|
| Number of additions in picture | 25 | 60 | 100 | 20 visible |
| *Participation payment* | | | | |
| € 2 | 2 | 2 | 2 | 2 |
| € 6 | 1 | 1 | 1 | 2 |
| € 10 | 1 | 1 | 1 | 2 |

**B. Session structure**

1. Main decisions (18 rounds)
2. Reservation price elicitation (4 rounds)
3. Raven's matrix test
4. Risk preference elicitation (9 rounds)
5. Survey of academic and demographic background variables.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


*Cognitive task performance.* Second, we measure performance on the Raven's Advanced Progressive Matrices task (Raven et al., 1962), using series I and the first 24 matrices of series II. This task predicts various life outcomes (see, e.g., Duckworth et al., 2011). It thus represents a persistent trait for which composition effects may be of direct interest in applications. We expect performance on this task to correlate with the cost of information acquisition in our decision tasks, as it is indicative of abilities like concentration and short-term memory. Previous research has shown that cognitive task performance is predictive of different outcomes depending on whether subjects are incentivized for performance (Borghans et al., 2008; Duckworth et al., 2011; Segal, 2012). We explore this dependency through two separate treatments. Corresponding to standard procedures, the *unincentivized IQ* condition does not provide incentives for performance. In the *incentivized IQ* condition, there is a 10% chance that a subjects' payment from the experiment may be determined entirely by their performance in this test. In that case, she is paid €0.30 for each correctly solved matrix.

*Risk preferences.* Third, we elicit subjects' risk preferences. We use lists of decisions to elicit certainty equivalents of various gambles. Each decision is of the form *Win €X with chance p and lose €Y with chance* $1 - p$ versus *win / lose €Z with certainty*. The structure of these decisions is the same as in our main treatments in which subjects also decide between a gamble and a certain payment. The lotteries we present are win 2 / lose 10, win 6 / lose 6, and win 10 / lose 2 with winning probabilities $p \in \{0.5, 0.75, 0.9\}$, resulting in a total of 9 lists. On each list, the certain option varies from *lose €10 with certainty* to *win €10 with certainty* in steps of €1.[17] Subjects' payment is determined by a risk preference elicitation question with a 20% probability (10% probability in case the cognitive test is also incentivized).

*Educational background.* Fourth, we elicit information about subjects' educational background in mathematics and in German literature. We include both subjects to demonstrate how

effects, those would countervail our hypothesis.

[17]Subjects make an active choice on each line of each list. We enforce single switching.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


the effects we document relate to the costs of acquiring the information specific to our tasks—namely, we expect that subjects' background in mathematics will have predictive power for information costs, whereas background in German literature will not. For both subjects, we elicit high school grades, as well as whether an honors class was taken in that subject. Additionally, we elicit whether subjects are enrolled in a STEM college major.[18]

**Implementation and payment** Subjects learn that the experiment has three parts—two "decision making parts," labelled "A" (main tasks and reservation price elicitation) and "B" (risk preference elicitation), as well as a part involving "logical puzzles" (the Raven's matrices) to be completed in between. The experimenter reads the initial instructions aloud. Subjects read all subsequent instructions on screen, and may keep reviewing them until they pass a comprehension check that allows them to proceed to the decision making part.[19] States of the world are drawn randomly and are i.i.d., and lists with correct and incorrect calculations are generated randomly on an individual level. To clearly differentiate between the different rounds, each list of calculations has a differently colored border, with colors randomly assigned on an individual level. If the border is red, for instance, subjects are asked to decide whether they want to "bet on the red picture." To minimize confusion, we present subjects with a choice of taking a win $(\pi_G + m)$ / lose $|\pi_B + m|$ gamble, as opposed to offering them $m$ to take a win $\pi_G$ / lose $|\pi_B|$ gamble. We do not provide materials to take notes. Hence, subjects have to keep track of the false and correct calculations they had checked in their head. Appendix C.5 contains the experimental instructions and screenshots of the interface.

[18]We elicit subjects' college major, which we then classify as STEM / non-STEM. We also elicit subjects' high school GPA. Because high school GPA is an average over many classes, including many that are presumably irrelevant to our task, we have no *ex ante* hypothesis about how it moderates the effect of incentives on participation decisions.

[19]Subjects must answer all of 12 true/false questions correctly, and in case of a mistake, are not told which of their 12 answers is wrong. Hence, they are highly unlikely to pass the check by merely guessing.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


One randomly selected decision from the entire experiment, as well as the payments from the elicitation of the reservation price to solve additional calculations, determine a subjects' payment. All gains are added to a budget of €15 and all losses are deducted.

## 4 Experiment results

We ran the experiment with 584 student subjects across 19 sessions in May and July 2017 at the University of Cologne's Laboratory for Economic Research.[20] Subjects could leave as soon as they were done, irrespective of other subjects' progress. The median time subjects spent inspecting each picture is 74 seconds. On average, subjects spent about one and a half hours on the experiment and received a total payment of €18.70. The average subject is 24.5 years old and 53.3% are female. Appendix C.2 displays further summary statistics; Appendix C.3 analyzes order effects, decision reversals, and shows data about the implementation of the reservation price elicitation task.

In Section 4.1 we study the empirical evidence for our predictions about the composition effect of incentives. In Section 4.2 we examine the effect of information costs and incentives on posteriors and disappointment. These sections focus on experimentally induced variation in information costs and reservation prices for checking additional calculations as measures of individual-specific information costs, since these directly map to our theoretical predictions. Section 4.3 repeats the analyses using educational background and cognitive task performance as alternative measures of individual-specific information costs.

### 4.1 Who Opts In?

We first show our results graphically and then proceed with econometric analysis. Panel A of Figure 3 displays the effects of incentives on the composition of subjects who opt into

[20]We obtained 300 subjects in May, and then decided to replicate the findings by roughly doubling the sample size. Appendix C.1 lists the details of each session. We conducted two pilot studies on Amazon Mechanical Turk with largely similar results before running the laboratory studies. These are available from the authors by request.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


the gamble using induced variation in information costs. We assign a cardinal index of 1, 2, and 3 to represent the low-, medium-, and high-cost treatments, respectively. We measure the composition effect using the average value of this index among those subjects who accept the gamble. As the bold line shows, the average information cost index amongst those who opt in is 1.7 for the €2 incentive and a substantially higher 2.05 for the €10 incentive. This increase confirms our main prediction, Proposition 1 (i).

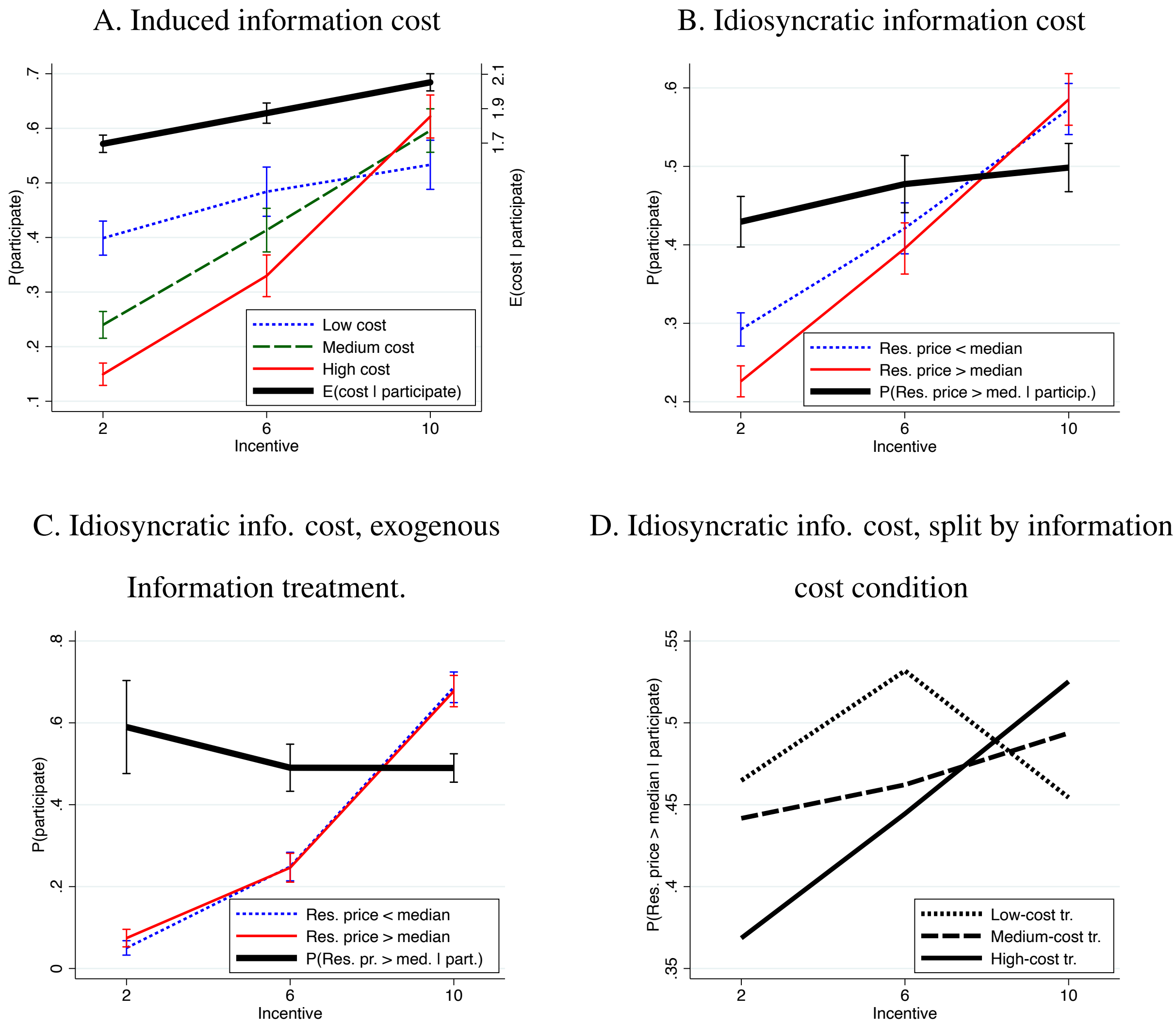
The graph also displays the participation curves for each cost level, which form the basis of the composition effect. Specifically, in the low-cost condition, the fraction of subjects who opt into the gamble increases from 40% to just under 55% as the incentive increases from €2 to €10. In the high-cost condition, by contrast, participation increases from 15% to over 60%. Hence, consistent with Proposition 1 (ii), an €8 increase in the payment has a 15 percentage point effect on participation in the low-cost treatment, and a 45 percentage point effect in the high-cost treatment (as well as an intermediate effect in the medium-cost treatment).[21]

Next, we test for incentive-induced composition effects using idiosyncratic variation in information cost, measured by reservation prices for checking a given number of calculations. We rank subjects according to their reservation price for each of the four elicitations and average these ranks within subjects. We then group subjects into two halves—those who more strongly dislike checking addition problems (above median reservation prices) and those who are less averse to it (below median reservation prices). The bold line in Panel B of Figure 3 plots the fraction of individuals with a high reservation price amongst those who accept the gamble (averaged across task difficulty levels). It shows that higher participation payments increase the fraction of high-cost types amongst those who elect to participate, consistent with Proposition

[21]In the boundary case of completely costless information, the participation curve should be constant at 50%. In the case of prohibitively expensive information and risk-averse subjects, participation should be zero for the €2 and €6 payments. For the €10 payment, participation should be equal to the fraction of subjects willing to take a 50/50 win 10 / lose 2 gamble.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Figure 3:** Composition effects and participation curves.




***Notes:*** Thin lines display participation probabilities. Bold lines show the composition of the set of subjects who take the bet. Panel A uses induced information cost. To show the composition of the set of subjects who bet, the low, medium, and high information cost conditions are encoded as 1, 2, 3, respectively. All other panels measure information cost by the reservation price for checking a fixed number of calculations. Panel B averages across Endogenous Information conditions. Panel C uses the Exogenous Information condition. Panel D shows effects on group composition separately for each Endogenous Information condition. Whiskers indicate 95% confidence intervals. Panel D omits whiskers for better visibility; see text for hypothesis tests.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


1 (i). We also see that the half of subjects with higher reservation prices responds more strongly to an increase in the participation payment, consistent with Proposition 1 (ii).[22]

In principle, the effects in Panel B could arise not because of information costs, but because of some other individual characteristic that is correlated with information costs such as risk attitudes or loss aversion. The Exogenous Information treatment addresses that possibility. If the effects in Panel B are caused by our proposed information cost channel, then they will vanish in this treatment. By contrast, if they are due to extraneous factors, we will continue to observe them, because the Exogenous Information treatment allows all factors other than endogenous information acquisition to affect choice. As Panel C shows, if anything, composition effects in the Exogenous Information treatment have the opposite sign from those we would expect based on our information cost mechanism. We conclude that endogenous information acquisition is the driving factor underlying our results in Panel B.

In Panel D, we check whether composition effects based on idiosyncratic variation in information costs become stronger as we raise the difficulty of information acquisition for all individuals, as suggested by Proposition 2. For this purpose, we show the composition effects based on reservation prices separately for each task difficulty level. Each line displays the fraction of subjects with an above-median reservation price amongst those who opt into the gamble. The composition effect in the high-cost condition is considerable: the proportion of high-reservation price participants rises from 37% to 53% as the payment increases from €2 to €10. Importantly, this increase is significantly more pronounced than in the medium-cost condition, where the fraction of high-cost participants increases from 44% to 49% over the same increase in payment. Unexpectedly, the composition effect in the low-incentive treatment is non-monotonic due to a high fraction of high-reservation price participants at the €6 incentive. Yet, we see nearly indistinguishable fractions of high-reservation price participants for the €2

[22] Appendix C.4 shows that these effects arise separately for each state $G$ and $B$.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


and the €10 incentive amounts.

To document these effects econometrically, we perform two types of estimations. We test for composition effects using OLS models of the form

$$Y_{it} = \beta' X_{it} b_{it} + \gamma' X_{it}(1 - b_{it}) + \delta' Z_{it} + \epsilon_{it}. \tag{2}$$

Here, $Y_{it}$ is a measure of the information costs subject $i$ faced in decision $t$, $X_{it}$ consists of a constant term and a predictor variable such as the incentive amount, $b_{it}$ is an indicator that equals 1 if subject $i$ accepts the bet in round $t$, and $Z_{it}$ is a vector of session and round fixed effects. Both $Y_{it}$ and $X_{it}$ vary across specifications. Our interest centers on the coefficient vector $\beta$ which indicates how the predictor $X_{it}$ changes the distribution of the information cost measure $Y_{it}$ amongst subjects who decide to take the gamble.

We examine slope effects in linear probability models that use the decision to bet as a dependent variable. Specifically, we consider models of the form

$$b_{it} = \beta' X_{it} + \delta' Z_{it} + \epsilon_{it}, \tag{3}$$

where $X_{it}$ includes the incentive amount $m_{it}$ and several interactions between $m_{it}$ and moderators of participation (such as information costs). $Z_{it}$ is a vector of session and round fixed effects.

In all regressions, we express the participation payment as a fraction of the loss amount $\pi_B$; doing so makes our coefficients independent of the particular value of $\pi_B$ used in our experiment. Thus, the €2, €6, and €10 participation payments are encoded as $2/12 = 0.167$, $6/12 = 0.5$, and $10/12 = 0.83$, respectively. Whenever a regression involves more than a single observation per subject, we cluster standard errors on the subject level. To ensure that our results do not depend on random realizations of the state during the experiment, we weight our regressions such that the weighted fraction of decisions for which the state is good *exactly* equals the prior

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Table 2:** Composition and slope effects.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Type | **Composition effect** | | | | **Slope effect** | | | |
| VARIABLES | Info. cost index | Res. price %ile | Res. price %ile | Res. price %ile | Gamble accepted | Gamble accepted | Gamble accepted | Gamble accepted |
| Proposition tested | 1(i) | 1(i) | - | 2[a)] | 1(ii) | 1(ii) | - | 2 |
| Sample | | | | | | | | |
| Endogenous Information | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ |
| Exogenous Information | | | ✓ | | | | ✓ | |
| *Panel A. Main regressions* | | | | | | | | |
| Predictor | Gamble accepted × | | | | 1 × | | | |
| × Incentive | **0.545***** | **0.061***** | **0.001** | -0.056 | 0.003 | 0.431*** | 0.956*** | 0.072 |
| | (0.044) | (0.017) | (0.041) | (0.035) | (0.056) | (0.034) | (0.039) | (0.081) |
| × Cost index | | | | -0.040*** | -0.167*** | | | |
| | | | | (0.012) | (0.012) | | | |
| × Incentive × cost index | | | | **0.065***** | **0.239***** | | | |
| | | | | (0.018) | (0.025) | | | |
| Predictor | Gamble rejected × | | | | (Res. Price > median) × | | | |
| × Incentive | -0.238*** | -0.025* | -0.014 | 0.028 | | **0.096**** | **-0.04** | -0.134 |
| | (0.034) | (0.013) | (0.018) | (0.029) | | (0.047) | (0.055) | (0.112) |
| × Cost index | | | | 0.007 | | | | -0.053** |
| | | | | (0.005) | | | | (0.024) |
| × Incentive × cost index | | | | -0.026** | | | | **0.115**** |
| | | | | (0.013) | | | | (0.050) |
| × 1 | 0.558*** | 0.064*** | 0.002 | -0.020 | | -0.073*** | 0.025 | 0.033 |
| | (0.039) | (0.016) | (0.036) | (0.034) | | (0.025) | (0.025) | (0.057) |
| Observations | 7,008 | 7,008 | 3,504 | 7,008 | 7,008 | 7,008 | 3,504 | 7,008 |
| Subjects | 584 | 584 | 584 | 584 | 584 | 584 | 584 | 584 |
| *Panel B. Pairs of incentive amounts (coefficient on relevant interaction)* | | | | | | | | |
| Low and middle | 0.544*** | 0.100** | -0.051 | 0.031 | 0.126** | 0.096 | -0.105 | 0.036 |
| | (0.090) | (0.035) | (0.111) | (0.041) | (0.046) | (0.085) | (0.089) | (0.064) |
| Middle and high | 0.540*** | 0.024 | 0.019 | 0.104** | 0.374*** | 0.104 | 0.009 | 0.603 |
| | (0.085) | (0.031) | (0.046) | (0.036) | (0.061) | (0.105) | (0.117) | (0.085) |
| *Panel C. Pairs of difficulty levels (coefficient on relevant interaction)* | | | | | | | | |
| Low and middle | 0.225*** | 0.034* | 0.000 | 0.051 | 0.318*** | 0.042 | 0.000 | 0.382 |
| | (0.030) | (0.019) | (0.000) | (0.034) | (0.050) | (0.056) | (0.000) | (0.068) |
| Middle and high | 0.191*** | 0.097*** | 0.000 | 0.082** | 0.162*** | 0.155 | 0.000 | 0.209 |
| | (0.034) | (0.023) | (0.000) | (0.038) | (0.044) | (0.055) | (0.000) | (0.058) |

[a)] Proposition 2 is stated in terms of participation curve slopes only, as tested in column 8. Absent countervailing level effects, Proposition 2 implies the comparative statics tested in column 4.

***Notes:*** Bold print indicates the parameter relevant for testing the proposition listed in the table header in each column. *Information Cost Index* is encoded as 1, 2, and 3 for the low, medium, and high cost treatments, respectively. Panels B and C display the estimates of the corresponding parameter on selected subsamples. *Gamble accepted* is an indicator variable (values 1 and 0) for whether the subject took the bet. *Incentive* equals 0.167, 0.5, and 0.833 for the incentive amounts € 2, 6, 10, respectively, representing a normalization of the incentive amounts over the entire relevant range from 0 to 12. Each column presents the estimates from a separate regression, controls for session and round fixed effects, and is weighted as detailed in footnote 23. All standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


of 50% in each relevant cell.[23]

We list our estimation results in Table 2, which parallels Figure 3. Estimates in columns 1 to 4 correspond to the composition effects displayed in panels A to D of the figure, respectively, while those in columns 5 to 8 correspond to the slope effects. Starting with induced information costs, Column 1 shows the estimates of model (2) using the information cost index (which takes values 1, 2, and 3, for the low, middle, and high cost conditions, respectively) as the dependent variable. The coefficient on the interaction *Gamble accepted* × *Incentive* shows that raising the incentive over the entire relevant range increases the average cost index of subjects who opt into the gamble by 0.545 units ($p < 0.01$).[24]

To check that our results are not simply due to the fact that a sufficiently large increase in the payment $m$ changes the prior-optimal action, we also estimate the model using only observations for which the incentive is either €2 or €6; for any risk-averse individual, the prior-optimal action is to refuse the gamble for both of these incentive amounts. For completeness, we also estimate the model using only observations in which the incentive is either €6 or €12. As Panel B shows, the estimated coefficients are similar to each other and are highly statistically significant ($p < 0.01$).[25] We also check that our results do not depend on our choice of information-cost index. To this end, we estimate the model using only the low and middle cost conditions, as well as using only the middle and high cost conditions. The estimated magnitudes are expected to be smaller because the maximal possible difference between information cost indices in these

[23]Specifically, for a given cost level $c$ and incentive $m$, let $r_{cm}$ denote the fraction of observations for which the realization of the state is good. We attach weight $1/r_{cm}$ to each observation with cost $c$ and incentive $m$ if the state is good, and weight $1/(1 - r_{cm})$ if the state is bad. For each definition of cost $c$ (experimentally induced, or reservation price), we calculate the corresponding set of weights.

[24]Appendix Figure 3 shows that these effects arise separately for each state.

[25]Taking an alternative approach, Appendix C.4 shows that our results are robust to controlling for risk preferences.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


regressions is only half of that across all difficulty levels. Panel C shows that the estimates of the relevant interaction effects are positive, as predicted ($p < 0.01$). As the estimates of model (3) in Column 5 show, these results are substantially due to a slope effect. Specifically, an increase in the cost index by one unit increases the slope of the participation curve by 0.239 units ($p < 0.01$). We also find positive estimates if we only include two incentive or task difficulty levels (Panels B and C, $p < 0.05$ in each case).

We now turn to our reservation price measure of information costs. As the coefficient on the interaction term *Gamble accepted* × *Incentive* in column 2 shows, raising the incentive over the entire relevant range raises the reservation price percentile amongst subjects who opt into the gamble by 6.1 percentage points ($p < 0.01$), consistent with Proposition 1 (i). Panel B shows that this effect is in large part due to changes that occur when increasing the incentive from €2 to €6 ($p < 0.05$), and is stronger when considering only the middle and high cost conditions ($p < 0.01$) than when considering only the low and middle cost conditions ($p < 0.1$), foreshadowing the effects predicted in Proposition 2. The coefficient on the interaction term *(Res. price > median)* × *Incentive* in column 6 isolates the slope effect of 0.96 units ($p < 0.05$; Proposition 1 (ii)).

Column 3 considers the Exogenous Information Condition to check that preventing endogenous information acquisition extinguishes its predicted effects. Indeed, composition effects vanish; the estimated coefficient on the interaction *Gamble accepted* × *Incentive* is close to zero. Slope effects also vanish (column 7).[26] Similar results arise in Panels B and C.[27]

[26]In a joint regression, the difference between the estimates of the interaction effects of columns 6 and 7 is statistically significant at the 5% level. The p-value of the test of the hypothesis that the coefficients on the incentive amount in columns 2 and 3 are equal 0.15, which decreases to 0.06 if the session and round fixed effects are excluded.

[27]Appendix Table C.8 complements this analysis by showing that the composition and slope effects of columns 2 and 7, respectively, remain once we control for risk preferences.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


Finally, we consider the effect of the interaction between task difficulty and idiosyncratic information costs. The significantly positive coefficient on the three-way interaction *Gamble accepted* × *Incentive* × *Cost index* in column 4 shows that greater task difficulty increases the strength of our main composition effect. The positive coefficient on the three-way interaction *(Res. price > median)* × *Incentive* × *Cost index* in column 8 shows that the slope effect is a substantial cause ($p < 0.05$ in both cases).

Appendix C.4 shows that these results appear to be driven by FOSD-shifts in the distribution of information costs among subjects who elect to participate in the gamble.

Overall, these results empirically validate the predicted composition effect of incentives and show that it results from endogenous information acquisition.

### 4.2 Posteriors

Our composition effect is relevant for providers of incentives who care about the type of individuals who participate in their transaction. We now examine how incentives change the quality of the participation decision. These effects matter if one is concerned about disappointment, for instance due to costs arising from participants' attempts to back out of their decision.

We begin with the observed frequencies of the good state conditional on the subject accepting or rejecting the gamble; we refer to these as *objective posteriors*.[28] Figure 4 shows how these posteriors depend on information costs and incentives. Panel A focuses on induced information costs. The upper half, labeled 'accept,' plots the fraction of times subjects won the bet if they decided to take it; the lower half, labeled 'reject,' shows the fraction of times subjects would have won the bet when they declined. These frequencies are estimates of the population averages of the posterior probabilities $P(s = G \mid accept)$ and $P(s = G \mid reject)$, respectively. The results are consistent with Proposition 3. First, higher information costs lead to less informed decision making, consistent with part (i) of the proposition. For example, a subject who

[28] This quantity is an estimate of the *revealed posterior* in the literature on state-dependent stochastic choice (see Caplin, 2016, for a review).

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


decided to participate in the gamble wins in around 90% of cases in the low cost condition, but wins in only 60 to 80% of cases (depending on the incentive) in the high cost condition. Second, incentives directly affect posteriors: for each task difficulty level, we find that a higher payment lowers both the chance that a subject who accepted the gamble will win, and the chance that a subject who rejected the gamble would have won, consistent with part (ii) of the proposition. As Panel B shows, the same effects appear for our reservation price measure of information costs (averaged across task difficulty levels).

To test these effects econometrically, we estimate OLS models of the form[29]

$$S_{it} = \beta' X_{it} b_{it} + \gamma' X_{it}(1 - b_{it}) + \delta' Z_{it} + \epsilon_{it}. \tag{4}$$

Here, $S_{it}$ is an indicator that equals 1 if the state for subject $i$ in round $t$ was good, $b_{it}$ indicates whether subject $i$ took the bet in round $t$, $X_{it}$ consists of a constant term and a predictor variable such as the incentive amount, and $Z_{it}$ is a vector of session and round fixed effects.

Table 3 displays the results. Using induced variation in information costs, column 1 shows that an increase in the information cost index by one unit decreases $P(s = G|accept)$ by 9.9 percentage points and increases $P(s = G|reject)$ by 11.6 percentage points. Moreover, an increase of the incentive over the entire relevant range decreases $P(s = G|accept)$ by 14.9 percentage points, and decreases $P(s = G|reject)$ by 29.1 percentage points ($p < 0.01$ for all four estimates). Column 2 uses reservation prices as measures of information cost and pools across task difficulty levels. Again we find that higher information costs are associated with a significantly lower $P(s = G|accept)$ and with a significantly higher $P(s = G|reject)$ ($p < 0.01$ for both estimates).

Are subjects aware of how incentives and information costs affect their choice quality? To answer this question, we study the alignment between mean objective posteriors and mean

[29]This model differs from model (2) only in that it uses a different dependent variable.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Table 3:** Posteriors.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | Indicator for $\{s = G\}$ | | Elicited belief that $\{s = G\}$ | | Elicited belief that $\{s = G\}$ $-$ indicator for $\{s = G\}$ | |
| Bet accepted × | | | | | | |
| Info. cost index | -0.099*** | | -0.067*** | | 0.032*** | |
| | (0.010) | | (0.005) | | (0.009) | |
| Res. price %ile | | -0.087*** | | -0.063*** | | 0.025 |
| | | (0.032) | | (0.023) | | (0.027) |
| Incentive | -0.149*** | -0.198*** | -0.112*** | -0.145*** | 0.037* | 0.053** |
| | (0.024) | (0.025) | (0.014) | (0.014) | (0.022) | (0.022) |
| Bet refused × | | | | | | |
| Info. cost index | 0.116*** | | 0.083*** | | -0.033*** | |
| | (0.008) | | (0.005) | | (0.008) | |
| Res. price %ile | | 0.125*** | | 0.109*** | | -0.016 |
| | | (0.028) | | (0.022) | | (0.025) |
| Incentive | -0.291*** | -0.315*** | -0.246*** | -0.262*** | 0.045* | 0.053** |
| | (0.024) | (0.023) | (0.014) | (0.014) | (0.023) | (0.023) |
| Observations | 7,008 | 7,008 | 7,008 | 7,008 | 7,008 | 7,008 |
| Subjects | 584 | 584 | 584 | 584 | 584 | 584 |

***Notes:*** Each column displays the coefficients of a separate regression that includes session and order fixed effects, and is weighted as detailed in footnote 23. Standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


elicited posterior beliefs. We estimate model (2) using elicited beliefs that the state is good as the dependent variable. Column 3 shows that the effect of induced information costs on subjective posteriors mirrors that on objective posteriors, but with some attenuation. Hence, while subjects appear to realize that they make less informed choices when the task difficulty is higher, they underestimate the extent of this effect. The difference between the estimated coefficients on objective and subjective posteriors is highly statistically significant ($p < 0.01$), as shown in column 5. Subjects also underestimate the extent to which higher incentives lower both $P(s = G|accept)$ and $P(s = G|reject)$ ($p < 0.1$). Subjects more accurately predict the effects of their idiosyncratic information costs on their choice quality. As column 4 shows, subjective posteriors vary with reservation prices just as much as objective posteriors do; the difference is far from statistically significant (column 6).

Overall, these results are consistent with Proposition 3. They also show that while subjective beliefs, on average, are well-calibrated, subjects become overly optimistic about their decision quality in contexts in which information is more costly to process for all individuals.

### 4.3 Educational background and cognitive task performance

We have shown that incentives change the composition of participants in terms of information costs when these are tightly connected to the participation decision. Does the predicted composition effect extend to measures of information cost that are often available in applied settings, such as educational background and cognitive test scores?

To answer this question, we run regressions of the form (2), using each of the background characteristics as a dependent variable and pooling across task difficulty levels. For comparability to other variables, we use percentile ranks for all non-binary variables. When examining the effect of cognitive task performance, we analyze the *unincentivized IQ* treatment separately from the *incentivized IQ* treatment. Based on previous research, we expect different predictive power across these treatments (Borghans et al., 2008; Duckworth et al., 2011; Segal, 2012), but

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


we have no *ex ante* hypothesis about the direction of the difference. In the case of cognitive task performance, we also control for the time taken to complete the Raven's matrix test.[30]

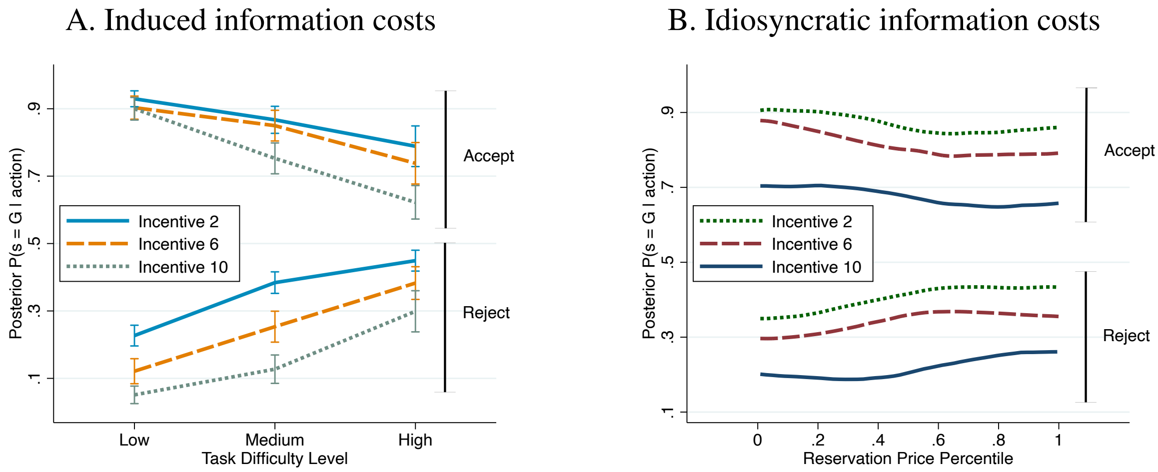
Panel A of Table 4 displays the results, starting with mathematics background. Column 1 shows that an increase in the incentive over the entire relevant range decreases the percentile rank in high-school math grades amongst those who take the bet by 3.5 points ($p < 0.1$). The change in the composition of participants measured by whether a subject has taken an honors course in math is 9.2 percentage points ($p < 0.01$) and measured by enrollment in a STEM major it is 9.1 percentage points ($p < 0.01$). Panel B shows that these characteristics are also associated with the predicted drop in informedness of subjects' decisions, using estimates of model (4). Column 1 shows that if the subject with the highest math grade in our sample decides to opt into the gamble, she is 13.8 percentage points more likely to win than if the subject with the lowest math grade enters the gamble ($p < 0.05$). We see directionally similar and statistically significant effects for enrollment in a math honors class and enrollment in a STEM major, though at lower magnitudes.

As a falsification test, we use subjects' background in German language and literature. As this background is not related to information acquisition in our experiment, we expect no composition effects on that dimension and no predictive power for posteriors. As columns 4 and 5 demonstrate, the estimated parameters are zero or take the opposite sign from what we would expect if background in German were related to information costs, both regarding composition (panel A) and posteriors (panel B).

[30]Some subjects appeared to stop paying attention while completing the Raven's matrix test. These subjects spend approximately the same time on each question block up to some point, after which their response time drops to nearly zero for the remaining question blocks. Including completion time for the test as a regressor controls the noise these subjects would otherwise induce in our regressions. If we run the regressions without controlling for time taken, estimated coefficients remain similar in magnitude but they lose statistical significance.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Figure 4:** Posterior probabilities conditional on the subject's action.




***Notes:*** Both panels show the probability of $s = G$ conditional on accepting (top half) or rejecting (bottom half) the gamble. Panel A: By task difficulty level and incentive condition. Panel B: By reservation price and incentive condition, averaged over task difficulty levels. Moving average, Epanechnikov kernel, bandwidth 0.15.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Table 4:** Composition effects and posteriors by background characteristics.

**A. Composition**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable | High school math | | STEM | High school German | | Raven's score | |
| | grade rank | honors | | grade rank | honors | unincentivized | incentivized |
| Dep. var. mean | 0.500 | 0.387 | 0.550 | 0.500 | 0.419 | 0.500 | 0.500 |
| | 0.013 | 0.021 | 0.021 | 0.013 | 0.021 | 0.017 | 0.019 |
| Incentive × | | | | | | | |
| Bet taken | -0.035* | -0.092*** | -0.091*** | 0.033* | 0.029 | -0.049** | -0.007 |
| | (0.019) | (0.031) | (0.031) | (0.019) | (0.031) | (0.021) | (0.028) |
| Bet refused | 0.025* | 0.056** | 0.030 | -0.007 | -0.019 | 0.034** | -0.003 |
| | (0.013) | (0.022) | (0.022) | (0.013) | (0.022) | (0.017) | (0.019) |
| Bet taken | 0.029 | 0.084*** | 0.101*** | -0.041** | -0.027 | 0.044** | 0.014 |
| | (0.018) | (0.030) | (0.030) | (0.019) | (0.031) | (0.018) | (0.029) |
| Observations | 6,240 | 6,636 | 7,008 | 6,180 | 6,624 | 3,600 | 2,652 |
| Subjects | 520 | 553 | 584 | 515 | 552 | 300 | 221 |

**B. Posteriors**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variable | Indicator for {s = G} | | | | | | |
| Predictor variable | | | | | | | |
| *Name* | HS math grade rank | HS math honors | STEM | HS German grade rank | HS German honors | Ravens score unincentivized | Ravens score incentivized |
| *Effect* | | | | | | | |
| Bet accepted | | | | | | | |
| × Predictor | 0.138*** | 0.035* | 0.064*** | 0.009 | -0.055*** | 0.117** | 0.085 |
| | (0.034) | (0.020) | (0.019) | (0.036) | (0.021) | (0.049) | (0.054) |
| Bet refused | | | | | | | |
| × Predictor | -0.070** | -0.035** | -0.006 | 0.012 | 0.032* | -0.132*** | 0.011 |
| | (0.030) | (0.017) | (0.016) | (0.032) | (0.017) | (0.041) | (0.049) |
| Bet accepted | 0.420*** | 0.488*** | 0.477*** | 0.519*** | 0.552*** | 0.427*** | 0.431*** |
| | (0.030) | (0.019) | (0.021) | (0.029) | (0.018) | (0.040) | (0.040) |
| Observations | 6,240 | 6,636 | 7,008 | 6,180 | 6,624 | 3,600 | 2,652 |
| Subjects | 520 | 553 | 584 | 515 | 552 | 300 | 221 |

***Notes:*** Regressions concerning cognitive task performance control for time taken to complete the test. All regressions include session and order fixed effects. Observation numbers vary across columns because some subjects did not answer the corresponding background questions. Standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


Finally, we turn to cognitive task performance as measured by (non-incentivized) scores on the Raven test.[31] Column 6 in panel A shows that the mean test score percentile amongst subjects who opt into the gamble drops by 4.9 percentage points as the incentive increases over the entire relevant range ($p < 0.05$). The same column in panel B shows that if the highest-scoring subject opts into the gamble, she is 11.7 percentage points more likely to win than if the lowest-scoring subject decides to opt in ($p < 0.05$). Interestingly, these effects vanish if we incentivize performance on the Raven's test (column 7). This finding is consistent with previous literature cited above that argues that unincentivized and incentivized performance on cognitive tests measure different underlying characteristics.

Overall, we conclude that our results obtain not only with highly controlled laboratory measures of information acquisition costs, but also with proxies for individual information costs that are more widely available in applied settings.

## 5 Discussion and Conclusion

Many economic transactions combine a monetary payment for participation in a transaction with consequences that are not entirely certain. This paper shows that higher participation payments select individuals for whom learning is more difficult, and more so in contexts in which information acquisition is more costly. The provider of the incentive may care about the types of subjects who opt in; he may also be concerned about the quality of the participation decision. Higher-cost individuals make less informed decisions and are more likely to experience disappointment from participation, which may have costly repercussions such as the agent trying to back out of the transaction. These findings matter whenever participation payments apply to a transaction with uncertain but learnable consequences. Applications extend to fields as diverse as consumer choice, finance, and labor economics.

One policy application concerns transactions for which participation payments are limited

[31]The Raven's test is usually administered without financial incentives for correct responses.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


by laws and guidelines, such as living tissue donation or clinical trial participation (Roth, 2007; Ambuehl, 2022; Elias et al., 2019). Our results highlight a conflict between participation payments and the principles of informed consent. Yet, banning or limiting these payments is not necessarily the optimal response for policy makers who subscribe to these principles. One alternative consists of stringent informed consent requirements, perhaps coupled with an assessment of participants' comprehension. Commenters in this debate also often voice the concern that participation payments would disproportionately increase participation by the poor. This raises the question of how economic inequality interacts with the composition effects we document in this paper. The answer depends on context. Economic inequality will compound the composition effects we document if two conditions hold. The first condition is that the utility consequences of participation, aside from the participation payment $m$, are the same for rich and poor individuals. This is plausible for transactions whose consequences concern physical wellbeing. The second condition is that poorer individuals tend to have higher information costs. This is plausible to the extent that cognitive ability and education are correlated with socioeconomic status. Importantly, survey evidence suggests that concerns about the failure to comprehend the consequences of a transaction might be a driving force underlying ethical qualms with incentivizing the poor, rather than vice versa: on the topic of human egg donation, respondents in Ambuehl and Ockenfels (2017) are substantially more concerned about incentivizing women who have trouble understanding the risks and consequences of the procedure than about incentivizing poorer women *per se*.

**References**

**Abeler, Johannes and Simon Jäger**, "Complex tax incentives," *American Economic Journal: Economic Policy*, 2015, *7* (3), 1–28.

**Almlund, Mathilde, Angela Lee Duckworth, James J Heckman, and Tim D Kautz**, "Personality psychology and economics," in "Handbook of the Economics of Education," Vol. 4, Elsevier, 2011, pp. 1–181.

**Ambuehl, Sandro**, "Can Incentives Cause Harm? Tests of Undue Inducement," 2022. WP.

_ **and Axel Ockenfels**, "The Ethics of Incentivizing the Uninformed. A Vignette Study," *American Economic Review, P&P*, 2017, *107* (5), 91–95.

_ **, Muriel Niederle, and Alvin E. Roth**, "More Money, More Problems? Can High Pay be Coercive and Repugnant?," *American Economic Review, P&P*, 2015, *105* (5), 357–60.

**Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka**, "Attention discrimination: Theory and field experiments with monitoring information acquisition," *American Economic Review*, 2016, *106* (6), 1437–75.

**Borghans, Lex, Huub Meijers, and Bas Ter Weel**, "The role of noncognitive skills in explaining cognitive test scores," *Economic Inquiry*, 2008, *46* (1), 2–12.

**Camerer, Colin F**, *Behavioral game theory: Experiments in strategic interaction*, Princeton University Press, 2011.

**Caplin, Andrew**, "Measuring and modeling attention," *Annual Review of Economics*, 2016, *8.*

_ **and Mark Dean**, "Rational Inattention, Entropy, and Choice: The Posterior-Based Approach," 2013. Working paper.

**Cheremukhin, Anton, Anna Popova, and Antonella Tutino**, "A theory of discrete choice with information costs," *Journal of Economic Behavior & Organization*, 2015, *113*, 34–50.

**Cryder, Cynthia E., Alex J. London, Kevin G. Volpp, and George Loewenstein**, "Informative inducement: Study payment as a signal of risk," *Soc. Sci. & Medicine*, 2010, *70.*

**Dean, Mark and Nathaniel Neligh**, "Experimental Tests of Rational Inattention," 2019. WP.

**Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde**, "Are risk aversion and impatience related to cognitive ability?," *American Economic Review*, 2010, *100* (3).

**Duckworth, Angela Lee, Patrick D Quinn, Donald R Lynam, Rolf Loeber, and Magda Stouthamer-Loeber**, "Role of test motivation in intelligence testing," *Proceedings of the*

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


*National Academy of Sciences*, 2011, *108* (19), 7716–7720.

**Elias, Julio J, Nicola Lacetera, and Mario Macis**, "Paying for Kidneys? A Randomized Survey and Choice Experiment," *American Economic Review*, 2019, *109* (8).

**Faden, Ruth R and Tom L Beauchamp**, *A History and Theory of Informed Consent*, Oxford University Press, 1986.

**Gabaix, Xavier**, "Behavioral inattention," in "Handbook of Behavioral Economics: Applications and Foundations 1," Vol. 2, Elsevier, 2019, pp. 261–343.

**Holt, Charles A. and Angela M. Smith**, "An Update on Bayesian Updating," *Journal of Economic Behavior & Organization*, 2009, *69*, 125–134.

**Hsee, Christopher K and Jiao Zhang**, "General evaluability theory," *Perspectives on Psychological Science*, 2010, *5* (4), 343–355.

**Kahneman, Daniel, Jack L Knetsch, and Richard Thaler**, "Fairness as a constraint on profit seeking: Entitlements in the market," *American Economic Review*, 1986, *76* (4), 728–741.

**Kamenica, Emir**, "Contextual inference in markets: On the informational content of product lines," *American Economic Review*, 2008, *98* (5), 2127–2149.

**Kanbur, Ravi**, "On obnoxious markets," in Stephen Cullenberg and Prasanta Pattanaik, eds., *Globalization, Culture and the Limits of the Market: Essays in Economics and Philosophy*, Oxford University Press, 2004.

**Karni, Edi**, "A Mechanism for Eliciting Probabilities," *Econometrica*, 2009, *77* (2), 603–606.

**Ke, T Tony and J Miguel Villas-Boas**, "Optimal learning before choice," *Journal of Economic Theory*, 2019, *180*, 383–437.

**List, John A, Sally Sadoff, and Mathis Wagner**, "So you want to run an experiment, now what? Some simple rules of thumb for optimal experimental design," *Experimental Economics*, 2011, *14* (4), 439–457.

*Review of Economics and Statistics* Just Accepted MS.
https://doi.org/10.1162/rest_a_01268


**Matějka, Filip and Alisdair McKay**, "Rational inattention to discrete choices: A new foundation for the multinomial logit model," *American Economic Review*, 2015, *105* (1), 272–98.

**Morris, Stephen and Philipp Strack**, "The Wald Problem and the Relation of Sequential Sampling and Ex-Ante Information Costs," 2019. Working paper.

**Oprea, Ryan**, "What Makes a Rule Complex?," *American Economic Review*, 2020, *110* (12).

**Pinkovskiy, Maxim L**, "Rational inattention and choice under risk: explaining violations of expected utility through a Shannon Entropy formulation of the costs of rationality," *Atlantic Economic Journal*, 2009, *37* (1), 99–112.

**Raven, John C, John C Raven, and John Hugh Court**, *Advanced Progressive Matrices*, HK Lewis London, 1962.

**Roth, Alvin E**, "Repugnance as a Constraint on Markets," *Journal of Economic Perspectives*, 2007, *21* (3), 37–58.

**Satz, Debra**, *Why Some Things Should Not Be For Sale: The Moral Limits of Markets*, Oxford University Press, 2010.

**Segal, Carmit**, "Working When No One Is Watching: Motivation, Test Scores, and Economic Success," *Management Science*, 2012, *58* (8), 1438–1457.

**Smith, Vernon L**, "Experimental economics: Induced value theory," *American Economic Review*, 1976, pp. 274–279.

**US Department of Health, Education, and Welfare (DHEW)**, *The Belmont report: Ethical principles and guidelines for the protection of human subjects of research*, National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, Washington DC, 1978.