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Who Opts In?

Abstract

Payments and discounts incentivize participation in many transactions about which people know little, but can learn more - payments 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 increasing participation payments disproportionately attracts individuals for whom learning about the transaction is harder. These participants decide based on worse information and are more likely to regret their decision ex post. The learning-based selection effect is stronger when information acquisition is more costly. Moreover, it outweighs selection on risk preferences in many of our treatments.

JEL-Codes: D010.

Keywords: rational inattention, incentives, risk preferences, selection effects, cognitive ability.

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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 consumer offered a teaser-rate on a credit card may ponder how she will use it; a purchaser of a product may investigate its quality; a job candidate may seek information about the work culture of the firm and the city in which it is located; and a potential participant in a clinical trial may contemplate its possible effects. 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, resulting in selection effects. In this paper, we answer three questions. 1. Who opts in when given incentives to participate in a transaction? 2. How do incentives change the quality of participation decisions? 3. What aspects of transactions determine the strength of the first two effects?

We show that stronger incentives to participate disproportionately increase take-up by individuals for whom learning is hard. Those individuals make less-informed decisions and are thus more likely to experience ex post regret. These effects are 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 magnitude of selection on learning costs can be large: in many of our conditions, it substantially exceeds selection on risk preferences.

Our findings reveal a new selection mechanism through which incentives affect outcomes. The effect is relevant in any transaction in which an individual makes or accepts a payment in exchange for an outcome with uncertain yet learnable consequences. It is of particular relevance when the provider of the incentive cares about the types of agents who participate or about the likelihood of ex post regret. Consider, for instance, the decision of whether to accept a job offer in a new city. Our findings imply that a higher signing bonus leads to a selection of less-informed decision makers who are more likely to regret their choice ex post and seek alternative opportunities, thus leading to higher employee turnover. In the context of consumer choice, consider a take-it-or-leave-it offer to buy a good whose quality can only be learned through costly inspection, such as a credit card with shrouded fees. A lower teaser rate raises the fraction of poorly informed individuals amongst those who take up the card, and these individuals may use the card differently from those with a lower cost of learning. Finally, our results inform the discussion surrounding participation payments in markets subject to ethical constraints, such as those for donated organs or clinical trial participation (Roth, 2007), as explained below.[1]

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 costlier—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 incentives. 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 *ex post* regret 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 three reasons. First, they rely on sophisticated information choice behavior. 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 incentives (Pinkovskiy, 2009; Cheremukhin, Popova and Tutino, 2015; Bartoš, Bauer, Chytilová and Matějka, 2016; Ambuehl, 2017; Dean and Neligh, 2017). Third, an empirical examination allows us to assess the magnitude of selection on information costs, which we benchmark against the magnitude selection on risk preferences.

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 *ex post* regret.

[1] Additional examples include the following. 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. In the context of firm strategy, 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 regret their purchase *ex post*. Hence, the monopolist may want to choose a higher price to avoid negative word-of-mouth reports or critical online reviews.

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. Hence, as in the model, subjects know the payment amount, but face uncertainty about the downside of this transaction. After learning the payment amount, but before deciding whether to participate in the transaction, subjects can reduce uncertainty by examining hard-to-process information about whether they will face a net gain or a net loss from participation. Subjects are shown a list of 60 solved addition problems, such as *23 + 45 = 68*. For gambles with a net gain, 35 of the additions 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, we vary information costs experimentally by changing the total number of addition problems in the list while 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, we measure each individual's information acquisition cost for the experimental task we employ, allowing us to directly observe selection of individuals into the transaction in an across-subjects analysis, and to compare the magnitude of that selection to selection on traits such as risk preferences. Third, we test whether the predicted comparative statics also apply for measures that are frequently available in real-world settings—such as cognitive ability 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. Depending on treatment, a €4 increase in the incentive leads to an increase in our direct measure of information costs by 4.9 percentile points amongst subjects who select into the transaction, for instance, and to a decrease in average cognitive ability by 2.4 percentile points. Moreover, averaged across conditions, a subject with the lowest level of cognitive ability is 18 percentage points more likely to regret their own decision to participate in the transaction *ex post* than a subject with the highest level of cognitive ability, as well as 17.2 percentage points more likely to *ex post* regret non-participation. Finally, selection effects are stronger when the list of addition problems is longer, indicating that differences across people become magnified for transactions of which 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.

To benchmark the extent of selection on information costs, we compare it to selection based on risk preferences. Whenever information acquisition is possible, we find that selection on information costs is pronounced, while selection on risk preferences is virtually zero. We observe selection on risk preferences only in the complete absence of information acquisition, in which case it is comparable in magnitude to selection on information costs when information is available.

There are alternative mechanisms that can generate selection effects related to information (detailed in Section 2), 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 neither systematic selection based on persistent personality characteristics such as cognitive ability, nor systematic differences in the magnitude of the selection effect across contexts.[2] 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, London, Volpp and Loewenstein, 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, inherent in many economic transactions, that arises from endogenous information acquisition. The mechanism is related to that of Ambuehl (2017), which studies how participation incentives affect optimal information acquisition. More generally, we add to an emerging literature that explores the informational foundations of individual-level economic choice (Azfar, 1999; Woodford, 2012a,b; Steiner and Stewart, 2016; Steiner, Stewart and Matějka, 2017; Dean, Kıbrıs and Masatlioglu, 2017; Gabaix and Laibson, 2017; Kőszegi and Matějka, 2017), as well as to an experimental literature studying complexity in economic choice (Kalaycı and Serra-Garcia, 2016; Abeler and Jäger, 2015; Carvalho and Silverman, 2017).

Second, by exploring how the effects of participation payments vary with personality characteristics, we contribute to the literature on personality psychology and economics (Almlund, Duckworth, Heckman and Kautz, 2011; Fréchette, Schotter and Trevino, 2017), specifically, traits related to motivation and cognitive ability (Benjamin, Brown and Shapiro, 2013; Segal, 2012; Dohmen, Falk, Huffman and Sunde, 2010; Borghans, Meijers and Ter Weel, 2008; Burks, Carpenter, Goette and Rustichini,

[2] Moreover, selection in this alternative model relies on the absence of information acquisition. Appendix A.4 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.

2009; Agarwal and Mazumder, 2013). Our finding that selection on risk preferences depends on the extent to which information acquisition is endogenous potentially contributes to explaining the varying magnitude of the correlation between experimentally measured risk attitudes and risky behaviors in the field (see, for instance, Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011; Andreoni and Kuhn, 2018).

Third, we contribute to the burgeoning literature on the moral constraints on markets (Kahneman, Knetsch and Thaler, 1986; Basu, 2003, 2007; Roth, 2007; Leider and Roth, 2010; Ambuehl, Niederle and Roth, 2015; Elias, Lacetera and Macis, 2015a,b; Ambuehl, 2017; Ambuehl and Ockenfels, 2017; Clemens, 2017; Exley and Kessler, 2017; Elias, Lacetera and Macis, 2019). Around the world, the principles of informed consent (DHEW 1978, The Belmont Report; Faden, Beauchamp, 1986) are fundamental to regulations concerning human research participation, as well as to transactions such as human egg donation, organ donation, and gestational surrogacy. 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.[3] While we take no normative stance, our results show that payments for participation can be in conflict with participants' understanding about the consequences of participation. They further show that the severity of this conflict grows with respect to both the amount of the payment and the difficulty of acquiring and processing information about the consequences of the transaction.[4]

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

2 Theoretical Predictions

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

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

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

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

unknown state of the world $s \in \{G, B\}$. The state is good ($s = G$) with prior probability μ, and bad ($s = B$) with 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 choice problem nontrivial for the agent.

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

In the model, there is a fixed set of possible signal realizations (containing at least two elements), and the agent chooses the distribution of signals in each state of the world. As in much of the rational inattention literature, we assume that cost of information is proportional to the expected reduction in the Shannon entropy of the agent's belief about the state from observing the signal. The use of information costs proportional to the reduction in entropy 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 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).[6] Under this interpretation, the cost of information is based 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 $\gamma_{\text{abst}} :=$

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

[6] The intuition for this result is as follows. Upon observing a signal realization from an information structure, the agent updates her beliefs about the state of the world. Given the posterior beliefs, she selects an action. Accordingly, each signal realization from a given information structure induces an action. Since the signal realizations depend on the state of the world, a given information structure thus induces a state-dependent probability distribution over actions. Conducting this exercise for all information structures then shows that choice of information structure amounts to choosing the probability of participation in each state.

$\mu(1-p_G)/\big(\mu(1-p_G)+(1-\mu)(1-p_B)\big)$ 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. 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 function*.

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. 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 (2017) shows that optimal sequential learning is behaviorally equivalent to optimal choice in a rational inattention problem with binary states.[7]

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, 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

[7] Hébert and Woodford (2017) identifies a related connection.

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

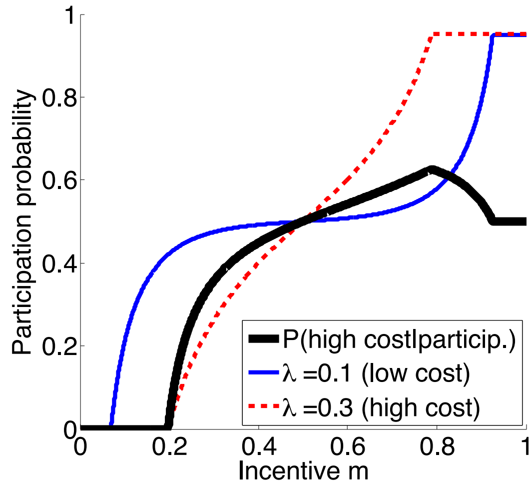


Figure 1: Supply curves predicted by the model with $\pi_G = 0$, $\pi_B = -1$ and $\mu = 0.5$. The proportion of high-cost participants is increasing up to the point at which the high-cost type participates with probability 1.

The following proposition shows that these observations hold for general parameter values.

Proposition 1.

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

$$\frac{\partial}{\partial \lambda}\left[\frac{\partial p(m, \lambda)}{\partial m}\right] > 0.$$

(ii) 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* $f : \mathbb{R} \longrightarrow \mathbb{R}$, $E[f(\lambda) \mid participate]$ *is increasing in* m.

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 (i) of the proposition says that this effect is stronger for higher cost types. The selection result in part (ii) relates to applications more directly, showing that the composition of the pool of participants shifts toward types with higher costs as the payment increases.[8]

[8]Equivalently, part (ii) shows that an increase in the payment m leads to a first-order stochastic dominance increase in the cost parameters of those agents who elect to participate.

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. The proofs of each part, which may be found in Appendix A, make use of the characterization of optimal choice behavior in Matějka and McKay (2015). In our model, their characterization leads to an explicit expression for the participation probability, which we can differentiate and sign. Part (ii) requires additional steps to handle the full distribution of types as well as the level effect noted above.

To gain some intuition for the result, consider the effect of marginal changes in the payment m on types that differ in the value of their information cost parameters. For types with very low cost, an increase in the payment has little effect: the agent obtains a precise signal, which makes her very likely to participate in the good state and abstain in the bad state. For types with very high cost, the decision to participate is necessarily based on limited information, making the agent responsive to changes in the payment. Similarly, intermediate types obtain partial information, leaving them somewhat responsive to changes in the payment, though less so than high-cost types. This intuition, though simple, neglects a crucial feature of the model: the probability of participation changes only if—and to the extent that—the agent changes her choice of information. It is this choice that responds to the change in payment m. 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. By choosing her information accordingly, she increases her probability of participating in both states, with a larger effect when information is less precise (and hence for higher cost types).

The next proposition shows that higher cost types will make less well-informed decisions, and are thus more likely to regret their choices *ex post*. Let $\gamma^*_{\text{part}}(\lambda, m)$ and $\gamma^*_{\text{abst}}(\lambda, m)$ denote, for type λ, 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 regret.

Proposition 2. *Suppose λ and m are such that $0 < p(m, \lambda) < 1$. Then, $\frac{\partial}{\partial \lambda}\gamma^*_{\text{part}}(\lambda, m) < 0$ and $\frac{\partial}{\partial \lambda}\gamma^*_{\text{abst}}(\lambda, m) > 0$.*

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 this result is straightforward. Whenever information is more expensive to acquire and process, it is optimal, *ceteris paribus*, to acquire and process less of it.

The magnitude of the effects identified in Proposition 1 depend on the context and, in particular, the difficulty of the information acquisition problem. The following result identifies a sense in which the magnitudes are larger in more opaque contexts (where acquiring information is more difficult for all types). More precisely, as we scale up the cost of information by some factor, the cross derivative of the participation probability with respect to m and λ increases.

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

$$\left.\frac{\partial}{\partial a}\right|_{a=1}\left[\frac{\partial}{\partial m}\frac{\partial}{\partial \lambda}\, p(m, a\lambda)\right] > 0.$$

A restatement of this result illuminates the intuition: individual differences lead to less pronouncedly different 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.

Robustness. Our results are robust to various extensions.

Risk aversion. Our model is presented based on the assumption of risk neutrality. A careful inspection of the proofs shows that they generalize to the case of agents who share the same nonlinear utility function u for money that is additively separable from the cost of information acquisition, so that the agent's expected utility is now given by $U(p_G, p_B; m) = \mu p_G u(\pi_G + m) + (1-\mu) p_B u(\pi_B + m) - \lambda \cdot c(p_G, 1 - p_B)$. If, however, risk preferences are heterogeneous and correlated with information cost, their presence could either reinforce or countervail our results. The direction and magnitude of such effects depend on the correlation between risk preferences and cost of information acquisition, thus warranting an empirical investigation of our predicted comparative statics.

Heterogeneous priors. Our results are also 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.[9]

[9]This statement concerns the case in which some subjects truly face different priors than others (for instance, due to idiosyncratic variation in risk), not the case of misperceptions about the data generating process. Appendix A.4 proves the result formally.

Robustness to alternative cost functions. Within the class of rational inattention models, simulations show that our results also apply for a variety of cost functions other than Shannon. We have found no counterexamples for any cost function that is separable in posterior beliefs, such as Tsallis entropy, or the expected waiting time in the Wald (1947) sequential information acquisition problem. For the class of Renyi-entropy cost functions, however, we have found isolated deviations.

Alternative interpretation. We have hitherto interpreted our setting as one with a known incentive payment and uncertain utility consequences of participation. Other interpretations are possible. 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 characterization 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.

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.

Consider, for instance, a model in which agents costlessly observe a normally distributed signal whose mean depends on the state of the world and whose precision varies across individuals. 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 incentive 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.2.1). 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. Consistent with this 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, see Appendix B.2.2).

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 *ex-post* regret is independent of the incentive.

3 Experiment design

We now study empirically whether higher participation incentives lead to a disproportionate selection of participants for whom learning is more difficult, and whether such individuals make less-informed decisions. In light of the sophisticated information choice behavior underlying our model, it is far from obvious that our predictions will describe empirical behavior. An empirical examination, moreover, allows us to gauge the magnitude of selection on information costs in comparison to other selection effects.

A central element of our experimental design consists in testing the contextual robustness of our comparative statics using multiple sources of variation in information costs. On the one hand, experimental variation in information costs, by design, allows for a direct test of the theoretical predictions while excluding all other factors that could affect behavior (such as risk preferences). On the other hand, measures such as cognitive ability and educational background show that our results apply for the kind of proxies for ease of learning that are more likely available in applied settings. Documenting our results for the collection of measures rather than a single isolated measure that maximizes a narrowly defined objective increases our confidence in the overall validity and relevance of our findings.

Our tests focus on the comparative statics of our model rather than its primitives, for two reasons. First, it is the comparative statics rather than the primitives that are of substantive interest for applications. Second, our predictions are not unique to our model, as argued in Section 2. By implication, our experiment does not permit inference about model primitives, such as the form of the information cost function.

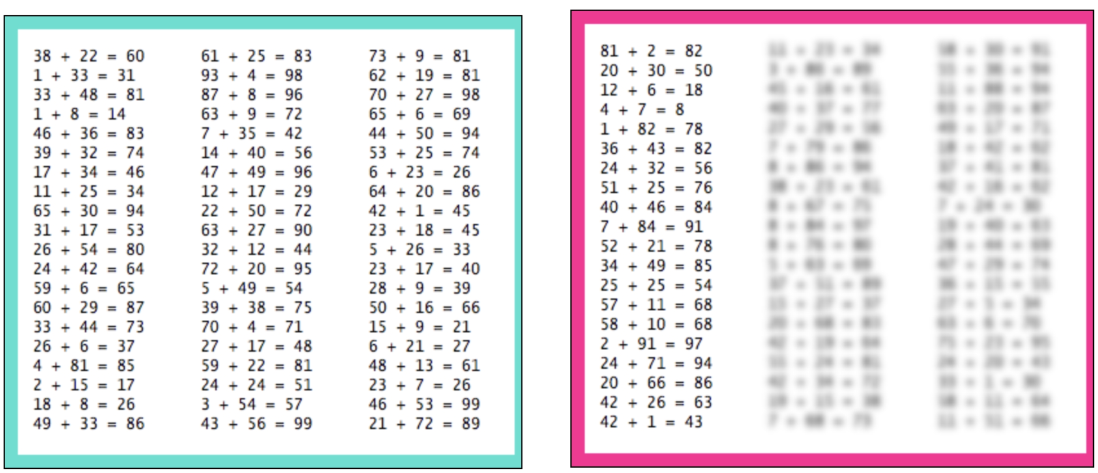
Task Subjects decide whether to take a gamble in which they receive π_G if the state is good, or π_B if the state is bad. In exchange for taking the gamble, they receive a payment m, regardless of whether they win or lose—but only if they take it. The prior probabilities of the states are 50/50. Before deciding whether to take the gamble, but after learning the value of 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.

This task is suitable for testing the effects of participation incentives on selection and decision quality as it satisfies the following three criteria.

First, it affords subjects a large opportunity set of state-dependent stochastic choice probabilities. 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. The more calculations a subject checks, for instance, the better is her information about the state of the world. Importantly, subjects can also *skew* their information acquisition. One way to do so consists in searching more intensely if the initial calculations they have checked suggest they would lose rather than win, similar to a researcher scrutinizing criticisms of her work but readily accepting praise. Doing so will raise the subject's probability of accepting the gamble in both the good and the bad state. There are many alternative approaches through which subjects may shape their information acquisition. For example, they may choose how carefully to check any given addition, and which ones to check (perhaps attempting to check easier ones first). The information cost subjects incur depends on the approach they take.

Second, our task allows us to experimentally vary the cost of information acquisition. We do so by varying the number of calculations in a list. By increasing the list length, and keeping the fraction of correct / incorrect calculations approximately constant, we ensure that checking any given calculation reveals less information about the state, thus 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. This generates natural variation in information acquisition costs. We measure this variation directly by eliciting subjects' reservation price to check a given number of calculations, by eliciting information about their choices and performance in school, and by testing their cognitive ability.



(A) (B)

Figure 2: Panel A depicts the presentation of information about the state of the world in the main treatments (60 calculations). Panel B depicts the presentation for the *fixed information* treatment; in this treatment, subjects are explicitly told the number of correct and incorrect calculations in the visible part of the picture, but the state of the world is likewise determined by all 60 calculations.

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.) Note that for

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

Our three *information cost* treatments vary the level of difficulty for information acquisition. The *low-cost* treatment has 25 addition problems, of which 60% are correct (incorrect) in the good (bad) state; the *medium-cost* treatment has 60 addition problems, of which 58.3% 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 *fixed information* treatment is an important control that effectively eliminates the possibility of endogenous information acquisition. It thus allows us to determine the extent to which our results are driven by factors other than information choice, such as different people drawing different conclusions from the same set of stochastic information.[11] Specifically, subjects are shown a picture similar to that in the medium cost treatment, but only a portion of it is visible, with the rest heavily blurred, while the state is still determined by the entire set of calculations, as shown in panel B of Figure 2. This places an upper limit on the amount of information a subject can acquire. A line of text above the picture explicitly informs the subject how many correct and incorrect calculations the visible part contains. For any subject who pays attention to these numbers, this places a lower limit on the amount of information a subject obtains. 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. The associated Bayesian posterior beliefs are $P(s = good|11 \text{ correct}, 9 \text{ incorrect}) = 72.6\%$ and $P(s = good|13 \text{ correct}, 7 \text{ incorrect}) = 94.9\%$.

Each subject participates in 18 rounds of decision making that cover all treatments in individually randomized order, as summarized in Table 1.[12] 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. Subjects know that their earnings are determined by at most one randomly selected round.

After each of the 18 rounds, subjects indicate their subjective 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

[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.

[11] It is conceivable, for instance, that more mathematically inclined people would deviate from Bayesian updating to a lesser extent.

[12] We employ a within-subject design for two reasons. First, some of our regressions employ specific decisions (such as choices in the fixed information treatment, or individual risk preferences) as statistical control variables for other decisions (such as choices in the information cost treatment), which requires each subject to make all these decisions. Second, our study is adequately powered with just over 10,000 observations from 18 decisions by each of 584 individuals. An across-subjects design with comparable statistical power would require thousands of participants.

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.[13]

Information Condition	Information Cost			Fixed Information
Number of calculations in picture	25	60	100	20 visible
Participation payment				
€ 2	2	2	2	2
€ 6	1	1	1	2
€ 10	1	1	1	2

Table 1: Type and number of decisions taken by each subject. All treatments were displayed in individually randomized order. States were drawn independently and pictures were generated randomly for each individual. For the fixed information condition, the visible part of the picture contained either 11 or 13 majority type (correct or incorrect) solutions, and 9 or 7 of the minority type.

Individual measures After subjects complete the first part of the experiment, we elicit four individual-level characteristics on which participation incentives may lead to selection effects.

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.[14]

Cognitive ability. Second, we measure cognitive ability, which has been shown to predict various life outcomes (see, e.g., Duckworth, Quinn, Lynam, Loeber and Stouthamer-Loeber, 2011). It thus represents a persistent trait on which selection may be of direct interest in applications. We use

[13]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.

[14]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. Our first prediction, for instance, maintains that subjects with higher information acquisition costs will respond more strongly to the payment for taking the gamble. Accordingly, we predict a *positive* relationship between reservation prices for checking calculations and responsiveness to participation payments. If income effects were dominant, we would expect the opposite: If our hypothesis is true, then someone who has paid more attention in the main part of the experiment will be less responsive to participation payments, and will expect a higher payment from that stage. Income effects predict a lower marginal utility of money for such a person. This would reveal itself in a higher reservation price for checking a given number of calculations. Accordingly one would expect an attenuated, or even a *negative* relationship between reservation prices for checking calculations and responsiveness to incentive payments.

series I and the first 24 matrices of series II of Raven's Advanced Progressive Matrices (Raven, Raven and Court, 1962). We expect this standard measure of cognitive ability to be related to the cost of information acquisition in our decision tasks, as it is indicative of abilities like concentration and short-term memory. We expect a weaker association, however, because this measure is less directly related to the experimental task than the elicitation of reservation prices for checking calculations.

Previous research has shown that measures of cognitive ability are predictive of different outcomes depending on whether subjects are incentivized for performance (Segal, 2012; Duckworth et al., 2011; Borghans et al., 2008; Dessi and Rustichini, 2015). To explore this dependency, we perform two separate treatments. The *unincentivized IQ* condition corresponds to the fashion in which this test is normally administered: subjects are not given 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,w *Win* €X *with chance* p *and lose* €Y *with chance* $1 - p$ versus *win / lose* €Z *with certainty.* The structure of these decisions is the same as in our main treatments in which subjects also decide between a gamble and a certain payment. The lotteries we present are win 2 / lose 10, win 6 / lose 6, and win 10 / lose 2 with winning probabilities $p \in \{0.5, 0.75, 0.9\}$, resulting in a total of 9 lists. On each list, the certain option varies from *lose €10 with certainty* to *win €10 with certainty* in steps of €1.[15] Subjects' payment is determined by a risk preference elicitation question with a 20% probability (10% probability in case cognitive ability elicitation is also incentivized).

Educational background. Fourth, we elicit information about subjects' educational background in mathematics and 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 mathematics and German literature, we elicit high school grades, as well as whether an honors class was taken in that subject. Additionally, we elicit whether subjects are currently enrolled in a STEM college major.[16]

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

[15] Subjects have to make an active choice on each line of each price list. We enforce single switching.

[16] We elicit subjects' current 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, some of which are relevant, and many that are presumably irrelevant to our task, we have no *ex-ante* expectation.

instructions on screen, and may keep reviewing them until they pass a comprehension check that allows them to proceed to the decision making part.[17] 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.[18] 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.4 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 willingness to accept to solve additional calculations, determine a subjects' payment. All gains are added to a budget of €15 and all losses are deducted. Our random incentive mechanism is incentive compatible, and accordingly we repeatedly exhort the subjects to "make every decision as if it is the one that counts—because it might."

4 Experiment results

We ran the experiment with a total of 584 student subjects across 19 sessions in May and July 2017 at the University of Cologne's Laboratory for Economic Research.[19] Subjects were permitted to leave as soon as they were done, irrespective of other subjects' progress. On average, subjects spent about one and a half hours on the experiment. The median time subjects spent inspecting each picture is 74 seconds. On average, subjects received a total payment of €18.70.[20] Table 2 presents an overview of our data. Each subject provides us with 18 observations, leading to 7,008 observations across the Information Cost conditions and 3,504 observations in the Fixed 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 Fixed Information condition. Given the limits on information acquisition in that condition, we would expect such behavior from risk averse individuals.[21]

The experiment includes three different levels of information costs. In order to run simple interactions (as opposed to using dummy variables for each cost level), we assign a cardinal value to each

[17] 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.

[18] Hence, in the €2 incentive treatment, for instance, subjects would decide whether they want to participate in a win €2/ lose €10 gamble.

[19] We had 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. Before conducting any of the laboratory sessions, we first conducted two pilot studies on Amazon Mechanical Turk with largely similar results, which are available from the authors by request.

[20] Appendix C.2 analyzes order effects.

[21] This is in addition to the fact that each subject makes a larger number of decisions in the Information Cost conditions than in the Fixed Information condition, which mechanically raises the number of subjects who refuse every offer in the Fixed Information condition as opposed to the Information Cost condition.

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

Table 2: Data overview. Each subject participated in each treatment, in random order. One subject chose to never bet in either condition.

treatment. For simplicity, we weigh each cost condition equally, and thus assign cost indices 1, 2, and 3 to pictures with 25, 60, and 100 calculations, respectively. To show comparisons that are independent of this assignment, we also display estimated coefficients involving comparisons between only two cost levels. To ensure our results do not depend on random realizations of the state that happened to occur in the experiment, we run weighted regressions such that the weighted fraction of decisions for which the state is good *exactly* equals the prior of 50% in each relevant cell.[22] Additionally, we include order and session fixed effects in all analyses.

In Sections 4.1, 4.2, and 4.3, we study the empirical evidence for our three predictions, beginning with selection. We first focus on experimentally induced variation in information costs, as well as reservation prices for checking additional calculations as measures of individual-specific information costs, since they directly map to our theoretical predictions. Next, Section 4.4 repeats the analyses using educational background and measures of cognitive ability as alternative measures of individual-specific information costs. We test the joint hypothesis consisting of our predicted comparative statics along with the assumption that a stronger mathematics background, or higher cognitive ability, respectively, are related to lower information costs. Finally, Section 4.5 studies the role of selection based on risk preferences and compares it to the role of selection based on information cost.

4.1 Selection based on information costs

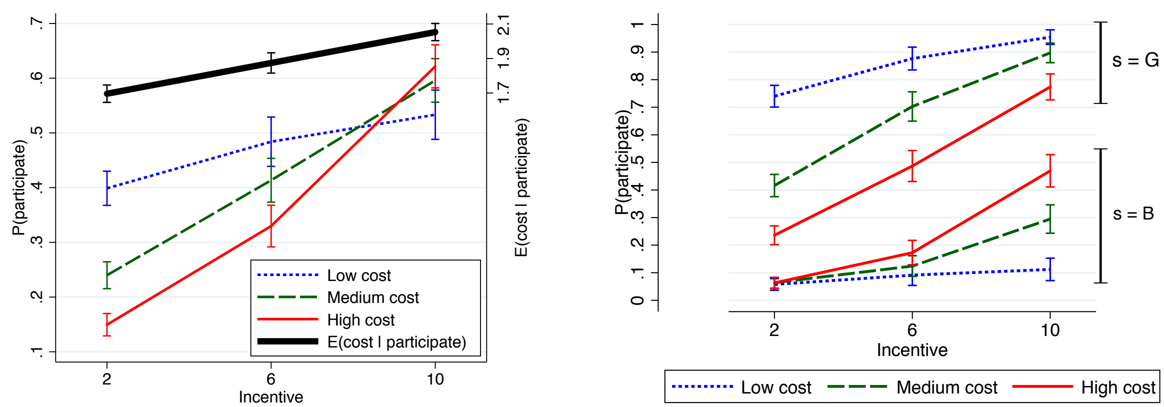
We begin by testing whether higher payments for participation in the transaction lead to selection toward participants with higher information acquisition costs, as predicted by Proposition 1. We find robust evidence that they do, both using experimentally induced variation in information costs, as well as using subjects' reservation prices for checking additional calculations.

Experimental variation in information acquisition costs The solid bold line in Panel A of Figure 3 shows how the composition of information costs changes among subjects who accept the gamble as the payment increases from €2 to €10. It displays the average information cost conditional on the subject accepting the gamble, assigning cardinal values 1, 2, and 3 to represent the low-,

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

medium-, and high-cost treatments, respectively. The slope of that curve is positive. The average information cost amongst subjects who choose to take the gamble is 1.7 for the low-incentive condition and increases to 2.05 in the high-incentive condition. Hence, as the participation payment increases, a subject who decides to participate in the gamble is more likely to come from a treatment in which information acquisition is more difficult. This is consistent with our main prediction. Additionally, the graph displays the supply curves for each cost level in our three Information Cost treatments, with the payment displayed on the horizontal axis. The supply curve is steeper in the higher cost treatments, consistent with part (i) of Proposition 1. It increases from 40% to just under 55% in the low-cost treatment, and from 15% to over 60% in the high-cost treatment. Hence, 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.[23]

Panel B shows that the result is consistent with the intuition outlined in Section 2. It displays the probabilities that a subject accepts the gamble separately for each state. 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 in each information cost condition, a higher participation incentive leads to an increase in the false positive probability and to a decrease in the false negative probability. Importantly, this change is larger in magnitude for higher information costs, leading to a more pronounced supply response in these conditions.



A. Supply curves and selection.

B. State-dependent participation.

Figure 3: Supply curves and state-dependent participation by information cost. Colored lines in Panel A display unconditional participation probabilities. Colored lines in Panel B display participation probabilities conditional on the state. The black line in Panel A displays information acquisition costs conditional on participation. For the latter statistic, low, medium, and high information costs are encoded as 1, 2, 3, respectively.

[23]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.

For the formal econometric analysis, let $m_{i,t} \in \{1, 2, 3\}$ denote the payment index of subject i's decision in round t, let $a_{i,t}$ denote the corresponding information cost index, and let $X_{i,t}$ denote a vector of control variables consisting of session and order fixed effects.[24] We estimate the following specification *on the sample of observations in which subjects take the gamble* using OLS with standard errors clustered at the subject level:

$$a_{i,t} = \beta_0 + \beta_1 m_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}. \tag{2}$$

Column 1 of Table 3 presents the estimated coefficient. It shows that an increase in the incentive by €4 increases the average cost index amongst subjects who decide to take the gamble by a highly statistically significant 0.185 units.

To check that these results do not depend on our choice of information-cost index, each of the bottom two rows of the table perform the same analysis including only two information cost treatments; in both cases, the results remain qualitatively unchanged. The estimated magnitudes are smaller when only two information cost treatments are included for the mechanical reason that the maximal possible difference between information cost indices is only half of the maximal difference when all information cost treatments are included.

To show 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 use two approaches. First, observe that for any risk-averse individual, the prior-optimal action is to refuse the gamble at both participation incentives €2 and €6. Accordingly, the fourth from the bottom of column 1 estimates the effect of an increase in the participation incentive including only observations with participation incentive €2 or €6. The third row from the bottom only uses observations with participation incentive €6 or €10. The estimated coefficients are highly similar to each other.

Our second approach is to use observations from the risk preference elicitation stage. Embedded in that stage, each subject decided whether to accept a 50/50 win €2 / lose €10 gamble, a 50/50 win €6 / lose €6 gamble, as well as a 50/50 win €10 / lose €2 gamble. These are precisely the lotteries a subject faces in the low, medium, and high incentive conditions if she makes a participation decision based on her prior alone. We find that 18.2%, 44.9%, and 87.5% of subjects accepted those gambles, respectively.

In column 2, we estimate model (2) including only observations for which choices in the risk elicitation stage indicate that a change in the participation incentive does not induce a change in the prior-optimal choice. Specifically, we only include observations for which one of the following two conditions hold. Either the participation incentive is €2 or €6, and the subject either refused or accepted both the 50/50 win €2 / lose €10 gamble and the 50/50 win €6 / lose €6 gamble. Or, the

[24]The order t_i of round t for subject i counts the number of decisions the subject has made up to and including the current decision. It takes on an integer value between 1 and 18; thus we include 17 order fixed effects.

participation incentive is either €2 or €6, and the subject either refused or accepted both the 50/50 win €2 / lose €10 gamble and the 50/50 win €6 / lose €6 gamble.

The estimated coefficient of the effect of an increase in the participation incentive on selection remains quantitatively similar, although it is slightly attenuated. The effect of increasing the participation incentive by €4 starting from €2 is comparable to that when starting from €6. The effect is stronger when comparing the medium-cost condition to the low-cost condition than when comparing the medium-cost condition to the high-cost condition.

We conclude that the observed behavioral response to an increase in incentives does not merely reflect a change in the prior-optimal action, but that the results are rather driven by changes in information acquisition.

As argued in Section 2, a change in information costs alters the supply response due to both a level effect and a slope effect, which may reinforce or countervail each other. To demonstrate that our results are, to a substantial extent, due to the slope effect, column 3 of Table 3 presents estimates of the slopes of the supply curves. They are based on the following linear probability model in which we regress an indicator of whether the subject takes the gamble on the payment amount, on the information cost index, and on the interaction between the two.

Specifically, letting $b_{i,t} = 1$ if subject i accepts the bet in round t, and 0 otherwise, we estimate

$$b_{i,t} = \beta_0 + \beta_1 a_{i,t} + \beta_2 m_{i,t} + \beta_3 \cdot a_{i,t} \cdot m_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}$$

using OLS with standard errors clustered at the subject level.

The hypothesis that higher information costs induce a more pronounced supply response to variations in the incentive payment implies that the coefficient on the interaction term should be positive. Indeed, as column 3 shows, the estimated coefficient is positive and highly statistically significant. As column 4 shows, this result continues to hold if we include only observations for which the change in the incentive does not affect the prior-optimal choice, defined in the same fashion as for column 2. The estimated coefficient magnitude remains similar and highly statistically significant.

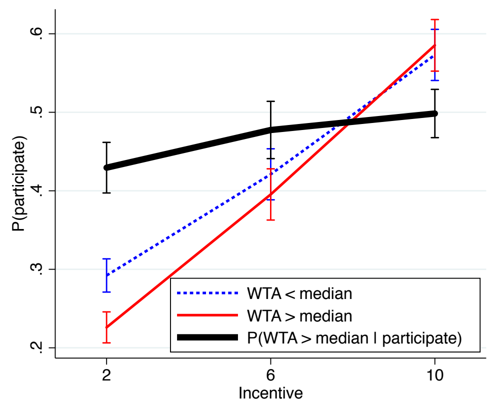
The bottom four rows perform these regressions using only two incentive levels or only two cost conditions, respectively. If all observations are included (column 3), the significantly positive effect remains on each subsample. If only observations without a change in the prior-optimal choice are included (column 4), the effect arises when comparing the medium-cost and high-cost conditions, but not when comparing the medium-cost and low-cost conditions.

Finally, columns 5 and 6 estimate model (3) separately on the set of observations for which $s = G$ and $s = B$, respectively. The coefficient on the interaction term, β_3, is statistically significantly positive. The higher the information costs, the faster the decrease in false negatives caused by a higher participation incentive (decisions in which the subject refuses the gamble even though she

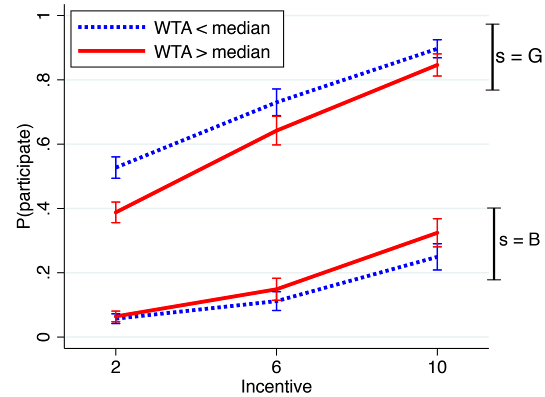
	(1)	(2)	(3)	(4)	(5)	(6)
	Selection		**Supply curves**		**State-dep. particip.**	
Dependent variable	Info. Cost Index		Bet taken		Bet taken	
Inclusion criterion						
Bet taken	Yes	Yes				
Unchanged prior-optimal choice		Yes		Yes		
State					$s = G$	$s = B$
Payment index	0.185***	0.150***	0.001	-0.002	0.067***	-0.058***
	(0.015)	(0.030)	(0.019)	(0.028)	(0.019)	(0.016)
Information cost index			-0.127***	-0.128***	-0.246***	-0.007
			(0.009)	(0.011)	(0.012)	(0.007)
Payment index × info. cost index			0.080***	0.074***	0.072***	0.084***
			(0.008)	(0.011)	(0.009)	(0.009)
Observations	2,645	1,831	7,008	4,992	3,520	3,488
Subjects	578	537	584	565	584	584
Subsamples	Coeff. on payment		Coeff. on interaction		Coeff. on interaction	
Only €2 and €6 payments	0.187***	0.162***	0.042**	0.038	0.046**	0.035**
	(0.031)	(0.046)	(0.015)	(0.042)	(0.020)	(0.015)
Only €6 and €10 payments	0.188***	0.140***	0.125***	-0.062	0.102***	0.140***
	(0.029)	(0.038)	(0.020)	(0.055)	(0.021)	(0.022)
Only small and medium picture	0.077***	0.083***	0.106***	-0.056	0.122***	0.086***
	(0.010)	(0.021)	(0.017)	(0.039)	(0.017)	(0.016)
Only medium and large picture	0.062***	0.032	0.054***	0.116**	0.025	0.083***
	(0.011)	(0.023)	(0.015)	(0.050)	(0.019)	(0.018)

Table 3: Selection effects due to participation incentives by experimental variation in cost of information acquisition. *Information Cost Index* is encoded as 1, 2, and 3 for the low, medium, and high cost treatments, respectively. *Bet Taken* is an indicator variable (values 1 and 0) for whether the subject took the bet. *Payment Index* is encoded as 1, 2, 3 for incentive amounts € 2, 6, 10, respectively. This assignment is without loss of generality when only two information cost treatments are included, as is the case in the bottom two rows. Each column presents the estimates from a separate regression, includes session and order fixed effects, and is weighted as detailed in footnote 22. Each coefficient in the bottom four rows of the table corresponds to a separate regression on the specified subsample. All standard errors are clustered at the subject level. Numbers in parentheses represent standard errors of the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

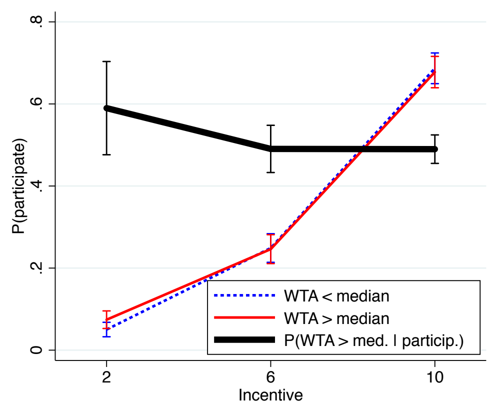
would have won, column 5), and the faster the increase in false negatives (decisions in which the subject accepts the gamble even though she will lose, column 6).



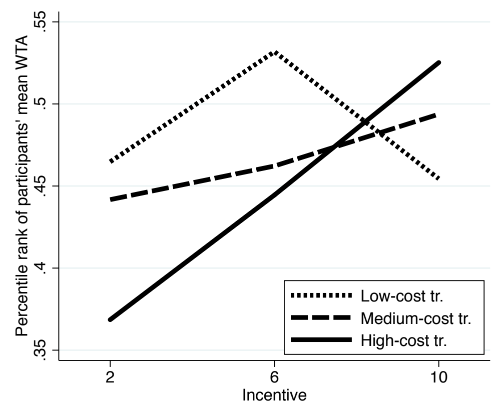
A. Supply curves and selection.



B. State-dependent participation.



C. Supply curves and selection in the Fixed Information treatment.



D. Selection on reservation prices by experimentally induced information cost.

Figure 4: Supply curves and selection by WTA (willingness to accept) to check additional calculations. In Panels A, B, and C, subjects are classified as below-median or above-median WTA. Panel D shows the average percentile rank in WTA of subjects who select into the gamble. Whiskers indicate 95% confidence intervals.

Elicited variation in information acquisition cost We now examine whether selection effects arise using naturally occurring rather than experimentally induced variation in information acquisition costs. Specifically, we study selection on reservation prices for checking a given number of calculations as a measure of information costs.[25] Our tests provide information beyond what can be inferred from the previous analysis on experimentally induced cost variation because reservation prices may

[25] 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.

be correlated with other individual characteristics that might influence the predicted selection effects, such as risk aversion.

We find that higher participation incentives lead to a selection into the transaction on this measure of information costs, as panel A of Figure 4 shows. It groups subjects into two halves by their elicited reservation price—those who more strongly dislike checking addition problems (above-median reservation price) and those who are less averse to it (below-median reservation price). The black line shows that higher participation incentives increase the fraction of high-cost types amongst those who elect to participate, as predicted (averaged across information cost treatments). Moreover, the supply curve is steeper for the half of subjects with higher reservation prices, as predicted in part (i) of Proposition 1. Panel B shows that the steeper supply curve for high-cost subjects is due to their more pronounced response in both false positives and false negatives as the incentive increases, consistent with the intuition outlined in Section 2.

Formally, we estimate model (2), but we replace the experimentally induced information cost $a_{i,t}$ with the percentile rank of an individual's mean reservation price across the four elicitations. In addition to session and order fixed effects, the vector of control variables $X_{i,t}$ now also includes fixed effects for the experimentally induced information costs $a_{i,t}$.

Column 1 of Table 4 displays the results. It shows that an increase in the payment m by €4 increases the mean reservation price amongst those who select into the bet by 2.3 percentile points. While the current analysis averages across information cost treatments, Section 4.3 shows that the effects are more pronounced in the high-cost treatments. The bottom two rows show that this selection effect arises to a greater extent when increasing the participation incentive from €2 to €6 than when increasing it from €6 to €10. Column 2 replicates the analysis on the subsample of observations for which a change in the incentive does not lead to a change in the prior-optimal choice. The resulting coefficient estimate is essentially unchanged.

Because we measure rather than induce variation in reservation prices for checking calculations, it is conceivable that our effects arise not because different individuals acquire systematically different information, but merely because reservation prices for checking calculations happen to be correlated with some other personality characteristic, such as risk aversion. If so, we should observe a similar selection effect in the fixed information treatments, in which subjects have no choice about what information to acquire.[26] Panel C of Figure 4 shows data from the fixed information treatment, regarding both the change in composition of subjects as a function of the payment m, as well as the supply curves of the two groups. If anything, the selection effect now has the opposite sign, and the supply curves lie virtually on top of each other. Hence, with flexible information acquisition, the

[26] Individuals with low reservation prices for checking additional calculations, for instance, might differ not only by what information they choose to acquire, but also in what conclusions they draw from a given piece of information. The fixed information condition presents subjects with a given piece of information, so that if behavior in that condition differs across subjects with different reservation prices, it must be because subjects draw different conclusions from that same information. Hence, by controlling for behavior in those treatments, we isolate the effect of reservation price for checking additional calculations that arises through information acquisition alone.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Selection			**Supply curves**			**State-dep. part.**	
Dependent variable	Mean res. price (%-ile)			Bet taken			Bet taken	
Inclusion criterion								
Bet taken	Yes	Yes	Yes				Yes	
Prior opt.		Yes			Yes			
State							$s = G$	$s = B$
Payment index	0.023***	0.025**	0.020	0.144***	0.127***	-0.176***	0.184***	0.092***
	(0.006)	(0.012)	(0.016)	(0.013)	(0.019)	(0.016)	(0.013)	(0.011)
Res. price $\geq$ median				-0.057***	-0.055**	-0.071***	-0.145***	0.009
				(0.019)	(0.023)	(0.022)	(0.029)	(0.015)
Payment index				0.032**	0.034*	0.049**	0.050***	0.034**
$\times$ (res. price $\geq$ median)				(0.016)	(0.020)	(0.022)	(0.018)	(0.016)
Controls (+ interactions)								
Risk aversion			Yes			Yes		
Fixed info. treatment			Yes			Yes		
Observations	2,645	1,831	3,808	7,008	4,992	10,512	3,520	3,488
Subjects	578	537	583	584	565	584	584	584
Subsamples	Coefficient on payment			Coefficient on interaction Payment $\times$ (res. price $\geq$ med.)			Coeff. on payment	
Only €2 and €6 payments	0.040***	0.034*	0.057	0.032	0.015	0.066*	0.061*	0.023*
	(0.012)	(0.019)	(0.036)	(0.028)	(0.028)	(0.038)	(0.036)	(0.024)
Only €6 and €10 payments	0.010	0.022	0.001	0.035	0.067	0.032	0.040	0.049
	(0.010)	(0.014)	(0.017)	(0.035)	(0.035)	(0.050)	(0.037)	(0.037)

Table 4: Selection effects due to participation incentives using reservation prices for checking calculations as a measure of information acquisition costs. *Bet Taken* is an indicator variable (values 1 and 0) of whether the subject took the bet. *Payment index* is encoded as 1, 2, 3 for incentive amounts € 2, 6, 10, respectively. This assignment is without loss of generality when only two information-cost-treatments are included, as is the case in the bottom two rows. Controls for risk aversion are based on the rank of the mean elicited certainty equivalent. All standard errors are clustered by subject. Each column corresponds to a separate regression that includes session, order, and cost treatment fixed effects, and is weighted as detailed in footnote 22. Each coefficient in the bottom two rows of the table corresponds to a separate regression on the specified subsample. Subject numbers vary across the columns because some subjects only ever took or only ever refused the bet in just one of the conditions. See Table 2 for details. The coefficient on *payment index* in column 5 has a negative sign, which results from controlling for the fixed information treatment. The interpretation of this coefficient is that the supply curve in the information cost treatments is flatter than in the fixed information condition. Numbers in parentheses display standard errors of the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

predicted selection effects arise because of differential information acquisition. They are not due to a correlation with some other individual characteristic.

To confirm this econometrically, column 3 of Table 4 replicates the analysis in column 1 including statistical controls for behavior in the fixed information treatment, as well as for risk preferences. Formally, we estimate the following model:

$$\lambda_i = d_{i,t} \cdot \left[\beta_0 + \beta_1 m_{i,t}\right] + \alpha_0 + \alpha_1 m_{i,t} + r_i \cdot \left[\gamma_0 + \gamma_1 m_{i,t}\right] + \delta' X_{i,t} + \epsilon_{i,t},$$

where λ_i is the percentile rank of an individual's mean reservation price across the four elicitations, $d_{i,t} = 1$ if individual i's round-t decision is in the information cost condition, and $d_{i,t} = 0$ if it is in the Fixed Information condition. Our coefficient estimate of the interaction between payments and reservation prices, β_1, is nearly unchanged, although the standard error is more than twice that of column 1, causing a loss in statistical significance.

To show that the selection effects just demonstrated are to a substantial extent due to a slope effect, we now analyze supply curves directly. We estimate the following model

$$b_{i,t} = \beta_0 + \beta_1 \tilde{\lambda}_i + \beta_2 m_{i,t} + \beta_3 \cdot \tilde{\lambda}_i \cdot m_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $\tilde{\lambda}_i$ is an indicator for whether λ_i is above the median.

Column 4 of Table 4 displays the results. Our interest centers on β_3, which measures the extent to which the slope of the supply curve of subjects with below-median costs differs from that of subjects with above-median costs. The magnitude of 0.032 is positive and statistically significant at the 5% level, consistent with our predictions. The estimate remains nearly unchanged if we focus on observations for which a change in the participation incentive does not change the prior-optimal choice (column 5). The estimate in column 6 controls for both risk preferences and behavior in the Fixed Information treatment.[27] The estimate of 0.49 is significantly positive at the 5% level.

Finally, columns 7 and 8 estimate model (3) separately on the set of observations for which the state is good and bad, respectively. As suggested in panel B of Figure 4, for subjects with higher information costs both the false positive rate and the false negative rate change significantly more rapidly as the participation incentive increases, consistent with the mechanics of our model outlined in Section 2.

[27] We estimate the following specification:

$$\begin{aligned} b_{i,t} = d_{i,t} \cdot \left[\beta_0 + \beta_1 \tilde{\lambda}_i + \beta_2 m_{i,t} + \beta_3 \tilde{\lambda}_i m_{i,t}\right] \\ + \alpha_0 + \alpha_1 \tilde{\lambda}_i + \alpha_2 m_{i,t} + \alpha_3 \cdot \tilde{\lambda}_i \cdot m_{i,t} + \\ + r_i \cdot \left[\gamma_0 + \gamma_1 \tilde{\lambda}_i + \gamma_2 m_{i,t} + \gamma_3 \tilde{\lambda}_i m_{i,t}\right] + \delta' X_{i,t} + \epsilon_{i,t}, \end{aligned}$$

Here, r_i denotes individual i's percentile rank of his or her mean certainty equivalent across the nine risk preference elicitation tasks. The parameter of interest is, again, β_3. It isolates the effect of information costs and incentive payments in addition to what is due to differential conclusions drawn from a given, costless piece of information alone, and in addition to what can be explained by correlation between risk preferences and individual-specific information costs λ_i.

Overall, we conclude that the selection effects as predicted in Proposition 1 obtain not only for highly-controlled experimentally induced variation of information acquisition costs but also for naturally occurring and individually elicited variation in information acquisition costs.

4.2 Posteriors

Objective posteriors We now test whether subjects with higher information costs make less informed decisions, as predicted by Proposition 2. To do so, we focus on objective posterior probabilities: conditional on accepting or rejecting the gamble, what is the chance that the state is good? These posterior probabilities are isomorphic to the probability of *ex-post* regret. Upon accepting the transaction, for instance, a subject experiences *ex-post* regret if the state is bad.

The upper half of Panel A of Figure 5 plots the fraction of times subjects won the bet if they decided to take it, for each of the nine treatments. This frequency is an estimate of the objective posterior probability $P(s = G \mid \textit{accept})$. As the information cost increases, it falls from about 90% to a value between 60% and 80%, depending on the incentive condition, indicating less informed decision making. Equivalently, the probability of *ex-post* regret conditional on accepting the transaction (given by $1 - P(s = G \mid \textit{accept})$) increases with the information cost. The lower half of the figure plots the fraction of times a subject who chose to reject the transaction would have won, providing an estimate of the objective probability $P(s = G \mid reject)$. This frequency increases with the information cost, again indicating less informed decision making.[28] Panel B shows that the same comparative statics apply when information costs are measured as subjects' reservation price for checking additional calculations, within each information cost condition (averaged across incentive conditions). Subjects with a higher reservation price are significantly less likely to win upon accepting the gamble (and thus significantly more likely to regret participation *ex post*), and if they chose to reject the gamble, it is significantly more likely they would have won.

To demonstrate these comparative statics formally, we estimate the following linear probability model, *separately on the subsamples of observations in which the subject accepted the bet, or refused the bet*, respectively.

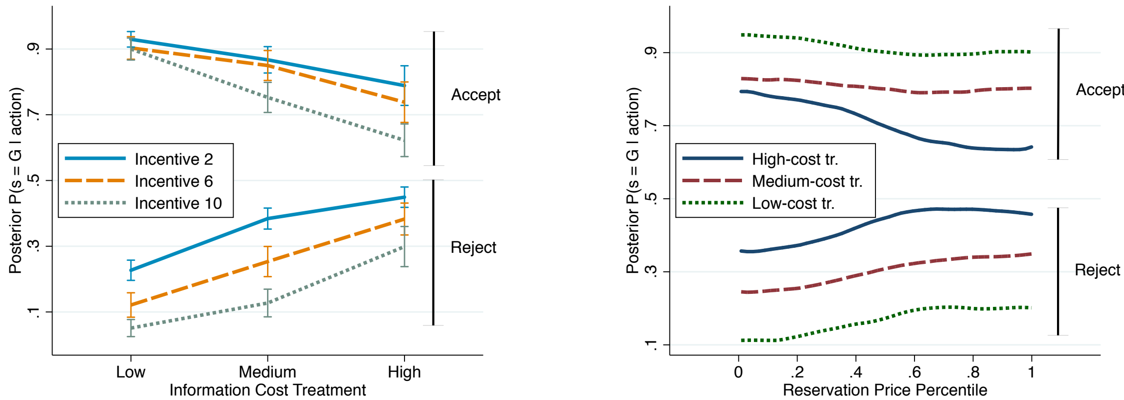
$$s_{i,t} = \sum_{k=1}^{3} (\beta_{0,k} + \beta_{1,k} a_{i,t})\, I(m_{i,t} = k) + \delta' X_{i,t} + \epsilon_{i,t}. \tag{4}$$

Here, $s_{i,t} = 1$ if $s = G$ for subject i in round t, and $s_{i,t} = 0$ otherwise. As in the previous section, $a_{i,t}$ denotes the information cost index. On the subsample of observations in which the subject accepted the bet, this model provides us with estimates of the comparative statics of $P(s = G \mid \textit{reject})$. On

[28] We also observe that incentive payments affect the posterior probabilities directly, replicating a result from Ambuehl (2017). With a higher payment, subjects accept the bet at posteriors that are closer to the prior (less informative), but reject at posteriors that are further from the prior (more informative). Moreover, the magnitude of the comparative statics of information costs and that of incentive payments are quite similar; they are both on the order of 10 to 20 percentage points.

Dependent variable	(1)	(2) Indicator $s = G$	(3)	(4) Elicited belief	(5) Deviation subj. vs. obj.
Cost variation	Experimental	WTA	WTA	Experimental	Experimental
Controls					
Risk aversion			Yes		
Fixed information			Yes		
			Bet accepted		
Effect of cost increase by incentive treatment					
€2	-0.067***	-0.067	-0.086**	-0.043***	0.024*
	(0.016)	(0.042)	(0.041)	(0.009)	(0.015)
€6	-0.080***	-0.101**	-0.152***	-0.057***	0.023
	(0.018)	(0.048)	(0.045)	(0.009)	(0.017)
€10	-0.140***	-0.086*	-0.073*	-0.092***	0.048***
	(0.016)	(0.046)	(0.039)	(0.007)	(0.015)
Observations	2,645	2,645	3,808	2,645	2,645
Subjects	578	578	578	578	578
			Bet rejected		
Effect of cost increase by incentive treatment					
€2	0.110***	0.154***	0.111***	0.085***	-0.026**
	(0.011)	(0.035)	(0.030)	(0.006)	(0.011)
€6	0.131***	0.076	0.069*	0.104***	-0.027*
	(0.016)	(0.046)	(0.038)	(0.009)	(0.016)
€10	0.122***	0.047	0.088*	0.054***	-0.068***
	(0.016)	(0.046)	(0.048)	(0.009)	(0.017)
Observations	4,363	4,363	6,704	4,363	4,363
Subjects	580	580	583	580	580

Table 5: Effect of information costs on posterior probabilities. Each column in each half of the table displays the coefficients of a separate regression that includes session, order, and cost treatment fixed effects, and is weighted as detailed in footnote 22. All standard errors are clustered by subject. Subject numbers for column 3 differ from the other columns because they include observations from the Fixed Information condition, and some subjects only ever took the bet in that condition. See Table 2 for details. Numbers in parentheses display standard errors of the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.



(A) (B)

Figure 5: Posterior probabilities conditional on the subject's action (accept or reject). (A) By information cost treatment and incentive treatment. (B) By reservation price and information cost treatment, averaged over incentive treatments. Moving average, Epanechnikov kernel, bandwidth 0.15.

the subset of observations for which the subject refused the bet, the comparative statics concern $P(s = G \mid reject)$.

Column 1 of Table 5 displays the results. For each incentive condition, an increase in the experimentally induced information cost index leads to a highly statistically significant decrease in the chance that a subject who decided to accept the gamble won that bet, as the upper half of the column shows. Higher information costs also lead to a statistically significant increase in the probability that a subject who decided to reject the gamble would have won the bet, as the lower half of the table demonstrates.

Column 2 replicates column 1 with subjects' reservation price percentiles λ_i instead of the information cost index $a_{i,t}$ as a measure of information costs. All coefficient estimates have the predicted sign. On the set of observations in which subjects accepted the gamble, the coefficient for the medium incentive condition is highly statistically significant, and the coefficient for the high-incentive condition is statistically significant at the 10% level. On the set of observations in which subjects rejected the gamble, the predicted coefficient estimate is statistically significantly positive in the low-incentive condition. Column 3 additionally controls for risk aversion as well as behavior in the fixed information treatment into the vector of control variables $X_{i,t}$. The signs of the estimated coefficients remain unchanged. Statistical significance improves to at least the 10% level for each coefficient estimate.

We conclude that as information costs increase, subjects make less-informed participation decisions, and experience more *ex-post* regret, as predicted in Proposition 2.

Subjective posteriors Finally, we examine the alignment between objective posterior probabilities and elicited posterior beliefs.[29] Deviations between the two are of interest from a welfare perspective, as they imply that subjects' choices are based on a misconception about objective facts, and are thus possibly at odds with their own preferences. Importantly, however, the extent of the alignment is not a test of our model predictions, as they concern objective probabilities, not subjective beliefs. Given a subjects' choice of action, her subjective beliefs are unrelated to the model predictions.

Column 4 of Table 5 estimates model (4) with elicited beliefs that the state is good as the dependent variable. It shows that elicited beliefs mirror the directional pattern of objective posterior probabilities. The higher the information cost, the less confident subjects who accept the bet are that they will win, and the less confident subjects who reject the bet are that they would have lost. Hence, subjects are aware that higher information costs lead to less informed decision making, in each incentive condition.

The coefficient estimates in column 4, however, are smaller in magnitude than those in column 1. While subjects are aware that higher information costs lead to less informed decision making, they underestimate the extent of this effect. To test the statistical significance of this difference, column 5 estimates model (4) with the dependent variable replaced with the difference between the indicator for the state and elicited beliefs. The resulting parameter estimates are the differences between those in column 1 and column 4. We see that for observations in which subjects accepted the gamble, the underestimation of the deterioration in decision quality with information costs is statistically significantly different from zero at the 10% level in the low-incentive condition, and at the 1% level in the high-incentive condition. For observations in which the subject refused the gamble, the estimates are all significantly negative, at least at the 10% level. In fact, averaged across incentive conditions, subjects overestimate the posterior probability of winning conditional on taking the bet by 6.07 percentage points (s.e. 1.62 percentage points, clustered by subject). Overall, therefore, subjects underestimate the extent to which their decision quality deteriorates as information acquisition becomes costlier, leading to significant overestimation in the highest information cost condition. In that condition, subjects are more likely to experience *ex-post* regret than they believe at the time they decide to accept the gamble.

4.3 Contextual information costs

We now test whether selection effects become stronger as we raise the contextual information acquisition cost, as suggested by Proposition 3. For this purpose, we disaggregate the selection effects on reservation prices for checking additional calculations by information cost condition.

Panel D of Figure 4 shows, for each information cost treatment, how the composition of subjects who elect to participate in the gamble changes with the payment m. Each line displays the fraction of

[29] 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.

subjects with an above-median reservation price for checking calculations. The selection effect in the high-cost condition is considerable: the proportion of high-cost 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. Yet the selection effect is more attenuated in the low-cost condition, with nearly indistinguishable fractions of high-cost participants between the €2 and the €10 treatments. Unexpectedly, however, selection in the low-incentive treatment is non-monotonic.[30]

Formally, we estimate the following model

$$\lambda_i = \beta_0 + \beta_1 m_{i,t} + \beta_2 a_{i,t} + \beta_3 a_{i,t} m_{i,t} + \delta' X_{i,t} + \epsilon_{i,t},$$

where $X_{i,t}$ is a vector of session and order fixed effects. Our parameter of interest, β_3, measures the difference in how quickly the composition of participants changes with the payment index $m_{i,t}$ as we vary the contextual information cost parameter $a_{i,t}$.[31]

Column 1 of Table 6 displays the estimates. The coefficient estimate is a highly statistically significant 0.021, showing that selection effects grow more pronounced as the contextual information costs rise. The estimate remains virtually unchanged and highly significant if we only include observations on which the change in the participation incentive does not alter the prior-optimal choice (column 2). The third and fourth row from the bottom show that these effects arise mainly due to the increase in payment from €6 to €10. Moreover, they are stronger for the medium and high information conditions, as the bottom two rows show. Both of these effects are likely due to the non-monotonicity in the low-cost condition (see Panel D of Figure 4). In column 3, we control for risk aversion and choice in the fixed information treatment.[32] The coefficient estimate of 0.018 is similar in magnitude to the previous estimates, albeit statistically significant only at the 10% level.

In column 4, we test whether the effect of individual-level variation in information costs on the supply curve increases with contextual information costs, which is the formal prediction of Proposition 3. Formally, we estimate

$$b_{i,t} = d_{i,t} a_{i,t} \cdot \left[\beta_0 + \beta_1 \lambda_i + \beta_2 m_{i,t} + \beta_3 \lambda_i m_{i,t}\right] + \alpha_0 + \alpha_1 \lambda_i + \alpha_2 m_{i,t} + \alpha_3 \lambda_i m_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}.$$

[30] Regressing the reservation price rank of those who select into the gamble on the payment amount, using observations that have both low costs as well as medium or high payment, reveals that the decrease is weakly significantly different from zero at $p = 0.09$.

[31] Recall that the value of $a_{i,t}$ is 1, 2, and 3 in the low, medium, and high information cost conditions, respectively.

[32] We estimate the following specification

$$\begin{aligned}\lambda_i = d_{i,t} \cdot \left[\beta_0 + \beta_1 m_{i,t} + \beta_2 a_{i,t} + \beta_3 \cdot m_{i,t} \cdot a_{i,t}\right] \\ + \alpha_0 + \alpha_1 m_{i,t} + r_i \cdot \left[\gamma_0 + \gamma_1 m_{i,t} + \gamma_2 a_{i,t} + \gamma_3 \cdot m_{i,t} \cdot a_{i,t}\right] + \delta' X_{i,t} + \epsilon_{i,t}.\end{aligned}$$

Our interest concerns the coefficient β_3 on the three-way interaction (res. price $\geq$ median) $\times$ payment $\times$ cost treatment. The coefficient estimate of 0.038 is statistically significantly positive, as column 4 shows. If we only include observations for which a change in payment does not alter the prior-optimal choice, however, the coefficient magnitude attenuates to 0.015 and becomes statistically insignificant (column 5). Finally, column 6 adds controls for risk aversion and behavior in the fixed information treatment.[33] The resulting coefficient estimate of 0.029 is highly statistically significant.

We conclude that, consistent with the suggestion of Proposition 3, the kind of selection effects reported in Section 4.1 are more pronounced in settings characterized by higher contextual information acquisition costs.

4.4 Educational background and cognitive ability

We now examine our predicted selection effects using the type of measures of information cost that are often available in applied settings, such as educational background and cognitive ability. These variables also help us demonstrate the extent of the contextual robustness of our predictions.[34]

For ease of presentation, we summarize background in mathematics as the first principal component of a subject's high school mathematics grade ranking, of whether she has taken an honors class in the subject, and of whether she is enrolled in a STEM major. We summarize background in German literature similarly.[35] For comparability to other variables, we normalize the resulting scores into the unit interval.[36] To study the effect of cognitive ability, we analyze selection in the *unincentivized IQ* treatment and *incentivized IQ* treatment separately from each other. According to previous research, we expect different predictive power (Segal, 2012; Duckworth, Quinn, Lynam, Loeber and Stouthamer-Loeber, 2011; Borghans, Meijers and Ter Weel, 2008; Dessi and Rustichini, 2015), but we have no *ex-ante* hypothesis about the direction.

We separately regress each characteristic on the participation incentive *using observations in which the subject elected to take the bet*. Formally, we run regressions of the following form

$$y_{i,t} = d_{i,t}(\beta_0 + \beta_1 m_{i,t}) + (1 - d_{i,t}) \sum_{k=1}^{3} (\beta_{0,k} + \beta_{1,k} m_{i,t}) \, I(a_{i,t} = k) + \delta' X_{i,t} + \epsilon_{i,t}, \tag{5}$$

[33] We estimate the following specification

$$\begin{aligned} b_{i,t} = a_{i,t} \cdot d_{i,t} \cdot \left[\beta_0 + \beta_1 \lambda_i + \beta_2 m_{i,t} + \beta_3 \lambda_i m_{i,t}\right] & \\ + \alpha_0 + \alpha_1 \lambda_i + \alpha_2 m_{i,t} + \alpha_3 \lambda_i \cdot m_{i,t} & \\ + r_i \cdot \left[\gamma_0 + \gamma_1 \lambda_i + \gamma_2 m_{i,t} + \gamma_3 \lambda_i m_{i,t}\right] + \delta' X_{i,t} + \epsilon_{i,t}. & \end{aligned}$$

[34] In our context, demonstrating selection effects based on cognitive ability is challenging. Because all our subjects are students of the University of Cologne, the subject pool is already selected on that dimension, which naturally attenuates the additional selection our experimental treatments can possibly generate.

[35] The latter measure does not include whether a subject is enrolled in a STEM major.

[36] 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%.

	(1)	(2)	(3)	(4)	(5)	(6)
		Selection			**Supply curves**	
Dependent variable		Mean reservation price (%-ile)			Bet taken	
Inclusion criterion						
Bet taken	Yes	Yes	Yes			
Prior opt. const.		Yes			Yes	
Payment index	-0.017	-0.025	-0.020	0.024	0.008	0.198***
	(0.012)	(0.018)	(0.018)	(0.027)	(0.037)	(0.022)
Cost treatment						
× 1	-0.028***	-0.026**	-0.025	-0.110***	-0.117***	0.042***
	(0.010)	(0.012)	(0.017)	(0.014)	(0.017)	(0.007)
× payment index	0.021***	0.020**	0.018*	0.060***	0.069***	-0.031***
	(0.006)	(0.008)	(0.009)	(0.012)	(0.017)	(0.006)
Res. price ≥ median						
× 1				0.011	-0.007	0.020
				(0.043)	(0.052)	(0.035)
× payment index				-0.045	0.006	-0.019
				(0.037)	(0.049)	(0.029)
× cost treatment				-0.034*	-0.024	-0.035***
				(0.018)	(0.022)	(0.009)
× payment index × cost treatment				0.038**	0.015	0.029***
				(0.017)	(0.022)	(0.009)
Controls						
Risk aversion (+ interactions)			Yes			Yes
Fixed information (+ interactions)			Yes			Yes
Observations	2,645	1,831	3,808	7,008	4,992	10,512
Subjects	578	537	583	584	565	584
Subsamples		Coefficient on interaction Payment × cost treatment			Coefficient on interaction payment × cost treatment × (res. price ≥ median)	
Only €2 and €6 payments	0.007	0.003	0.026	-0.063**	-0.074**	0.003
	(0.013)	(0.015)	(0.023)	(0.031)	(0.034)	(0.015)
Only €6 and €10 payments	0.034**	0.042**	0.013	0.159***	0.142**	0.058**
	(0.012)	(0.014)	(0.017)	(0.040)	(0.049)	(0.021)
Only small and medium picture	0.017	0.014	0.024	0.045	-0.003	0.025*
	(0.012)	(0.015)	(0.016)	(0.033)	(0.043)	(0.014)
Only medium and large picture	0.027**	0.029*	0.026*	0.033	0.036	0.033
	(0.013)	(0.016)	(0.014)	(0.030)	(0.037)	(0.030)

Table 6: Magnitude of selection effects by contextual information acquisition costs. *Bet Taken* is an indicator variable (values 1 and 0) whether the subject took the bet. *Information Cost Index* is encoded as 1, 2, and 3 for the low, medium, and high cost treatments, respectively. *Payment index* is encoded as 1, 2, 3 for incentive amounts € 2, 6, 10, respectively. This assignment is without loss of generality when only two information-cost-treatments are included, as is the case in the bottom two rows. Includes session and order fixed effects. Controls for risk aversion are based on the rank of the mean certainty equivalent elicited. Each column corresponds to a separate regression that includes session, order, and cost treatment fixed effects, and is weighted as detailed in footnote 22. Numbers in parentheses indicate standard errors of the estimates. All standard errors are clustered by subject. Standard errors for columns 4–6 are bootstrapped. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

where y_i is an individual-level characteristic such as educational background, $d_{i,t}$ is an indicator for whether subject i's round-t decision was in an information cost condition, and k is the information cost index. The vector of control variables consists of session, order, and information cost treatment fixed effects. When the dependent variable is cognitive ability, $X_{i,t}$ additionally includes the time taken to complete the Raven's matrix test.

Panel A of Table 7 displays the results. In each information cost condition, strength of mathematics background amongst subjects who elect to take the gamble drops with the incentive amount, as column 1 shows. In the high-cost condition, an increase in the participation incentive by €4 leads to a 3.4 percentile points drop in mathematics background, which is highly statistically significant. Selection effects regarding German literature are either absent, as expected (in the low and medium cost conditions), or even display the opposite of the effect one would expect if a stronger background in German literature were associated with lower information acquisition costs (column 2). Column 3 analyzes selection on cognitive ability when the elicitation is not incentivized, as is the standard fashion of administering this test. For the medium- and high-cost conditions, we find that an increase in participation incentive by €4 causes a drop in the average cognitive ability of subjects who select into the gamble by 2.4 and 2.2 percentile points, significant at the 5% and 10% levels, respectively. Interestingly, while we did not entertain *ex-ante* expectations along these lines, we find no such selection effects once the elicitation of cognitive ability is incentivized (column 4). This finding is consistent with previous literature that argues that unincentivized and incentivized performance on tests of cognitive ability measure different underlying characteristics (Segal, 2012; Duckworth, Quinn, Lynam, Loeber and Stouthamer-Loeber, 2011). (Columns 5 to 8 will be discussed in the next section.)

To examine the robustness of our predictions of Proposition 2, we now examine the effects of educational background and cognitive ability on posterior beliefs. For each of these characteristics, we regress an indicator for whether the state is good on the characteristic using the *subsample of observations in which the subject has accepted the gamble*. We include fixed effects for order, session, information cost condition, and incentive condition. This regression provides information about the effect of each characteristic on $P(s = G \mid accept)$. To estimate the effects on $P(s = G \mid reject)$, we estimate the same model using the *subsample of observations in which the subject has rejected the gamble*.

Column 1 in Panel B of Table 7 shows that conditional on deciding to accept the gamble, the subject with the strongest background in mathematics is 15 percentage points more likely to win than the subject with the weakest background. Moreover, conditional on rejecting the gamble, the chance that the subject with the strong mathematics background would have won is 6.6 percentage points lower than the chance that the subject with the weak background would have won. Subjects with a stronger mathematics background make more informed decisions in our task. As expected, no such statement holds regarding background in German literature. If anything, subjects with a stronger

A. Selection

VARIABLES	(1) Educ. Background (1st PC)	(2)	(3) Cognitive Ability (%-ile rank)	(4)	(5) Info. cost (%-ile rank)	(6)	(7) CE (%-ile rank)	(8)
	Maths	German	Non-inc.	Inc.	Res. Price	all	$EV \leq 0$	$EV > 0$
Inclusion crit.								
Bet taken	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Info. cost index								
1	-0.014*	0.007	-0.009	-0.012	0.005	0.003	0.001	0.001
	(0.008)	(0.008)	(0.009)	(0.011)	(0.008)	(0.008)	(0.004)	(0.006)
2	-0.022**	0.006	-0.024**	-0.000	0.022**	0.011	0.003	0.006
	(0.010)	(0.010)	(0.011)	(0.016)	(0.010)	(0.010)	(0.005)	(0.007)
3	-0.034***	0.023*	-0.022*	0.015	0.049***	-0.011	-0.014**	-0.004
	(0.011)	(0.013)	(0.012)	(0.019)	(0.010)	(0.012)	(0.006)	(0.008)
Fixed info.	-0.018	0.007	0.010	0.053**	0.003	-0.014	-0.017*	0.004
	(0.012)	(0.015)	(0.016)	(0.021)	(0.013)	(0.016)	(0.009)	(0.011)
Observations	3,287	3,263	1,977	1,436	3,808	3,808	3,808	3,808
Subjects	503	500	300	220	583	583	583	583

B. Posteriors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$P(s = G \mid accept)$							
Independent variable								
Name	Backgr. Maths	Backgr. German	Cog. ab. Non-inc.	Cog. ab. Inc.	Res. Price	CE all	CE $EV \leq 0$	CE $EV > 0$
Effect	0.150***	-0.074*	0.173***	0.095*	-0.084***	-0.035	-0.170***	0.011
	(0.038)	(0.039)	(0.052)	(0.054)	(0.032)	(0.035)	(0.064)	(0.046)
Observations	2,286	2,276	1,371	993	2,645	2,645	2,645	2,645
Subjects	499	496	298	217	578	578	578	578
Dependent variable	$P(s = G \mid reject)$							
Independent variable								
Name	Backgr. Maths	Backgr. German	Cog. ab. Non-inc.	Cog. ab. Inc.	Res. Price	CE all	CE $EV \leq 0$	CE $EV > 0$
Effect	-0.066**	0.027	-0.162***	-0.008	0.117***	0.007	-0.053	0.017
	(0.033)	(0.033)	(0.046)	(0.051)	(0.028)	(0.029)	(0.054)	(0.042)
Observations	3,762	3,736	2,229	1,659	4,363	4,363	4,363	4,363
Subjects	500	497	299	219	580	580	580	580

Table 7: Selection effects and posterior probabilities by educational demographics, cognitive ability, and risk preferences. Regressions concerning cognitive ability control for time taken to complete the test. All regressions include session and order fixed effects. Regressions in Panel A also include information cost treatment fixed effects. All standard errors are clustered by subject. Numbers in parentheses display standard errors of the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

background in German literature are more likely to lose once they decide to participate in the gamble (column 2).

The informedness of decisions is also strongly predicted by cognitive ability, as column 3 shows. If the top-ranked subject accepts the gamble, she is 17.3 percentage points more likely to win the gamble than if the bottom-ranked subject chooses to accept it. And if she refuses it, she is 16.2 percentage points less likely to have won than if the bottom-ranked subject chooses to reject it. The effects are weaker for the incentivized measure of cognitive ability, diminishing to 9.5 percentage points (significant at the 10% level) and 0.8 percentage points (not significantly different from 0), respectively (column 4). (We will discuss columns 5 to 8 in the next section.)

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.

4.5 Selection based on risk preferences

Any subject who makes a decision under incomplete information faces uncertain payoffs. Accordingly, incentives may lead to selection based not only on information costs, but also on risk preferences.[37] We now gauge the magnitudes of the two mechanisms.

VARIABLES	(1) CE %-ile rank in $p = 0.5$ gambles	(2)	(3) CE %-ile rank in $p = 0.75$ gambles	(4)	(5) CE %-ile rank in $p = 0.9$ gambles	(6)
Inclusion criterion Participates with	$p' = 0.75$	$p' = 0.9$	$p' = 0.5$	$p' = 0.9$	$p' = 0.5$	$p' = 0.75$
Payment index	-0.071***	-0.039***	-0.047***	-0.038***	-0.013	-0.040***
	(0.007)	(0.005)	(0.012)	(0.005)	(0.012)	(0.008)
Observations	1,149	1,395	879	1,395	879	1,149
Subjects	552	573	527	573	527	552

Table 8: Selection due to participation incentives by risk preference when no information acquisition is possible. CE stands for certainty equivalent. All regressions include session and order fixed effects. Standard errors clustered by subject. Numbers in parentheses display standard errors of the estimates. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As a benchmark, we examine the extent of selection on risk preferences when information plays no role. We make use of the fact that each of the multiple decision lists used for risk preference elicitation entails a decision that is equivalent to the choice of whether to participate in a win 0 / lose 12 gamble in exchange for a specific participation incentive $m \in \{2, 6, 10\}$, and for a specific

[37] Indeed, our subjects' risk preferences are considerably heterogeneous. The population-level standard deviation of within-subject averages of risk premia, defined as the difference between the expected value and certainty equivalent of a gamble, for the nine gambles used for elicitation is €1.89 (the mean risk premium is 1.04).

success probability $p \in \{0.5, 0.75, 0.9\}$. Accordingly, we can use the three decision lists corresponding to a given success probability p to study how an increase in the participation incentive changes the composition of subjects who opt for the gamble. We characterize subjects by their risk preferences by ranking them according to their mean certainty equivalent in all gambles involving a different success probability p'.

Formally, let $r_i^{p'}$ denote the percentile rank of subject i's mean certainty equivalent across gambles involving success probability p', and let p denote a second, different, success probability. Using the subsample of risk-elicitation observations in which the success probability is p and the subject accepts the gamble, we then run the regression

$$r_i^{p'} = \beta_0 + \beta_1 m_{i,t} + \beta_2' X_i + \epsilon_i, \tag{6}$$

where the vector of controls X_i consists of session and order fixed effects.

Table 8 displays the results. In column 1, $p = 0.5$ and $p' = 0.75$. An increase in the participation incentive by €4 causes a drop in the risk preference rank, measured on 50/50 gambles, amongst subjects who select into the 75/25 gamble by a highly statistically significant 7.1 percentile points. With the exception of column 5, the selection effects in the remaining columns are also highly statistically significant, with magnitudes of the selection effect ranging between 3.9 and 4.7 percentile points.

Next, we study selection by risk preferences when subjects can acquire information. We expect a stronger influence in the Fixed Information treatment, because the Information Cost treatments afford subjects the opportunity to alter a risk profile they view as undesirable by acquiring further information. Column 6 in Panel A of Table 7 shows the estimates of model (5) on the sample of observations in which the subject accepted the gamble, with subjects' mean certainty equivalent percentile as a dependent variable. We find no selection based on risk preferences in either the Fixed Information condition, or in any of the Information Cost conditions. Hence, the mere introduction of a belief updating stage greatly attenuates selection on risk preferences.

To scrutinize this absence of an effect, we separately consider the three risk preference elicitation tasks with a weakly negative value and the six with a strictly positive expected value.[38] For each set we separately average certainty equivalents within individuals, and calculate the subjects' percentile rank. Column 7 in Panel A of Table 7 shows that an increase in the participation incentive by €4 does lead to a selection of more risk averse subjects by 1.7 percentile points in the Fixed Information condition, and by 1.4 percentile points in the high-cost condition. There is no selection based on risk preferences over gambles with positive expected value (column 8). We note that these results are not due to an unusual correlation between risk preferences and information costs in our sample. As

[38]Subjects' attitudes towards these two types of gambles contain a substantial amount of independent variation. A principal component analysis of the nine certainty equivalents identifies two components with Eigenvalue exceeding one. While the first component loads approximately uniformly on each lottery, the second component loads positively on all lotteries with a weakly negative mean certainty equivalent, as well as on the lottery with a certainty equivalent of €0.8, and negatively on all remaining lotteries, whose certainty equivalent exceeds 0.8.

Appendix C.3 shows, the relations between our measures of risk preferences and information costs largely replicate those in the review article by Dohmen, Falk, Huffman and Sunde (2018).

Finally, we compare these magnitudes to selection on information costs. Column 5 in Panel A of Table 7 shows selection by reservation price to check additional calculations. In the medium and high Information Cost conditions, selection on that variable ranges between 2.2 and 4.8 percentage points. These magnitudes much exceed that of selection on risk preferences in settings with information, and are roughly comparable to the selection effects on risk preferences in the setting without information (Table 8). They are also comparable to selection on mathematics grades, as well as on our non-incentivized measure of cognitive ability.

Overall, we thus conclude that while selection by risk preferences is substantial when no information acquisition is possible, that effect is largely muted when subjects can decide what information to acquire. The magnitude of selection on information costs is comparable to that of selection on risk preferences when no information acquisition is possible.

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 incentives disproportionately select individuals for whom learning is more difficult. These subjects make less informed decisions, and are more likely to regret participation *ex post*. The magnitude of the selection effect is larger when the contextual information acquisition costs are higher. When information acquisition is possible, selection on ease-of-learning dominates selection on risk preferences.

These findings are of interest whenever participation incentives 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 the controversial topic of transactions for which incentive payments are limited by laws and guidelines (Becker and Elias, 2007; Roth, 2007; Ambuehl, 2017; Elias et al., forthcoming), such as living tissue donation or clinical trial participation. Our results highlight a conflict between incentive payments and the principles of informed consent. While we take no normative stance regarding these principles, we highlight that even for policy makers who subscribe to this principle, banning or limiting these payments is not necessarily the optimal response. One alternative consists of stringent informed consent requirements, perhaps coupled with an assessment of participants' comprehension. Another alternative involves reducing information costs through regulatory measures. In the domain of finance, for instance, the European Union now requires that retail investors interested in certain investment products must be provided with a standardized information sheet no longer than three pages describing the costs and risk/reward profile of the product.

A frequently voiced concern with payments for transactions like living tissue donation or gestational surrogacy is that they 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.[39] For example, economic inequality will compound the selection effects we document if the following two conditions hold. The first condition is that the utility consequences of participation, aside from the incentive payment m, are the same for rich and poor individuals. This may be considered an appropriate assumption for transactions such as living tissue donation or gestational surrogacy wherein the 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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[39] The dependence rests on two factors: which model elements scale with a change in the marginal utility of money, and whether wealthier individuals have higher or lower information costs. To see how, observe that our model consists of three elements: the consequences of participation π_G and π_B, the payment m (which we take to be monetary), and the information costs c (which we take to be non-monetary). If the consequences of participation do not scale with the marginal utility of money, the only factor affected by a change in that variable is the payment. For a poorer individual, a given change in the payment is more substantial (under the assumption of diminishing marginal utility of money). Accordingly, if poorer individuals tend to have higher costs of information acquisition, wealth heterogeneity compounds the selection effect of incentive payments in Proposition 1; otherwise it counteracts that effect. If the consequences do scale with the marginal utility of money, the only non-monetary variable is the information cost. Such an assumption is appropriate for purely financial transactions such as credit card contracts with shrouded fees. *Ceteris paribus*, being richer is now akin to having lower stakes in the transaction, at unchanged information costs. Accordingly, if wealth and information costs are negatively correlated, wealth heterogeneity may counteract the selection effect in Proposition 1; otherwise, it will compound it.

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ONLINE APPENDIX

Attention and Selection Effects

Sandro Ambuehl, Axel Ockenfels, and Colin Stewart

Table of Contents

A Proofs

A.1 Proof of Proposition 1

A.1.1 Proof of part (i)

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

$$p = -\frac{\mu}{b-1} - \frac{1-\mu}{g-1}. \tag{7}$$

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 (ii)

Lemma 1. *Let X be a continuously distributed real-valued random variable and let $f : \mathbb{R} \longrightarrow \mathbb{R}_+$ and $g : \mathbb{R} \longrightarrow \mathbb{R}_+$ 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 $\Gamma = \{(b, g) \mid b \in (0, 1) \text{ and } g \in (1, \infty)\}$.

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. $\square$

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 (ii) 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 $\Psi(\cdot \mid [a,b])$, $E[\lambda \mid \text{participate}]$ 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

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

Differentiating with respect to m gives

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

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

$$p \frac{\partial^2 p}{\partial \lambda \partial m} > \frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m}. \tag{8}$$

Differentiating (7) gives

$$\begin{aligned} \frac{\partial p}{\partial \lambda}\frac{\partial p}{\partial m} &= \left(\frac{1-\mu}{(g-1)^2}\left(-\frac{g}{\lambda}\log g\right) + \frac{\mu}{(b-1)^2}\left(-\frac{b}{\lambda}\log b\right)\right)\left(\frac{1-\mu}{(g-1)^2}\frac{g}{\lambda} + \frac{\mu}{(b-1)^2}\frac{b}{\lambda}\right) \\ &= -(1-\mu)^2 \frac{g^2 \log g}{\lambda^2 (g-1)^4} - \mu(1-\mu)\frac{bg\log b + bg \log g}{\lambda^2 (b-1)^2 (g-1)^2} - \mu^2 \frac{b^2 \log b}{\lambda^2 (b-1)^4}, \end{aligned} \tag{9}$$

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 (7) and expanding leads to

$$
\begin{aligned}
p\frac{\partial^2 p}{\partial\lambda\partial m} = -(1-\mu)^2\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(g-1)^4}\right) \\
-\mu(1-\mu)\left(\frac{g(g+1)\log g - g(g-1)}{\lambda^2(b-1)(g-1)^3} + \frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^3(g-1)}\right) \\
-\mu^2\left(\frac{b(b+1)\log b - b(b-1)}{\lambda^2(b-1)^4}\right).
\end{aligned} \tag{10}
$$

Comparing the $(1-\mu)^2$ terms in (9) and (10), 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 (9) and (10), 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 (10) is larger than that in (9) 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

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

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 (8) 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

$$\mu g + (1 - \mu)b \leq 1. \tag{11}$$

Suppose this holds with equality; that is, suppose $\mu g + (1 - \mu)b = 1$. The derivative of the left-hand side of (11) 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 (11) 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 (11) is increasing in m).

A.2 Proof of Proposition 4

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

$$\max_{\gamma_{\text{part}}, \gamma_{\text{abst}}, p \in [0,1]} pN_{\text{part}} + (1 - p)N_{\text{abst}} \quad \text{s.t.} \quad p\gamma_{\text{part}} + (1 - p)\gamma_{\text{abst}} = \mu, \tag{12}$$

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 (12) 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:

$$-\lambda h'(\gamma_{\text{abst}}) = \Delta - \lambda h'(\gamma_{\text{part}}), \tag{13}$$

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:

$$-\lambda h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h'(\gamma_{\text{abst}}) = \Delta\gamma_{\text{part}} + \pi_B + m - \lambda h(\gamma_{\text{part}}). \tag{14}$$

Taking derivatives of (13) and (14) with respect to λ, we obtain

$$-h'(\gamma_{\text{abst}}) - \lambda h''(\gamma_{\text{abst}})\frac{\partial\gamma_{\text{abst}}}{\partial\lambda} = -h'(\gamma_{\text{part}}) - \lambda h''(\gamma_{\text{part}})\frac{\partial\gamma_{\text{part}}}{\partial\lambda} \tag{15}$$

and

$$\begin{aligned} -h(\gamma_{\text{abst}}) - \lambda h'(\gamma_{\text{abst}})\frac{\partial\gamma_{\text{abst}}}{\partial\lambda} &= -h(\gamma_{\text{part}}) - \lambda h'(\gamma_{\text{part}})\frac{\partial\gamma_{\text{part}}}{\partial\lambda} + \left(\frac{\partial\gamma_{\text{part}}}{\partial\lambda} - \frac{\partial\gamma_{\text{abst}}}{\partial\lambda}\right)\lambda h'(\gamma_{\text{abst}}) \\ &\quad + (\gamma_{\text{part}} - \gamma_{\text{abst}})\left(h'(\gamma_{\text{abst}}) + \lambda h''(\gamma_{\text{abst}})\frac{\partial\gamma_{\text{abst}}}{\partial\lambda}\right) + \Delta\frac{\partial\gamma_{\text{part}}}{\partial\lambda}. \end{aligned} \tag{16}$$

Cancelling $-\lambda h'(\gamma_{\text{abst}})\frac{\partial\gamma_{\text{abst}}}{\partial\lambda}$ from both sides of (16) 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 (13), the term in square brackets is equal to 0. Further rearranging yields

$$\begin{aligned} (\gamma_{\text{part}} - \gamma_{\text{abst}})\lambda h''(\gamma_{\text{abst}})\frac{\partial\gamma_{\text{abst}}}{\partial\lambda} &= h(\gamma_{\text{part}}) - h(\gamma_{\text{abst}}) - (\gamma_{\text{part}} - \gamma_{\text{abst}})h'(\gamma_{\text{abst}}) \\ &= \frac{1}{\lambda}(\Delta\gamma_{\text{part}} + \pi_B + m), \end{aligned} \tag{17}$$

where the second line follows by substituting from (14). Since participation is optimal at γ_{part}, we have $\Delta\gamma_{\text{part}} + \pi_B + m = \gamma_{\text{part}}\pi_G + (1 - \gamma_{\text{part}})\pi_B + m > 0$.

Rearranging (15) and substituting $h'(\gamma_{\text{part}}) - h'(\gamma_{\text{abst}}) = \frac{\Delta}{\lambda}$ from (13) 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 (17). Because $h'' > 0$ and because the quantity on the right-hand side is negative, we conclude that $\frac{\partial\gamma_{\text{part}}}{\partial\lambda} < 0$.

A.3 Proof of Proposition 3

From equation (7) 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

$$\left.\frac{\partial}{\partial c}\right|_{c=1} \left[-c\frac{1}{\lambda^2}\frac{\partial^2}{\partial\eta\partial m} f(x, c\eta)\right] \geq 0, \tag{18}$$

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

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

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

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

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,

$$\cosh(z) + 2 > \frac{3}{z}\sinh(z). \tag{19}$$

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

$$\frac{3}{z}\sinh(z) = \frac{3}{z}\sum_{k=0}^{\infty}\frac{z^{2k+1}}{(2k+1)!} = 3 + 3\sum_{k=1}^{\infty}\frac{z^{2k}}{(2k)!}\frac{1}{2k+1} \leq 3 + \sum_{k=1}^{\infty}\frac{z^{2k}}{(2k)!} = 2 + \cosh(z), \tag{20}$$

as needed.

Finally, the two sides of inequality (19) are equal only if $z = 1$. Because $\pi_B + m < \pi_G + m$, inequality (18) is strict for at least one $x \in \{\pi_B + m, \pi_G + m\}$.

A.4 Heterogeneous priors

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,

$$p(m, \lambda) = \frac{\mu - \gamma_{abst}}{\gamma_{part} - \gamma_{abst}} \tag{21}$$

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 (21) is linear in μ. □

B Simulations

B.1 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 4 is formally valid for the entire class of posterior-separable 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, 2017). In each case, the cost of the information associated with a pair of state-contingent choice probabilities (p_G, p_B) is given by $c(p_G, p_B) = h(\mu) - ph(\gamma_{\text{part}}) - (1-p)h(\gamma_{\text{abst}})$, 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: $h_{\text{Tsallis}}(x,\sigma) = \frac{1}{\sigma-1}\left(x(1-x^{\sigma-1}) + (1-x)(1-(1-x)^{\sigma-1})\right) = \frac{1}{\sigma-1}\left(1 - x^\sigma - (1-x)^\sigma\right)$ for $\sigma \in \mathbb{R}$, $\sigma \neq 1$. Note that as $\sigma \to 1$, $h_{\text{Tsallis}}(x,\sigma) \to h_{\text{Shannon}}(x)$.
- Renyi costs: $h_{\text{Renyi}}(x,\sigma) = \frac{1}{\sigma-1}\log\left(x^\sigma + (1-x)^\sigma\right)$, 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, 2017). 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.6, 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

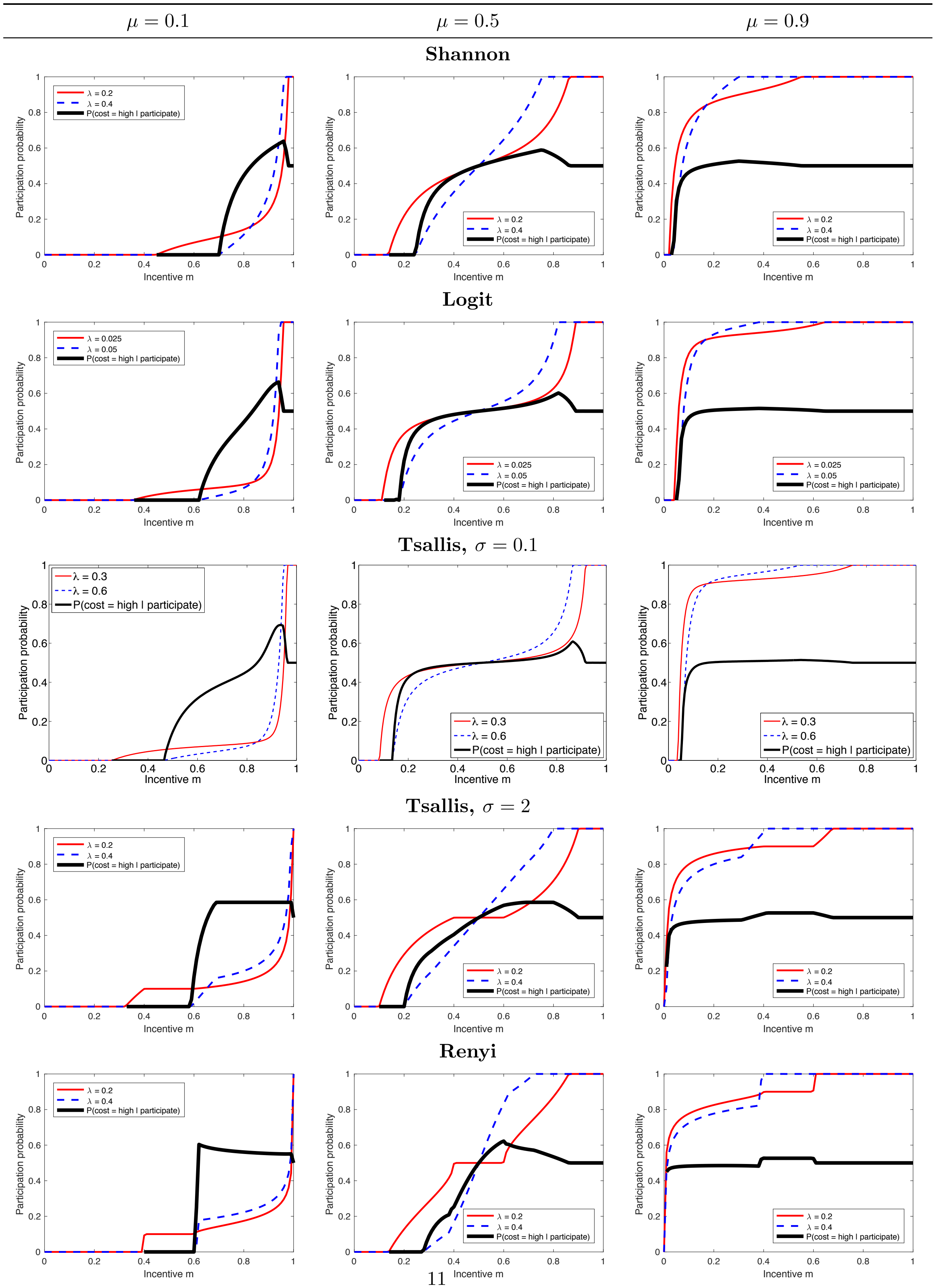


Figure B.6: Simulation tests of Proposition 1 with Shannon, logit, Tsallis, and Renyi cost functions.

costs, is different. For this cost function, the low-cost type sometimes responds more strongly to a change in incentive 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 incentive 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 incentive 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.2 Gaussian signals

Models that employ noisy signals about an imperfectly known state of the world often consider the case of normally distributed signals (e.g. Morris and Shin, 2002). Here, we explore the robustness of our findings in a case with Gaussian signals. We first consider the case of exogenously given signal precision. We then study the case in which the agent can choose the precision of her signal at a cost.

B.2.1 Exogenous signals

Setting 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.

Analysis 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

$$Pr(s = G|n) \geq \frac{-(\pi_B + m)}{\pi_G - \pi_B}. \tag{22}$$

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

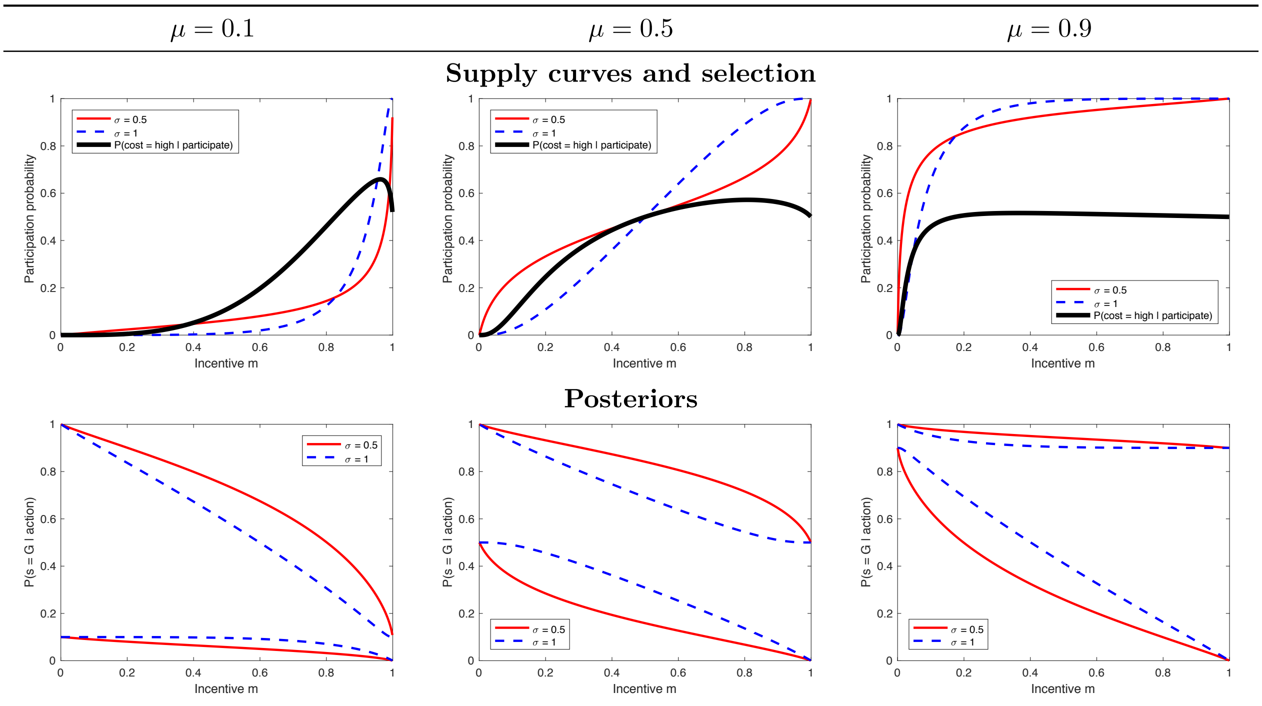


Figure B.7: Comparative statics similar to those of Proposition 1 in a model with exogenous Gaussian signals. Graphs in the top row depict supply curves for each level of the signal precision, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|$ participate$)$ and $P(s = G|$ abstain$)$.

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 (22), the agent will thus participate if

$$n \geq \frac{1}{2} - \sigma^2 \log \gamma, \tag{23}$$

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 $p_B = 1 - \Phi\left(\frac{\frac{1}{2} - \sigma^2 \log \gamma}{\sigma}\right)$.

Simulation Figure B.8 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 2.

B.2.2 Choice of signal precision

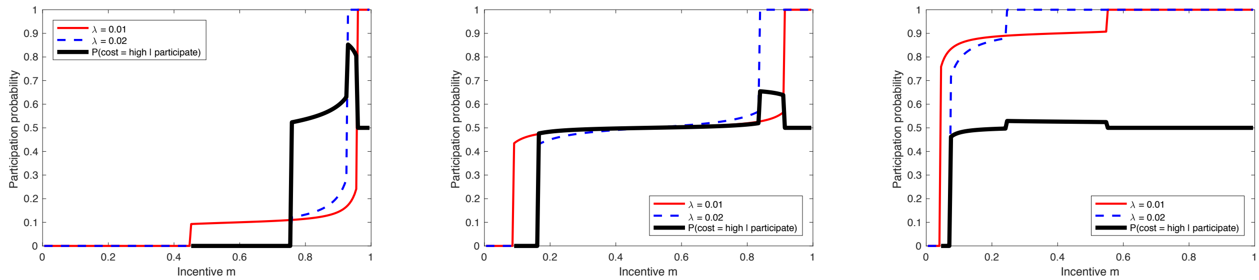
Setting We consider the same information technology as in Section B.2.1, with the exception that the agent can now choose the precision of the Gaussian signal at a cost. Specifically, the agent pays cost $c(\sigma) = \lambda \frac{1}{\sigma}$ to observe a signal with variance σ^2. As in the main text, λ captures individual heterogeneity in information acquisition costs, and information acquisition costs are discounted from the agent's utility.

Analysis Conditional on the signal variance σ^2, the analysis parallels that of Section B.2.1. 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 (23). 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.

Simulation Figure B.8 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.

$\mu = 0.1$	$\mu = 0.5$	$\mu = 0.9$

Supply curves and selection



Posteriors

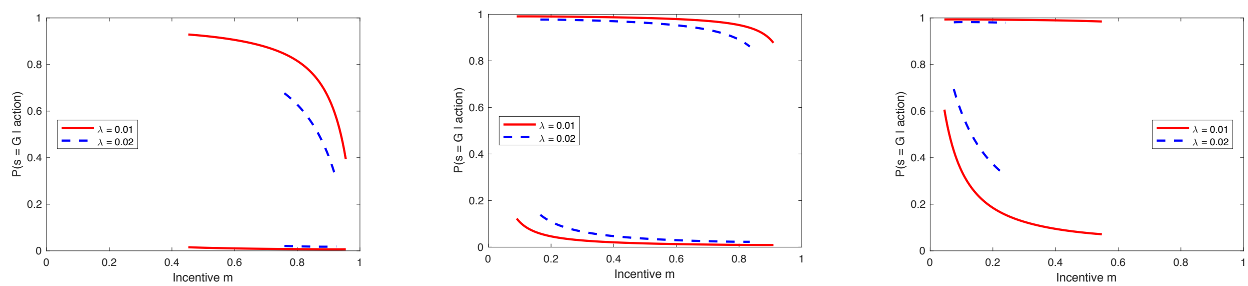


Figure B.8: Comparative statics similar to those of Proposition 1 in a model with Gaussian signals with optimally chosen costly precision. Graphs in the top row depict supply curves for each cost level, as well as the fraction of high-cost types amongst participants, assuming equal population frequencies of the types. Graphs in the bottom row depict posteriors $P(s = G|\text{ participate})$ and $P(s = G|\text{ abstain})$ 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.9 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.

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.9: Laboratory Sessions.

C.2 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 substantial learning component and reflects to a lesser extent a change in how careful subjects make decisions.

C.3 Relation between risk preferences and measures of information costs

The relations between our measures of risk preferences and information costs largely replicate the stylized facts highlighted in the review by Dohmen, Falk, Huffman and Sunde (2018). Table C.10 displays pairwise correlations between our individual-level measures. Proceeding through the rows in sequence, we note that the associations in the first two rows to the certainty equivalent over all gambles are purely mechanical. The relation in column 2 of row 2, however, is not. The fact that certainty equivalents for gambles with weakly negative expected value and those for gambles with positive expected value are significantly correlated with each other, with a correlation coefficient of 0.35 ($p < 0.01$), shows that there is internal consistency in how subjects assess different gambles. The third row displays relations to the reservation price for checking calculations, and none of them is statistically different from zero. Proceeding to measures of cognitive ability in rows 4 and 5, we find a negative association between cognitive ability and certainty equivalents. Column 2 shows that this is driven by the fact that individuals of higher cognitive ability tend to have lower certainty equivalents for gambles with negative expected values, and are thus more risk averse over such gambles, consistent with Dohmen et al. (2018). The correlation coefficients are -0.28 for the non-incentivized elicitation of cognitive ability and -0.21 for the incentivized elicitation ($p < 0.01$). Column 3 shows that this relation disappears for gambles with positive expected value. Finally, proceeding to row 6, the relation between ability and risk preferences attenuates if we consider mathematics background as proxy for ability (to -0.11, $p < 0.05$), though in that case we do find the reverse relation for gambles involving positive expected value (0.09, $p < 0.05$), again consistent with Dohmen et al. (2018). Moreover, our measure of mathematical background is related to the other measures of information cost in the expected fashion. A stronger background lowers reservation prices for checking calculations and is associated with higher cognitive ability for both the incentivized and non-incentivized elicitations. Finally, our measure of background in German literature is negatively related to cognitive ability and background in mathematics, but unrelated to the other variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CE (%-ile rank)			Info. cost (%-ile rank)	Cognitive Ability (%-ile rank)		Educ. Background (1st PC)	
	all	$EV \leq 0$	$EV > 0$	Res. Price	Non-inc.	Inc.	Maths	German
CE								
$EV \leq 0$	0.67**	1.00						
	(0.00)							
$EV > 0$	0.88**	0.35**	1.00					
	(0.00)	(0.00)						
Res. Price	-0.02	-0.04	-0.02	1.00				
	(0.59)	(0.33)	(0.64)					
Cog. ability								
non-inc.	-0.12**	-0.28**	-0.02	-0.14	1.00			
	(0.03)	(0.00)	(0.76)	(0.01)				
inc.	-0.06	-0.21**	0.04	-0.02	-	1.00		
	(0.40)	(0.00)	(0.59)	(0.72)	-			
Educ. backgr.								
Maths	0.02	-0.11**	0.09**	-0.09*	0.15**	0.32**	1.00	
	(0.61)	(0.01)	(0.05)	(0.05)	(0.01)	(0.00)		
German	-0.02	0.01	-0.02	0.07	-0.03	-0.18**	-0.16**	1.00
	(0.60)	(0.89)	(0.59)	(0.12)	(0.65)	(0.01)	(0.00)	

Table C.10: Pairwise correlations between subject characteristics. Numbers in parentheses display p-values.

C.4 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%**.

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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.

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Instructions for part 1

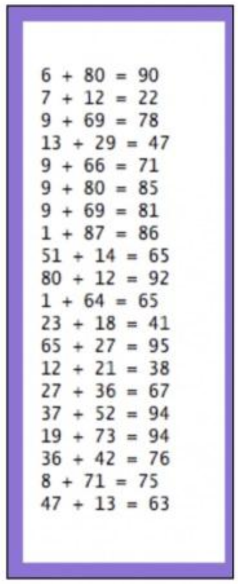
You will be able to continue with the study only if you correctly answer multiple test questions about these instructions. Therefore, it is in your best interest to pay close attention.

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.

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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.

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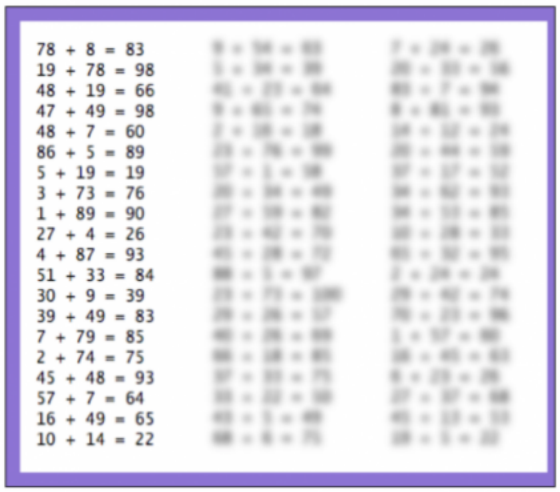
Blurry Calculations

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.

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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.

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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.

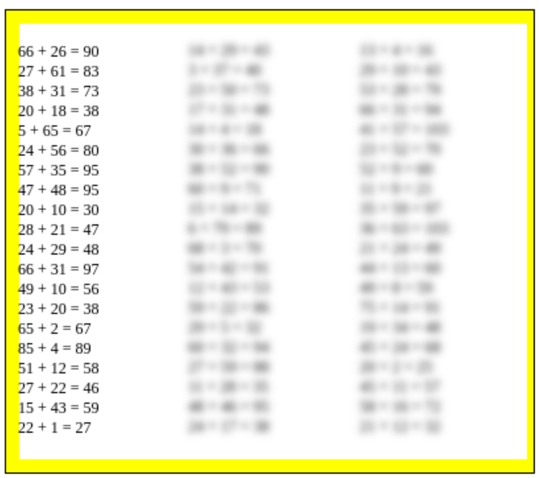
<< >>

Round 6 out of 18

	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



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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