Source Dependence in Effort Provision

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Abstract

We examine source dependence in the setting of effort provision. Our first experiment elicits preference over uncertain piece-rate schemes to perform a real effort task. The second experiment elicits effort after receiving an uncertain gift. We vary the likelihood of winning and the familiarity of natural source of uncertainty. We show that subjects are averse to unfamiliar sources for moderate or high likelihood, but less so for low likelihood. Moreover, effort exhibits more insensitivity to the likelihood under the unfamiliar source compared with the familiar source. Our findings support the validity and generalizability of source dependence in applied settings.

Keyword: risk, uncertainty, source dependence, effort provision, experiment

JEL Classification: C91, D81

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1 Introduction

Keynes (1921) famously poses the following question in his *A Treatise on Probability*: "If two probabilities are equal in degree, ought we, in choosing our course of action, to prefer that one which is based on a greater body of knowledge?" He illustrates this point using the two-urn example, in which people prefer betting on an urn with a known composition of 50 white and 50 black balls over another urn with an unknown composition of white and black balls that sum to 100. This example is later independently proposed by Ellsberg in his 1961 paper to illustrate ambiguity aversion. Going beyond the comparison between known and unknown probabilities, subsequent studies explore more variations of sources of uncertainty, in terms of the degree of competence, familiarity, and so forth (Health and Tversky, 1991; Fox and Tversky, 1995). For example, Fox and Tversky (1995) show that participants from the University of California at Berkeley prefer to bet on the temperature in San Francisco over that in Istanbul. Tversky and Kahneman (1992) incorporate *source dependence* in cumulative prospect theory, to account for the phenomenon whereby the source of uncertainty affects probability weighting in addition to the likelihood.

While various theories have been developed to model source dependence and numerous studies provide experimental evidence in support of its importance,[1] two

[1]For theories, see Tversky and Fox (1995); Tversky and Wakker (1995); Nau (2006); Chew and Sagi (2008); Ergin and Gul (2009); Abdellaoui et al. (2011); Gul and Pesendorfer (2015); Cappelli et al. (2020). For experiments, see Keppe and Weber (1995); Abdellaoui, Vossmann, and Weber (2005); Abdellaoui et al. (2011); Chew, Ebstein, and Zhong (2012); Ahn et al. (2014); Baillon et al. (2018); Li et al. (2018); Chew and Li (2019); Li, Turmunkh, and Wakker (2019); Calford (2020); Li, Turmunkh, and Wakker (2020); Aoyagi, Masuda, and Nishimura (2021). See also Trautmann and van de Kuilen (2015) for a review

questions remain largely unexplored in this literature. The first question concerns the external validity of source dependence. Since most studies rely on traditional experimental paradigms, such as binary risky choice, certainty equivalent elicitation, or probability matching, it is not clear whether source dependence can be extended to applied settings. The second question concerns the generalizability of source dependence. Trautmann and van de Kuilen (2015) summarize a twofold pattern for ambiguity attitudes whereby individuals exhibit ambiguity aversion for gains with moderate to high likelihoods and a tendency of switching to ambiguity seeking for unlikely gains. This pattern implies that individuals are less responsive to changes in likelihood under ambiguity than risk, which suggests *source-dependent likelihood insensitivity*. Whether this dependency can be generalized to natural sources of uncertainty remains a question. This paper aims to investigate these two aspects of source dependence.

We examine source dependence in effort provision when payments involve different sources of uncertainty and different likelihoods. We build the experimental framework based on DellaVigna and Pope (2018) with substantial enrichment. First, we adopt two distinct experimental paradigms. In one experiment, subjects choose between two uncertain payment schemes to pay for the effort to be inputted subsequently. In the other experiment, subjects choose the effort level under a given uncertain payment scheme. Therefore, source dependence is revealed in both individuals' preference for payment schemes and their effort provision, which allows us to examine its external validity and consistency across settings. Second, we incorporate natural sources of uncertainty with different degrees of familiarity and with different likelihoods of winning. This feature is designed to examine the rich domain of source dependence and its generalizability.

We propose a theoretical framework to link source dependence with effort provision. Under the standard model with certain payment schemes, individuals obtain monetary and nonmonetary rewards from working and trade off against the cost of effort (DellaVigna and Pope, 2018; DellaVigna et al., 2022). When the payment scheme is uncertain, individuals assign source-dependent probability weights to different monetary or nonmonetary rewards (Abdellaoui et al., 2011). Based on this model, we show that sources of uncertainty can affect both the preference for uncertain payment schemes as well as the effort provision, and test this in the two experiments.

In Experiment 1, we elicit subjects' preference between uncertain payment schemes in which they have a chance to earn a piece rate of \$0.1 for each word they correctly encrypt. We randomly assign subjects to three conditions with the likelihood of winning being 10 percent, 50 percent, or 90 percent. In Stage 1, subjects make a set of binary choices between two uncertain piece-rate payment schemes based on the future value of two stocks with different degrees of familiarity. In Stage 2, subjects make a set of binary choices between two lotteries of winning \$4, based on identical pairs of stocks that differ in the degrees of familiarity. Stage 2 follows the existing literature that uses binary choice between lotteries to elicit source dependence. In the end, we randomly choose one of the selected stocks in Stage 1 as the payment scheme for subjects to provide effort in the word encryption task for 10 minutes.

We have three main findings from Experiment 1. First, regarding the preference for payment schemes, individuals exhibit strong unfamiliarity aversion and this tendency significantly decreases as the likelihood of winning gets smaller. Specifically, the proportions of choosing the familiar source of uncertainty are 75.26 percent, 72.16 percent, and 68.56 percent, when the likelihoods of winning are 90 percent, 50 percent, and 10 percent, respectively. Second, in Stage 2 using traditional tasks, the pattern of unfamiliarity aversion is analogous to that in Stage 1—namely, the proportions of choosing the familiar source of uncertainty are 73.81 percent, 69.41 percent, and 63.40 percent for the three likelihoods correspondingly. Moreover, source dependence is highly consistent between the two stages. Third, source dependence is also revealed in the effort provision. The average numbers of encrypted words are 9.73, 8.43, and 7.77 for the subgroup with the familiar stocks, and 6.61, 6.94, and 7.00 for the subgroup with the unfamiliar stocks, for the likelihood of winning of 90 percent, 50 percent, and 10 percent, respectively. That is, subjects with the familiar source encrypt 47.2 percent, 21.6 percent, and 11.0 percent more words than those with the unfamiliar source, for the three likelihoods correspondingly. There is a monotone increase of effort with the likelihood of winning under the familiar stocks, but not under the unfamiliar stocks, in support of a stronger likelihood insensitivity for more unfamiliar sources of uncertainty.

Whereas we observe that the sources of uncertainty affect effort provision in Experiment 1, the assignment of sources in Experiment 1 is endogenous to individuals' choices. To resolve this concern, we adopt a between-subjects design in Experiment 2. We randomly assign subjects to eight conditions by varying the payment provided. The payment is unexpected and is independent of performance, which can be regarded as a gift. In two baseline conditions, subjects receive no additional gift in the *No Gift* condition and \$2 for sure in the *Sure Gift* condition. The six remaining treatment conditions use lotteries as gifts, which differs in terms of (1) the winning probability for an additional \$2 (otherwise \$0) as 10 percent, 50 percent or 90 percent, and (2) the source of uncertainty as the last digit of the future closing price of the New York Stock Exchange Composite Index (*NY*) or the Laos Securities Exchange Composite Index (*Laos*). Compared with *Laos*, *NY* is the more familiar source of uncertainty, since more than 93 percent of our subjects are American.

Experiment 2 reports two main findings. First, in line with Experiment 1, we observe unfamiliarity aversion under a moderate to high likelihood of winning. Specifically, subjects who receive the *NY*-based lottery with 90 percent/50 percent winning probability increase their effort by 4.77 percent/3.15 percent, compared with those who receive the corresponding *Laos*-based lottery. Unlike Experiment 1, when the likelihood of winning is low, subjects tend to be unfamiliarity seeking and thus the *Laos*-based lottery motivates higher effort than the *NY*. This twofold pattern is significant and is more pronounced among subjects who exert high effort and among American-based subjects. Second, we also observe that subjects exhibit source-dependent insensitivity to likelihoods: Effort increases monotonically with the likelihood of winning under the familiar source but not under the unfamiliar source. These observations are robust to different specifications.

In summary, our experimental findings are consistent with the proposed theoretical framework that incorporates source dependence in effort provision. We find empirical support for source dependence in both preference for payment schemes and effort inputs. We also document robust evidence for unfamiliarity aversion under a high likelihood of winning and stronger likelihood insensitivity under more unfamiliar sources of uncertainty. Moreover, source dependence is internally consistent across different choice environments.

1.1 Related Literature

Our study contributes to the emerging literature on generalizing source dependence to a richer and more realistic environment (see Trautmann and van de Kuilen (2015)). First, following the work of Tversky and colleagues, studies are gradually shifting from the artificial uncertainty induced by urns and balls to the natural uncertainty of stocks, temperature, and so forth (Keppe and Weber, 1995; Abdellaoui, Vossmann, and Weber, 2005; Abdellaoui et al., 2011; Chew, Ebstein, and Zhong, 2012; Baillon et al., 2018; Li et al., 2018). Second, studies of source dependence show rich variations across gains and losses and across likelihoods, such as the twofold pattern summarized by Trautmann and van de Kuilen (2015). Third, source dependence is applied in a wide range of settings, which include portfolio choices (Ahn et al., 2014; Chew and Li, 2019) and social and strategic interactions (Calford, 2020; Li, Turmunkh, and Wakker, 2019, 2020; Aoyagi, Masuda, and Nishimura, 2021).

However, most prior observations are documented using attitudes toward objective risk as the benchmark. For example, the twofold pattern is commonly observed in the comparison between ambiguity and risk.[2] For attitudes toward natural uncertainty, Baillon et al. (2018) introduce two indexes based on the elicited matching probability of natural events. The observed likelihood insensitivity under this method reveals the twofold pattern between natural uncertainty and risk. Moreover, prior studies mostly adopt either choice tasks or valuation tasks and use student samples.[3]

This paper adds to the literature from several perspectives. First, we adopt an applied setting of the real effort task to examine source dependence. Second, we extend the notion of source dependence to the comparison of natural sources of uncertainty rather than using objective risk as a benchmark. Third, we examine the

[2]Numerous studies observe ambiguity affinity for a low likelihood of winning (Becker and Brownson, 1964; Kahn and Sarin, 1988; Abdellaoui et al., 2011; Baillon and Bleichrodt, 2015; Kocher, Lahno, and Trautmann, 2018), and evidence on ambiguity attitudes in Ellsberg's (1961) three-color paradox tends to be mixed (i.e., Charness, Karni, and Levin, 2013; Binmore, Stewart, and Voorhoeve, 2012).

[3]Some studies examine choices between betting on urns with different compositions, as in Ellsberg's (1961) two-urn paradox, while other studies elicit certainty equivalents for different bets (Halevy, 2007; Machina, 2009; Chew, Miao, and Zhong, 2017; Epstein and Halevy, 2019, 2020; Cubitt, van de Kuilen, and Mukerji, 2020; Liang, 2020). Elicitation of probability equivalents for different events is another popular method, especially for events that arise from natural sources of uncertainty (Baillon et al., 2018; Li et al., 2018). Some studies experimentally measure ambiguity attitude among non-student participants and examine the link between ambiguity attitude and actual behavior, including the adoption of new technologies, stock market participation, and foreign stock ownership (e.g., Dimmock, Kouwenberg, and Wakker, 2015; Bryan, 2019; Berger and Bosetti, 2020).

cross-domain consistency in source dependence in monetary lotteries and uncertain payment schemes. Fourth, we observe that individuals exhibit increasing unfamiliarity aversion with the likelihood of winning and show stronger likelihood insensitivity under the unfamiliar source than the familiar one. Our findings lend support to the external validity and generalizability of source dependence.

This study is also related to the literature on effort provision, which is a popular environment for studying behavioral motivators. Our experiment is closely related to a large-scale experiment that involves actual effort by DellaVigna and Pope (2018). Their experiment compares 18 incentive schemes to motivate effort, including standard monetary incentives of piece rates, behavioral incentives based on social preference, reference dependence, present bias, and overweighting of small probabilities, as well as psychological motivations using task significance and social comparison. Using more than 500 MTurk participants in each scheme, they find strong effects of monetary incentives and relatively weak effects of behavioral and psychological motivators. Moreover, they do not find support for overweighting small probabilities in the real effort task. Other studies on effort provision with uncertainty examine the effect of reference dependence (Abeler et al., 2011; Gneezy et al., 2017); information avoidance (Huck, Szech, and Wenner, 2018); and social preference (Erkal, Gangadharan, and Nikiforakis, 2011). This paper introduces the richness of uncertainty to the consideration of effort provision, and provides support for the importance of source dependence as a behavioral motivator when designing lotteries in applied settings.

Our study is also related to the experimental literature on gift exchange. While previous research primarily compares conditions with and without gifts (Akerlof, 1982; Fehr, Kirchsteiger, and Riedl, 1993; Gneezy and List, 2006; Falk, 2007; DellaVigna et al., 2022), increasingly more studies test whether different forms of gifts motivate effort differently (Kube, Maréchal, and Puppe, 2012; Bradler and Neckermann, 2019; Cao, Li, and Liu, 2020). Here we consider lotteries as gifts and examine the effect in a real effort task. Our study shows that the effectiveness of lotteries as gifts depends on the sources of uncertainty and the likelihoods.

The paper is organized as follows. Section 2 provides the theoretical framework. In Section 3 and Section 4, we describe our experimental design and findings from the two experiments. Section 5 discusses and concludes.

2 Theoretical Framework

We present a framework for how workers choose the optimal effort under an uncertain payment scheme, then discuss how workers choose among different payment schemes. Standard models under certainty commonly propose that a worker's utility from inputting effort consists of three parts: monetary rewards, nonmonetary rewards, and the cost of effort (DellaVigna and Pope, 2018; DellaVigna et al., 2022). We denote a payment scheme as m. For example, m can be a piece rate or an unconditional lump sum payment, the latter of which is commonly framed as a gift. Considering a worker who receives a payment scheme m and chooses the level of effort e, we have the following utility function:

$$\max_{e \geq 0} \; M(m,e) + NM(m,e) - C(e). \tag{1}$$

The first component, $M(m,e)$, captures the monetary incentive for working. If the payment scheme is a piece rate m, we have $M(m,e) = me$. Alternatively, if the payment scheme is a lump sum payment or a gift m, we can specify $M(m,e) = m$. The second component, $NM(m,e)$, indicates the nonmonetary incentive for working. For each unit of inputted effort, the worker gains utility from reciprocating the payment, which could be motivated by moral imperatives (Bénabou, Falk, and Tirole, 2020); warm glow (Andreoni, 1989, 1990); the tendency to conform to the norm of working (Akerlof, 1982); and so on. For example, if the worker receives a piece rate, that is, $M(m,e) = me$, we can specify $NM(m,e) = f(m)e$, in which $f(m)$ captures the preference to conform to the working norm for the given piece rate with $f(0) = 0$. If the worker receives a gift, that is, $M(m,e) = m$, we can specify $NM(m,e) = ame$ with $a > 0$ to capture the sense of reciprocity underlying the gift exchange.[4] The third component is the cost of effort function, in which $C'(\cdot) > 0$, $C''(\cdot) > 0$.

We build on this framework to incorporate uncertainty in the payment scheme, with different sources of uncertainty. In our setting, the worker receives a positive payment scheme m if an uncertain event E occurs and receives 0 otherwise. Let p_E

[4]Under this two specifications, we have $NM(0,e) = 0$, which facilitates subsequent analyses. However, we can further relax this assumption. Our predictions still hold if the nonmonetary incentive satisfies the characteristic that $NM_{21} > 0$—namely, the marginal utility increases with the value of the payment scheme. This characteristic is intuitive and common in the literature.

denote the subjective probability of event E. Event E is generated from a given source of uncertainty. Based on prospect theory, the worker specifies a decision weight $w(p_E)$ for the state of winning m, which gives the following utility:

$$\max_{e \geq 0} \; w(p_E)[M(m,e) + NM(m,e)] + (1 - w(p_E))[M(0,e) + NM(0,e)] - C(e). \tag{2}$$

Hence, the decision weighting function is directly linked to the optimal effort and the overall utility level. Chew and Sagi (2008) provide an axiomatization of probabilistic sophistication within the sources of uncertainty, in which risk preference across sources can differ and risk preference within each source can be of either expected utility or non-expected utility. Abdellaoui et al. (2011) further incorporate source dependence in prospect theory. Specifically, the source method transforms subjective probability p_E for the event E generated from source s into source-dependent decision weight $w_s(p_E)$. Here $w_s(0) = 0$, $w_s(1) = 1$, and $w'_S(\cdot) > 0$. $w_s(p_E)$ can be interpreted as the matching probability of the event E—namely, the worker is indifferent between winning payment scheme m with objective probability $w_s(p_E)$ and winning if E occurs. Given $M(0,e) = NM(0,e) = 0$, the utility maximization problem becomes:

$$\max_{e \geq 0} \; w_s(p_E)[M(m,e) + NM(m,e)] - C(e) \tag{3}$$

This function indicates that higher decision weight yields higher overall utility. The worker thus prefers the uncertain payment scheme with the higher $w_s(p_E)$. Moreover, under regular conditions, the optimal effort e^* is determined by

$$w_s(p_E)[M_2(m, e^*) + NM_2(m, e^*)] = C'(e^*) \tag{4}$$

The left-hand side is the marginal benefit of effort and the right-hand side is the marginal cost of effort. The function $M_2(m, e) + NM_2(m, e)$ captures the marginal utility for the inputted effort under payment scheme m, with both monetary and nonmonetary concerns. This function is a decreasing function of effort e, which is intuitive and standard to guarantee the existence of an optimal effort e^*. With this assumption, the inputted effort increases with the decision weight $w_s(p_E)$ assigned to the winning event E and source s. As for $w_s(p_E)$, it is increasing in subjective probability p_E and is dependent on the source of uncertainty. In summary, we have the following two predictions.

(1)(*Monotonicity*) With the same source of uncertainty, individuals prefer the payment scheme with a higher subjective probability of winning and input more effort accordingly.

(2)(*Source Dependence*) With the same subjective probability of winning, individuals prefer the payment scheme with a higher source-dependent decision weight and input more effort accordingly.

The stylized twofold pattern documented by Trautmann and van de Kuilen (2015) suggests that in comparing risk and ambiguity as two sources of uncertainty, the former is preferred under a moderate to high likelihood of winning, and this difference diminishes or reverses under a low likelihood of winning. This pattern also implies that within each source, individuals exhibit a higher degree of likelihood insensitivity under ambiguity. We expect a similar pattern for effort provision when comparing between familiar and unfamiliar sources of uncertainty.

3 Experiment 1

We design a two-stage experiment to test the two hypotheses. In Stage 1, we elicit individuals' preference between two uncertain payment schemes for a subsequent real-effort task. In Stage 2, we elicit individuals' source dependence using traditional binary risky choice tasks. This experiment enables us to examine the generalizability of source dependence in effort provision and its consistency across different behavioral domains. Moreover, our hypothesis of source dependence is built on a high correlation of behavioral patterns between these two stages. We first introduce our experimental design and then report our findings.

3.1 Design

In Stage 1, subjects are informed that they will conduct a real-effort task of encrypting words (Erkal, Gangadharan, and Nikiforakis, 2011). An encryption table specifies a number or symbol for each letter of the alphabet. Subjects should encrypt words by replacing the letters with the corresponding numbers or symbols. We use this task to elicit effort provision, since it requires no prior knowledge and has little need for learning. Before conducting the task, subjects learn about the payment scheme that determines how their effort will be paid.

For each word they successfully encrypt, subjects have the chance to earn a piece rate \$0.1. We randomly assign subjects to three groups, among which we vary the chance of winning the piece rate to be 10 percent, 50 percent, or 90 percent. We denote these three groups as *Prob10*, *Prob50*, and *Prob90*. In all groups, the chance is determined by the future value of a given stock. More specifically, we construct the likelihood based on the first decimal point of the stock's closing price, denoted as the number a. As a trailing digit, the number a can be regarded as randomly drawn from 0 to 9, and thus the objective probability for a to be any specific digit is 10 percent. Accordingly, the conditions to win the piece rate are set to be $a \in \{5\}$, $a \in \{1, 3, 5, 7, 9\}$, and $a \in \{0, 1, 2, 3, 4, 6, 7, 8, 9\}$ to realize the probabilities of 10 percent, 50 percent, and 90 percent.

After learning about the likelihood of winning the piece rate, subjects are given the chance to choose a stock as the source of uncertainty. Specifically, subjects make 10 binary choices between two stocks, one familiar stock and one unfamiliar stock. We assume that stocks with higher market caps are better known. Accordingly, we construct these 10 pairs of stocks based on the NASDAQ's stock list, which sorts stocks according to the market cap from highest to lowest. We pick 10 stocks from the top 100 stocks as familiar sources—Microsoft, Alphabet, Amazon, Meta, Walmart, Pfizer, Coca-Cola, Walt Disney, Nike, and Netflix. For the unfamiliar source, we randomly choose 10 more stocks with rankings between 1,000 and 6,000. Given the two sets of stocks, we randomly form 10 pairs of stocks for the binary choice task (see Table A.1 for the list). In each task, subjects are shown the logos of the two stocks and choose one. Subjects are told that one of their 10 choices will be randomly selected to determine whether they can earn the piece rate for their performance in the real-effort task.

The sources of uncertainty are chosen with several practical considerations. First, following the literature (Fox and Tversky, 1995; Kilka and Weber, 2001; Abdellaoui et al., 2011; Chew, Ebstein, and Zhong, 2012), we examine natural sources—i.e., stock prices of companies with varying degrees of familiarity. As public information, stock prices enable subjects to verify the results and reduce suspicion about possible manipulation by experimenters. A common approach to control subjective probabilities is constructing exchangeable natural events (Baillon, 2008; Chew and Sagi, 2008). Abdellaoui et al. (2011) ask subjects to partition the domain of home/foreign city temperature into disjoint intervals with equal likelihoods, and measure the certainty equivalents for bets on these intervals. This method requires the elicitation of likelihoods prior to randomly assigning subjects to different conditions. Given this consideration, we use the trailing digit of the stock price in the future to construct uncertainty (Chew, Ebstein, and Zhong, 2012), which generates a sense of probability and is simple to implement. Similar to the Ellsberg paradox, in which decision makers are indifferent between betting on the two colors within one urn, we assume that our workers are indifferent among betting on the 10 numbers from 0 to 9 within one stock. Under this symmetry assumption, our experiment controls for the judgment of likelihood, and directly elicits the source dependence based on familiarity.

In Stage 2, subjects make binary choices of risky prospects. This is the traditional type of tasks used to elicit risk attitudes (Kahneman and Tversky, 1979; Fox and Tversky, 1995), and it is also widely adopted in recent large-scale studies on decision making under uncertainty (Peterson et al., 2021). Specifically, subjects have the chance to earn \$4. To be consistent with Stage 1, the winning probability is set to be 10/50/90 percent for subjects in *Prob10*/*Prob50*/*Prob90*, respectively. The uncertainty is also determined by the trailing digit of a given stock. Here we use the second decimal point of the stock price, which is independent of the uncertainty in Stage 1. This is to avoid the possibility that subjects hedge across the two stages. Similar to Stage 1, given the probability of winning the \$4, subjects make 10 binary choices between one familiar stock and one unfamiliar stock to determine the source of uncertainty.

We recruited MTurk workers with a rating of 95 percent or above. The rating is the percentage of the completed tasks of a worker that are approved by requesters, which is an effective tool for guaranteeing data quality (Martínez-Marquina, Niederle, and Vespa, 2019). After they saw the advertisement that stated *"Earn \$1.5 for a 15 minutes experiment,"* subjects who were interested in our task could participate in the experiment through a Qualtrics link.

In Stage 1, subjects first learned about the real-effort task and answered two training questions about encrypting a 2-letter and an 8-letter word. Next, we randomly assigned them to three groups: *Prob10*, *Prob50*, and *Prob90*. Subjects were informed of the corresponding chance of earning a piece rate for their effort and the use of stocks as sources of uncertainty. For example, subjects in *Prob10* were told, *"The 10 percent chance will be based on your bet on a given stock's first decimal point of its closing price tomorrow...If the number is 5, you earn \$0.1 for each word you successfully encrypted."* To improve the quality of responses, we asked four questions to test subjects' understanding of the instructions.[5] Subsequently, we explain the binary decisions for choosing between two sources of uncertainty based stocks. Subjects then started making the 10 binary decisions in random order, in which the location of the two stocks was also randomized individually in each decision. In Stage 2, subjects learned that they had a chance to earn \$4, which was determined by the second decimal point of a given stock. Like Stage 1, they made 10 binary decisions on stocks to choose the source of uncertainty.

In total, each subject made 10 decisions in both Stages 1 and 2. Afterward, we randomly chose one of the 10 stocks selected by each subject in Stage 1 and presented the chosen stock to them. Subjects learned that if Stage 1 was chosen to pay them, this stock would be the source of uncertainty to determine whether they got

[5]One question asked subjects to encrypt the word "he," which was also the first training task. Two questions tested subjects' understanding of the payment scheme, by asking about the contingent payments with two different amounts of successfully encrypted words. The last question asked about the probability of winning. While the first three questions were used to screen subjects, the last question was not. This allowed for the possibility that subjective probability is not equal to the objective possibility (Chew, Ratchford, and Sagi, 2018). For the last question, we provided feedback and explanations of the objective likelihood of winning regardless of subjects' answers.

the piece rate. All subjects performed the 10-minute real-effort task and encrypted a sequence of 8-letter words using an identical encryption table.

The experiment finished with a short survey to collect subjects' demographic characteristics and levels of familiarity with each of the 20 stocks. After the experiment, we randomly decided whether Stage 1 or Stage 2 would be realized to pay each subject. If Stage 1 is chosen, subjects' payment would be determined according to the uncertainty and their effort. If Stage 2 was chosen, we would randomly choose one of the 10 stocks selected by each subject in Stage 2 as the source of uncertainty to determine whether the subject won the $4.

We recruited 296 MTurk workers and randomly assigned them to one of the three groups. Detailed experiment instructions are presented in Online Appendix B. The median duration of Experiment 1 was around 18.6 minutes and the average payment was $2.69 (see Table A.2 for summary statistics and Table A.3 for the balance check).

3.2 Results

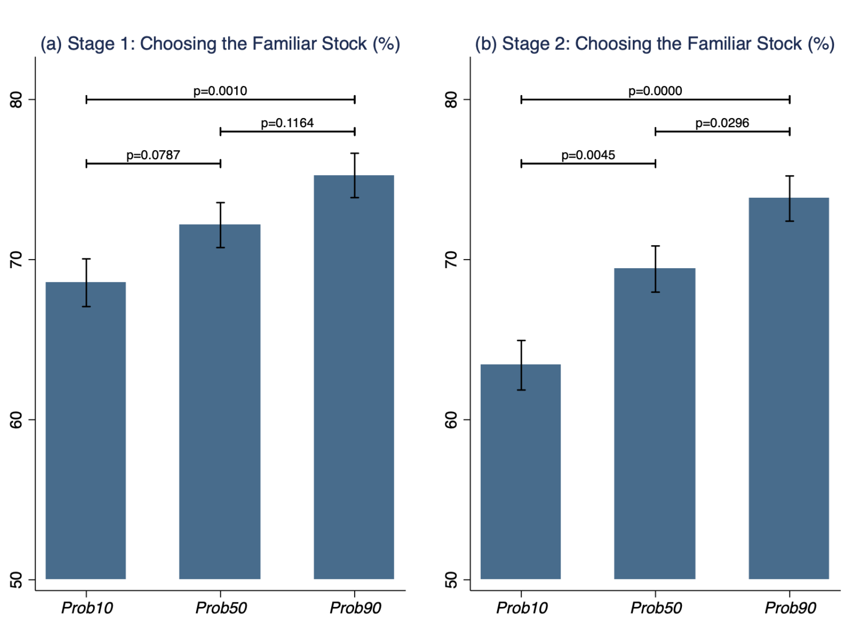
Familiarity of the Sources.—We measure the self-reported levels of familiarity with stocks between 0 and 10, with a higher number indicating a higher level of familiarity. In summary, subjects report that they are more familiar with stocks from the top 100 list of NASDAQ than those with rankings between 1,000 and 6,000 (8.17 vs. 6.33, p <0.0001, two-sided t test). Henceforth we denote the former group as the familiar stocks and the latter group as the unfamiliar stocks.

Source Dependence in Uncertain Payment Schemes.—We find that subjects exhibit source dependence in the preference for a payment scheme. Panel (a) in Figure 1 displays subjects' decisions in Stage 1, whereby they choose the source of uncertainty for their payment scheme. The proportions of subjects who chose the familiar stock are 68.56 percent, 72.16 percent, and 75.26 percent in groups *Prob10*, *Prob50*, and *Prob90*, respectively. All of these proportions are significantly higher than 50 percent, which indicates a strong tendency towards unfamiliarity aversion (or familiarity seeking) in all groups. Moreover, this tendency is affected by the likelihood of winning. For example, compared with *Prob90*, the proportion choosing the familiar stock is significantly lower in *Prob10* (p =0.001, two-sided test of proportions).

Source Dependence in Traditional Binary Risky Choice.—We replicate source dependence in traditional binary risky choices. Panel (b) displays subjects' decisions in Stage 2 in choosing the source of uncertainty to win $4. The proportions of choosing the familiar stock are significantly higher than 50 percent and increase with the likelihood of winning (63.40 percent, 69.41 percent, and 73.81 percent in groups *Prob10*, *Prob50*, and *Prob90*, respectively).

Robustness Check.—Our main observations of source dependence are robust under different definitions of familiar sources. For example, instead of assuming that subjects are more familiar with bigger companies, we can define whether subjects choose the familiar source according to their self-reported level of familiarity with each stock. Figure A.1 shows the results under this new definition and supports the robustness of our main findings.

Figure 1: Experiment 1 - Tendency to Choose the Familiar Source

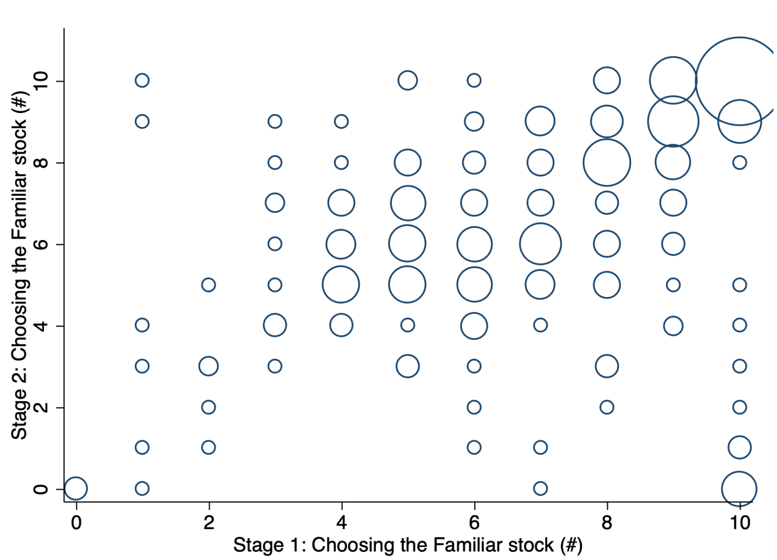


Notes: Panel (a) displays the proportions of decisions in which subjects choose the familiar stock in Stage 1, for groups *Prob10*, *Prob50*, and *Prob90*, respectively. Standard error bars correspond to +/- one standard error. Top horizontal bars indicate the p-values for two-sided tests of proportions for equality of proportions between different groups. Similarly, Panel (b) displays the proportions of choosing the familiar stock in Stage 2.

Consistency.—Figure 1 presents a similar pattern of decisions in Stages 1 and 2, which suggests the consistent source dependence in different domains. We further investigate consistency at individual level. First, for each pair of stocks, subjects make a binary choice in both Stages 1 and 2, which are internally consistent (p <0.001, Pearson's chi-squared test). Second, we can denote each subject's decisions as (x, y), where x is the number of decisions in which the subject chooses the familiar stock in

Stage 1 and y is that in Stage 2. Figure 2 displays the size of the population in each combination of (x, y), and shows that subjects are clustered around the diagonal line and at the upper right corner (Spearman's rank correlation = 0.541). This is in support of consistency of source dependence across different domains of choices.

Figure 2: Experiment 1 - Consistency of Source Dependence across Stages

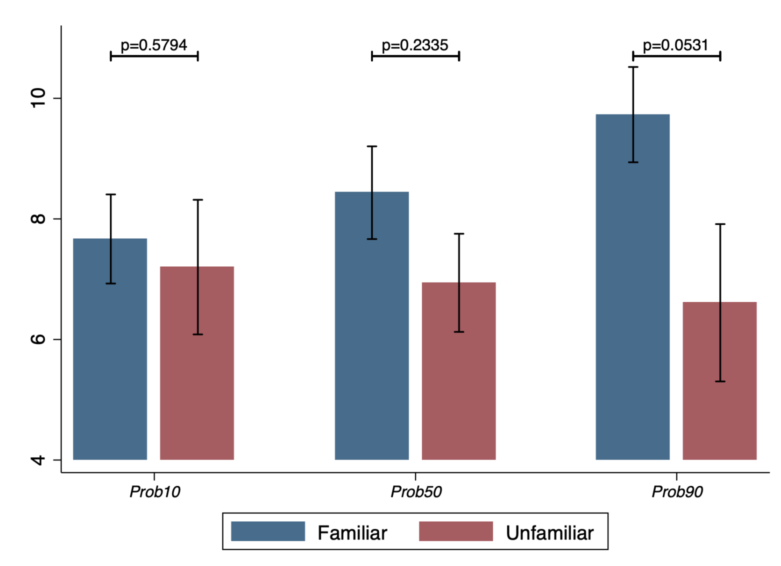


Notes: In this figure, the x-axis is the number of decisions whereby the subject chooses the familiar stock in Stage 1 and the y-axis is that in Stage 2. This figure represents all combinations of (x, y) and the size of each circle shows the population of subjects with the corresponding combination.

Source Dependence in Effort Provision.—We find that subjects also exhibit source dependence in the domain of effort provision. Before the real effort task, for each subject, we randomly draw one of the 10 decisions in Stage 1 as the source of uncertainty of the piece rate. Subjects input effort after knowing the selected stocks. Hence, for each group, we can classify subjects into two subgroups according to whether they receive the familiar or the unfamiliar stock. Figure 3 shows the level of effort provision in each subgroup under different likelihoods of winning, whereby effort is measured by the number of words subjects correctly encrypt. First, for the subgroup with the familiar stock, the average numbers of encrypted words are 7.77, 8.43, and 9.73 in groups *Prob10*, *Prob50*, and *Prob90*, respectively (7.77 vs. 9.73, p =0.071, two-sided t test). This indicates a monotone increase of effort for the likelihood of winning under the familiar source. By contrast, for the subgroup with the unfamiliar stock, the average numbers of encrypted words are 7.00, 6.94, and 6.61 in groups *Prob10*, *Prob50*, and *Prob90*. This suggests that effort provision is insensitive to the likelihood of winning under the unfamiliar source. Second, compared with the unfamiliar stock, the familiar counterpart motivates higher effort input in *Prob90* but not in *Prob10* and *Prob50*, which suggests that subjects exhibit unfamiliarity aversion when the likelihood of winning is high.

In summary, Experiment 1 provides evidence for our two hypotheses. In the binary risky tasks for both uncertain payment schemes and monetary lotteries, we observe a consistent pattern of unfamiliarity aversion across all likelihoods of winning, while the unfamiliarity aversion decreases with the likelihood of winning. These lend support to the hypothesis of source dependence and its internal consistency across domains. In the real effort task, we observe unfamiliarity aversion for high likelihood of winning. Taken together, we find robust and strong unfamiliarity aversion with high likelihood of winning and mixed evidence of unfamiliarity attitudes when the likelihood of winning is low. This pattern implies that individuals are less sensitive to likelihoods under unfamiliar sources of uncertainty than familiar sources, which is in line with the twofold pattern in ambiguity attitudes whereby likelihood insensitivity is stronger under ambiguity than risk. The observation that the hypothesis of monotonicity holds under the familiar but not unfamiliar source of uncertainty further supports this finding.

Figure 3: Experiment 1 - Average Effort across Subgroups



Notes: This figure displays the average number of words subjects correctly encrypt in each subgroup. Standard error bars correspond to +/- one standard error. Top horizontal bars indicate the p-values for two-sided t tests.

4 Experiment 2

One concern about the results of effort provision is that the selection of source is endogenous to subjects' decisions on risky payment schemes. For example, it is possible that subjects who prefer the unfamiliar stock are generally less responsive to likelihood. To overcome this problem, we conduct a between-subjects experiment whereby risky payment schemes are assigned to subjects exogenously. In addition, to further explore the generalizability of our observations, we use an unconditional lump sum payment to examine gift exchange (Akerlof, 1982; Fehr, Kirchsteiger, and Riedl, 1993; Gneezy and List, 2006; Falk, 2007; DellaVigna et al., 2022). Different from Experiment 1, which focuses on the binary choice task, we are specifically interested in the real-effort task in Experiment 2. Experiment 2 adopts a between-subjects design, in which subjects are randomly assigned to receive an uncertain lump-sum payment as a gift, with varying likelihoods of winning and sources of uncertainty. This design allows us to test the hypotheses in our theoretical framework by investigating subjects' effort provision under different conditions. In this section, we describe the experimental design and observations.

4.1 Design

Experiment 2 shares several features with Experiment 1. These include using the word encryption task to elicit effort and adopting almost objective uncertainty based on natural sources. Subjects first learn about their payment scheme and then decide whether and how much to work on the word encryption task. Instead of giving subjects a piece rate for each word they encrypt, the payment scheme here is a lump sum payment that is unconditional on subjects' exerted effort. Moreover, this payment is offered to subjects on top of their participation fee and as a surprise, which is commonly regarded as a gift in the literature. We refer to the amount of this payment as the *Bonus*.

We vary the chance of winning the *Bonus* among eight conditions, with two baselines that involve no uncertainty and six treatments that entail uncertainty with different sources and likelihoods of winning. For the two baselines, subjects in the *No Gift* condition have no chance to earn the *Bonus*, and subjects in the *Sure Gift* condition receive the *Bonus* for sure. These two conditions are designed to test whether a gift can motivate subjects to input more effort.

The six remaining treatment conditions involve uncertainty, which is our main interest. We vary two factors of the uncertainty: the likelihood of winning the *Bonus*—10 percent, 50 percent, or 90 percent; and the source of uncertainty—the New York Stock Exchange Composite Index (NY) or the Laos Securities Exchange Composite Index (*Laos*). Different from Experiment 1, which uses stock prices as natural sources of uncertainty, Experiment 2 employs stock indexes in regions with varying degrees of familiarity. This variation allows us to test the robustness of source dependence based on familiarity. More importantly, it simplifies our exogenous control of the degree of familiarity. It is natural to assume that our subjects, with the majority being American, are more familiar with NY than with *Laos*.

For the six treatment conditions, we explicitly inform subjects of the corresponding likelihoods of winning the *Bonus* and use of the stock index to implement the probability. More specifically, the winning condition is based on the second decimal point of the future value of the given index. Subjects win the *Bonus* if this number is contained in $\{5\}$, $\{1, 3, 5, 7, 9\}$, or $\{0, 1, 2, 3, 4, 6, 7, 8, 9\}$, for the winning probabil-

Table 1: Experiment 2 - Design

Likelihood of Winning	Condition	
0 percent	*No Gift*	
	Sources of Uncertainty	
	NY	*Laos*
10 percent	*10-NY*	*10-Laos*
50 percent	*50-NY*	*50-Laos*
90 percent	*90-NY*	*90-Laos*
100 percent	*Sure Gift*	

ity of 10 percent, 50 percent, or 90 percent, respectively. In summary, for the six conditions with uncertainty, we employ a 3 (probabilities of winning: 10 percent, 50 percent, 90 percent) $\times$ 2 (sources of uncertainty: *NY*, *Laos*) design. We display the eight conditions in Table 1.

We recruited MTurk workers following the same procedure as Experiment 1, with the participation fee being \$1.5 consistently. The first part presented the benchmark instructions. Subjects learned about the real effort task of word encryption and the payment scheme. The payment was specified as a participation fee of \$1.5, regardless of the amount of successfully encrypted words.[6]

Afterward, subjects were randomly assigned to one of the eight conditions through

[6]We set understanding tests and training tasks similar to Experiment 1. In the two questions that tested the understanding of the payment scheme, subjects were asked about the contingent payments with two different amounts of successfully encrypted words, whose correct answers were both \$1.5. Subjects were informed that they were not allowed to continue the study if they made any mistakes on these questions. The duration of the training tasks is used as a proxy for individual productivity in the subsequent analysis.

Qualtrics. Among these eight conditions, we varied the instructions concerning our unconditional gifts, which were specified as chances to win the *Bonus* \$2. Subjects in the *No Gift* condition received no information about the *Bonus* and only read the summary of the benchmark instructions. Apart from the same summary, subjects in the *Sure Gift* condition were informed that they would receive an additional \$2 one day after they submitted their responses.[7] Payment of the *Bonus* for the *Sure Gift* condition was to be consistent with the six remaining conditions. Subjects in the six treatment conditions learned about their probabilities of winning the *Bonus* and the method for implementing the probabilities.[8]

The next part of the study was the real effort task. The page was fixed to remain for 10 minutes. All subjects were given an identical encryption table to encrypt a sequence of 8-letter words. Our key outcome variable is the number of words successfully encrypted. At the end of the study, a short survey was presented to collect subjects' demographic characteristics, as well as their familiarity with different regions. Detailed experiment instructions are presented in Online Appendix B.

[7]We did not frame these two baseline conditions using different sources, since artificially introducing a source to implement the probability of 0 percent or 100 percent seems unnatural in a between-subjects design. Subjects in baseline conditions did not answer the subsequent testing question. We note that without similar cues, the treatment and baseline conditions may not be comparable. Our baseline conditions mostly aim to verify the standard gift exchange under certainty in the MTurk sample.

[8]For example, the instruction for the *10-NY* condition was *"Before starting the experiment, we would like to give you a lottery with a chance of receiving \$2 as bonus tomorrow (the day after you submit your response). With the probability of 10 percent, you get a bonus of \$2. . . . The 10 percent chance will be based on the second decimal point of the New York Stock Exchange Composite Index close price tomorrow. If the number is 5, you get a bonus of \$2".* For each of these six conditions, a question asked subjects about the probability of winning the *Bonus*. This verified whether subjects held an objective belief and perceived the likelihood as the stated chance.

The study sample consisted of 4,203 unique MTurk workers who were randomly assigned to one of the eight conditions, with approximately 520 subjects per condition. The entire experiment's median duration was 18.9 minutes, and the average payment was \$2.51. Table A.2 shows summary statistics of the sample and Table A.4 is the balance check.

4.2 Results

Familiarity of the Sources.—Subjects choose a number between 1 and 5 to indicate their level of familiarity with New York and Laos, with a higher number indicating a higher level of familiarity.[9] As expected, subjects are more familiar with New York than Laos (3.58 vs. 1.66, p <0.0001, two-sided t test). Hereafter we refer to *NY* and *Laos* as the familiar and the unfamiliar source, respectively.

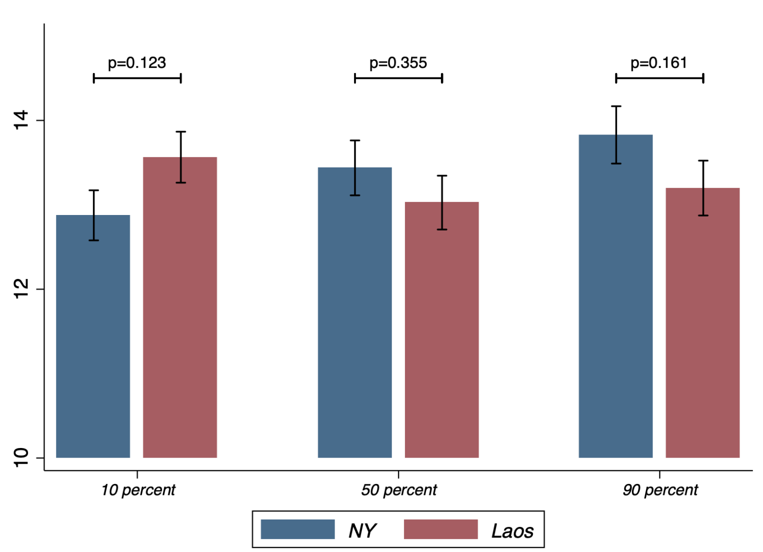
Gift Exchange with Certainty.—The *Bonus* as a certain gift motivates subjects to work more. We compare the effort provision between the two baseline conditions. Our key outcome variable, *Effort*, is measured by the number of successfully encrypted words during the 10-minute real effort task. Subjects on average successfully encrypt 13.20 words in the *No Gift* condition with the participation fee of \$1.5, and 14.17 words in the *Sure Gift* condition with both the \$1.5 and the \$2 as an

[9]We adopt a between-subjects design whereby each subject receives only one source of uncertainty, either *NY* or *Laos*. In the question asking about the degree of familiarity, the source that subjects have not seen in the experiment may appear to be saliently unnatural and affect the reports of familiarity. To avoid this problem, we included another city, Rotterdam, in the task that asked about familiarity, for which subjects report the lowest level of familiarity (1.56).

unconditional gift. We observe that the unexpected increase in payoff significantly increases subjects' effort by 7.35 percent ($p = 0.028$, two-sided t test). In the study by DellaVigna and Pope (2018), compared with the control condition with a participation fee of \$1, an additional \$0.4 increases effort by 5.33 percent. This comparison indicates a diminishing marginal effect of gifts. In Table A.5, we further verify the phenomenon of the gift exchange by regressing *Effort* on a binary variable, which equals 1 for subjects in the *Sure Gift* condition and 0 for subjects in the *No Gift* condition.

Monotonicity in Effort Provision.—Figure 4 plots the average *Effort* across the six treatment conditions, with the y-axis being the number of successfully encrypted words (see also Figure A.2 for different percentiles of *Effort*). Below, we provide details on observations from this figure. Under the source *NY*, effort increases monotonically with the likelihood of winning, while under the source *Laos*, effort exhibits likelihood insensitivity. Specifically, the average *Effort* is 12.88, 13.44, and 13.83 in *10-NY*, *50-NY*, and *90-NY*, respectively (12.88 vs. 13.83, $p = 0.034$, two-sided t test), which shows a clear monotone increasing relationship between winning probability and inputted effort. For *Laos*, the average levels of *Effort* at 10 percent, 50 percent, and 90 percent winning probabilities are 13.56, 13.03, and 13.20, respectively, which indicates the failure of monotonicity. The observations are supported by separate estimations using an Ordinary Least Squares regression (OLS) for different sources. For each source, we regress *Effort* on two dummies, $1_{\text{Prob}=50}$ and $1_{\text{Prob}=90}$, that index the winning probabilities of 50 percent and 90 percent. For *NY*, both coefficients are positive and that of $1_{\text{Prob}=90}$ is significant at the 5 percent level, without and with controls (Table 2, columns 1-2). This pattern is consistent with the theoretical prediction of monotonicity. The same OLS regressions for *Laos* show no significant effect of $1_{\text{Prob}=50}$ and $1_{\text{Prob}=90}$ without and with controls (Table 2, columns 3-4).

Figure 4: Experiment 2 - Average Effort across Treatment Conditions



Notes: This figure displays the average number of words subjects correctly encrypt in each treatment condition. Standard error bars correspond to +/- one standard error. Top horizontal bars indicate the p-values for two-sided t tests.

Taken together, these results suggest a source-dependence likelihood insensitivity—namely, a flatter probability weighting function for *Laos* than for *NY*.[10] This is in line with the hypothesis of source dependence in our theoretical framework. The observed higher level of likelihood insensitivity under the unfamiliar source than the

[10]Likelihood insensitivity is not only commonly observed in decision making under risk and uncertainty, but also in belief updating and expectations about economic variables (see Enke and Graeber (2019) for discussions).

familiar source is also consistent with our findings in Experiment 1 (Figure 3). This observation adds to the existing literature on likelihood insensitivity (Abdellaoui et al., 2011; Li et al., 2018).

Table 2: Experiment 2 - Source Dependence in Effort Provision

	OLS: *Effort*					
	NY		*Laos*		All	
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{\text{Prob}=50}$	0.562	2.366*	-0.538	-1.696	-0.538	-0.106
	(0.440)	(1.362)	(0.439)	(1.374)	(0.439)	(1.015)
$1_{\text{Prob}=90}$	0.953**	2.420**	-0.366	0.419	-0.366	0.757
	(0.451)	(1.204)	(0.444)	(1.112)	(0.444)	(0.879)
1_{NY}					-0.689	-0.405
					(0.423)	(0.769)
$1_{\text{Prob}=50} \times 1_{NY}$					1.100*	0.997*
					(0.622)	(0.578)
$1_{\text{Prob}=90} \times 1_{Laos}$					1.319**	1.307**
					(0.633)	(0.617)
Controls	N	Y	N	Y	N	Y
Constant	12.88***	6.355	13.56***	-2.161	13.56***	4.233
	(0.297)	(10.96)	(0.302)	(3.614)	(0.302)	(8.063)
Observations	1,569	1,569	1,576	1,576	3,145	3,145
R-squared	0.003	0.195	0.001	0.175	0.002	0.160

Notes: Columns 1-2 use the samples of *10-NY*, *50-NY*, and *90-NY*, while columns 3-4 use samples of *10-Laos*, *50-Laos*, and *90-Laos*. These four columns display the regressions about monotonicity. The variable $1_{\text{Prob}=50}/1_{\text{Prob}=90}$ equals 1 if the likelihood of winning is 50/90 percent and 0 otherwise. Columns 5-6 examine the twofold pattern using all six conditions under uncertainty. The variable 1_{NY} equals 1 if the source of uncertainty is NY and 0 otherwise. Controls include *Productivity*, *ObjectiveBelief* and its interactions with treatment dummies, demographics, and the time and date of the experiment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source Dependence in Effort Provision.—Figure 4 also reveals a twofold pattern in effort provision. When the likelihood of winning the $2 is 90 percent (50 percent), the exerted effort motivated by *NY* is 4.77 percent (3.15 percent) higher than that by *Laos*. At a low winning probability of 10 percent, the effect of the source is the reverse—*Laos* induces 5.28 percent more effort than *NY*. To further test the interactive effect between sources and likelihoods of winning on motivating effort, we conduct regression analysis. We regress *Effort* on the probability indexes, the source index NY that equals 1 if the source of uncertainty is NY, and their interaction terms. From Table 2, we observe that the coefficients of the interaction terms are positive and significant (column 5). With additional controls, the coefficient of the interaction term remains significantly positive, and the coefficient for 1_{NY} turns out to be significantly negative (column 6). These findings are consistent with the twofold pattern of ambiguity attitudes—namely, ambiguity aversion (seeking) under moderate to high (low) likelihood of winning. Here we report a similar pattern using natural sources of uncertainty in a real effort task.

Heterogeneity.—In Experiment 2, the monetary incentives for working are invariant with effort, and thus subjects are motivated to work through nonmonetary incentives according to our theoretical framework. Put differently, the sense of the gift exchange converts the evaluation of uncertain gifts into behavioral motivators. A strong social preference elicits effective conversion and thus generates observable variation in the behavior that responds to treatments. In contrast, when the sense of the gift exchange is weak, the difference in the value of gifts may not be revealed in effort significantly. Therefore, the manifestation of source dependence may be positively related to the degree of social preference. Further, since the level of effort is an indicator of social preference, we hypothesize that source dependence, which is captured by the twofold pattern in our results, is more salient among high-performance samples. We use quantile regression to verify this hypothesis, in which the coefficients are interpreted as the effect of the corresponding variables on the conditional quantile of *Effort*. With a full set of controls, we estimate the model at quantiles 0.1, 0.25, 0.5, 0.75, and 0.9 to identify the range in which the source dependence is revealed effectively. Table 3 shows that both the significance and magnitude of source dependence increase as the quantile rises. One interpretation is that relatively weak social preference, implied by low effort input, limits the transformation of gift value to performance. In addition, stronger social preference may motivate careful reading and understanding of instructions, and thereby strengthen the perception of uncertainty and familiarity.

Table 3: Experiment 2 - Heterogeneity (Quantile Regressions)

	Quantile Regression: *Effort*				
	Q(0.1)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.9)
	(1)	(2)	(3)	(4)	(5)
$1_{\text{Prob}=50}$	0.0887	-1.025	-0.159	-0.831**	-0.647
	(0.725)	(0.790)	(0.494)	(0.383)	(1.758)
$1_{\text{Prob}=90}$	0.420	-0.408	0.119	-0.819**	0.365
	(0.670)	(0.580)	(0.541)	(0.401)	(1.234)
1_{NY}	-0.293	-0.616	-0.119	-0.686	-0.163
	(0.504)	(0.774)	(0.512)	(0.467)	(1.119)
$1_{\text{Prob}=50} \times 1_{NY}$	-0.0372	0.501	0.0590	1.246**	1.492*
	(0.719)	(1.024)	(0.718)	(0.509)	(0.843)
$1_{\text{Prob}=90} \times 1_{NY}$	0.0759	0.582	0.358	1.943***	2.277**
	(0.892)	(1.002)	(0.651)	(0.726)	(0.942)
Controls	Y	Y	Y	Y	Y
Constant	6.718	-0.621	-5.016	-4.423	42.03*
	(5.351)	(3.511)	(12.33)	(20.80)	(23.83)
Observations	3,145	3,145	3,145	3,145	3,145

Notes: This table examines the model of column 6 in Table 2 using quantile regression. In column 1, the dependent variable is the 10 percent quantile of *Effort*, and so on. Controls include *Productivity*, *ObjectiveBelief* and its interactions with treatment dummies, demographics, and the time and date of the experiment. Bootstrap standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Experiment 2 - Heterogeneity (SubSample Analyse)

	OLS: *Effort*					
	Nationality		Race		Familiarity	
	American	Non-American	Non-Asian	Asian	New York Higher	Other
	(1)	(2)	(3)	(4)	(5)	(6)
$1_{\text{Prob}=50}$	-0.0953	4.010	0.130	-4.812	-0.0218	-0.856
	(1.045)	(5.115)	(1.024)	(10.45)	(1.078)	(3.272)
$1_{\text{Prob}=90}$	0.835	2.268	0.764	-2.334	0.421	0.315
	(0.908)	(4.982)	(0.901)	(6.045)	(0.926)	(2.861)
1_{NY}	-0.467	4.102	-0.648	5.950	-0.418	0.239
	(0.796)	(3.398)	(0.785)	(5.100)	(0.822)	(2.818)
$1_{\text{Prob}=50} \times 1_{NY}$	0.985	0.456	0.945	-0.161	1.092*	0.778
	(0.602)	(2.970)	(0.586)	(3.675)	(0.614)	(2.265)
$1_{\text{Prob}=90} \times 1_{NY}$	1.379**	-3.295	1.484**	-1.297	1.330**	-0.134
	(0.633)	(3.595)	(0.629)	(4.104)	(0.637)	(3.018)
Controls	Y	Y	Y	Y	Y	Y
Constant	5.340	-8.038	3.798	0.847	5.125	-11.71
	(8.873)	(13.33)	(8.074)	(8.942)	(9.045)	(10.24)
Observations	2,942	203	2,921	224	2,837	308
R-squared	0.159	0.400	0.175	0.272	0.167	0.299

Notes: In columns 1-2, we separate the whole sample into two subsamples according to self-reported nationality. For both the American and the Non-American subsample, we estimate the model of column 6 in Table 2. Columns 3-4 divide subjects based on the self-reported race of either Non-Asian or Asian. Column 5 includes subjects who report a strictly higher level of familiarity with New York than Laos, with the remaining subjects included in column 6. Controls include *Productivity*, *ObjectiveBelief* and its interactions with treatment dummies, demographics, and the time and date of the experiment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Next, in the previous analysis, we implicitly assumed that subjects in our experiment felt more familiar with *NY* than with *Laos*. The assumption is satisfied intuitively by the fact that 93 percent of the sample are Americans, whose geographical locations are closer to New York than Laos. Next, we conduct subsample analyses to further confirm that our findings are driven by subjects who are more familiar with *NY* (Table 4). We observe that the coefficient of interaction term remains significantly positive among self-reported Americans, whereas is insignificant but negative among self-reported non-Americans (columns 1-2). Similarly, the stylized pattern is significant for non-Asian samples but not for the Asian sample (columns 3-4). In columns 5 and 6, we divide subjects into two groups based on whether they report a strictly higher level of familiarity with New York than Laos or not. Results show that the interaction terms of 1_{NY} and probability indexes are only significantly positive for subjects who are more familiar with New York. Overall, these results suggest that the observed source dependence is likely to be driven by subjects with higher familiarity with *NY* than *Laos*.

Robustness Check.—First, we use an alternative specification of the model by replacing the dummy indexes of probabilities with a continuous variable. Our main results of monotonicity and twofold pattern are robust under this new specification (Table A.6). Second, we use an alternative measure of effort. The variable *Attempts* measures the number of non-empty inputs in the real-effort task. The difference between *Effort* and *Attempts* is the mistake(s) made by subjects. We use a regression similar to that of column 6 in Table 2, with the dependent variable being *Attempts*, and report the results in Table A.7. We find that the coefficients of interaction terms are significant after we exclude the subjects with more than five mistakes (column 1). The key coefficients remain significant if we exclude the subjects with more than 10 mistakes or 20 mistakes (columns 2-3), and they become statistically insignificant when the entire sample is included (column 4). This suggests that when the number of mistakes is excessively high, the data may be noisy for various reasons such as random typing. Third, given that the previous analyses are based on the entire sample, whether the results are robust to the exclusion of potentially low-quality samples remains to be tested. We use six criteria to identify low-quality responses (see the notes in Figure A.3 for more details). Based on these six criteria, we classify subjects into two subsamples, high quality and low quality, and examine the main results in Figure 1 separately (Figure A.3). We observe that the pattern is robust across these two subsamples, which indicates that our main findings are not driven by inattention or mistakes.

5 Discussions and Conclusion

This paper examines source dependence in effort provision. Table 5 summarizes our main experimental findings. We document that unfamiliarity aversion diminishes as the likelihood of winning gets smaller, and likelihood insensitivity is more pronounced for unfamiliar sources of uncertainty compared to familiar ones. Moreover, we show that source dependence is internally consistent across domains. Taken together, our observations support the external validity and generalizability of source dependence. We end this paper with the following discussions.

Table 5: Attitudes toward Unfamiliarity in Our Experiments

	10 percent	50 percent	90 percent	Variation
	(1)	(2)	(3)	(4)
Choose Payment Schemes	Aversion	Aversion	Aversion	Aversion ↑
Choose Lotteries	Aversion	Aversion	Aversion	Aversion ↑
Input Effort (Experiment 1)			Aversion	Indifferent → Aversion
Input Effort (Experiment 2)				Seeking → Aversion

Notes: This table summarizes our main experimental findings. Based on the comparison between familiar and unfamiliar sources of uncertainty, we list the observed attitudes toward unfamiliarity that are statistically significant. Columns 1-3 present the within-likelihood comparison between sources, while column 4 describes the cross-likelihood variation of attitudes toward unfamiliarity.

Underpinnings of Unfamiliarity.—A related and important question is the psychological underpinning of source dependence. In our design, we use almost-objective uncertainty to construct probabilities. Responses to sources of uncertainty under this design are more likely to be due to *feelings* rather than information. This mechanism is in line with the literature that highlights the emotional reaction to uncertainty (Loewenstein et al., 2001; Rottenstreich and Hsee, 2001). For example, Rottenstreich and Hsee (2001) observe a similar twofold pattern whereby participants value 1 percent probability of winning a vacation coupon (affect-rich) more than 1 percent probability of winning an equivalent tuition coupon (affect-poor), while the comparison reverses under 99 percent likelihood of winning. As affect-rich prizes increase the degree of hope, participants are more sensitive to changes around certainty and impossibility, and thus present insensitivity among intermediate probability. In this paper, we generally use the term familiarity, in which sentiments such as affection or trust may play an important role. From this perspective, our work highlights the potential to apply the framework of source dependence to explain a wider range of phenomena, such as brand preference and taste-based discrimination.

Comparative Ignorance.—In Experiment 1, subjects choose between uncertain payment schemes or lotteries from different sources of uncertainty. We find that they exhibit a significant unfamiliarity aversion across each of the likelihoods of winning (Figure 1). In Experiment 2, however, with a between-subjects design, subjects choose the effort in response to the uncertain gift from one source of uncertainty. We do not find significant unfamiliarity aversion within each likelihood of winning (see Table A.8 for the pairwise comparisons using t-tests and Kolmogorov–Smirnov tests). When pooling all conditions together, we find marginally significant twofold pattern (see Table 2). The observed weaker evidence of source dependence in Experiment 2 compared to Experiment 1 can be due to various differences between the two experiment. One main difference has to do with the notion of comparative ignorance proposed by Fox and Tversky (1995). In their pioneer study, source dependence is present in comparative settings in which there is a direct comparison across sources—evaluating risky and ambiguous prospects simultaneously, or betting on the future temperature in both familiar and unfamiliar cities. By contrast, the pattern of source dependence is insignificant in noncomparative settings. They suggest that when facing one source of uncertainty, individuals *"pay little or no attention to the quality or precision of their assessment of the likelihood of the event."* However, when facing more than one source, individuals are *"sensitive to the contrast in their knowledge regarding the two events."* This provides an explanation for the significant results in Experiment 1 and weaker results in Experiment 2. Nevertheless, under the influence of comparative ignorance in Experiment 2, even though the within-likelihood comparisons are not significant, the variation in attitudes with likelihood remains significant. Taken together the evidence from both experiments, our study supports the role of source dependence in effort provision.

Likelihood Insensitivity.—In the effort provision in both experiments, we observe a monotone increase in effort with the probability to win the uncertain payment based on the familiar source but not the unfamiliar source. This finding adds to the mixed evidence in the literature. Abdellaoui et al. (2011) observe greater insensitivity to ambiguity compared with that to risk, while the difference in insensitivity across different natural sources is not significant. Li et al. (2018) find that the estimated insensitivity indices are lower for natural uncertainty than for Ellsbergian uncertainty. These findings support source-dependent likelihood insensitivity. Enke and Graeber (2019) show that cognitive uncertainty may underpin the commonly observed likelihood insensitivity in various settings including decision making under risk and uncertainty, belief updating, and expectations about economic variables. Our observation is in line with their explanation: Subjects are likely to be more cognitively uncertain about unfamiliar sources compared to familiar ones, and thus exhibit greater likelihood insensitivity.

Internal Consistency.—From Experiment 1, we observe that source dependence is internally consistent across uncertain incentive schemes (Stage 1) and standard lotteries (Stage 2). This pattern may be related to the own-company stock puzzle whereby individuals choose to work in a specific company and, at the same time, hold suboptimally high amounts of their employer's stock (Benartzi, 2001). Dimmock et al. (2016) documents the positive relationship between ambiguity aversion and own-company stock ownership, which supports the intuition that this puzzle is a manifestation of source dependence. Therefore, the notion of source dependence has the potential to explain some regularities in empirical settings.

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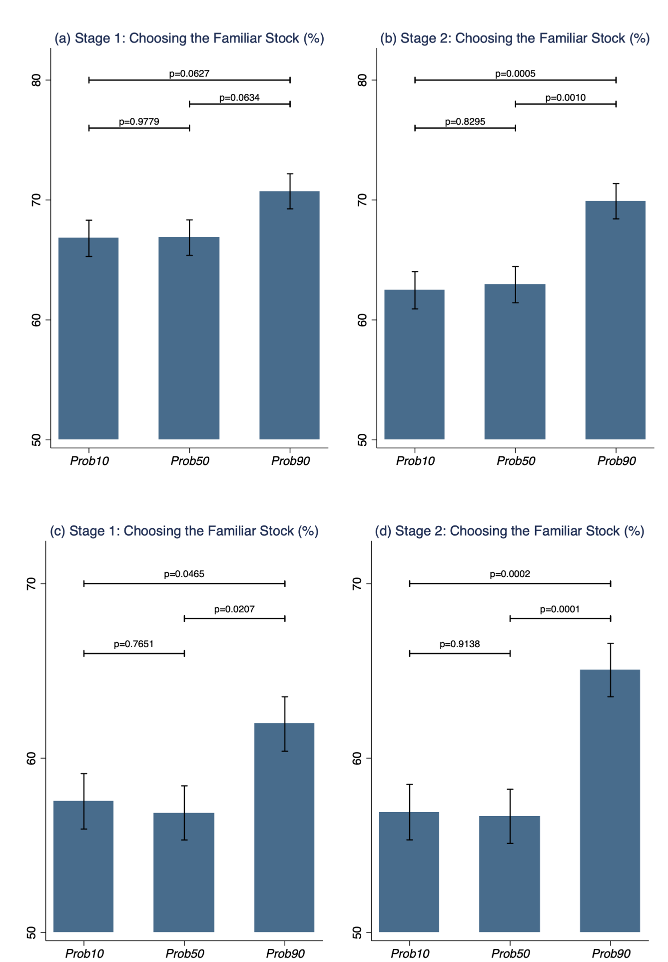
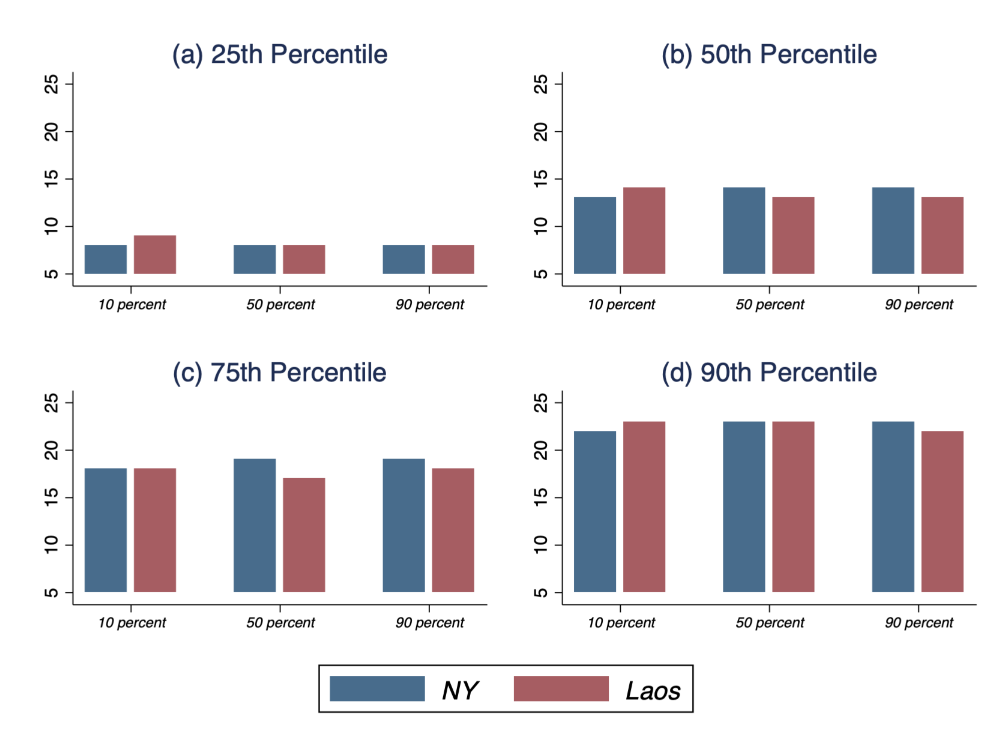
A Online Appendix A: Additional Figures and Tables

Figure A.1: Experiment 1 - Robustness Checks



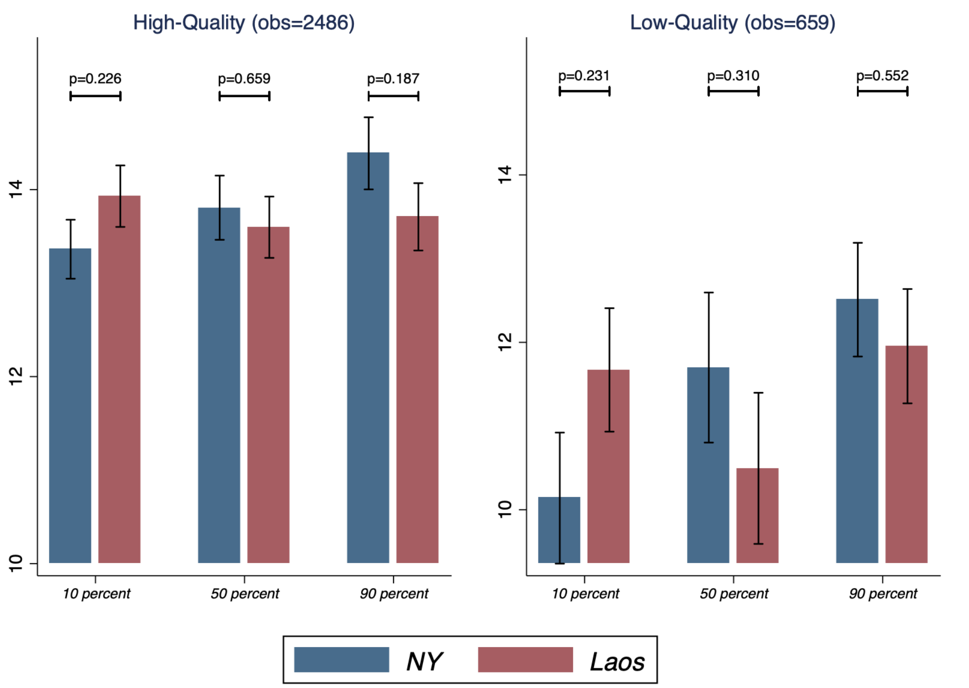
Notes: This figure displays robustness checks of the main observations in Figure 1. Here we define whether a subject chooses the familiar stock according to whether she chooses the stock with a higher self-reported level of familiarity. There are some cases in which subjects indicate the same level of familiarity toward the two stocks in a pair (26.11 percent, denoted as the indifference group). Directly dropping these observations may cause a sample selection problem. Instead, in Panels (a) and (b), we regard the indifference group as being more familiar with the top 100 stocks, while in Panels (c) and (d), we regard them as being more familiar with stocks with rankings between 1,000 and 6,000.

Figure A.2: Experiment 2 - Different Percentiles of Effort Across Treatment Conditions



Notes: This figure plots the 25th, 50th, 75th, and 90th percentiles of *Effort* across the six treatment conditions.

Figure A.3: Experiment 2 - Average Effort across Conditions (by Quality)



Notes: We separate subjects into two samples based on the following six criteria. Criterion 1 captures subjects with a duration for the whole study exceeding 1 hour and a duration for training tasks exceeding 5 minutes, while criterion 2 is used to exclude subjects who successfully encrypt more than 60 8-letter words in 10 minutes. Since the experiment allows re-entering for those who fail in the screening (randomization in the assignment of groups occurs later than screening), criterion 3 identifies those who re-enter the experiment more than three times. Criterion 4 excludes subjects who do not complete the whole survey at the end of the experiment. In the training tasks, encrypting "he" and "software," only the former is used as a screening question. Subjects who successfully encrypt "he" but not "software" is captured by criterion 5. Criterion 6 identifies those with $ObjectiveBelief = 0$, whose perceived likelihood of winning is not equal to the specified objective likelihoods. Subjects who do not satisfy any of the six criteria will be considered High Quality, and the remaining will be considered Low Quality. We report the main result in Figure 4 using these two samples.

Table A.1: Experiment 1 - The List of Stocks

Pair	Familiar (Common Stock)	Unfamiliar (Common Stock)
1	Microsoft Corporation	Monte Rosa Therapeutics Inc.
2	Alphabet Inc. Class A	The Duckhorn Portfolio Inc.
3	Amazon.com Inc.	Apollo Medical Holdings Inc.
4	Walt Disney Company	Priority Technology Holdings Inc.
5	Meta Platforms Inc. Class A	IronNet Inc.
6	Netflix Inc.	IO Biotech Inc.
7	Nike Inc.	Seaport Calibre Materials Acquisition Corp. Class A
8	Walmart Inc.	TELA Bio Inc.
9	Pfizer Inc.	Tarsus Pharmaceuticals Inc.
10	Coca-Cola Company	Mercer International Inc.

Table A.2: Experiment 1&2 - Summary Statistics

Variable	Experiment 1 obs = 296	Experiment 2 obs = 4203
Productivity	1.363	1.072
ObjectiveBelief	0.706	0.871
1 if Female	0.402	0.531
1 if Age: 35-54	0.324	0.413
1 if Age: >54	0.0743	0.138
1 if White	0.892	0.796
1 if American	0.973	0.934
1 if Bachelor's	0.834	0.415
1 if >Bachelor's	0.0743	0.148
1 if Employed	0.939	0.718
1 if Married	0.845	0.442
1 if Has child(ren)	0.797	0.494
1 if Protestant	0.0676	0.267
1 if Catholic	0.706	0.209
1 if No religion	0.0541	0.386

Notes: This table reports the summary statistics of our samples in Experiments 1 and 2. The variable *Productivity* is the reciprocal of the time that subjects spent on the training task. The variable *ObjectiveBelief* equals 1 if subjects' reported probability of winning is the objective probability and 0 otherwise.

Table A.3: Experiment 1 - Balance Check

Variable	OLS: Condition indicator			OLS: $\bar{1}_{\text{Familiar}}$	
	Prob10	*Prob50*	*Prob90*	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)
Productivity	0.0297**	-0.00319	-0.0265***	-0.00195	0.00843
	(0.0117)	(0.0120)	(0.00866)	(0.00511)	(0.00536)
ObjectiveBelief	0.0611	0.0991	-0.160**	-0.0106	0.0101
	(0.0600)	(0.0605)	(0.0635)	(0.0297)	(0.0348)
1 if Female	0.0526	-0.0221	-0.0305	-0.00407	-0.0252
	(0.0637)	(0.0684)	(0.0675)	(0.0343)	(0.0366)
1 if Age: 35-54	-0.0688	0.0751	-0.00626	0.0509	0.0881**
	(0.0697)	(0.0750)	(0.0711)	(0.0385)	(0.0386)
1 if Age: >54	-0.00147	0.0529	-0.0515	0.0268	0.0981*
	(0.113)	(0.118)	(0.110)	(0.0451)	(0.0524)
1 if White	-0.0791	0.120	-0.0407	-0.147***	0.101
	(0.0940)	(0.0889)	(0.0946)	(0.0480)	(0.0722)
1 if American	-0.608***	0.394***	0.215**	0.258**	0.0160
	(0.118)	(0.0670)	(0.0973)	(0.109)	(0.103)
1 if Bachelor's	0.167	-0.134	-0.0327	-0.0587	-0.0315
	(0.117)	(0.133)	(0.120)	(0.0858)	(0.0913)
1 if >Bachelor's	0.234	-0.171	-0.0623	-0.00173	-0.00219
	(0.160)	(0.172)	(0.150)	(0.101)	(0.102)
1 if Employed	0.162	0.0290	-0.191	-0.0526	-0.0335
	(0.117)	(0.122)	(0.130)	(0.0733)	(0.0912)
1 if Married	0.0208	-0.103	0.0827	-0.0596	-0.0501
	(0.111)	(0.117)	(0.109)	(0.0673)	(0.0806)
1 if Has child(ren)	-0.0229	-0.0204	0.0433	0.0871	0.0208
	(0.0927)	(0.0948)	(0.0900)	(0.0600)	(0.0711)
1 if Protestant	-0.0797	-0.129	0.209	0.0778	0.116
	(0.116)	(0.125)	(0.130)	(0.0731)	(0.0936)
1 if Catholic	-0.00616	-0.110	0.116	0.0430	0.0769*
	(0.0738)	(0.0781)	(0.0714)	(0.0358)	(0.0441)
1 if No religion	0.0878	-0.440***	0.352**	0.0505	0.122
	(0.147)	(0.115)	(0.148)	(0.0850)	(0.105)
Constant	0.605***	0.0806	0.314*	0.634***	0.553***
	(0.186)	(0.148)	(0.171)	(0.123)	(0.136)
Observations	296	296	296	296	296
R-squared	0.078	0.064	0.069	0.085	0.072

Notes: This table reports the balance check for Experiment 1. In columns (1) to (3), the dependent variable is the indicator variable that equals to 1 if the subject is in *Prob10*, *Prob50*, and *Prob90*, respectively. In column (4)/(5), the dependent variable is the proportion of decisions (out of 10 decisions) in which the subject chooses the familiar stock in Stage 1/Stage 2. Even though there is a slight imbalance driven by chance, this could not explain the systematic preference for the familiar source we observe in Stages 1 and 2. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Experiment 2 - Balance Check

	OLS: Condition indicator								OLS: *Effort*
	Sure Gift	*90-NY*	*90-Laos*	*50-NY*	*50-Laos*	*10-NY*	*10-Laos*	*No Gift*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Productivity	-0.0129	0.0104	0.00245	0.00872	-0.0153	-0.00380	0.00592	0.00448	5.453***
	(0.0128)	(0.0117)	(0.0127)	(0.0120)	(0.0117)	(0.0123)	(0.0119)	(0.0129)	(0.362)
1 if Female	0.00718	-0.0171	-0.0128	0.00375	0.0154	0.0101	0.00509	-0.0116	1.295***
	(0.0107)	(0.0106)	(0.0106)	(0.0106)	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.216)
1 if Age: 35-54	0.00440	-0.0188	0.00756	-0.00293	-0.00392	-0.00754	0.00606	0.0151	0.721***
	(0.0117)	(0.0118)	(0.0116)	(0.0118)	(0.0113)	(0.0115)	(0.0114)	(0.0119)	(0.247)
1 if Age: >54	0.00108	-0.0157	-0.0108	-0.0123	0.0276	0.0119	0.0221	-0.0238	0.0192
	(0.0177)	(0.0170)	(0.0167)	(0.0171)	(0.0179)	(0.0177)	(0.0177)	(0.0167)	(0.300)
1 if White	-0.0128	-0.00974	0.00670	-0.00985	0.0147	-0.0175	0.00388	0.0246*	0.908***
	(0.0135)	(0.0132)	(0.0127)	(0.0134)	(0.0125)	(0.0131)	(0.0130)	(0.0126)	(0.272)
1 if American	-0.0127	0.00439	0.0288	-0.00186	-0.00243	-0.0449*	0.0405**	-0.0119	-2.932***
	(0.0217)	(0.0212)	(0.0189)	(0.0216)	(0.0206)	(0.0234)	(0.0183)	(0.0214)	(0.455)
1 if Bachelor's	0.00836	-0.0107	0.0170	-0.0173	0.00394	0.0245**	-0.00828	-0.0175	0.0293
	(0.0116)	(0.0113)	(0.0114)	(0.0115)	(0.0113)	(0.0115)	(0.0113)	(0.0115)	(0.228)
1 if > Bachelor's	-0.0142	0.000650	-0.00533	-0.0164	0.00862	0.0242	0.0148	-0.0123	0.204
	(0.0154)	(0.0159)	(0.0150)	(0.0158)	(0.0159)	(0.0162)	(0.0163)	(0.0156)	(0.332)
1 if Employed	-0.0127	0.000320	-0.00358	-0.00519	0.00716	0.0106	-0.00500	0.00840	-1.100***
	(0.0124)	(0.0118)	(0.0118)	(0.0121)	(0.0120)	(0.0117)	(0.0121)	(0.0117)	(0.227)
1 if Married	-0.00832	0.00647	-0.00526	0.0277**	0.00862	0.0139	-0.0190	-0.0241**	-0.551**
	(0.0118)	(0.0123)	(0.0117)	(0.0121)	(0.0124)	(0.0122)	(0.0123)	(0.0120)	(0.239)
1 if Has child(ren)	0.0157	0.0121	0.00157	-0.0113	-0.0189	-0.00728	-0.00292	0.0110	0.187
	(0.0125)	(0.0127)	(0.0122)	(0.0125)	(0.0125)	(0.0124)	(0.0128)	(0.0126)	(0.248)
1 if Protestant	0.000536	-0.0341**	0.00582	0.0122	0.0139	-0.0219	0.00459	0.0189	-0.381
	(0.0179)	(0.0171)	(0.0172)	(0.0167)	(0.0166)	(0.0180)	(0.0164)	(0.0164)	(0.340)
1 if Catholic	-0.00967	-0.0234	-0.0122	0.0192	0.00258	-0.0169	0.0225	0.0179	-0.730*
	(0.0186)	(0.0181)	(0.0177)	(0.0178)	(0.0174)	(0.0189)	(0.0176)	(0.0173)	(0.375)
1 if No religion	-0.0175	-0.00462	-0.00539	0.0143	0.0121	-0.0326*	0.0158	0.0178	-0.430
	(0.0167)	(0.0170)	(0.0162)	(0.0160)	(0.0159)	(0.0170)	(0.0160)	(0.0156)	(0.342)
Constant	0.170***	0.145***	0.0956***	0.122***	0.110***	0.178***	0.0723***	0.107***	9.919***
	(0.0299)	(0.0285)	(0.0283)	(0.0274)	(0.0300)	(0.0314)	(0.0257)	(0.0267)	(0.712)
Observations	4,203	4,203	4,203	4,203	4,203	4,203	4,203	4,203	4,203
R-squared	0.003	0.004	0.002	0.002	0.003	0.006	0.003	0.005	0.131

Notes: Columns 1-8 report the results of the balance check. In each column, the dependent variable is the corresponding condition indicator. Taking column 1 as an example, the dependent variable, a condition indicator that equals 1 if the subject is in condition *Sure Gift* and 0 otherwise, is regressed on subjects' demographic characteristics. None of the independent variables are statistically significant. Similarly, for regressions with the dependent variables being the other seven condition indicators, demographic variables are not significant in most cases, with few exceptions (columns 2-8). Column 9 reports OLS regression result of *Effort* on demographics. Female, middle-aged, and unemployed workers perform better on average, with other related features such as race and nationality.

Consequently, we are able to predict the effect of sample imbalance on *Effort*. Comparing *90-NY* with *90-Laos*, the former has fewer Protestants than the latter. However, according to column 9, being a Protestant has no influence in *Effort*. Comparing *50-NY* with *50-Laos*, the higher proportion of married subjects in *50-NY* predicts a lower *Effort*. Similarly, compared with *10-NY*, the performance of *10-Laos* should be lower, since it contains more American, which negatively relates to average effort input. Therefore, the predictions of slight sample imbalance are contrary to the observed twofold pattern in this paper. These observations are consistent with the results in Table 2, in which the significance and magnitude of key explanatory variables increase after controlling for demographics.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Experiment 2 - Testing Gift Exchange with Certainty

	OLS: *Effort*	
	(1)	(2)
Gift	0.978**	1.259***
	(0.437)	(0.412)
Controls	N	Y
Constant	13.20***	7.167**
	(0.320)	(2.917)
Observations	1,058	1,058
R-squared	0.005	0.197

Notes: This table reports the effect of gift exchange with certainty on motivating effort using samples of two baseline conditions. The variable *Gift* equals 1 if subjects are in *Sure Gift* and equals 0 if subjects are in *No Gift*. Controls include *Productivity*, demographics, and the time and date of the experiment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Experiment 2 - Alternative Specification

	OLS: *Effort*					
	NY		*Laos*		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Prob	1.192**	2.651*	-0.458	1.256	-0.458	1.059
	(0.563)	(1.456)	(0.555)	(1.395)	(0.555)	(1.075)
1_{NY}					-0.707	-0.494
					(0.454)	(0.813)
Prob $\times 1_{NY}$					1.650**	1.641**
					(0.790)	(0.771)
Controls	N	Y	N	Y	N	Y
Constant	12.79***	6.363	13.49***	-3.165	13.49***	3.968
	(0.320)	(10.98)	(0.323)	(3.656)	(0.323)	(8.073)
Observations	1,569	1,569	1,576	1,576	3,145	3,145
R-squared	0.003	0.194	0.000	0.174	0.002	0.160

Notes: This table displays the results of an alternative specification of the models in Table 2. The variable Prob is a continuous variable that equals 0.1, 0.5, and 0.9 for the 10 percent, 50 percent, and 90 percent likelihood of winning, respectively. Controls include *Productivity*, *ObjectiveBelief* and its interactions with treatment dummies, demographics, and the time and date of the experiment. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.7: Experiment 2 - Alternative Measure

	OLS: *Attempts*			
	Error≤5	*Error*≤10	*Error*≤20	All
	(1)	(2)	(3)	(4)
$1_{\text{Prob=50}}$	-0.599	-0.561	-0.592	-3.366**
	(1.046)	(1.032)	(1.035)	(1.705)
$1_{\text{Prob=90}}$	0.402	0.596	0.778	-1.308
	(0.917)	(0.915)	(0.920)	(1.681)
1_{NY}	-0.429	-0.147	-0.394	0.433
	(0.820)	(0.813)	(0.823)	(1.184)
$1_{\text{Prob=50}} \times 1_{NY}$	1.320**	1.013*	1.147*	0.453
	(0.611)	(0.605)	(0.617)	(0.700)
$1_{\text{Prob=90}} \times 1_{NY}$	1.448**	1.267**	1.448**	0.801
	(0.636)	(0.642)	(0.660)	(0.760)
Controls	Y	Y	Y	Y
Constant	-3.616	-4.600	5.600	8.208
	(2.852)	(2.840)	(9.662)	(9.679)
Observations	3,015	3,105	3,129	3,145
R-squared	0.163	0.159	0.150	0.125

Notes: This table displays the results with an alternative measure of effort provision of the models in Table 2. In each column, the dependent variable is *Attempts*, the number of non-empty inputs in the real-effort task. The variable *Error=Attempts-Effort* is used to indicate the validity of using *Attempts* to measure effort. Larger *Error* suggests larger noise of using *Attempts* to measure effort. Column 1 uses data from subjects with *Error*≤ 5, and the samples used in columns 2, 3, and 4 are specified accordingly. Controls include *Productivity*, *ObjectiveBelief* and its interactions with treatment dummies, demographics, and the time and date of the experiment. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Experiment 2 - Pairwise Comparisons

Panel A: t test, two-sided p values

	No Gift	*10-NY*	*10-Laos*	*50-NY*	*50-Laos*	*90-NY*	*90-Laos*	*Sure Gift*
No Gift								
10-NY	0.475							
10-Laos	0.409	0.123						
50-NY	0.586	0.207	0.776					
50-Laos	0.706	0.736	0.228	0.355				
90-NY	0.159	0.034	0.556	0.383	0.074			
90-Laos	0.994	0.47	0.413	0.592	0.7	0.161		
Sure Gift	0.028	0.004	0.171	0.097	0.01	0.44	0.028	

Panel B: Kolmogorov-Smirnov test, combined p values

	No Gift	*10-NY*	*10-Laos*	*50-NY*	*50-Laos*	*90-NY*	*90-Laos*	*Sure Gift*
No Gift								
10-NY	0.989							
10-Laos	0.601	0.474						
50-NY	0.795	0.467	0.779					
50-Laos	1	0.995	0.301	0.341				
90-NY	0.561	0.191	0.897	0.988	0.219			
90-Laos	0.999	0.983	0.522	0.721	0.977	0.485		
Sure Gift	0.108	0.046	0.3	0.032	0.021	0.167	0.022	

Notes: This table presents the results of pairwise comparisons among the eight conditions in Experiment 2.

B Online Appendix B: Experimental Instructions

B.1 Instructions for Experiment 1

Welcome to our study.

Contact Information
This study is conducted by a research team in the Department of Economics, National University of Singapore. If you have any questions, concerns, or complaints about this study, its procedures, risks, and benefits, please write to e0193210@u.nus.edu.

Confidentiality
This study is anonymous. The data collected in this study do not include any personally identifiable information about you. By participating, you understand and agree that the data collected in this study will be used by our research team and aggregated results will be published.

Duration
This study lasts approximately **20 minutes**.
You may choose to stop participating in this study at any time.

Payment
You will receive a **$1.5 participation fee** after you finish the entire study.
You may receive **an additional payment**. What you finally receive depends partly on your decisions and partly on chance. The transfer of the additional payment will take up a week. All payments and procedures will be implemented in exactly the manner described in this experiment and on the Amazon Mechanical Turk platform.

Qualification
A set of instructions will be given at the start. Please read the instructions carefully. There will be simple questions to check your understanding. You may not be able to continue the study if you make mistakes.

Please click the following boxes to indicate that you have understood and accept the rules.

I am a US resident and 21 years or older.

I would like to participate in this study and agree to the above rules.

This experiment has two parts.
We will randomly choose one part to determine your bonus.

The first part of the experiment is a 10-minute real-effort task of encrypting words.

You will receive the following Encryption Table in every task. You need to encrypt the given word by substituting the letters with numbers or symbols using this Encryption Table.

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

For example, if you receive the word "**she**", you need to encrypt it into "**1322@**". That is, based on the Encryption Table, you need to substitute "s" with "13", "h" with "22" and "e" with "@". When you combine these together, you have "1322@".

Understanding Test 1

Please encrypt the following words according to the given Encryption Table (please do NOT put quotes, directly input a sequence of numbers or symbols, for example, !121410@#2422).

he

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

software

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

From this point, we randomly assigned subjects to the eight conditions. The followings are the screenshots for conditions *Prob50*. The remaining two conditions are similar to *Prob50*.

In the first part of the experiment, your bonus is determined as follows.

- With probability **50%**, you earn **$0.1 for each word** you successfully encrypt;
- With probability **50%**, you earn **$0**, regardless of how many words you successfully encrypt.

For example, suppose you successfully encrypt 20 words, with probability 50%, you earn $(0.1*20)=$2; with probability 50%, you earn $0.

Understanding Test 2

You successfully encrypt 30 words. Which of the following statements is correct?

I earn $30 for sure.

I earn $(0.1*30)=$3 for sure.

I earn $0 for sure.

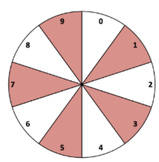
With probability 50%, I earn $(0.1*30)=$3; with probability 50%, I earn $0.

Understanding Test 3

You successfully encrypt 2 words. Which of the following statements is correct?

- I earn $2 for sure.
- I earn $(0.1*2)=$0.2 for sure.
- I earn $0 for sure.
- With probability 50%, I earn $(0.1*2)=$0.2; with probability 50%, I earn $0.

The 50% chance will be based on your bet on **a given stock's first decimal point of its closing price tomorrow**. As the first decimal, it is **equally likely** to be one of the ten numbers: 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9.

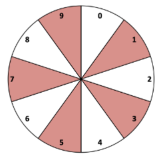


- If the number is **1, 3, 5, 7, or 9**, you earn **$0.1 for each word** you successfully encrypt;
- If the number is **0, 2, 4, 6, or 8**, you earn **$0**, regardless of how many words you successfully encrypt.

You may verify the bets from the stock index through: https://finance.yahoo.com/.

Understanding Test 4

As described before, you bet on the first decimal point of a stock tomorrow. As the first decimal, it is **equally likely** to be **one of the ten numbers**: 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9. The probability for the number **to be 1, 3, 5, 7, or 9** is:



10%

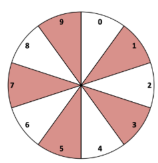
40%

50%

90%

Understanding Test 4

Your answer is **correct**. The first decimal point of a stock is equally likely to be one of the ten numbers: 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9. Therefore, the probability for this number to be 1, 3, 5, 7, or 9 is **50%**.

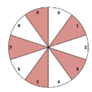


Before you start the word encryption task, you will first choose which stock to bet on. In each of the following rounds, you will be shown two stocks. You are asked to choose one stock to bet on its price.

Example:

You bet on the first decimal point of the company's stock closing price tomorrow.

- If the number is **1, 3, 5, 7, or 9**, you earn **$0.1 for each word** you successfully encrypt;
- If the number is **0, 2, 4, 6, or 8**, you earn **$0**, regardless of how many words you successfully encrypt.



Please choose one company to make a bet.

THOR
Go Everywhere. Stay Anywhere.

You make the decision by selecting the company's logo.

In each round, you will choose one out of the two stocks. There are 10 rounds. We will randomly choose one round to count. Your bet in the chosen round will decide how to calculate your bonus in the word encryption task later.

Please start to make your choice.

Now you have finished making choices for the first part of the experiment.

You will do the 10-minute real-effort task at the end of the study. We will tell you which bet is chosen to count at the point.

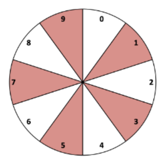
Before that, **please continue to finish the other main part of the study**.

In the second part of the experiment, your bonus is determined as follows.

- With probability **50%**, you earn **$4**.
- With probability **50%**, you earn **$0**.

Similar to the first part, the 50% chance will be based on your bet on a stock.

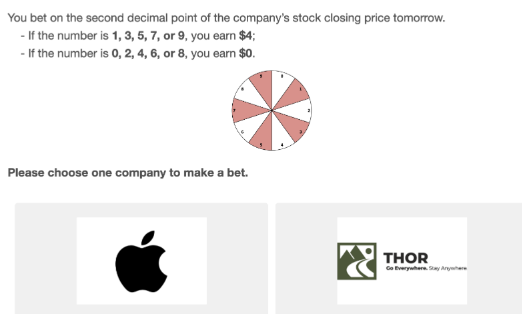
For a given stock, you bet on the **second decimal point of its closing price tomorrow**. As the second decimal, it is **equally likely** to be one of the ten numbers: 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9.



- If the number is **1, 3, 5, 7, or 9**, you earn **$4**;
- If the number is **0, 2, 4, 6, or 8**, you earn **$0**.

In each of the following rounds, you will be shown two stocks. You are asked to choose one stock to bet on its price.

Example:



You make the decision by selecting the company's logo.

In each round, you will choose one out of the two stocks. There are 10 rounds. We will randomly choose one round to count. Your bet in the chosen round will decide how to calculate your bonus in the second part of the experiment.

Please start to make your choices.

Now you have finished the main part of the study.

You will start the 10-minute real-effort task now. According to your choices in Part 1, the following stock is randomly chosen.

Coca-Cola

For the chosen stock, you bet on the first decimal point of its closing price tomorrow. As the first decimal, it is equally likely to be one of the ten numbers: 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9.

- If the number is **1, 3, 5, 7, or 9**, you earn **$0.1 for each word** you successfully encrypt;
- If the number is **0, 2, 4, 6, or 8**, you earn **$0**, regardless of how many words you successfully encrypt.

The next page is for the real-effort task of encrypting words.
You will stay on the same page for 10 minutes.
You can choose whether to encrypt words and if so, how many words to encrypt.

The followings are the screenshots for the real-effort task, which is identical across all eight conditions.

You will stay in this page for 10 minutes.

Please encrypt the following words according to the given Encryption Table (please do NOT put quotes, directly input a sequence of numbers or symbols, for example, !121410@#2422).

physical

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

B.2 Instructions for Experiment 2

- You will take part in an experiment that will last approximately 15 minutes.
- All payments and procedures will be implemented in exactly the manner described in this experiment and on the Amazon Mechanical Turk platform.
- You may choose to stop participating in this experiment at any time.
- The experiment is anonymous.
- You may print a copy of this information sheet for your own records.
- If you have any questions, concerns or complaints about this experiment, its procedures, risks and benefits, you could contact Associate Professor Songfa Zhong (ecszs@nus.edu.sg), Department of Economics, National University of Singapore.

- A set of instructions will be given at the start of the experiment. In order to ensure that you read the instructions carefully and closely, questions will be asked.
- Please note that if you make mistakes in these understanding questions, you may not be allowed to complete the experiment.

- The experiment includes two parts:
  - A 10-minute real-effort task;
  - A 3-5-minute survey.
- You will receive $ 1.5 participation fee after you finish these two parts.

- The first part of the experiment is a 10-minute real-effort task of encrypting words.
- You will receive the following Encryption Table in every task. You need to encrypt the given word by substituting the letters with numbers or symbols using this Encryption Table.

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

- For example, if you receive the word "she", you need to encrypt it into "1322@". That is, based on the Encryption Table, you need to substitute "s" with "13", "h" with "22" and "e" with "@". When you combine these together, you have "1322@".

Please encrypt the following words according to the given Encryption Table (please do NOT put quotes, directly input a sequence of numbers or symbols, for example, !121410@#2422).

he

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

software

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		

- In the first part of the experiment, you are supposed to successfully encrypt as many words as you can.
- However, your payment is fixed as $ 1.5 regardless of how many words you successfully encrypt.
- That is, once you go through the two parts in the experiment, you will gain $ 1.5 participation fee.

Worker A successfully encrypted 30 words in the first part and completed the second part. The participation fee is $ 1.5. How much would worker A receive from this experiment?

$ 1.5

$ 3

$ 4.5

$ 1

Worker A successfully encrypted 10 words in the first part and completed the second part. The participation fee is $ 1.5. How much would worker A receive from this experiment?

$ 4.5

$ 3

$ 1

$ 1.5

Please click the following arrow to see whether you can complete the following experiment or not.

From this point, we randomly assigned subjects into the eight conditions. The followings are the screenshots for conditions *No Gift*, *Sure Gift*, and *90-NY*. The remaining six conditions are similar to *90-NY*.

No Gift

- You already completed the instruction part and you are qualified to complete the following experiment.

To summary:

- You will receive $1.5 participation fee in this experiment.
- Your performance in the first part and your responses in the second part will NOT affect the payoff you get.
- That is, once you go through the 10-minute real-effort task in the first part and complete the survey in the second part, you will gain $ 1.5 participation fee.

Sure Gift

- You already completed the instruction part and you are qualified to complete the following experiment.
- Before starting the experiment, we would like to give you $ 2 as bonus tomorrow (the day after you submit your response).

To summary:

- You will receive $1.5 participation fee and $ 2 additional bonus in this experiment.
- Your performance in the first part and your responses in the second part will NOT affect the payoff you get.
- That is, once you go through the 10-minute real-effort task in the first part and complete the survey in the second part, you will gain $ 1.5 participation fee. In addition, you will gain $2 as bonus tomorrow.

90-NY

- You already completed the instruction part and you are qualified to complete the following experiment.
- Before starting the experiment, we would like to give you a lottery with a chance of receiving $ 2 as bonus tomorrow (the day after you submit your response).
  - With the probability of 90%, you get a bonus of $ 2.
  - With the probability of 10%, you do not get the bonus.
- The 90% chance will be based on the second decimal point of the New York Stock Exchange Composite Index close price tomorrow.
  - If the number is NOT 5, you get a bonus of $ 2.
  - If the number is 5, you do not get the bonus.
- You can verify whether you get the bonus tomorrow by checking New York Stock Exchange Composite Index close price through Bloomberg: https://www.bloomberg.com/quote/NYA:IND.

The second decimal point of New York Stock Exchange Composite Index close price in the next opening date will be one of the 10 numbers {0, 1, 2, 3, 4, 5, 6, 7, 8, 9}. The probability for the number NOT to be 5 is:

10%

40%

50%

90%

To summary

- You will receive $1.5 participation fee and a lottery to receive additional bonus (either $2 or $0) in this experiment.
- Your performance in the first part and your responses in the second part will NOT affect the payoff you get.
- That is, once you go through the 10-minute real-effort task in the first part and complete the survey in the second part, you will gain $ 1.5 participation fee. In addition, you will have 90% chance of receiving additional $2 as bonus tomorrow according to the New York Stock Exchange Composite Index close price tomorrow.

The followings are the screenshots for the real-effort task, which is identical across all eight conditions.

- You will stay in this page for 10 minutes.
- Please encrypt the following words according to the given Encryption Table (please do NOT put quotes, directly input a sequence of numbers or symbols, for example, !121410@#2422).

physical

Letters	Code	Letters	Code	Letters	Code
A	!	B	12	C	14
D	10	E	@	F	#
G	24	H	22	I	$
J	^	K	11	L	%
M	18	N	&	O	21
P	16	Q	23	R	*
S	13	T	19	U	25
V	?	W	26	X	17
Y	20	Z	15		