Who Opts In?

Selection and Disappointment through Participation Payments

Sandro Ambuehl, Axel Ockenfels, and Colin Stewart*

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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 show theoretically and experimentally that incentives can act as a selection mechanism that disproportionately selects individuals for whom learning is harder. Moreover, these individuals use less information to decide whether to participate, which makes disappointment more likely.

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*Ambuehl: University of Zurich, Department of Economics, Blüemlisalpstrasse 10, 8006 Zürich, sandro.ambuehl@econ.uzh.ch. Ockenfels: University of Cologne, Department of Economics, Universitätsstrasse 22a, 50923 Cologne, Germany, ockenfels@uni-koeln.de. Stewart: University of Toronto, Department of Economics, 150 St. George Street, Toronto, ON M5S 3G7, Canada, colinbstewart@gmail.com. This paper was 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 Research Ethics Board 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.

The learning-based selection effect is stronger in settings in which information acquisition is more difficult. *Keywords: Rational inattention, incentives, selection, screening, evaluability.*

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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? How does the strength of any selection effect vary with the intrinsic difficulty of learning?

Participation decisions depend on several interacting elements, making the effect of monetary incentives on selection 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.

Despite the potentially complicated interaction of these elements, we identify general answers to our questions. First, we show that incentives to participate act as a selection mechanism: they disproportionately increase take-up by individuals for whom learning is hard. Higher incentives lead to less informed participants through this selection mechanism. They 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 selection 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 that is motivated by novel theoretical predictions derived from a standard model of attention allocation (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 attract a disproportionate selection of 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 selection result—that stronger incentives to participate disproportionately attract 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 selection 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 on sophisticated information choice behavior. In fact, our selection result does not generally hold 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 selection through participation payments (Pinkovskiy, 2009; Cheremukhin et al., 2015; Bartoš et al., 2016; Ambuehl, 2021; 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 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 selection of individuals 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 select 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, selection effects on our reservation price measure of information costs are stronger when the list 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, the differential selection should survive. Instead, we find that eliminating endogenous information acquisition entirely eliminates differential selection on learning costs.

There are alternative mechanisms that can generate selection 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.,

[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.

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 endogenous information acquisition. The mechanism is related to that of Ambuehl (2021), 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). Our results also have a flavor similar to work in General Evaluability Theory (Hsee and Zhang, 2010) insofar as both consider how responsiveness varies according to the difficulty of evaluating an alternative. However, they consider evaluability of the variable factor (the participation payment, in our case), whereas we focus on learning about the consequences of the alternative. In addition, evaluability theory does not consider the selection effects that are the main focus of this paper.

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, 2021; 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 comprehended.[2] 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.[3]

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]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.

[3]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.

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 on an unknown state of the world $s \in \{G, B\}$. The state is good ($s = G$) with prior probability μ, and bad ($s = B$) with the remaining probability $1 - \mu$. If the agent participates and the state is s, she obtains utility π_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.[4] 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

[4]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, π_G and π_B represent expected utilities from participation conditional on the best available information.

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 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 μ 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 γ.

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

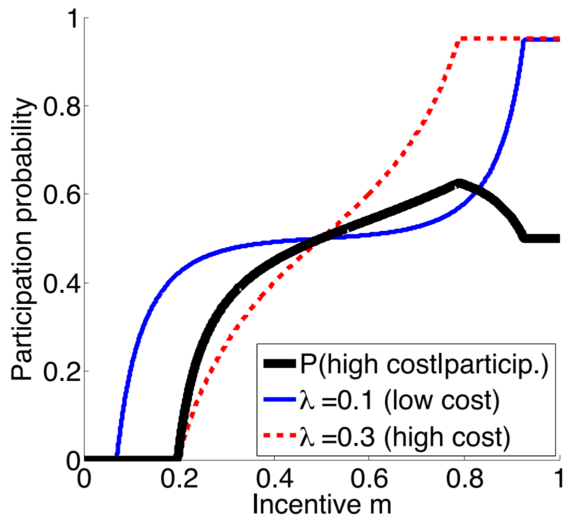
$$p(m, \lambda) = \mu p_G(m, \lambda) + (1-\mu)p_B(m, \lambda)$$

be the corresponding *ex ante* participation probability. We refer to $p(\cdot, \lambda)$ as type λ's *supply 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 λ 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.

Figure 1: Selection effects and supply 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.

Analysis Before we state our formal results, it is instructive to examine an example of the supply 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 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 λ 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 increasing function $f : R \longrightarrow R$, $E\left[f(\lambda) \mid participate\right]$ is increasing in m.*

(ii) *Suppose λ 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. While increasing the payment increases the likelihood of participation for any given type, the slope result in part (ii) of the proposition says that this effect is stronger for higher cost types. The selection result in part (i) relates to applications more directly, showing that the composition of the pool of participants shifts toward types with higher costs as the payment increases (in the sense of first-order stochastic dominance). The selection result applies as long as m is not so high that some type participates without acquiring any information. Unlike the slope result, which requires that the agent has an interior participation probability, the selection result allows 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 (i), but also causes a level effect that may countervail the slope effect in terms of the composition of the pool of participants.[5]

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

[5]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 ℓ, that are equally frequent in the population. 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, $p_{h1}/p_{h0} > p_{\ell 1}/p_{\ell 0}$.

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. 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 types).

Proposition 2. *Suppose λ 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 supply curves converge across the different types of agents.

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 λ 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 λ participating), a lower value of $\gamma_{\text{part}}(\lambda, m)$ corresponds to a higher likelihood of disappointment.

Proposition 3. *Suppose λ 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 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 (2021). 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.[6]

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.

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

[6]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.

but they cannot tailor their signals to the choice problem, increasing the participation payment does not generally lead to disproportionate selection of those with less informative signals.

3 Experiment design

Our theory makes strong and testable predictions concerning the selection 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.[7]

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.[8] Second, our task allows us to experimentally vary the cost of

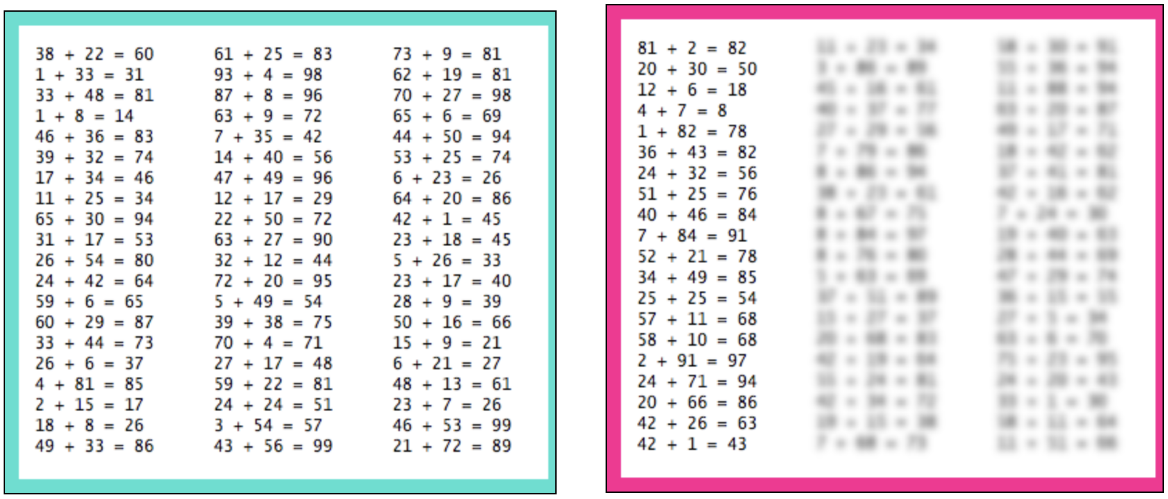
[7]Moreover, our theoretical predictions appear to be robust to some changes in primitives, as discussed in Section 2.

[8]In particular, subjects can bias their information acquisition. To implement a bias towards participation, a subject can, for instance, accept the gamble soon after the first signs that the state is

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.

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

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.

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. Note that for $m \leq 6$, any risk-averse subject who bases her participation decision on the prior alone would reject the gamble.[9]

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 problems, of which 55 are correct (incorrect) in the good (bad) state.[10]

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

[9]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.

[10]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.

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.[11] Subjects know that their earnings are determined by at most one randomly selected round.

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.[12]

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 infor-

[11]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.

[12]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.

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.

mation 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.[13]

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 on which selection 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

[13]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 effects, those would countervail our hypothesis.

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.[14] 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 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.[15]

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

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

[15] 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.

allows them to proceed to the decision making part.[16] 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 π_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.

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.[17] Subjects could leave as soon as they were done, irrespective of other subjects' progress. The median time subjects spent inspecting each

[16]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.

[17]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.

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.

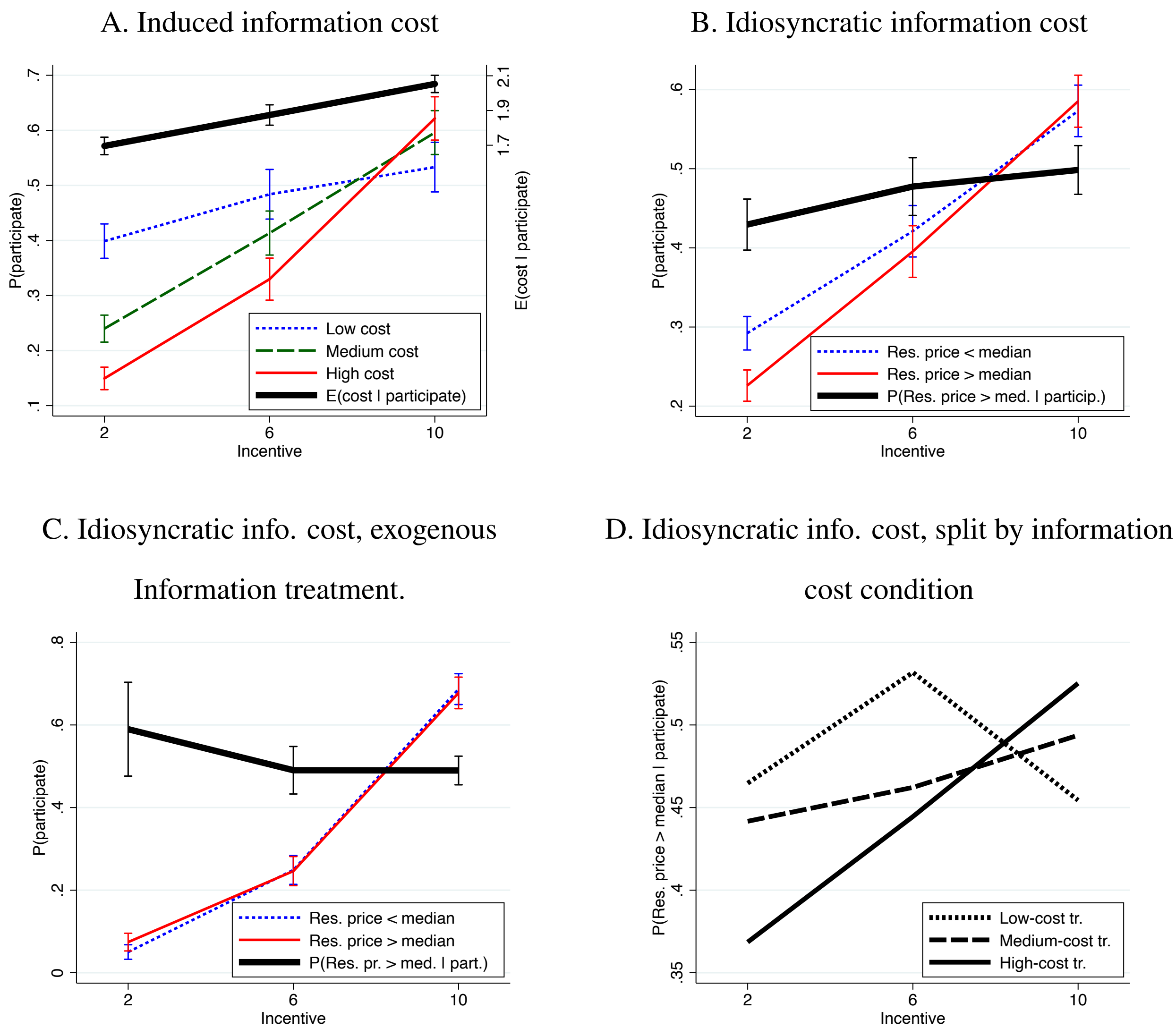
In Section 4.1 we study the empirical evidence for our predictions about the selection effect of incentives. In Section 4.2 we examine the effect of information costs and incentives on posteriors and disappointment. These sections focus on experimentally induced variation in information costs and reservation 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 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 selection 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 supply curves for each cost level, which form the basis of the selection effect. Specifically, in the low-cost condition, the fraction of subjects who opt into the gamble

Figure 3: Selection and supply curves.



Notes: Colored lines display participation probabilities. Black 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 selection separately for each Endogenous Information condition. Whiskers indicate 95% confidence intervals. Panel D omits whiskers for better visibility; see text for hypothesis tests.

increases from 40% to just under 55% as the incentive increases from €2 to €10. In the high-cost condition, by contrast, supply 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 supply 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).[18]

Next, we test for incentive-induced selection 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 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).[19]

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

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

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

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, selection 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 selection 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 selection 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 selection 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, selection 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 and the €10 incentive amounts.

To document these effects econometrically, we perform two types of estimations. We test for selection 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 β 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 supply (such as information costs). Z_{it} is a vector of session and round fixed effects.

In all regressions, we normalize the participation payment by the loss amount π_B to make our coefficients independent of the specific magnitude of that parameter used in our experiment. Hence, 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 of 50% in each relevant cell.[20]

[20]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.

Table 2: Selection and participation effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type	**Selection**				**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(ii)	1(ii)	-	2[a)]	1(i)	1(i)	-	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 supply 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 20. All standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We list our estimation results in Table 2, which parallels Figure 3. Estimates in columns 1 to 4 correspond to the selection 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 ($p < 0.01$).[21]

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 ($p < 0.01$).[22] 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 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

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

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

results are substantially due to a slope effect. Specifically, an increase in the cost index by one unit increases the slope of the supply curve by 0.239 units ($p < 0.01$). We also find positive estimates if we only include two incentive levels or two 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, selection effects vanish; the estimated coefficient on the interaction *Gamble accepted* × *Incentive* is close to zero. Slope effects also vanish (column 7).[23] Similar results arise in Panels B and C.[24]

Finally, we consider the effect of the interaction between task difficulty and idiosyncratic infor-

[23]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.

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

mation 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 selection 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).

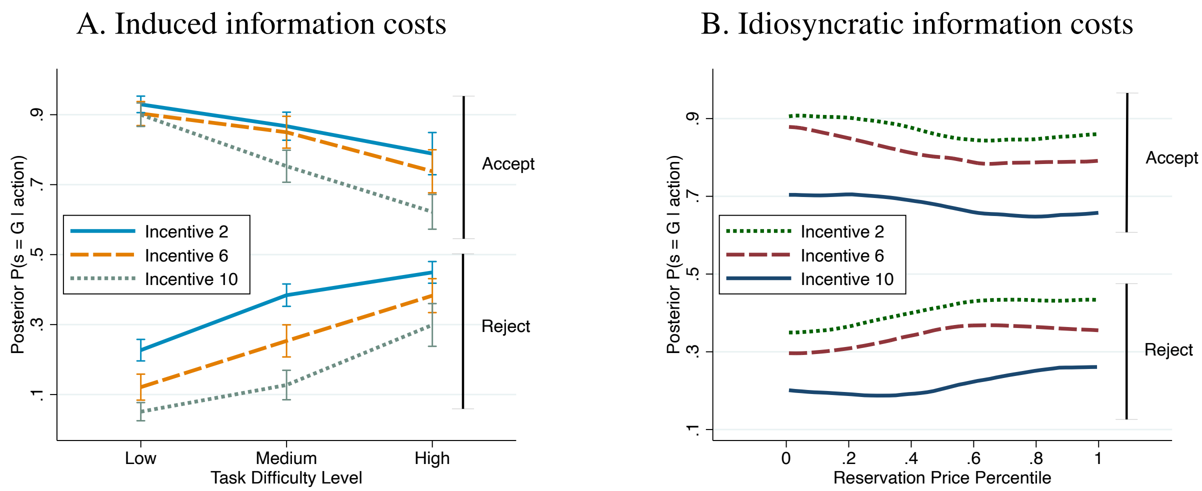
Overall, these results empirically validate the predicted selection effect of incentives and show that it results from endogenous information acquisition.

4.2 Posteriors

Our selection 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 objective posterior probabilities: conditional on accepting or rejecting the gamble, what is the likelihood that the state is good? 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 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 incen-

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.

tive) 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 also 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[25]

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

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.

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

Table 3: Posteriors.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	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 20. Standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 objective posterior probabilities and 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 select subjects by information costs when these are tightly connected to the participation decision. Does the predicted selection 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 selection in the *unincentivized IQ* treatment separately from that in 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 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.[26]

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 selection of participants measured by whether a subject has taken an honors course in math is 9.2

[26] 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.

Table 4: Selection effects and posteriors by background characteristics.

A. Selection

	(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. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 selection 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 selection (panel A) and posteriors (panel B).

Finally, we turn to cognitive task performance as measured by (non-incentivized) scores on the Raven test.[27] 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.

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

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 by laws and guidelines, such as living tissue donation or clinical trial participation (Roth, 2007; Ambuehl, 2021; 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 selection effects we document in this paper. The answer depends on context. Economic inequality will compound the selection 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*.

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ONLINE APPENDIX

Who Opts In?

Sandro Ambuehl, Axel Ockenfels, and Colin Stewart

Table of Contents

A Proofs

A.1 Proof of Proposition 1

We first prove part (ii) and then draw on some of the same calculations in the proof of part (i).

A.1.1 Proof of part (ii)

For simplicity of notation, we omit the arguments from $p_s(m, \lambda)$ and $p(m, \lambda)$. A direct application of Theorem 1 in Matějka and McKay (2015) shows that for each $s \in \{G, B\}$, the state-contingent participation probabilities p_s are given by

$$p_s = \left[1 + \left(\frac{1}{p} - 1\right) \exp\left\{-\frac{1}{\lambda}(\pi_s + m)\right\}\right]^{-1}.$$

Substituting these expressions into the equation $p = \mu p_G + (1-\mu)p_B$ defining p and dividing both sides by p gives

$$1 = \frac{\mu}{p + (1-p)/g} + \frac{1-\mu}{p + (1-p)/b},$$

where $g := \exp\left((\pi_G + m)/\lambda\right)$ and $b := \exp\left((\pi_B + m)/\lambda\right)$. Note that, since $\pi_G + m > 0 > \pi_B + m$, $g > 1 > b$. Rearranging gives

$$-\mu \frac{g-1}{g\frac{p}{1-p} + 1} = (1-\mu)\frac{b-1}{b\frac{p}{1-p} + 1}.$$

Solving for $\frac{p}{1-p}$ then yields

$$\frac{p}{1-p} = -\frac{(1-\mu)(b-1) + \mu(g-1)}{(1-\mu)(b-1)g + \mu b(g-1)},$$

from which we obtain

$$p = -\frac{\mu}{b-1} - \frac{1-\mu}{g-1}. \tag{5}$$

Differentiating with respect to m gives

$$\frac{\partial p}{\partial m} = \frac{1-\mu}{(g-1)^2}\frac{g}{\lambda} + \frac{\mu}{(b-1)^2}\frac{b}{\lambda}.$$

Let A denote the first of the two terms on the right-hand side. We will show that $\frac{\partial A}{\partial \lambda} > 0$; a similar argument applies to the second term, thereby proving the result. We have

$$\frac{1}{1-\mu}\frac{\partial A}{\partial \lambda} = \frac{2g^2 \log g}{\lambda^2(g-1)^3} - \frac{g \log g}{\lambda^2(g-1)^2} - \frac{g}{\lambda^2(g-1)^2},$$

which is positive if and only if

$$(g+1)\log g - g + 1 > 0.$$

The left-hand side of this inequality is equal to 0 when $g = 1$ and its derivative is positive everywhere. Therefore, the inequality holds for all $g > 1$, as needed.

A.1.2 Proof of part (i)

Lemma 1. *Let X be a continuously distributed real-valued random variable and let $f : R \longrightarrow R_+$ and $g : R \longrightarrow R_+$ be such that $\frac{f(x)}{g(x)}$ is increasing in x and $E[f(X)] > 0$ and $E[g(X)] > 0$. Then*

$$\frac{E[Xf(X)]}{E[f(X)]} > \frac{E[Xg(X)]}{E[g(X)]}.$$

Proof. Let γ be the density of X. Let $\hat{f}(x) = f(x)\gamma(x)/E[f(X)]$ and $\hat{g}(x) = g(x)\gamma(x)/E[g(X)]$. Note that $\hat{f}$ and $\hat{g}$ are probability density functions. Since $\frac{f(x)}{g(x)}$ is increasing, so is

$$\frac{f(x)\gamma(x)}{E[f(X)]} \cdot \frac{E[g(X)]}{g(x)\gamma(x)} = \frac{\hat{f}(x)}{\hat{g}(x)}.$$

That is, $\hat{f}$ and $\hat{g}$ satisfy the monotone likelihood ratio property. In particular, the distribution associated with $\hat{f}$ first-order stochastically dominates that associated with $\hat{g}$. It follows that

$$\int_{-\infty}^{\infty} x\hat{f}(x)dx > \int_{-\infty}^{\infty} x\hat{g}(x)dx.$$

By definition of $\hat{f}$ and $\hat{g}$, this last inequality is equivalent to

$$\frac{E[Xf(X)]}{E[f(X)]} = \int_{-\infty}^{\infty} x\frac{f(x)\gamma(x)}{E[f(X)]}dx > \int_{-\infty}^{\infty} x\frac{g(x)\gamma(x)}{E[g(X)]}dx = \frac{E[Xg(X)]}{E[g(X)]},$$

as needed. □

Lemma 2. *The function*

$$h(b,g) = -\left((b-1)g + b(g-1)\right)(b-1)(g-1) + (b-1)g(2b-g-1)\log g + (g-1)b(2g-b-1)\log b$$

is positive everywhere on the set $\Gamma = \{(b,g) \mid b \in (0,1)$ *and* $g \in (1,\infty)\}$.

Proof. Note that $h(1,g) \equiv 0$, so it suffices to show that $h_b(b,g)$ is negative everywhere on Γ, where h_b denotes the partial derivative of h with respect to b. We have

$$h_b(b,g) = -(g-1)(4bg-5g-b+2) + (4b-g-3)g\log g + (g-1)(2g-2b-1)\log b.$$

In particular, $h_b(b,1) \equiv 0$. Hence h_b is negative everywhere on Γ if h_{bg} is. We have

$$h_{bg}(b,g) = -8bg + 9b + 9g - 10 + (4b-2g-3)\log g + (4g-2b-3)\log b.$$

Note that $h_{bg}(b,1) \equiv b-1+(1-2b)\log b$, which is negative for all $b \in (0,1)$. Hence h_{bg} is negative everywhere on Γ if h_{bgg} is. We have

$$h_{bgg}(b,g) = -8b + 7 + \frac{4b-3}{g} - 2\log g + 4\log b.$$

Note that

$$h_{bgg}\left(\frac{1}{4}, g\right) \equiv 5 + 4\log\left(\frac{1}{4}\right) - \frac{2}{g} - 2\log g,$$

which is negative for all $g > 1$ since $5 + 4\log(1/4) < 0$. Now note that

$$h_{bggb}(b,g) = -8 + \frac{4}{g} + \frac{4}{b}$$

is positive whenever $b < 1/4$ and $g > 1$. It follows that h_{bgg} is negative whenever $b \in (0, 1/4]$ and $g \in (1,\infty)$.

Now consider $b > 1/4$. Note that $h_{bgg}(b,1) \equiv 4(1-b+\log b)$, which is negative for all $b \in (0,1)$. Note also that

$$h_{bggg}(b,g) = -\frac{4b-3}{g^2} - \frac{2}{g},$$

which, for $g > 1$, is negative if and only if $g > 3/2 - 2b$, which holds if $b > 1/4$ and $g > 1$. It follows that h_{bgg} is negative whenever $b \in (1/4, 1)$ and $g \in (1,\infty)$. Combining this with the above gives that h_{bgg} is negative everywhere on Γ, as needed. □

We first argue that it suffices to show that, under the conditions stated in the proposition, $E[\lambda \mid \text{participate}]$ is increasing in m. To see this, note first that an equivalent statement of part (i) of the proposition is that if m_1 and m_2 are such that $m_2 > m_1$ and $p(m_i, \lambda) \in [0, 1)$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$ and $i = 1, 2$, then the distribution of λ conditional on participation at m_2 first-order stochastically dominates (FOSDs) that at m_1. Let Ψ denote the distribution of λ. For each $i = 1, 2$, let F_i denote the distribution function for λ conditional on participation at m_i. Note that F_1 and F_2 are continuous since Ψ is. Suppose that F_2 does not FOSD F_1; we will show that this implies that, for some distribution of λ satisfying the conditions of the proposition, $E[\lambda \mid \text{participate}]$ is not increasing in m. Then there exists some λ_0 such that $F_1(\lambda_0) < F_2(\lambda_0)$. By continuity of F_1 and F_2 and the fact that they agree at $\underline{\lambda}$ and $\overline{\lambda}$, there exists an interval $[a, b]$ containing λ_0 such that $F_1(a) = F_2(a)$, $F_1(b) = F_2(b)$, and $F_1(x) < F_2(x)$ for all $x \in (a, b)$. Thus, for each $\lambda \in (a, b)$,

$$F_1(\lambda|[a,b]) = \frac{F_1(\lambda) - F_1(a)}{F_1(b) - F_1(a)} = \frac{F_1(\lambda) - F_2(a)}{F_2(b) - F_2(a)} < \frac{F_2(\lambda) - F_2(a)}{F_2(b) - F_2(a)} = F_2(\lambda|[a,b]),$$

and hence $F_1(\cdot \mid [a, b])$ FOSDs $F_2(\cdot \mid [a, b])$. Note that $F_i(\cdot \mid [a, b])$ is the distribution of λ conditional on participation at m_i when the prior distribution of λ is $\Psi(\cdot \mid [a, b])$. It follows that, for the prior distribution $\Psi(\cdot \mid [a, b])$, $E\left[\lambda \mid \text{participate}\right]$ is higher at m_1 than it is at m_2, as needed.

We now show that $E[\lambda \mid \text{participate}]$ is indeed increasing in m. First suppose $p(m, \lambda) > 0$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$. We have

$$E\left[\lambda \mid \text{participate}\right] = \frac{E[\lambda p]}{E[p]}.$$

Differentiating with respect to m gives

$$\frac{\partial}{\partial m} E\left[\lambda \mid \text{participate}\right] = \frac{E[p]E\left[\lambda \frac{\partial p}{\partial m}\right] - E[\lambda p]E\left[\frac{\partial p}{\partial m}\right]}{(E[p])^2}.$$

This is positive if and only if the numerator is positive, which, since p and $\partial p/\partial m$ are positive for each λ, may be rewritten as

$$\frac{E\left[\lambda \frac{\partial p}{\partial m}\right]}{E\left[\frac{\partial p}{\partial m}\right]} > \frac{E[\lambda p]}{E[p]}.$$

By Lemma 1 (with $X = \lambda$, $f = \frac{\partial p}{\partial m}$, and $g = p$), it suffices to show that

$$\frac{1}{p}\frac{\partial p}{\partial m}$$

is increasing in λ. Differentiating with respect to λ gives

$$\frac{\partial}{\partial \lambda}\left(\frac{1}{p}\frac{\partial p}{\partial m}\right) = -\frac{1}{p^2}\frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m} + \frac{1}{p}\frac{\partial^2 p}{\partial \lambda \partial m}.$$

Thus it suffices to show that

$$p\frac{\partial^2 p}{\partial \lambda \partial m} > \frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m}. \tag{6}$$

Differentiating (5) gives

$$\begin{aligned}\frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m} &= \left(\frac{1-\mu}{(g-1)^2}\left(-\frac{g}{\lambda}\log g\right) + \frac{\mu}{(b-1)^2}\left(-\frac{b}{\lambda}\log b\right)\right)\left(\frac{1-\mu}{(g-1)^2}\frac{g}{\lambda} + \frac{\mu}{(b-1)^2}\frac{b}{\lambda}\right)\\ &= -(1-\mu)^2\frac{g^2\log g}{\lambda^2(g-1)^4} - \mu(1-\mu)\frac{bg\log b + bg\log g}{\lambda^2(b-1)^2(g-1)^2} - \mu^2\frac{b^2\log b}{\lambda^2(b-1)^4},\end{aligned} \tag{7}$$

and

$$\frac{\partial^2 p}{\partial \lambda \partial m} = (1-\mu)\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(g-1)^3}\right) + \mu\left(\frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3}\right).$$

Multiplying the latter by the expression for p in (5) and expanding leads to

$$\begin{aligned}p\frac{\partial^2 p}{\partial \lambda \partial m} = -(1-\mu)^2&\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(g-1)^4}\right)\\ &- \mu(1-\mu)\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(b-1)(g-1)^3} + \frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3(g-1)}\right)\\ &- \mu^2\left(\frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^4}\right).\end{aligned} \tag{8}$$

Comparing the $(1-\mu)^2$ terms in (7) and (8), we see that the latter is larger if and only if

$$-(g(g+1)\log g - g(g-1)) > -g^2\log g,$$

or, equivalently, if

$$g - 1 - \log g > 0,$$

which holds for all $g > 1$. Similarly, comparing the μ^2 terms in (7) and (8), we see that the latter is larger if and only if

$$b - 1 - \log b > 0,$$

which holds for all $b \in (0,1)$.

Finally, for the $\mu(1-\mu)$ terms, that in (8) is larger than that in (7) if and only if

$$-\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(b-1)(g-1)^3} + \frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3(g-1)}\right) > -\frac{bg\log b + bg\log g}{\lambda^2(b-1)^2(g-1)^2}.$$

Rearranging gives the equivalent inequality

$$\begin{aligned}(b-1)(g-1)bg(\log b + \log g)& \\ > (b-1)^2\left(g(g+1)\log g - g(g-1)\right) &+ (g-1)^2\left(b(b+1)\log b - b(b-1)\right).\end{aligned}$$

Further rearranging leads to

$$-\left((b-1)g + b(g-1)\right)(b-1)(g-1) + (b-1)g(2b-g-1)\log g + (g-1)b(2g-b-1)\log b < 0,$$

which, by Lemma 2, holds for all $b \in (0,1)$ and $g \in (1,\infty)$.

Combining these three comparisons, we see that (6) holds for all b and g.

Now suppose $p(m,\lambda) = 0$ for some $\lambda \in [\underline{\lambda}, \overline{\lambda}]$. By Lemma 2 of Matějka and McKay (2015), for any such λ, $p = 0$ maximizes

$$\mu\log(pg + 1 - p) + (1-\mu)\log(pb + 1 - p).$$

The corresponding first-order condition (evaluated at $p = 0$) is

$$\mu g + (1-\mu)b \leq 1. \tag{9}$$

Suppose this holds with equality; that is, suppose $\mu g + (1-\mu)b = 1$. The derivative of the left-hand side of (9) with respect to λ is

$$-\mu g\frac{\log g}{\lambda} - (1-\mu)b\frac{\log b}{\lambda}.$$

Since $f(x) = -x\log x$ is a strictly concave function, Jensen's Inequality implies that

$$-\mu g\frac{\log g}{\lambda} - (1-\mu)b\frac{\log b}{\lambda} < -\frac{1}{\lambda}(\mu g + (1-\mu)b)\log(\mu g + (1-\mu)b),$$

the right-hand side of which is equal to 0 whenever (9) holds with equality. It follows that if there is some λ for which $p = 0$, then there is a cutoff value $\tilde{\lambda}$ such that $p = 0$ if and only if $\lambda > \tilde{\lambda}$.

Since the result holds if $p > 0$ for all $\lambda \in [\underline{\lambda}, \overline{\lambda}]$, it also holds if we condition on $\lambda \in [\underline{\lambda}, \tilde{\lambda}]$. Removing this condition only strengthens the result since $\tilde{\lambda}$ is increasing in m (which follows from the fact that the left-hand side of (9) is increasing in m).

A.2 Proof of Proposition 2

From equation (5) we have

$$p(m, a\lambda) = -\mu f(\pi_B + m, c\eta) - (1-\mu) f(\pi_G + m, c\eta),$$

where $\eta = 1/\lambda$, $c = 1/a$, and $f(x,\eta) = \frac{1}{e^{\eta x}-1}$. Thus it suffices to show that

$$\frac{\partial}{\partial c}\bigg|_{c=1} \left[-c \frac{1}{\lambda^2} \frac{\partial^2}{\partial \eta \partial m} f(x, c\eta) \right] \geq 0, \tag{10}$$

and that this inequality is strict for at least one $x \in \{\pi_B + m, \pi_G + m\}$. Differentiating the left-hand side leads to the equivalent expression

$$\frac{\partial}{\partial c}\bigg|_{c=1} \left[-\frac{c}{\lambda^2} \frac{e^{cx\eta}\,(cx\eta + 1 + e^{cx\eta}(cx\eta - 1))}{(e^{cx\eta}-1)^3} \right]$$
$$= \frac{1}{8\lambda^2} \left(\sinh\left(\frac{z}{2}\right)\right)^{-4} \big(-1 + 2z^2 + (1+z^2)\cosh(z) - 3z\sinh(z)\big),$$

where $z = x\eta$. Because the above expression is symmetric (in the sense that each side yields the same value, regardless of whether it is evaluated at z or at $-z$, for all z), it suffices to show that it is positive whenever z is (it holds trivially for $z = 0$). This expression is positive if and only if

$$z^2(\cosh(z) + 2) + \cosh(z) > 1 + 3z\sinh(z).$$

Because $\cosh(z) \geq 1$ for all z, it suffices to show that $z^2\big(\cosh(z)+2\big) > 3z\sinh(z)$, or, equivalently,

$$\cosh(z) + 2 > \frac{3}{z}\sinh(z). \tag{11}$$

To prove this inequality, we employ the fact that sinh and cosh are analytic functions. Inserting their series representations, we get

$$\frac{3}{z}\sinh(z) = \frac{3}{z}\sum_{k=0}^{\infty} \frac{z^{2k+1}}{(2k+1)!} = 3 + 3\sum_{k=1}^{\infty} \frac{z^{2k}}{(2k)!}\frac{1}{2k+1} \leq 3 + \sum_{k=1}^{\infty}\frac{z^{2k}}{(2k)!} = 2 + \cosh(z), \tag{12}$$

as needed.

Finally, the two sides of inequality (11) are equal only if $z = 1$. Because $\pi_B + m < \pi_G + m$, inequality (10) is strict for at least one $x \in \{\pi_B + m, \pi_G + m\}$.

A.3 Proof of Proposition 3

Caplin and Dean (2013) show that the agent's choice problem is equivalent to the choice of posterior beliefs $(\gamma_{\text{part}}, \gamma_{\text{abst}})$ solving

$$\max_{\gamma_{\text{part}}, \gamma_{\text{abst}}, p \in [0,1]} pN_{\text{part}} + (1-p)N_{\text{abst}} \quad \text{s.t.} \quad p\gamma_{\text{part}} + (1-p)\gamma_{\text{abst}} = \mu, \tag{13}$$

where

$$\begin{aligned} N_{\text{abst}} &:= -\lambda h(\gamma_{\text{abst}}) \\ \text{and} \qquad N_{\text{part}} &:= \gamma_{\text{part}}(\pi_G + m) + (1-\gamma_{\text{part}})(\pi_B + m) - \lambda h(\gamma_{\text{part}}) \end{aligned}$$

are the net utilities associated with the two posteriors (under the assumption that the agent abstains at γ_{abst} and participates at γ_{part}).

Caplin and Dean (2013) show that the solution to (13) is given by the posteriors γ_{part} and γ_{abst} that support the concavification of the upper envelope of the net utility functions, as in Aumann, Maschler, and Stearns (1995) and Gentzkow and Kamenica (2011), with $\gamma_{\text{part}} \geq \mu \geq \gamma_{\text{abst}}$. Under the assumption that each action is chosen with positive probability, these inequalities are strict, and participation is optimal at posterior γ_{part} while abstention is optimal at posterior γ_{abst}.

By concavification, the solution satisfies two conditions. First, the slopes of the tangent lines to the net utility function at γ_{abst} and γ_{part} must coincide:

$$-\lambda h'(\gamma_{\text{abst}}) = \Delta - \lambda h'(\gamma_{\text{part}}), \tag{14}$$

where $\Delta := \pi_G - \pi_B$. Second, the tangent line to the net utility function at γ_{abst} has the same value at γ_{part} as the net utility function itself:

$$-\lambda h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h'(\gamma_{\text{abst}}) = \Delta\gamma_{\text{part}} + \pi_B + m - \lambda h(\gamma_{\text{part}}). \tag{15}$$

To prove part (i), we start by taking derivatives of (14) and (15) with respect to λ to obtain

$$-h'(\gamma_{\text{abst}}) - \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} = -h'(\gamma_{\text{part}}) - \lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} \tag{16}$$

and

$$\begin{aligned} -h(\gamma_{\text{abst}}) - \lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} &= -h(\gamma_{\text{part}}) - \lambda h'(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} + \left(\frac{\partial \gamma_{\text{part}}}{\partial \lambda} - \frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right)\lambda h'(\gamma_{\text{abst}}) \\ &\quad + (\gamma_{\text{part}} - \gamma_{\text{abst}})\left(h'(\gamma_{\text{abst}}) + \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right) + \Delta\frac{\partial \gamma_{\text{part}}}{\partial \lambda}. \end{aligned} \tag{17}$$

Cancelling $-\lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}$ from both sides of (17) and rearranging yields

$$h(\gamma_{\text{part}}) - h(\gamma_{\text{abst}}) = \frac{\partial \gamma_{\text{part}}}{\partial \lambda}\left[\lambda h'(\gamma_{\text{abst}}) - \lambda h'(\gamma_{\text{part}}) + \Delta\right] + (\gamma_{\text{part}} - \gamma_{\text{abst}})\left(h'(\gamma_{\text{abst}}) + \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}\right).$$

By (14), the term in square brackets is equal to 0. Further rearranging yields

$$\begin{aligned} (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} &= h(\gamma_{\text{part}}) - h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})h'(\gamma_{\text{abst}}) \\ &= \frac{1}{\lambda}(\Delta\gamma_{\text{part}} + \pi_B + m), \end{aligned} \tag{18}$$

where the second line follows by substituting from (15). Since participation is optimal at γ_{part}, we have $\Delta\gamma_{\text{part}} + \pi_B + m = \gamma_{\text{part}}\pi_G + (1 - \gamma_{\text{part}})\pi_B + m > 0$. Because $\gamma_{\text{part}} > \bar{\gamma} > \gamma_{\text{abst}}$ and $h'' > 0$, it follows that $\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} > 0$.

Rearranging (16) and substituting $h'(\gamma_{\text{part}}) - h'(\gamma_{\text{abst}}) = \frac{\Delta}{\lambda}$ from (14) leads to

$$\begin{aligned} \lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial \lambda} &= \lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda} - \frac{\Delta}{\lambda} \\ &= \frac{1}{\lambda}\left(\frac{\gamma_{\text{abst}}\pi_G + (1 - \gamma_{\text{abst}})\pi_B + m}{\gamma_{\text{part}} - \gamma_{\text{abst}}}\right), \end{aligned}$$

where the second equality subsitutes for $\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial \lambda}$ using (18). Because $h'' > 0$ and because the quantity on the right-hand side is negative, we conclude that $\frac{\partial \gamma_{\text{part}}}{\partial \lambda} < 0$.

The proof of part (ii) proceeds similarly. Taking the derivatives of (14) and (15) with respect to m, we obtain

$$-\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} = -\lambda h''(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial m} \tag{19}$$

and

$$- \lambda h'(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} - \left(\left(\frac{\partial \gamma_{\text{part}}}{\partial m} - \frac{\partial \gamma_{\text{abst}}}{\partial m} \right) \lambda h'(\gamma_{\text{abst}}) + (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} \right)$$
$$= \Delta \frac{\partial \gamma_{\text{part}}}{\partial m} + 1 - \lambda h'(\gamma_{\text{part}})\frac{\partial \gamma_{\text{part}}}{\partial m}.$$

Simplifying and rearranging this last equation gives

$$-1 - (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m} = \frac{\partial \gamma_{\text{part}}}{\partial m} \left(\Delta - \lambda h'(\gamma_{\text{part}}) + \lambda h'(\gamma_{\text{abst}}) \right).$$

By (14), the right-hand side of this equation is equal to zero. Which gives:

$$-1 = (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial \gamma_{\text{abst}}}{\partial m}$$

Note that $\gamma_{\text{part}} > \gamma_{\text{abst}}$ and $h'' > 0$. It follows that $\frac{\partial \gamma_{\text{abst}}}{\partial m} < 0$ and, by (19), $\frac{\partial \gamma_{\text{part}}}{\partial m} < 0$ as well.

B Robustness

B.1 Heterogeneous priors

Our results are robust to heterogeneity in prior beliefs, as long as all types have an interior participation probability. In this case, the probability that an agent with cost parameter λ participates depends only on the mean prior amongst all agents with that cost of information acquisition. By implication, all our comparative statics on p generalize to the case of heterogeneous priors. Formally, the following result holds.

Proposition 4. *(Robustness to dispersion in prior) Fix m, π_G, and π_B. Consider a population with joint distribution of priors and costs of information $f(\mu, \lambda)$ such that $0 < p(m, \lambda, \mu) < 1$ for all $(\lambda, \mu) \in \text{supp}(f)$. For each λ, let $\nu(\lambda) = \int \mu f(\mu, \lambda) d\mu$. Then,*

$$\int p(m, \lambda, \mu) f(\lambda, \mu) d\mu = p\big(\lambda, \nu(\lambda)\big)$$

Proof. Let $\gamma_{part} = P(s = G|\text{participate})$ and $\gamma_{abst} = P(s = G|\text{abstain})$ denote the optimal posteriors. By the law of iterated expectations, $\mu = p\gamma_{part} + (1 - p)\gamma_{abst}$. The participation probability can thus be written as a function of the chosen posteriors,

$$p(m, \lambda) = \frac{\mu - \gamma_{abst}}{\gamma_{part} - \gamma_{abst}} \tag{20}$$

Posterior separability implies that the optimal γ_{part} and γ_{abst} are independent of μ as long as $0 < p(m; \lambda) < 1$. The claim thus follows from the fact that (20) is linear in μ. □

B.2 Information cost functions

In this section we test the robustness of our main results, stated in Proposition 1, regarding alternative functional form assumptions on the costs of information acquisition. (Recall that Proposition 3 is formally valid for the entire class of posterior-separable cost functions.)

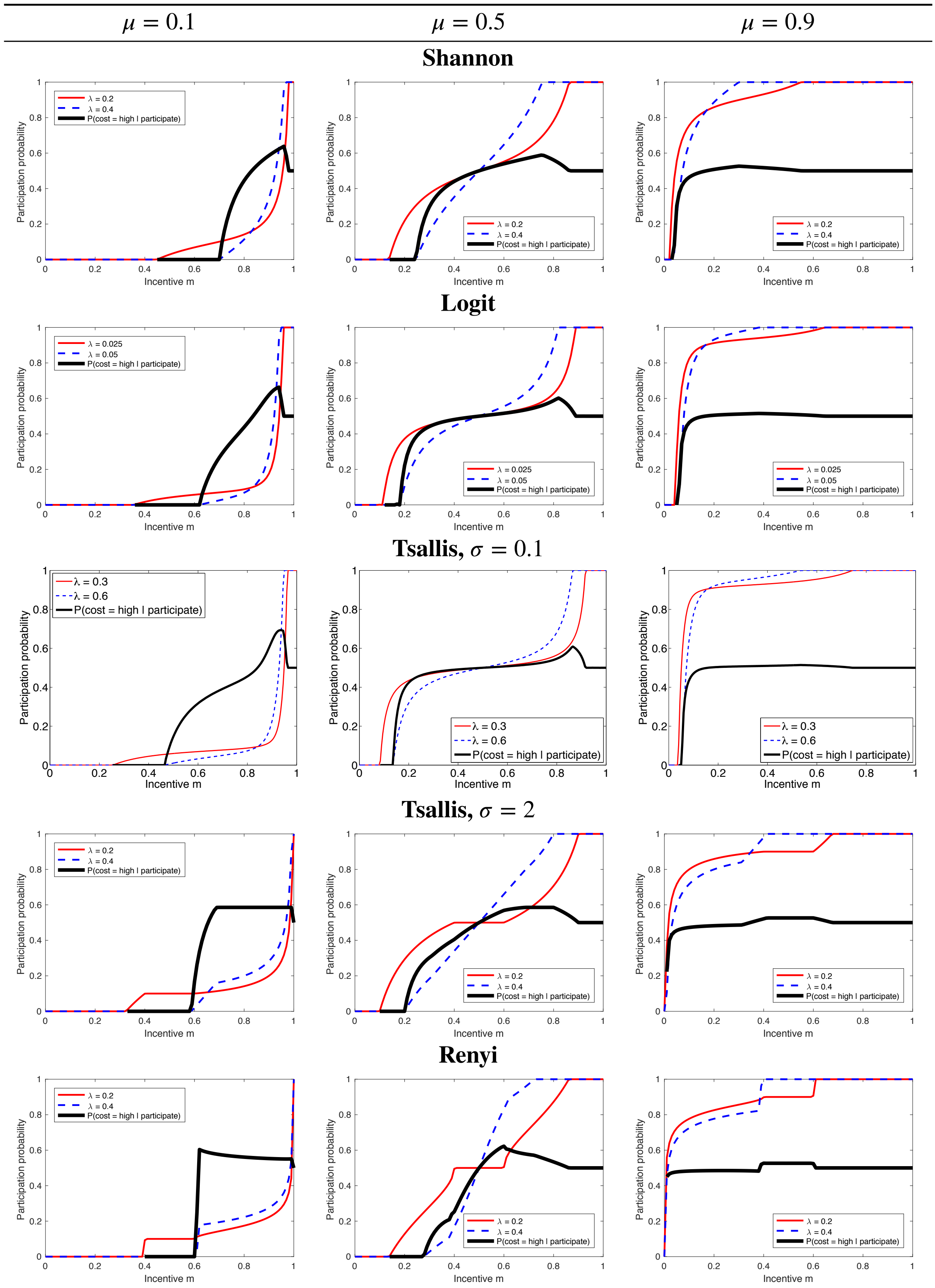


Figure B.5: Simulation tests of Proposition 1 with Shannon, logit, Tsallis, and Renyi cost functions.

We simulate the model for the following four cost-of-information functions studied in the recent theoretical literature on decision making under rational inattention (Caplin, Dean, and Leahy, 2017; Morris and Strack, 2019). In each case, the cost of the information associated with a pair of state-contingent choice probabilities (p_G, p_B) is given by $c(p_G, p_B) = \lambda(h(\mu) - ph(\gamma_{\text{part}}) - (1-p)h(\gamma_{\text{abst}}))$, where γ_{part} and γ_{abst} are the posteriors in case of participation and abstention, respectively. The cost functions differ by the functional form of h, which can take the following forms.

- Shannon costs: $h_{\text{Shannon}}(x) = -x\log(x) - (1-x)\log(1-x)$.
- Logit costs: $h_{\text{logit}}(x) = -x\text{logit}(x) - (1-x)\text{logit}(1-x)$, where $\text{logit}(y) = \log\left(\frac{y}{1-y}\right)$.
- Tsallis costs: $h_{\text{Tsallis}}(x,\sigma) = \frac{1}{\sigma-1}\left(x(1-x^{\sigma-1}) + (1-x)(1-(1-x)^{\sigma-1})\right) = \frac{1}{\sigma-1}(1 - x^{\sigma} - (1-x)^{\sigma})$ for $\sigma \in R$, $\sigma \neq 1$. Note that as $\sigma \to 1$, $h_{\text{Tsallis}}(x,\sigma) \to h_{\text{Shannon}}(x)$.
- Renyi costs: $h_{\text{Renyi}}(x,\sigma) = \frac{1}{1-\sigma}\log(x^{\sigma} + (1-x)^{\sigma})$, for $\sigma > 0$, $\sigma \neq 1$. Note that as $\sigma \to 1$, $h_{\text{Renyi}}(x,\sigma) \to h_{\text{Shannon}}(x)$.

Our analytical results apply to the case of Shannon costs, which we include here for reference. The logit case is of interest because it corresponds to the Wald (1947) sequential information acquisition problem with linear time costs (Morris and Strack, 2019). Tsallis entropy is of interest because the selection of parameter σ allows us to differentially vary the relative cost of marginal changes in the posterior depending on the distance between the posterior and the prior. In our simulations, $\sigma = 2$ is a case in which the relative cost of adjusting posteriors that are near the prior is low (h has a U-shaped appearance), and $\sigma = 0.1$ is a case in which that relative cost is high (h has more of a V-shaped appearance). Renyi entropy is of interest because it is not separable across states. We parametrize these costs with $\sigma = 2$.

The results are shown in Figure B.5, which displays supply curves and the fraction of high-cost individuals amongst participants for three different prior probabilities, $\mu \in \{0.1, 0.5, 0.9\}$. We derive the fraction of high-cost participants under the assumption that both types are equally prevalent in the population. In each of the first four cases, the supply curve is steeper for the high-cost type than for the low-cost type as soon as it is interior for both types, paralleling the analytical result for the case of Shannon costs in Proposition 1 (i). For the case of Tsallis entropy, we additionally observe that if $\sigma = 2$ and information acquisition costs are low ($\lambda = 0.2$), the supply curve is flat at the level of the prior belief μ. This indicates perfect information acquisition. The fifth case, Renyi costs, is different. For this cost function, the low-cost type sometimes responds more strongly to a change in participation payments than does the high-cost type. This tends to occur near regions of perfect information acquisition.

Regarding the robustness of part (ii) of Proposition 1, we again find in each of the first four cases that the fraction of high-cost individuals among participants monotonically increases until participation payments are so high that high-cost individuals participate with probability one. Again, behavior with Renyi costs exhibits a pattern different from that under Shannon costs; the composition of participants no longer changes monotonically as the participation payment increases, even in regions in which both types participate with an interior probability. These results are suggestive regarding the extent of the generality of the results we have analytically derived for the Shannon case.

B.3 Alternative models

There are alternative models of endogenous information acquisition with heterogeneous information acquisition costs. Some alternative models are ostensibly simpler but are analytically intractable, such as the Gaussian case we consider in detail below. While there exist simpler models that are also tractable, these models are not rich enough to capture the set of comparative statics we document in this paper. This occurs if agents cannot tailor their desired level of certainty to the incentive amount. Consider, for instance, a model in which there is a single binary information structure and agents can pay a fixed cost that is heterogeneous across individuals to access a signal from that information structure. While a higher incentive leads to the selection of higher cost participants, such selection is inconsequential in this model. The reason is that all agents observe the same information structure or abstain, so the probability of disappointment is independent of the incentive.

We now turn to exploring a model with normally distributed signals about an imperfectly known state of the world, as is often considered in the literature (e.g., Morris and Shin, 2002). We first consider the case of exogenously given signal precision. This model shares with ours the feature that the decision-maker, by choosing the threshold belief required for participation, can tailor the degree of certainty required for participation based on the incentive amount. In this model, a change in the participation payment has the same effect on the threshold belief regardless of the precision of the signal. Therefore, the effect of such a change on the participation probability is larger for individuals with less precise information. Consequently, if we associate higher cost in our model with lower precision in this model, the two models, to some extent, generate qualitatively similar comparative statics (which we verify numerically, see Appendix B.3.1). However, our main result on selection holds only for some parameters of this model.

This difference suggests that selection is driven in part by the decision-maker's ability to choose the quality of information. Therefore, we then study the case in which the agent can choose the precision of her signal at a cost. Consistent with the foregoing hypothesis, we find no violations of our results in numerical simulations of a model with normally distributed signals in which the decision-maker chooses the precision of information (with higher precision incurring greater cost).

B.3.1 Exogenous Gaussian signals

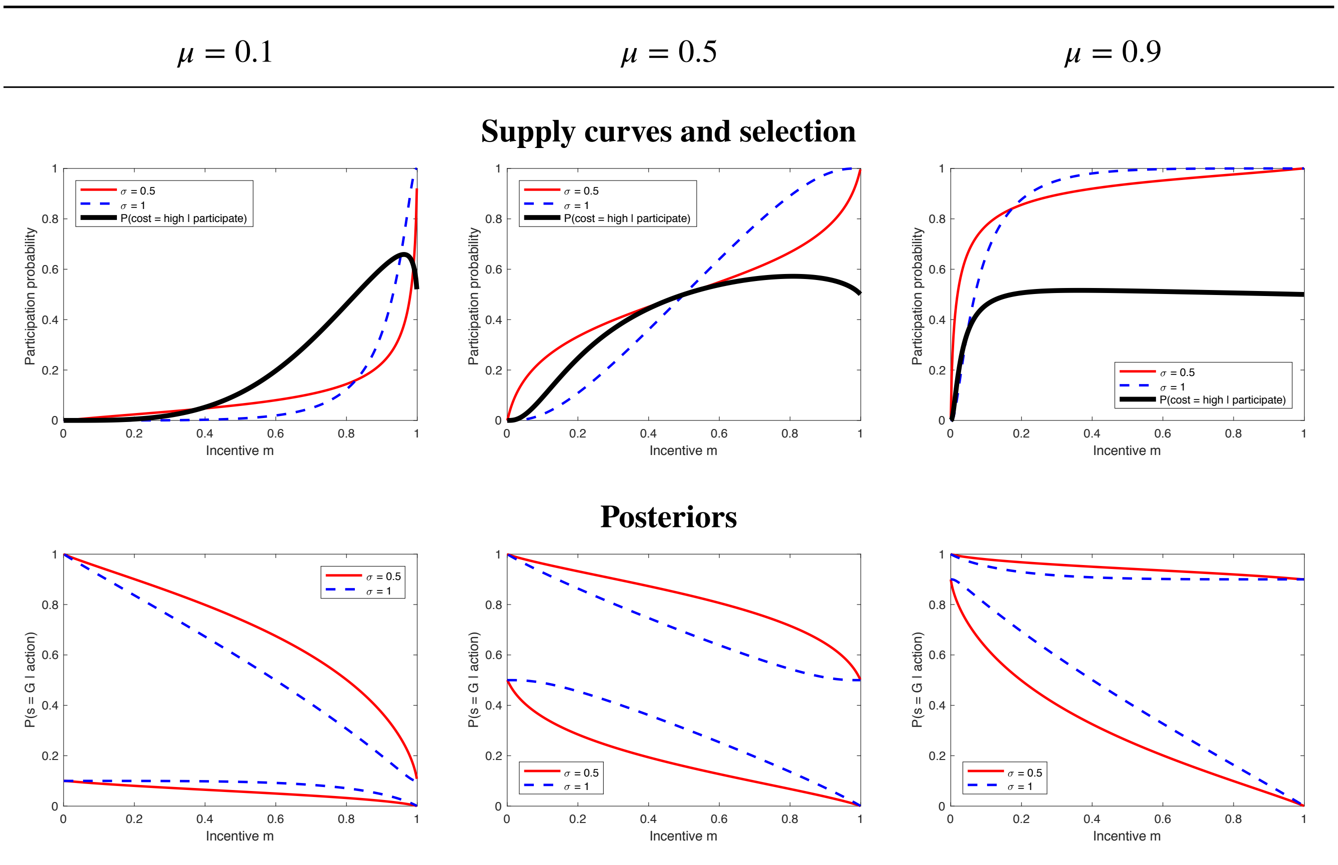


Figure B.6: Comparative statics similar to those of Proposition 1 in a model with exogenous Gaussian signals. Graphs in the top row depict supply curves for each level of the signal precision, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|$ participate) and $P(s = G|$ abstain).

As in the main text, an agent decides whether or not to participate in a transaction in exchange for a payment m. There are two states $s \in \{G, B\}$ with prior distribution $P(s = G) = \mu$. If the agent participates in state s, she receives utility $\pi_s + m$, which is positive if $s = G$ and negative otherwise. Non-participation gives utility 0.

The information acquisition technology differs from that in the main text. The agent observes a stochastic signal n that is normally distributed. If $s = G$, the mean of the signal is 1, if $s = B$, the mean is 0. The variance of the signal is σ^2, and is heterogeneous across subjects. While the normal signal is free to observe, the fact that this signal provides only incomplete information about the state, and the fact that the extent of incompleteness varies across agents corresponds to an implicit assumption that information is costly, and that information costs are heterogeneous across subjects.

Conditional on signal realization n, the agent will participate if $(\pi_G + m)Pr(s = G|n) + (\pi_B + m)Pr(s = B|n) \geq 0$, or equivalently, if

$$Pr(s = G|n) \geq \frac{-(\pi_B + m)}{\pi_G - \pi_B}. \tag{21}$$

As noted in the main text, this threshold belief is independent of the signal variance σ^2.

To derive the participation probability, observe that the posterior belief of the agent after observing signal realization n is given by

$$Pr(s = G|n) = \frac{\mu \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(n-1)^2}{2\sigma^2})}{\mu \frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{(n-1)^2}{2\sigma^2}) + (1-\mu)\frac{1}{\sqrt{2\pi\sigma}} \exp(-\frac{n^2}{2\sigma^2})} = \frac{\mu}{\mu + (1-\mu)\exp(\frac{1-2n}{2\sigma^2})}.$$

By (21), the agent will thus participate if

$$n \geq \frac{1}{2} - \sigma^2 \log \gamma, \tag{22}$$

where $\gamma = -\frac{\mu(\pi_G+m)}{(1-\mu)(\pi_B+m)}$. This yields the state-dependent participation probabilities $p_G = 1 - \Phi\left(\frac{-\frac{1}{2}-\sigma^2 \log \gamma}{\sigma}\right)$ and $p_B = 1 - \Phi\left(\frac{\frac{1}{2}-\sigma^2 \log \gamma}{\sigma}\right)$.

Figure B.7 shows the supply curves implied by this model for $\mu \in \{0.1, 0.5, 0.9\}$, and two levels of σ each. Over a part of the domain, the figures are consistent with both parts of Proposition 1. First, supply increases more steeply for the high-cost type whenever the prior-based expected value of the gamble is sufficiently close to zero. Second, as long as m is sufficiently small, the probability that a participant is a high-cost type increases with the payment m.

The figure also shows posterior probabilities that $s = G$ conditional on each action (the upper two curves in each graph correspond to $P(s = G|\text{accept})$, and the lower two curves correspond to $P(s = G|\text{reject})$). Mechanically, a lower variance of the signal corresponds to more dispersed posteriors (that is, posteriors that incorporate more information), which parallels Proposition 3.

B.3.2 Choice of Gaussian signal precision

We consider the same information technology as in Section B.3.1, with the exception that the agent can now choose the precision of the Gaussian signal at a cost. Specifically, the agent pays cost $c(\sigma) = \lambda/\sigma$ to observe a signal with variance σ^2. As in the main text, λ captures individual heterogeneity in information acquisition costs, and information acquisition costs are discounted from the agent's utility.

Conditional on the signal variance σ^2, the analysis parallels that of Section B.3.1. Specifically, if the agent finds it optimal to base her decision on a signal with precision σ^2, she will participate for signal realizations that weakly exceed the bound in equation (22). If the agent finds it optimal to reach a decision without acquiring any information, she will participate with probability 1 if $\mu(\pi_G + m) + (1 - \mu)(\pi_B + m) \geq 0$, and abstain otherwise. The condition determining whether the agent acquires information is somewhat complicated; if she does, one can show that the optimal signal precision satisfies the first-order condition

$$\frac{(\frac{1}{2} + \sigma^2 \log \gamma)^2}{2\sigma^2} = \log \frac{\mu(\pi_G + m)}{\sqrt{2\pi}\lambda},$$

where $\gamma = -\frac{\mu(\pi_G+m)}{(1-\mu)(\pi_B+m)}$. When combined with the above expressions for the participation probability, the second derivatives required for our comparative statics results become analytically intractable. We therefore solve the model numerically.

Figure B.7 shows the supply curves implied by this model for $\mu \in \{0.1, 0.5, 0.9\}$, and two levels of λ each. The figures are consistent with both parts of Proposition 1. First, supply increases more steeply for the high-cost type whenever it is interior. Second, as long as neither type participates with probability 1, the probability that a participant is a high-cost type increases with the payment m. We have not found any counterexamples for a wide range of alternative parameter values we have checked.

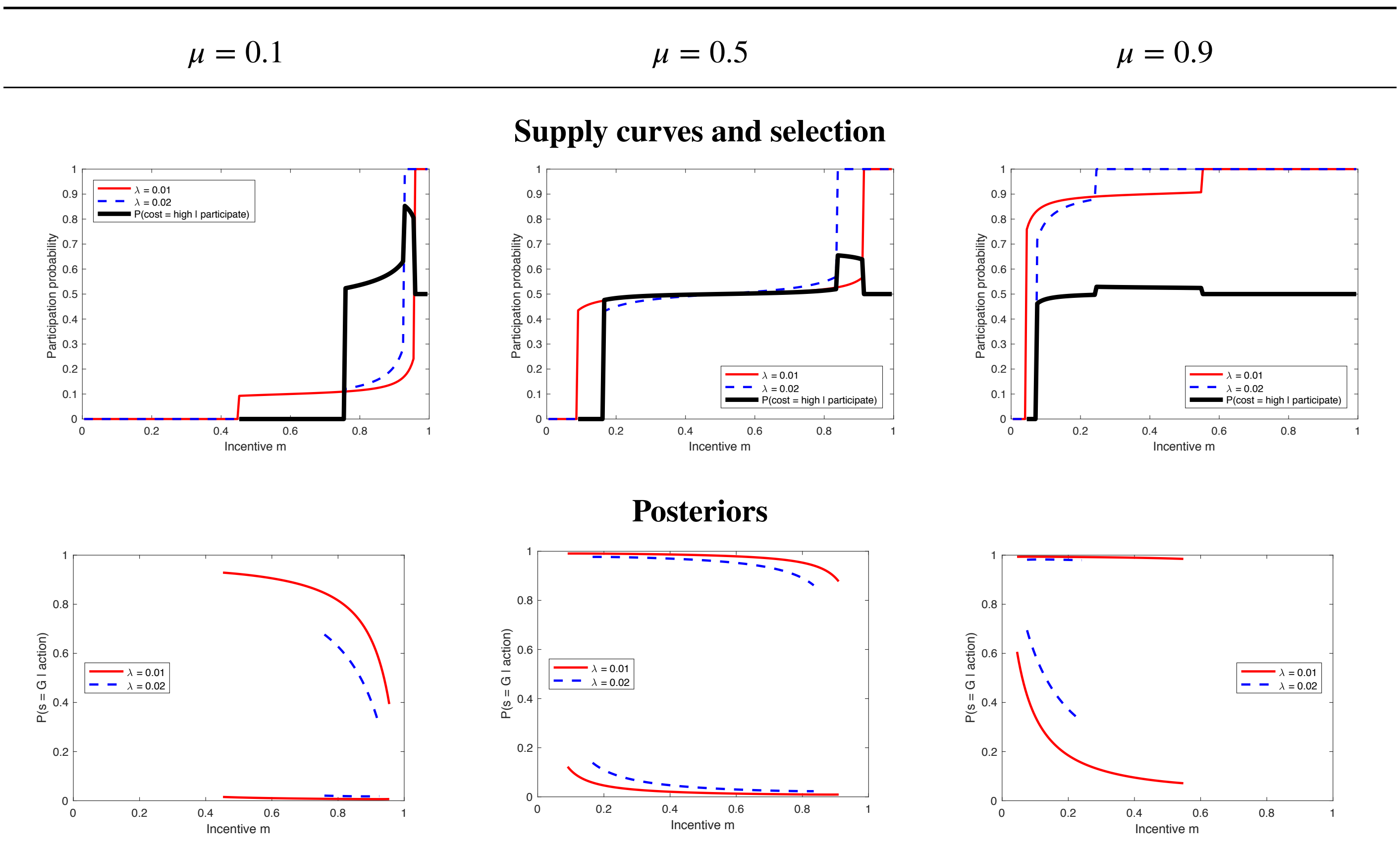


Figure B.7: Comparative statics similar to those of Proposition 1 in a model with Gaussian signals with optimally chosen costly precision. Graphs in the top row depict supply curves for each cost level, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|$ participate) and $P(s = G|$ abstain) and are drawn over the domain on which the agent chooses based on information rather than on priors alone.

C Experiment: Additional Materials

C.1 Laboratory sessions

Table C.5 presents details regarding each session. All sessions were conducted by a doctoral student research assistant in Cologne. We recruited subjects from the existing subject pool of the University of Cologne's Laboratory for Economic Research without any targeting of particular demographics.

The experiment was computerized, based on the Qualtrics survey platform and javascript. Lists of additions such as in Figure 2 were displayed in a graphic format (HTML5 canvas) rather than as text in order to prevent computerized checking and searching.

After analyzing the data from the sessions in May, we decided to replicate the results, using a condition in which performance on the IQ test was incentivized. In sessions 18 and 19, a clerical error caused an inconsistency in the instructions the experimenter read aloud and the IQ-incentive condition subjects were actually given. Since responses to incentives can depend significantly on expectations (Abeler, Falk, Goette, and Huffman, 2011), we discard the IQ data from these sessions.

C.2 Summary statistics

Data overview Table C.6 presents an overview of our data. Each subject provides us with 18 observations, leading to 7,008 observations across the task difficulty levels and 3,504 observations in the Exogenous Information condition. A handful of subjects choose to take the bet in all rounds of a condition, or in none of them. The latter behavior is more frequent in the Exogenous Information condition. Given the limits on information acquisition in that condition, we would expect such behavior from risk averse individuals.

Session	Date	Weekday	Time	#Subjects	Low-cost condition		IQ incentives
					# correct if $s = G$	# incorrect if $s = G$	
1	4/27/17	Mon	10 AM	19	12	8	No
2	5/3/17	Wed	10 AM	32	18	12	No
3	5/3/17	Wed	1 PM	29	18	12	No
4	5/3/17	Wed	4:30 PM	31	18	12	No
5	5/10/17	Wed	10 AM	32	15	10	No
6	5/10/17	Wed	1 PM	31	15	10	No
7	5/11/17	Thur	10 AM	30	15	10	No
8	5/11/17	Thur	1 PM	32	15	10	No
9	5/12/17	Fri	10 AM	32	15	10	No
10	5/12/17	Fri	1 PM	32	15	10	No
11	7/7/17	Fri	1 PM	29	15	10	Yes
12	7/10/17	Mon	10 AM	32	15	10	Yes
13	7/10/17	Mon	1 PM	32	15	10	Yes
14	7/17/17	Mon	10 AM	32	15	10	Yes
15	7/17/17	Mon	1 PM	32	15	10	Yes
16	7/18/17	Tue	10 AM	32	15	10	Yes
17	7/18/17	Tue	1 PM	32	15	10	Yes
18	7/24/17	Mon	10 AM	32	15	10	N.A.
19	7/24/17	Mon	1 PM	31	15	10	N.A.

Table C.5: Laboratory Sessions.

Information condition	Subjects	Decisions	% bet	Always take bet in condition	Never take bet in condition
Endogenous information	584	7008	37.74%	4	6
Exogenous information	584	3504	33.19%	4	91

Table C.6: Data overview. Each subject participated in each treatment, in random order. One subject chose to never bet in either condition.

Subjects' background characteristics The average subject is 24.5 years of age. 53.3% are female. 54.8% of our subjects are enrolled in a STEM major. Amongst those, 11.8% have taken an honors class in both mathematics and German, 29.9% have taken neither, 33.6% have taken only mathematics, and 24.7% have taken only German. Amongst those not enrolled in a STEM major, the respective numbers are 10.5%, 31.9%, 19.8%, and 37.9%.

Correlations between individual-level measures Table C.7 displays pairwise correlations between our individual-level measures.

C.3 Auxiliary analysis

Order effects There are pronounced order effects regarding the time subjects take to complete each decision. On average, they examine the first picture for over 2.7 minutes, whereas they examine the last one for just 1.2 minutes (with standard deviations in the population test subjects of 2 and 1.3 minutes, respectively). The fraction of betting-decisions that are aligned with the state is 79.5% for the first round, and 71.2% for the last round. Regressing the fraction of decisions that align with the state on the decision order yields a slope coefficient of 0.38 percentage points per round (SE 0.10). While this change is statistically significant, it is less pronounced than one might expect from a 60% drop in examination time. We conclude that the drop in examination time includes a

Table C.7: Pairwise correlations between subject characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CE rank	Res. price	Raven's test rank		High school mathematics		STEM	HS German
		rank	Non-inc.	Inc.	Honors	Grade rank		Honors
CE rank	1.0000							
Reservation price rank	-0.0225	1.0000						
	(0.5878)							
Raven's test rank								
Non-incentivized	-0.1241	-0.1449	1.0000					
	(0.0316)	(0.0120)						
Incentivized	-0.0564	-0.0240	.	1.0000				
	(0.4039)	(0.7224)	.					
High school mathematics								
Honors	0.0258	-0.0735	0.0416	0.2199	1.0000			
	(0.5442)	(0.0841)	(0.4929)	(0.0011)				
Grade rank	-0.0560	-0.0712	0.1527	0.2352	0.2284	1.0000		
	(0.2026)	(0.1048)	(0.0123)	(0.0010)	(0.0000)			
STEM	0.0686	0.0010	0.0935	0.1687	0.1566	0.1479	1.0000	
	(0.0977)	(0.9802)	(0.1062)	(0.0120)	(0.0002)	(0.0007)		
High school German								
Honors	-0.0302	0.0485	-0.0585	-0.2071	-0.2047	-0.1018	-0.1197	1.0000
	(0.4793)	(0.2551)	(0.3355)	(0.0022)	(0.0000)	(0.0225)	(0.0049)	
Grade rank	-0.0138	0.0475	-0.0311	-0.1183	-0.1004	0.1780	-0.1483	0.1757
	(0.7554)	(0.2815)	(0.6209)	(0.0960)	(0.0247)	(0.0001)	(0.0007)	(0.0001)

Notes: CE rank is the percentile rank of a subjects' mean certainty equivalent in the risk elicitation task. Higher ranks correspond to lower risk aversion. Numbers in parentheses display *p*-values.

substantial learning component and reflects to a lesser extent a change in how careful subjects make decisions.

Implementation of the reservation price elicitation task Of the subjects selected to check a given number of calculations (according to the reservation price elicitation stage), 90.23% of subjects verified 90% or more correctly, and thus exceeded the quality required for receiving payment for this task (and avoiding punishment). This statistic is based solely on sessions 5–19; sessions 1–4 are excluded as there was an error with recording the fraction of correctly verified calculations.

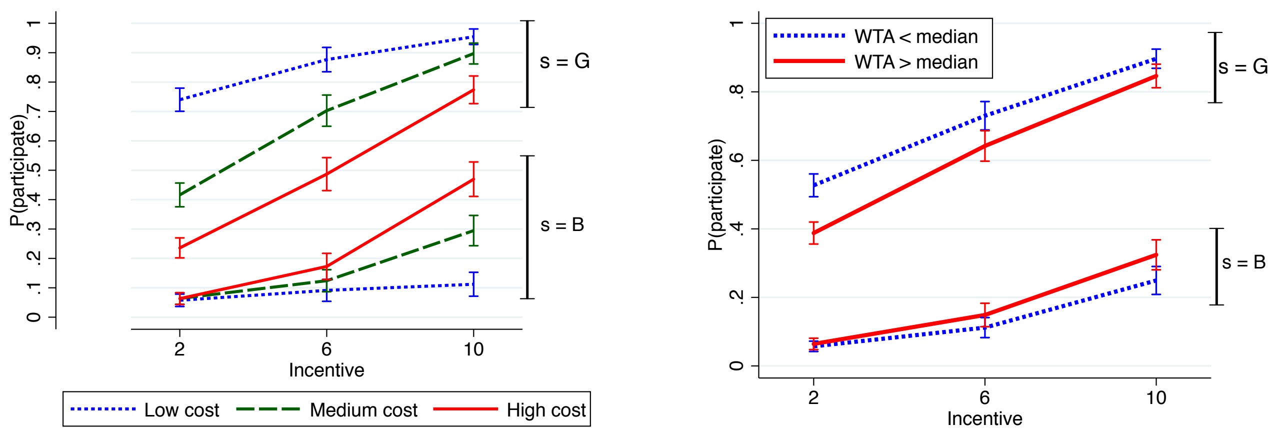
Decision reversals After stating their posterior beliefs, subjects had the opportunity to return to the previous screen to change their decision of whether to accept or refuse the bet. Overall, 1.05% of all decisions were changed, and 15.6% of subjects changed their decision at least once over the 18 rounds of the experiment.

C.4 Robustness of the empirical results

Participation by state Figure C.8 shows the effect of incentives on participation separately by state as an additional check whether our results arise for the right reasons. Panel A splits the data by information cost condition. It that our results are consistent with the intuition outlined in Section 2. A subject who participates in the good state avoids a false negative error; a subject who participates in the bad state commits a false positive error. The graph shows that a higher participation payment leads to an increase in the false positive probability and to a decrease in the false negative probability within each information cost condition, and that this change is larger in magnitude for higher information costs, leading to a more elastic supply in these conditions. Panel B shows that the same result obtains if we instead split the data by whether a subject has an above or below median reservation price for checking a given number of calculations.

Figure C.8: State-dependent participation.

A. Supply and selection. B. State-dependent participation.



Notes: Panel A: Induced information cost. Panel B: Information cost measured as reservation price (WTA) for checking a fixed number of calculations.

Alternative regression specifications Table C.8 replicates our main table, Table 2, including a control for subjects' percentile rank of their mean certainty equivalent to the risk preference elicitation questions, as well as the interaction between that variable and the incentive amount. The parameter estimates and significance levels generally remain similar to Table 2.

Table C.8: Selection and participation effects controlling for risk preferences.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type	**Selection**				**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(ii)	1(ii)	-	2[a)]	1(i)	1(i)	-	2
Sample								
Endogenous Information	✓	✓		✓	✓	✓		✓
Exogenous Information			✓				✓	
Panel A. Main regressions								
	Gamble accepted				1 ×			
× Incentive	0.577***	0.064***	0.007	-0.053	-0.073	0.350***	0.785***	-0.008
	(0.049)	(0.019)	(0.042)	(0.036)	(0.069)	(0.051)	(0.065)	(0.091)
× Cost index				-0.040***	-0.167***			
				(0.012)	(0.012)			
× Incentive × cost index				0.065***	0.239***			
				(0.018)	(0.025)			
	Gamble rejected				Res. Price > median			
× Incentive	-0.208***	-0.023**	-0.009	0.030		0.099**	-0.042	-0.130
	(0.033)	(0.011)	(0.016)	(0.028)		(0.047)	(0.054)	(0.112)
× Cost index				0.007				-0.053**
				(0.005)				(0.024)
× Incentive × cost index				-0.026**				0.115**
				(0.013)				(0.050)
× 1	0.559***	0.064***	0.001	-0.020		-0.072***	0.024	0.034
	(0.039)	(0.016)	(0.036)	(0.034)		(0.025)	(0.025)	(0.057)
CE rank								
×1	0.033*	-0.011	-0.010	-0.011	0.026	0.022	-0.026	0.022
	(0.018)	(0.041)	(0.041)	(0.041)	(0.044)	(0.044)	(0.049)	(0.044)
× Incentive	-0.061**	-0.005	-0.013	-0.005	0.151*	0.157**	0.336***	0.157**
	(0.026)	(0.005)	(0.009)	(0.005)	(0.078)	(0.078)	(0.102)	(0.078)
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

[a)] Proposition 2 is stated in terms of slopes on the supply curves only, as tested in Column (8). If there are no countervailing level effects, proposition 2 implies the comparative statics on selection effects tested in column 4.

Notes: This table replicates Table 2 including controls for a subject's risk-preference percentile (CE rank) and its interaction with the incentive amount, as well as an indicator of the cost condition for cases in which information costs are measured as reservation price for checking a given number of calculations. Standard errors in parentheses, clustered by subject. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.5 Experiment instructions

Note: Horizontal lines represent screen breaks. The instructions reproduced here concern the unincentivized IQ condition. In the incentivized IQ condition, subjects were told that there are three parts, that they could earn money in each of them, and that the chance of each of the parts counting for payment was 80%, 10% and 10%, respectively.

Welcome to this experiment!

Study structure and time involvement

This study has 3 parts:

1. Decision making part A
2. Logical puzzles
3. Decision making part B

Parts 1 and 2 will take you between 30 and 40 minutes to complete, and part 3 will take you approximately 10 minutes.

Payments

At the end of this study, you will be paid cash for your participation.

You start this experiment with a **budget** of **€15.** Depending on your decisions, and on luck, you can win or lose money. Money that you win will be added to your budget of €15. Money that you lose will be subtracted from your budget. The final sum of money will be paid to you in cash.

Whether you win or lose money depends on **a single decision** that you will make in one of the two decision making parts. The computer will **randomly** select the decision for which you will be paid.

Hence, you **should make every decision as if it was the one that counts – it could be the one!**

You will probably be paid for a decision from **decision making part A**. The exact probability of being paid according to that part is **80%**. The probability of being paid for a decision made in **decision making part B** is **20%**.

<<   >>

ABOUT CHANCE

Some of your decision, as well as your payout, may be partially determined by chance.

We guarantee, that when we tell you that something will happen with some chance out of 100, it will happen with exactly that chance.

Rules

This is a study about individual decision making. This means that you must not talk during this study. If you have questions, raise your hand. We will come to you and answer your questions privately.

Please do not use cell phones or other electronic devices until the study is finished. Do not surf the internet and do not check your emails. Should we ascertain that you do one of these things, the rules of this study prescribe that we deduct €10 from your payout.

(Sometimes, the continue button will appear only after a few seconds.)

To start the study, please enter the password given to you by the administrator of this experiment.

losgehts

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Instructions for part 1

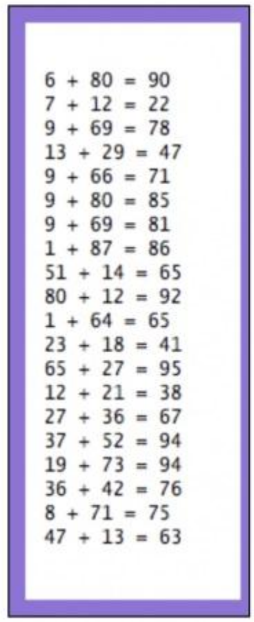
You will be able to continue with the study only if you correctly answer multiple test questions about these instructions. Therefore, it is in your best interest to pay close attention.

Part 1 one of this study has 18 rounds. Each round has two steps, the betting decision and the probability assessment.

<< >>

In each round, you will see a NEW picture like this, consisting of multiple calculations. Some calculations are CORRECT, others are WRONG.

For example, in this picture, the first two calculations are wrong and the third one is correct.



A picture can be GOOD or BAD. A picture is Good if it has more correct calculations than it has wrong calculations. Otherwise, it is Bad.

In each round, you will decide whether to bet on the picture or not. If you bet on the picture and the picture is Good, you win money. If you bet and the picture is Bad, you will lose money.

Important: A picture can be Good, even if it has many wrong calculations, as long as it has more correct calculations than wrong ones. Similarly, a picture can be Bad if it has some correct calculations, as long as it has more wrong calculations that correct ones.

In each round, it is **exactly equally likely** that you see a Good picture or a Bad picture. Each round, the computer will randomly decide which is the case.

The calculations in a picture appear in a **completely random order**!

None of this depends at all on what happened in previous rounds.

<< >>

Betting decision

This is how your betting decision works:

If you **bet** on on a picture and the **picture is Good** (i.e. it has more correct calculations than wrong ones), you **win** money.

If you **bet** on a picture and the **picture is Bad** (i.e. it has more wrong calculations than correct ones), you **lose** money.

If you do **not bet** on the picture, you **neither** win **nor** lose money.

Before deciding whether to bet on the picture or not, you may inspect the picture as long **as you wish** to get an idea of whether the picture is Good or Bad.

In a table like this one you will be able to see how much money you can win or lose if you bet on the picture in the current round. You can also see exactly how many correct and wrong calculations a Good or Bad picture contains.

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	12	8
Wrong calculations	8	12
If you bet on the picture	***WIN €5***	***LOSE €5***

In each round, you will see a different picture.

How much money to win or lose by betting can differ from round to round!

If you are getting paid for a round of this part, the probability is 80% that your payment is determined by a betting decision. The remaining 20% are the probability of being paid for your answer in a probability assessment, which we will explain now.

<< >>

Probability assessment

After inspecting the picture and deciding whether to bet on the picture or not, we will ask you in each round how certain you are that the picture that you just saw was Good or Bad by showing you a question like this:

definitely good	most likely good	very likely good	quite likely good	fairly likely good	slightly likely good	slightly likely bad	fairly likely bad	quite likely bad	very likely bad	most likely bad	definitely bad
100%	90-99%	80-90%	70-80%	60-70%	50-60%	40-50%	30-40%	20-30%	10-20%	1-10%	0%
○	○	○	○	○	○	○	○	○	○	○	○

The number below each possible choice is the probability in percent with which you believe that the picture was Good.

There is a 1 in 5 chance that your earnings from this study are determined by your answer to such a question. Depending on your answer, the picture you have seen, and luck, your bonus may rise by €3 or fall by €3.

The payment procedure is designed such that it in your best interest to give your best, genuine answer to this question.

If you believe, for example, that it is about 75% likely that you have seen a good picture, it is in your best interest to select “quite likely good (70 - 80%)”. If you believe, for example that it is about 25% likely that you have seen a good picture (that is, you believe it is about 75% likely that you have seen a bad picture), then it is in your best interest to select “quite likely bad (20 - 30%)".

One of your decisions from this study will be randomly selected for payment. Thus, you will be paid for EITHER for your bet on a picture (with a 4 in 5 chance), OR for the answer you give to the questions explained above, but never for both.

Read this if you would like to know more about the payment mechanism and about WHY it is in your best interest to answer this questions according to you true beliefs.

(We will ***not*** ask you test questions about the remaining content on this page.)

The payment procedure works like this.

For most choices you can select, there is a range of chances (for example 50 - 60%). Your payment is determined by the number in middle of the range you select (for example 55%, if you select the range 50 - 60 %).

Suppose you select a choice for which the middle of the range is some number X. The computer will randomly and secretly draw another number Y between 0 and 100. If the number the computer randomly draws is the larger one, that is if Y > X, then you will win €3 with chance Y in 100 (and lose €3 if you don't win). If the number you stated is the larger one, that is, if X > Y, then you will win if the picture you have seen is good. So if X is your genuine belief that the picture you have seen was good, you will win with chance X or with chance Y, whichever of the two is larger.

WHY is it in my best interest to answer this question according to my genuine beliefs?

Simply, the reason is that you lower your chance of winning if you state a chance that is lower than you genuinely believe, and you also lower your chance of winning if you state something that is higher than you genuinely believe. So the best you can do is state what you genuinely believe.

To see why, it's best to go through an example.

Here's why you lose from stating a chance that is higher than you genuinely think is true. For example, suppose you genuinely believe the chance that the picture is good 60%, but in the survey question you select a higher chance, say 90%. Suppose the number Y that the computer draws is between 60% and 90%, let's say it is 80%. This is lower than what you've told us (you've told us 90%), so you will not play the computers' bet. Instead, you will win if the picture is good, which you genuinely think only occurs with 60% chance. The computers' bet would have given you a higher, 80%, chance instead. Hence, you hurt your chance of winning by stating the picture was more likely good than you genuinely think.

And here's why you lose from stating a lower chance than you genuinely think is true. For example, suppose again you genuinely believe the chance that the picture is good 60%, but in the survey question you select a lower chance, say 10%. Suppose the number Y that the computer draws is between 10% and 60%, let's say it is 30%. That is higher than what you told us (which is 10%), so you will play the computers' bet and win with chance 30%. That is lower than if you had instead received the bet on the picture, which, according to your genuine belief, has a 60% chance. Hence, you hurt your chance of winning by stating the picture was less likely good than you genuinely think.

Therefore, the best you can possibly do is to select exactly the answer that corresponds to your genuine beliefs.

If you have any questions about this payment mechanism, please raise your hand.

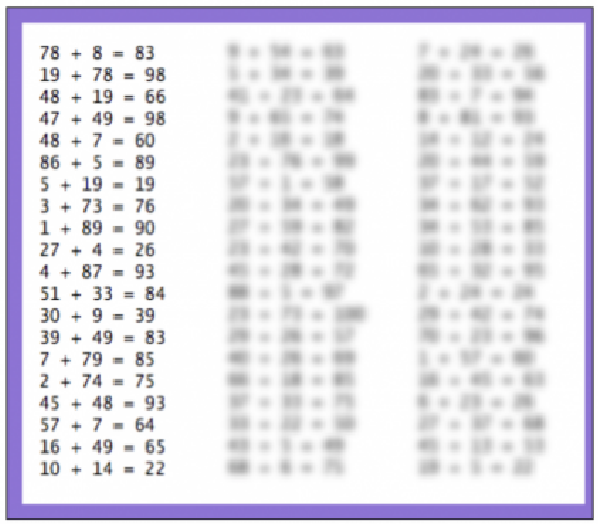
<< >>

Blurry Calculations

In some rounds, a part of the picture will be blurred, such as in the one below.

Amongst the area that is *not* blurred, the computer will automatically count for you how many correct and incorrect calculations there are, as below.

Number of CORRECT calculations in the visible part: 7
Number of WRONG calculations in the visible part: 13



You cannot see the other calculations, but they are just as relevant for winning or losing should you decide to bet on the picture. This means that winning or losing the bet depends on how many correct and wrong calculations are in the *whole* picture, counting those calculations that you cannot see.
Apart from what you can see and are told about the picture, these rounds are like all others.

<< >>

To make sure you got all of this, check all statements below that are true. You can only continue if you tick all boxes correctly.

Use the back button on the bottom if you would like to revisit the instructions.

(Do not try random combinations, there are far too many possible combinations. If you feel you understand the instructions, but still cannot continue, or have some other question, please raise your hand.)

- [ ] A picture is bad ONLY if ALL the calculations in that picture are incorrect.
- [x] A bad picture has both correct and incorrect calculations (but more incorrect ones).
- [x] At the end of the study, the computer will randomly select one decision I made. I will be paid for that and only that decision.
- [ ] When I am asked about how certain I am about a picture, I will earn most from this study if I state something a little lower than I truly think.
- [x] I can examine the picture FOR AS LONG AS I LIKE before I make a decision.
- [ ] If a part of the picture is blurred, whether I will win or lose from taking the lottery ONLY depends on those calculations that I can see, not on those that are blurred.
- [x] A good picture has both correct and incorrect calculations (but more correct ones).
- [ ] A picture is good ONLY if ALL the calculations in that picture are correct.
- [ ] When I am asked about how certain I am about a picture, I will earn most from this study if I state something a little higher than I truly think.
- [x] f a part of the picture is blurred, whether I will win or lose from taking the lottery depends on all calculations in the picture, even those that are blurry.
- [x] When I am asked about how certain I am about a picture, I will earn most from this study if I state exactly what I truly think.
- [x] If I am paid for a part with a picture, I will be paid EITHER for the bet I take on that picture, OR for the my answer to the question how certain I am about the picture I have seen, but NOT for BOTH.

<< >>

Before we begin the study, please conform your participation, if you still want to participate.

Protocol officers: Axel Ockenfels, Professor, Department of Economics, University of Cologne and Sandro Ambuehl, Assistant Professor for Management, Department of Management UTSC, Rotman School of Management, University of Toronto

PAYMENT: On average, you will receive **€10 per hour** as payment for your participation, depending on luck and the decisions that you and other participants make. All participants will receive a payment. The minimum payment is €4 show-up fee. (To understand the next paragraph, please keep in mind that the payment is *not* to be understood to be utility. You will definitely receive a payment as described in the next paragraph.)

RISKS AND BENEFITS: We do not promise that you derive any kind of benefit from this study. There are no other risks relating to this study.

SCHEDULE: Your participation in this study will take between **60 and 120 minutes**.

YOUR RIGHTS: If, after reading this form and deciding to participate in this study, know that your participation is voluntary and that you can abort the study without any consequences or loss of due payments at all times. You have the right to not give an answer to individual questions. Your privacy will be protected in all published or written works that result from this study. If you have questions about your rights as a participant, you can contact the Research Oversight and Compliance Office - Human Research Ethics Program at ethics.review@utoronto.ca, 416-946-3273.

ACCESS TO INFORMATION, PRIVACY AND PUBLICATION OF RESULTS: At the end of the experiment, you have the opportunity to enter your email address should you want to receive information about the hypotheses and results of this study as soon as it is finished. This email address is the sole identifiable information that we elicit from you and it is your right to withhold this information. All of your information will be stored on an encrypted and password protected computer for up to five years. An anonymized version of the data will be shared with coauthors and published on the Harvard dataverse platform indefinitely. The results of this study will be published in academic seminars and journals. The study in which you take part may be subjected to a quality control to ensure that applicable laws and regulations are fulfilled. Should it be selected, (one) representative(s) of the Human Research Ethics Program (HREP) may review data related to this study and/or declarations of consent as part of the audit. All informations accessed by HREP are governed by the same level of privacy as the level indicated by the research team.

CONFLICTS OF INTEREST:

None of the researchers that are involved with this study have any conflict of interest. This study is financed by the University of Cologne (Chair Prof. Dr. Axel Ockenfels).

CONTACT INFORMATION:

***If** you believe that you were injured by participating in this study, please contact Sandro Ambuehl, University of Toronto, Rotman School of Management, 105 St. George Street, Toronto, M5S 3E6, sandro.ambuehl@utoronto.ca, (647) 981 63 84.

***Questions**, concerns or complaints: If you have any kind of questions, concerns or complaints, the procedure, risks or benefits regarding this **research study**, please ask protocol officer Sandro Ambuehl, University of Toronto, Rotman School of Management, 105 St. George Street, Toronto, M5S 3E6, sandro.ambuehl@utoronto.ca, (647) 981 63 84.

***Independent** contact: If you disagree with how this study was conducted or if you have any concerns, complaints or general questions about this research or your rights, please contact the University of Toronto Research Ethics Board, McMurrich Building, 2nd Floor, 12 Queen's Park Crescent W, Toronto, ON, M5S 1S8, ethics.review@utoronto.ca, 416-946-3273, to talk to someone who is independent of the research team.

I do **NOT** agree to participate in this study and would like to withdraw from my participation now.

I agree to participate in this experiment and would like to continue.

<< >>

The study starts now.

Your decisions are about real money.

<< >>

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	55	45
Wrong calculations	45	55
If you bet on the picture	***WIN €2***	***LOSE €10***

3 + 47 = 55	62 + 11 = 73	49 + 44 = 93	23 + 31 = 54	5 + 37 = 41
23 + 50 = 73	60 + 31 = 91	31 + 64 = 95	33 + 42 = 72	19 + 71 = 90
83 + 7 = 90	77 + 5 = 82	20 + 63 = 83	40 + 2 = 40	18 + 49 = 63
66 + 8 = 78	4 + 74 = 82	3 + 77 = 77	17 + 5 = 22	20 + 43 = 64
2 + 58 = 60	8 + 49 = 55	54 + 25 = 79	35 + 39 = 72	18 + 73 = 91
31 + 61 = 92	53 + 23 = 71	5 + 39 = 48	67 + 12 = 79	32 + 52 = 89
53 + 17 = 70	11 + 5 = 14	51 + 47 = 103	38 + 12 = 49	17 + 14 = 31
18 + 38 = 60	33 + 51 = 82	21 + 69 = 85	29 + 16 = 45	33 + 7 = 44
1 + 96 = 97	34 + 59 = 92	42 + 53 = 96	62 + 15 = 77	18 + 9 = 27
13 + 73 = 86	9 + 67 = 76	7 + 40 = 47	11 + 27 = 38	5 + 22 = 27
3 + 36 = 43	11 + 23 = 34	8 + 30 = 38	15 + 74 = 92	32 + 58 = 91
7 + 68 = 70	46 + 6 = 52	5 + 33 = 38	21 + 19 = 40	62 + 29 = 91
2 + 80 = 84	38 + 49 = 87	64 + 25 = 89	51 + 30 = 81	49 + 47 = 99
25 + 33 = 58	9 + 76 = 82	32 + 16 = 43	12 + 15 = 22	15 + 28 = 38
27 + 43 = 70	53 + 16 = 69	79 + 10 = 85	57 + 28 = 87	58 + 26 = 84
34 + 7 = 36	53 + 40 = 93	29 + 4 = 33	41 + 43 = 84	71 + 18 = 84
12 + 79 = 87	68 + 27 = 95	47 + 16 = 63	8 + 17 = 30	17 + 65 = 82
48 + 41 = 89	21 + 44 = 68	3 + 74 = 77	55 + 19 = 74	18 + 75 = 96
75 + 18 = 93	17 + 81 = 95	93 + 2 = 95	64 + 23 = 86	11 + 86 = 97
28 + 50 = 83	21 + 30 = 51	80 + 17 = 97	32 + 11 = 43	35 + 22 = 56

Look at the purple image as long as you like to see if you want to bet on the image or not.

Click CONTINUE to make your decision.

(You can NOT return to this page once you have clicked CONTINUE.)

<< >>

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	55	45
Wrong calculations	45	55
If you bet on the picture	***WIN €2***	***LOSE €10***

Make a decision.

- (●) I bet on the picture. I WIN €2 if the purple picture is Good, and LOSE €10 if it is Bad.
- ( ) I do not bet on the purple picture.

<< >>

How certain are you that the purple picture is Good?

It is...

definitely good	most likely good	very likely good	quite likely good	fairly likely good	slightly likely good	slightly likely bad	fairly likely bad	quite likely bad	very likely bad	most likely bad	definitely bad
100%	90-99%	80-90%	70-80%	60-70%	50-60%	40-50%	30-40%	20-30%	10-20%	1-10%	0%
○	○	○	●	○	○	○	○	○	○	○	○

(The number below each option is the probability in percent that you think the purpurrote image is good.)

If you like, you can go back now to change your decision whether you want to bet on the picture.

<< >>

	Good picture (probability 50%)	Bad picture (probability 50%)
Correct calculations	35	25
Wrong calculations	25	35
If you bet on the picture	***WIN €10***	***LOSE €2***

This picture also has 60 calculations, but you can only see 20 of them as the remainder is blurred.

Number of CORRECT calculations in the visible area: 7
Number of WRONG calculations in the visible area: 13

66 + 26 = 90
27 + 61 = 83
38 + 31 = 73
20 + 18 = 38
5 + 65 = 67
24 + 56 = 80
57 + 35 = 95
47 + 48 = 95
20 + 10 = 30
28 + 21 = 47
24 + 29 = 48
66 + 31 = 97
49 + 10 = 56
23 + 20 = 38
65 + 2 = 67
85 + 4 = 89
51 + 12 = 58
27 + 22 = 46
15 + 43 = 59
22 + 1 = 27

Look at the yellow image for as long as you like to see if you want to bet on the picture or not.

Click CONTINUE to make your decision.

(You can NOT return to this page once you have clicked CONTINUE.)

<< >>

[The subject completes all 18 rounds]

Additional calculation tasks for bonus payment

You now have the option of solving additional calculations to earn a bonus.

You will receive this bonus payment *in addition* to your other payouts from this study.

To determine the amount of your bonus payment, you will complete four decision lists like the one below.

Are you willing to solve

60 calculations

in exchange for the given amount of money?

(One of your decisions will be randomly selected and executed!)

Solve calculations, receive €0	O	O	Don't solve, receive no bonus
Solve calculations, receive €0.25	O	O	Don't solve, receive no bonus
Solve calculations, receive €0.50	O	O	Don't solve, receive no bonus
Solve calculations, receive €0.75	O	O	Don't solve, receive no bonus
Solve calculations, receive €1	O	O	Don't solve, receive no bonus
Solve calculations, receive €1.50	O	O	Don't solve, receive no bonus
Solve calculations, receive €2	O	O	Don't solve, receive no bonus
Solve calculations, receive €2.50	O	O	Don't solve, receive no bonus
Solve calculations, receive €3	O	O	Don't solve, receive no bonus
Solve calculations, receive €3.50	O	O	Don't solve, receive no bonus
Solve calculations, receive €4	O	O	Don't solve, receive no bonus

When we speak of "60 calculations", each of these tasks is like the ones you saw in the picture before. This means that each task has a calculation like "45 + 37 = 67" and it is your task to indicate if the calculation is right or wrong. (In this example, the calculation is wrong.)

<< >>

Once you have completed all four decision lists, the computer will **randomly pick one of these lists and one of the decisions** you made. This decision will then be executed at the very end of the experiment, after you finish the part with the logic puzzle. (Your decisions have absolutely no effect on the choice that the computer makes!)

This means that if you have decided not to solve the calculations for the amount of money offered, you will end the study without having to perform further calculations. If you have agreed to solve the specified amount of calculations for the amount of money offered, you will complete the tasks and receive the corresponding additional bonus.

You will **only receive the estimated amount for the additional tasks if you solve the tasks well enough**. This means that you are allowed to solve 1 out of 10 calculations incorrectly. (For example, if you solve 30 tasks, that means you can answer three of them incorrectly.) **If you solve more than 1 in 10 tasks incorrectly**, you will not only lose the extra bonus you would have got if you had completed the task correctly but there are an additional **€** deducted from your bonus.

Example: Suppose that in the randomly chosen task you decided to solve 30 calculations for €2. If you solve at least 90% of them correctly, €2 will be added to your bonus. But if you solve less than 90% correctly, you will (i) *not* receive the 2€ you would have received had you solved at least 90% correctly and (ii) €10 will be deducted from your bonus.

A second example: Suppose that in the randomly chosen task you decided to solve 30 calculations for €8. If they solve at least 90% of them correctly, €8 will be added to your bonus. But if you solve less than 90% correctly, you will (i) *not* receive the €8 you would have received had you solved at least 90% correctly and (ii) €10 will be deducted from your bonus.

Therefore, it is in your best interests to agree to solving the additional tasks only if you are genuinely willing to solve them well, and otherwise refuse to solve the additional tasks.

Please complete the following four lists according to your true preferences.

<< >>

Are you willing to solve

30 calculations

in exchange for the given amount of money?

(One of your decisions will be randomly selected and executed!)

Solve calculations, receive €0	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.25	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.50	○	●	Don't solve, receive no bonus
Solve calculations, receive €0.75	○	●	Don't solve, receive no bonus
Solve calculations, receive €1	○	●	Don't solve, receive no bonus
Solve calculations, receive €1.50	○	●	Don't solve, receive no bonus
Solve calculations, receive €2	○	●	Don't solve, receive no bonus
Solve calculations, receive €2.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €3	●	○	Don't solve, receive no bonus
Solve calculations, receive €3.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €4	●	○	Don't solve, receive no bonus
Solve calculations, receive €4.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €5	●	○	Don't solve, receive no bonus
Solve calculations, receive €5.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €6	●	○	Don't solve, receive no bonus
Solve calculations, receive €6.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €7	●	○	Don't solve, receive no bonus
Solve calculations, receive €7.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €8	●	○	Don't solve, receive no bonus
Solve calculations, receive €8.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €9	●	○	Don't solve, receive no bonus
Solve calculations, receive €9.50	●	○	Don't solve, receive no bonus
Solve calculations, receive €10	●	○	Don't solve, receive no bonus

<< >>

(Note: The selection of options in the above list is illustration purposes only. For all subjects, no options were selected until the subject made a selection. Subjects had to make an active choice on

each line, but could only switch from the option on the right to the option on the left once, or never, and never in the opposite direction. Subjects also saw corresponding lists for totals of 60, 100, and 200 calculations)

Part 2

of this study will now start. You can take as much time as you like.

<< >>

Logic Puzzles

In this task, please select the answer that best suits each of the 32 questions on the following pages.

(Your answers to these questions will not affect your payout in this experiment.)

>>

Note: At this stage, subjects solve the Raven's matrices (not reproduced here for copyright reasons).

Part 3

Note: There is a 20% chance that your payout in this study will be determined solely by a decision in this section. (With the remaining probability of 80%, it is determined by a decision you made in Part 1).

In this part of the experiment, you will complete 9 decision lists. Here is an example of a decision list.

What exactly "Lottery X" is will vary from round to round.

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Lottery X

In each line, choose the option that you prefer.

Participate in the lottery	○	○	Lose €10 with certainty
Participate in the lottery	○	○	Lose €9 with certainty
Participate in the lottery	○	○	Lose €8 with certainty
Participate in the lottery	○	○	Lose €7 with certainty
Participate in the lottery	○	○	Lose €6 with certainty
....	○	○	....
....	○	○	....
Participate in the lottery	○	○	Win €6 with certainty
Participate in the lottery	○	○	Win €7 with certainty
Participate in the lottery	○	○	Win €8 with certainty
Participate in the lottery	○	○	Win €9 with certainty
Participate in the lottery	○	○	Win €10 with certainty

Each line is a separate decision.

In each line, you can either select the option on the right or left side.

If, at the end, the computer randomly decides that your payout in this experiment is determined by a decision list, the following will happen:

The computer will randomly pick a line from the decision list. Your payout will then match the decision you made in this line. Your decision has absolutely no influence on which line the computer selects.

So it's in your best interest to pick the option that fits your true preferences in each line.

There are no correct or wrong decisions!

>>

For example, suppose you completed the decision list as follows:

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Win €6 with a probability of **50%**,
lose €6 with a probability of **50%**.

In each line, choose the option that you prefer.

Participate in the lottery	○	○	Lose €10 with certainty
Participate in the lottery	○	○	Lose €9 with certainty
Participate in the lottery	○	○	Lose €8 with certainty
Participate in the lottery	○	○	Lose €7 with certainty
Participate in the lottery	○	○	Lose €6 with certainty
....	○	○	....
....	○	○	....
Participate in the lottery	○	○	Win €6 with certainty
Participate in the lottery	○	○	Win €7 with certainty
Participate in the lottery	○	○	Win €8 with certainty
Participate in the lottery	○	○	Win €9 with certainty
Participate in the lottery	○	○	Win €10 with certainty

Suppose that the computer randomly selects the decision on the third line. In this line you have chosen the possibility on the left side. Therefore, your payout for this experiment will depend on Lottery X (described in more detail later) and whether you win or lose it.

Instead, assume that the computer randomly selects the decision in the third-bottom line. In this line you have chosen the possibility on the right side. That's why you will win €8.

Most people start such a decision-making list by making a choice on the left side and eventually switching to the right side (as in the example above).

<< >>

WHY is it in my best interest to answer that question with my true valuation?

Simply put, the reason is that you will receive a worse payout if you choose anything other than what you actually prefer.

For example, suppose you would rather lose €2 in a certain round than participate in the lottery. Also, suppose that you state that you would prefer the lottery to the safe loss of €2 (for example, because you can lose a lot of money in the lottery). If, by chance, the computer chooses this decision to determine your payout, you will play the lottery, although you would have preferred to lose €2 with certainty.

Simply put, if at the end of the experiment a particular decision is chosen from this part of the experiment to determine your payout, you will receive exactly what you have selected. But you have no influence on which decision will be selected.

Therefore, the best thing you can do is to pick exactly the option on each line of each decision list that you would rather be paid for.

If you have questions about this payout mechanism, please raise your hand.

<< >>

Part 3 of the experiment starts now.

Your decisions are about real money.

<< >>

List 1 out of 9

Would you rather participate in the following lottery or receive / lose the certain amount on the right-hand side?

Win €6 with a probability of **50%**,
lose €6 with a probability of **50%**.

In each line, choose the option that you prefer.

Participate in the lottery	Lose €10 with certainty
Participate in the lottery	Lose €9 with certainty
Participate in the lottery	Lose €8 with certainty
Participate in the lottery	Lose €7 with certainty
Participate in the lottery	Lose €6 with certainty
Participate in the lottery	Lose €5 with certainty
Participate in the lottery	Lose €4 with certainty
Participate in the lottery	Lose €3 with certainty
Participate in the lottery	Lose €2 with certainty
Participate in the lottery	Lose €1 with certainty
Participate in the lottery	Win €0 with certainty
Participate in the lottery	Win €1 with certainty
Participate in the lottery	Win €2 with certainty
Participate in the lottery	Win €3 with certainty
Participate in the lottery	Win €4 with certainty
Participate in the lottery	Win €5 with certainty
Participate in the lottery	Win €6 with certainty
Participate in the lottery	Win €7 with certainty
Participate in the lottery	Win €8 with certainty
Participate in the lottery	Win €9 with certainty
Participate in the lottery	Win €10 with certainty

<< >>

(Note: The selection of options in the above list is illustration purposes only. For all subjects, no options were selected until the subject made a selection. Subjects had to make an active choice on each line, but could only switch from the option on the right to the option on the left once, or

never, and never in the opposite direction. Subjects decided for 8 further lotteries, in random order.

We would like to ask you some questions about yourself.

Please answer truthfully.

What is your gender?

[male; female; other (e.g. genderqueer)]

How old are you?

At which faculty do you study?

[Faculty of Economics, Management and Social Science; Faculty of Law; Faculty of Medicine; Faculty of Philosophy; Faculty of Mathematics and Natural Sciences; Faculty of the Humanities; I am not a student]

Which state conferred your Abitur (university entrance diploma)?

[Baden-Württemberg; Bayern; Berlin; Brandenburg; Bremen; Hamburg; Hesse; Mecklenburg-Vorpommern; Niedersaxen; Nordrhein-Westfalen; Rheinland-Pfalz; Saarland; Sachsen; Sachsen-Anhalt; Schleswig-Holstein; Thüringen; I received the International Baccalaureate; I do not have an Abitur; I prefer not to say]

What was your Grade Point Average in the Abitur?

[1.0, 1.1, 1.2, . . . , 3.9, 4.0; I do not have an Abitur; I do not remember; I prefer not to say]

What was your Abitur grade in Mathematics?

[15 points (1+), 14 points (1), 13 points (1-), 12 points (2+), 11 points (2), 10 points, (2-), . . . , 3 points (5+), 2 points (2), 1 point (2-), 0 points; I do not have an Abitur; I do not remember; I prefer not to say]

What was your Abitur grade in German?

[15 points (1+), 14 points (1), 13 points (1-), 12 points (2+), 11 points (2), 10 points, (2-), . . . , 3 points (5+), 2 points (2), 1 point (2-), 0 points; I do not have an Abitur; I do not remember; I prefer not to say]

Have you taken an honors class in Mathematics in high school (Leistungskurs im Abitur)?

[Yes; No; I do not have an Abitur]

Have you taken an honors class in German in high school (Leistungskurs im Abitur)?

[Yes; No; I do not have an Abitur]

How much money do you spend on average each month (incl. rent, food, transportation, etc.)

[€ 0 - € 150; € 150 - € 300; € 300 - € 450; € 450 - € 600; € 600 - € 750; € 750 - € 900; € 900 - € 1050; € 1050 - € 1200; € 1200 - € 1350; € 1350 - € 1500; € 1500 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

How much money do you earn each month through your own labor?

[€ 0 - € 50; € 50 - € 100; € 100 - € 150; € 150 - € 200; € 200 - € 250; € 250 - € 300; € 300 - € 350; € 350 - € 400; € 400 - € 450; € 450 - € 500; € 500 - € 600; € 600 - € 700; € 700 - € 800; € 800 - € 900; € 900 - € 1000; € 1000 - € 1250; € 1250 - € 1500; € 1500 - € 1750; € 1750 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

How much money do you receive from your parents each month?

[€ 0 - € 50; € 50 - € 100; € 100 - € 150; € 150 - € 200; € 200 - € 250; € 250 - € 300; € 300 - € 350; € 350 - € 400; € 400 - € 450; € 450 - € 500; € 500 - € 600; € 600 - € 700; € 700 - € 800; € 800 - € 900; € 900 - € 1000; € 1000 - € 1250; € 1250 - € 1500; € 1500 - € 1750;

€ 1750 - € 2000; € 2000 - € 2500; € 2500 - € 3000; more than € 3000; I prefer not to say]

What is the net wealth of your parents (incl. real estate)?

[€ 0k - € 25k; € 25k - € 50k; € 50k - € 75k; € 75k - € 100k; € 100k - € 125k; € 125k - € 150k; € 150k - € 175k; € 175k - € 200k; € 200k - € 250k; € 250k - € 300k; € 300k - € 350k; € 350k - € 400k; € 400k - € 450k; € 450k - € 500k; € 500k - € 600k; € 600k - € 700k; € 700k - € 800k; € 800k - € 900k; € 900k - € 1 mio.; € 1 mio. - € 1.5 mio.; € 1.5 mio. - € 2 mio.; € 2 mio. - € 2.5 mio.; € 2.5 mio. - € 3 mio.; € 3 mio. - € 3.5 mio.; € 3.5 mio. - € 4 mio.; more than € 4 mio.; I prefer not to say]

Would you like to be informed by e-mail about the results and hypotheses of this study?

If yes, please enter your email address here.
(You are also allowed to leave this field blank.)

<< >>

As a reminder, you have made various decisions about whether you want to solve extra calculations for additional bonuses in decision lists.

The computer has randomly selected a list and one of your decisions, which is now being executed.

The decision that was randomly chosen is the following:

Solve 200 calculations for €2.5.

You decided to REJECT this transaction.

<< >>

We're done!

Thank you for your participation in this study!

Again, on behalf of the University of Cologne and the University of Toronto, we guarantee that your payout is exactly as we described it to you. Specifically, this means that if we told you something would happen with a certain probability out of 100, then it was with that very probability.

As explained in the introduction, you will receive €15 for your participation in this experiment, plus any winnings you made in this experiment and less any losses you have suffered. Your total payout is calculated as follows.

Your payout is determined by your probability assessment in part 1, round 11 so that you receive €3.

You do not receive a bonus payment for solving additional calculations.

Now, therefore, your final payout is €18.

You have completed the experiment now. Please go quietly to the experimenter room to receive your payout. Bring the completed receipt with you.

<<

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