Information Avoidance and Medical Screening: A Field Experiment in China[1]

Yufeng Li[1], Juanjuan Meng[2], Changcheng Song[3], and Kai Zheng[4]

March 2018

Abstract: Are high-risk individuals more likely to avoid a disease test because of information avoidance? We conduct a randomized field experiment in rural China to investigate this issue. We vary the price of a diabetes test (price treatments) and offer both a diabetes test and a cancer test (disease treatments) after eliciting participants' subjective beliefs about the risk of having the corresponding disease. We find evidence that both low- and high-risk groups avoid testing, and this pattern is more salient when the test price is higher and the disease is more severe. We derive new predictions using the optimal expectation model of Oster et al. (2013) to explain our empirical findings. Structural estimation suggests that individuals attach about half of the weight to anticipatory utility compared to consumption utility, which leads to information avoidance. Simulation also suggests that the neoclassical view systematically underestimates the importance of subsidies or mandate policies.

JEL Classification: D84, I12
Key Words: Anticipation Utility; Information Avoidance; Health Anxiety; Health Screening

---

[1] We would like to thank Hunt Allcott, Daniel Benjamin, Eric Finkelstein, Teck-Hua Ho, Botond Kőszegi, Agus Salim, Shyong Tai, and participants in seminars at the National University of Singapore for helpful comments. This work was carried out with the aid of a research grant from the NUS Initiative to Improve Health in Asia (NIHA) coordinated by the Global Asia Institute of the National University of Singapore and supported by the Glaxo Smith Kline-Economic Development Board (Singapore) Trust Fund. Juanjuan Meng acknowledges financial support from the National Natural Science Foundation of China (Grant No. 71103003 and Grant No. 71471004); Beijing Higher Education Young Elite Teacher Project (Grant No. YETP0040); (Solareast Corporation) Guanghua Research Fellow; and the Key Laboratory of Mathematical Economics and Quantitative Finance (Peking University). We thank Xinyao Qiu and Fuyang Zhao for their excellent work as research assistants. We also thank Jianghan Gu, Weisi Wang, Weiting Yuan, and Yufei Zhang for their efforts in collecting the survey data in China, and Xiangshuang Kong in particular for his help in facilitating the field work.
[1] Capital Medical University Beijing, Pinggu Hospital; email: doctorlyf@126.com
[2] Guanghua School of Management, Peking University; email: jumeng@gsm.pku.edu.cn
[3] Department of Economics, National University of Singapore; email: songcc02@gmail.com
[4] Department of Informatics, University of California, Irvine; email: kai.zheng@uci.edu

1. Introduction

Information is valuable in standard economic analysis because it improves decision-making. However, there are many situations in which people avoid useful information (see Golman et al. (2017) for a literature review). For instance, many empirical studies find that people tend to avoid important information regarding their health status (Lyter et al. 1987; Lerman et al., 1999; Sullivan et al., 2004; Thornton 2008; Oster et al. 2013; Ganguly and Tasoff, 2016), and this tendency can generate a huge welfare loss because of the lack of proper treatment of the disease. Even so, most studies focus on the overall information avoidance effect rather than the heterogeneous effect. Therefore, we cannot explain why some people seek or avoid health information. In particular, we do not have systematic evidence on whether high-risk individuals are more likely to avoid medical tests and how a tendency to avoid information varies with the test price and the type of disease.

We collaborate with a local hospital to conduct a randomized field experiment with approximately 1,200 individuals in rural China to answer these questions. The field experiment has two designs: price treatments and disease treatments. In the price treatments, we vary the price of a diabetes test. Individuals were randomly assigned to one of three groups: the free group (T0), the 10 RMB group (T10), or the 30 RMB group (T30).[1] In the disease treatments, individuals were randomly assigned to one of two groups: the diabetes group or the cancer group. We provided the disease test for free after blood had been drawn for another free blood test (so there was no additional cost of taking the test), but varied the disease type to be tested, diabetes or cancer. In all treatments, we elicited individuals' self-reported beliefs about their corresponding disease risk before they made their testing decisions so that we could investigate the heterogeneous effect across the disease risk.

A simple neoclassical model that assumes the best treatment can only be implemented after being formally diagnosed would predict that individuals with higher subjective beliefs about the disease risk should be more likely to take the disease test,

[1] 1 USD=6.6 RMB in October 2017. A price of 30 RMB is more comparable to the market price.

because the test outcome allows them to take proper treatment action, and hence the information is more valuable.[2] However, we find the opposite results in some of our treatments: The take-up rate of the disease test changes non-monotonically with the subjective risk of having diabetes in T30; i.e., those who with lower and higher subjective risk are less likely to take the diabetes test. The same pattern also appears when the cancer test is provided in the disease treatment.

The simple neoclassical view also suggests that as test price increases, only high-risk individuals would remain in the testing group; hence the average test outcome should indicate higher probability of having the disease. However, if information avoidance exists in the sense that both low- and high-risk groups are less likely to take the test, as price increases, only median-risk individuals should remain in the testing group. As a result, the average test outcome should remain the same, and dispersion of the test outcome should decrease. Our results in the price treatments suggest that there is no significant difference in the mean value of blood glucose levels across treatments in the sample that took the diabetes test. More interestingly, distribution of the blood glucose level becomes significantly less dispersed when the test price increases, clearly suggesting that as test price increases, both high- and low-risk individuals select out of the test.

To the best of our knowledge, this is the first experimental study from the field that provides both within-treatment and cross-treatment evidence that high-risk individuals may be more likely to avoid medical tests. This is the first contribution of our paper.

We also find an interesting heterogeneous effect that deepens our understanding of when we can empirically observe the tendency for high-risk individuals to avoid the test. In T0 and T10 of the price treatments, when the test price is low, we find that the probability of taking the test does not vary significantly with the subjective risk of having the disease. Similarly, when the diabetes test was provided for free in the disease

[2] If we assume that individuals can also take other actions of the same treatment quality at the formal medical system without taking the medical screening, then the neoclassical model predicts that high-risk individuals are less likely to take the test. See Section 4.3 for a detailed discussion.

treatments, although there is weak evidence that the high-risk group tends to avoid the test, this effect is not significant. In general, the effect of the information avoidance phenomenon on the high-risk group is more salient when the test price is high and when the disease is more severe. This heterogeneous effect is the second empirical contribution of our paper.

To provide a unified theoretical framework to explain the above results, we apply the optimal expectation model from Oster et al. (2013) and Brunnermeier and Parker (2005) to our setting. The model assumes that individuals derive anticipatory utility from beliefs on future health status, but allows for self-manipulation on beliefs. When taking the medical test, individuals' beliefs are forced to be rational—but when avoiding the test, individuals have the flexibility to manipulate their beliefs optimally to balance the tradeoff between the optimistic belief of feeling healthy today and the cost of not taking the proper action today. We derive new model predictions that are not explicitly stated in Oster et al. (2013). First, the take-up rate is predicted to be lower for both the low- and high-risk group because without taking the test, high-risk individuals can maintain an optimistic belief, which generates positive utility. Second, the model predicts that the threshold level for high-risk individuals to avoid the test decreases with the test price. Therefore it is more likely to observe a non-monotonic pattern empirically when the test price is high, because individuals with extremely high subjective risk may be scarce in reality. Third, when the disease becomes more serious (e.g., diabetes vs. cancer in our setting), the threshold for the high-risk group to avoid the test is also lower. Then we are more likely to observe the information avoidance among high-risk individuals when the disease is more serious, given the same distribution of risk levels

To summarize, our third contribution is to derive new predictions from the optimal expectation model that explain why high-risk individuals tend to avoid the test, as well as why this tendency is more likely to be observed empirically when the test price is high and when the disease is severe.

There are a couple of alternative explanations for the low take-up rate for medical tests. One explanation for the general tendency to avoid the test, based on the

neoclassical model, is the high price elasticity (Thornton, 2008); another behavioral explanation is procrastination generated by present bias. However, neither of the two explanations would predict that high-risk individuals are more likely to avoid the test. Our experimental design also excludes procrastination, because all individuals have already paid the upfront cost of being onsite. Alternative explanations for why high-risk individuals are less likely to take the test include the possibility that they do not understand the benefits of testing and medical treatment, incur higher compliance costs for undergoing the treatment, or are financially constrained from undergoing the proper treatment. Based on our survey data, we test these alternatives by regressing subjective risk on the above variables and find that none of the variables is significant, except that higher risk is significantly associated with better knowledge of diabetes; this is not consistent with the alternative explanation.

We also structurally estimate the model and perform some welfare analyses under different pricing policies. We find that individuals attach about half of the weight to anticipatory utility compared to consumption utility, which leads to some degree of information avoidance. Simulating the testing decisions under both the neoclassical model and the anticipatory utility model, we find that the traditional view underestimates the welfare-improving effect of subsidies or mandate policies, because they are more effective when there is information avoidance. However, the most effective policy is to provide subsidies to those who tend to avoid the test due to information avoidance. This could inform a new direction for effective policy design.

This paper is related to both empirical and theoretical studies on information avoidance. Golman et al. (2017) provide an excellent review of this literature. Many empirical studies find that people tend to avoid important information regarding their health status (Lyter et al. 1987; Lerman et al., 1999; Sullivan et al., 2004; Thornton 2008; Oster et al. 2013; Ganguly and Tasoff, 2016). For instance, participants in Thornton's (2008) study generally avoided learning their HIV test outcomes, but even small incentives reduced the avoidance rate significantly. Most previous studies focus on the overall information avoidance effect; only a few investigate the heterogeneous

effect across the probability of having the disease. The latter group produces mixed results. Some find that people with higher risk of having cancer tend to delay a visit to the doctor (Caplan, 1995; Meechan et al., 2002; Persoskie et al., 2014). However, using elicited subjective beliefs, Oster et al. (2013) find that individuals with higher subjective belief about disease risk were more likely to pursue being tested for Huntington's disease, and people were generally overly optimistic about the risk of having such disease. Okeke et al. (2013) conducted a randomized trial in Nigeria with varying prices for cervical cancer screening. Despite the lack of statistics significance, they found that high-risk subjects (for both subjective and objective risk) tended to accept a higher test price in general.

To our best knowledge, our paper is the first field experiment to find that individuals with high subjective belief about the disease risk tend to avoid testing. We also identify some conditions under which this effect is more likely to appear. In terms of cross-disease comparison, Ganguly and Tasoff (2016) find that more people are willing to forgo a $10 payment to avoid learning the results of the herpes simplex virus 2 (HSV-2) test than an HSV virus 1 (HSV-1) test, where HSV-2 is viewed as a more serious condition. Our comparison of diabetes and cancer shows a similar result.

Three types of belief-based utility models can help to explain information avoidance in a medical testing context: the model of anxiety (Caplin and Leahy, 2001; Kőszegi, 2003; Eliaz and Spliegler, 2006; Epstein, 2008), the model of optimal expectations (Brunnermeier and Parker, 2005; Oster et al., 2013), and the model of news utility (Kőszegi and Rabin, 2009; Kőszegi 2010). Both the model of anxiety and the model of optimal expectation assume that individuals derive anticipatory utility from beliefs about future health status.[3] However, the model of anxiety also maintains the assumption of rational beliefs. Individuals avoid the test because it increases the uncertainty of beliefs, which increases anxiety when the utility over beliefs is concave. This type of model predicts that the tendency to avoid information is independent of prior probability of having the disease (Eliaz and Spliegler, 2006). The optimal

[3] Information avoidance in the setting of self-confidence can also be explained by the model of self-deception with endogenous memory (Bénabou and Tirole 2002). In this model, the agent weighs the benefits of preserving his effort motivation against the risk of becoming overconfident, and might choose to avoid bad news to conserve the self-confidence necessary to motivate their action.

expectations model allows for self-manipulation on beliefs. This model can be distinguished from the model of anxiety's predictions in two respects: whether there is overoptimism and whether high-risk individuals are more likely to avoid the test. Oster et al. (2013) provide empirical evidence to distinguish the two models based on their documentation of overoptimism, while our study distinguishes the two from the perspective of information avoidance among high-risk individuals. The model of news utility assumes that utility depends not on the absolute level of beliefs, but the change in beliefs (e.g., Kőszegi and Rabin, 2009). In this case, individuals with a median level of subjective belief about disease risk should be the most unwilling to take the test, because information shocks from taking the test are more severe.

The paper proceeds as follows. Section 2 introduces the experimental design for the field study, and Section 3 presents empirical results. Section 4 builds a theoretical model of information avoidance based on anticipatory utility to explain our findings. Section 5 concludes.

2. Experimental Design

2.1. Background

As of 2016, 422 million people have diabetes worldwide, up from 108 million in 1980.[4] The prevalence of diabetes is 8.5% among adults—nearly double the rate of 4.7% in 1980 (WHO, 2016). Approximately 673 billion USD were spent on diabetes, which accounts for about 12% of global health expenditure (International Diabetes Federation, 2015). Many people remain undiagnosed, because often there are few symptoms during the early years of type 2 diabetes. About 46.5% of people with diabetes worldwide do not know they have the disease (International Diabetes Federation, 2015). The number is higher in Asian countries. For example, 9.7% of the adult population in China has diabetes, and 60.7% of Chinese with diabetes do not know they have the disease (Yang et al., 2010). This lack of knowledge generates a huge welfare cost; diabetes mellitus caused 1.6 million deaths in 2015, making it the sixth leading cause of death (WHO,

[4] Diabetes mellitus is a group of metabolic diseases in which high blood sugar levels are present over a prolonged period. The chronic hyperglycemia of diabetes is associated with long-term dysfunction, damage, and failure of various organs, especially the eyes, kidneys, nerves, heart, and blood vessels.

2017).

Screening is potentially an important strategy to mitigate the effects of diabetes, since early detection and prompt treatment may reduce the burden of diabetes and its complications. Screening typically involves drawing venous blood to measure blood sugar and glycated hemoglobin. We offer the following types of blood tests for diabetes: random plasma glucose (RPG), fasting plasma glucose (FPG), and oral glucose tolerance (OGTT). The RPG consists of a blood check at any time of day that does not require fasting, but is also not very accurate for diagnosing diabetes compared to the other two. The FPG requires fasting for at least 8 hours before the test. The two-hour OGTT, which checks blood glucose levels before and two hours after drinking a solution of glucose and water, reveals how the individual processes glucose.[5]

We also included one test related to cancer in our study. The carcinoembryonic antigen (CEA) blood test is commonly used to follow patients with known cancers. It can also be used as a tumor marker, especially for cancers of the gastrointestinal tract. A rising CEA level is correlated with progression or recurrence of the disease. Note that the CEA by itself is not specific enough to substantiate a recurrence of a cancer, and further tests are required for confirmation. Details of these tests are provided in Appendix 1.

2.2. Experimental Design

We collaborate with a large local hospital in one rural county in Beijing, China, to study demand for these disease tests. The collaboration offers two advantages. First, doctors and nurses from the hospital can provide medical knowledge, medical tests, and related services. Second, the hospital can help us earn the trust of residents, which is necessary in order to conduct the study. In 2014, 10 villages were randomly selected in the county. We first collected administrative data—name, gender, birthdate, and

[5] Belief-based models may predict particular preferences toward the resolution of uncertainty. For instance, decision makers in Kőszegi and Rabin's (2009) study preferred quicker resolution of uncertainty—i.e., more accurate information. Since the RPG is less accurate than the other two, one might wonder whether the choice of test helps to distinguish various models. However, this is very likely in our setting, because participants were not given information about accuracy, and the costs of different tests also differ.

address—for all individuals in the sample villages from the local government. We asked village leaders to instruct all individuals who did not have diabetes to come to the village office on the day of the study, which allowed us to survey the full sample of eligible individuals. Upon arrival at the study site, we asked households to complete a survey in a separate room. We provided a free basic medical examination for all individuals after the survey, which included height, weight, and blood pressure.

We designed two experiments to investigate what determines demand for diabetes screening: a price treatment and a disease treatment. We conducted the price treatment in five villages and the disease treatment in the other five villages. Randomization is at the individual level to increase the power. Figure 1 presents the experimental design. In the price treatment, we varied the price of the diabetes test. When individuals arrived for the study, enumerators first conducted surveys. Individuals were randomly assigned to one of three groups *after* completing the survey: the free group (T0), the 10 RMB group (T10), or the 30 RMB group (T30). Individuals chose one of three sealed envelopes offered by enumerators, and the voucher inside the envelope stated the price they would have to pay to receive the diabetes test. The actual price to conduct the diabetes test in the hospital used for the study is 30 RMB. We then asked whether they would like to take a diabetes test. If they chose to do the test, nurses from the local hospital drew their blood after the physical examination. We choose diabetes tests that use venous blood to measure blood sugar and glycated hemoglobin that requires laboratory analysis and produces results several days later. If individuals had eaten breakfast before taking the blood test, we drew blood once and measured the random blood sugar level. If they had fasted before the blood test, we conducted the fasting blood sugar test or the oral glucose tolerance test, depending on the individual's choice.

[Figure 1]

In the disease treatment, we varied the disease being tested after blood had been drawn. Village leaders informed all individuals that there would be a free blood test to obtain basic blood counts and that they should fast before coming to the study. When individuals arrived, nurses first drew venous blood from all individuals and

enumerators conducted surveys. Individuals were randomly assigned to one of two groups: the diabetes group or the cancer group. Randomization was conducted by the researcher using a computer, and individuals were not aware of their assignment. In the diabetes group, after taking the blood and conducting the survey we asked whether participants would like to use the blood that had been drawn for an additional free diabetes test (fasting blood sugar). The procedure was the same for the cancer group, except we asked whether they would like to have an additional free test for cancer risk (carcinoembryonic antigen).[6] Participants in both groups were told that if they chose to have the additional test, nurses would send their test results via text message several days later.

We are interested in (1) what is the impact of different treatments on take-up of the screening test; and (2) who selected to be screened under different treatments. The key information necessary to understand question (2) is diabetes risk, which can be determined by both objective and subjective measures. Objective measures include test outcomes (which are only available for those who take the test).[7] The subjective measure is self-reported beliefs about diabetes risk and cancer risk. We asked participants the following question: "What do you think is the probability that you have diabetes/cancer?" To indicate their answers, participants were given 10 small paper balls and asked to distribute them across two areas: (1) No diabetes/cancer and (2) have diabetes/cancer. If participants put 2 paper balls into (2) and 8 paper balls into (1), the perceived probability that they have diabetes/cancer is around 20%.

The survey also includes the individual's socioeconomic background, lifestyle, knowledge about diabetes, risk attitudes, time preference, and information avoidance. The preference measures are hypothetical. Risk attitudes were elicited by asking sample households to choose between increasing amounts of certain money (riskless option A) and risky gambles (risky option B). We used the number of riskless options as a measurement of risk aversion following Holt and Laury (2002). Time preferences were

[6] The price of the CEA test in the same hospital is 40 RMB.

[7] In theory, one can predict the diabetes risk from health measures such as BMI, blood pressure, and smoking habit but such prediction is highly inaccurate. We also lack of a consistent formula to do such prediction for the population in our experience, and such formula can vary greatly by population.

elicited by asking households to choose between receiving some amount of money now (option A) and a larger amount of money one year later (option B). We used the number of patient options (option B) as a measurement of patience. We also asked three questions about monitoring and blunting strategies (Miller 1987) and nine questions from the Big Five Inventory. Appendix 4 presents all survey questions, and Table A1 in Appendix 3 explains how the variable was constructed for analytic purposes.

3. Experimental Results

3.1. Summary Statistics

We surveyed 664 individuals, with a response rate of about 93%, in the price treatment and 531 individuals, with a response rate of about 96%, in the disease treatment. The high response rate is due to the free medical examinations and high trust in village leaders and the local hospital. We begin by performing randomization checks across treatments: the price treatments and the disease treatments. Table 1 reports the mean and standard deviations of four groups of variables: screening decisions, demographic information, health conditions and behaviors, and preference measures. Table A1 in Appendix 3 provides detailed explanations of how we constructed these variables from the survey questions. We use stars on the T30 variable to indicate whether the variables in T0, T10, and T30 are significantly different in the multivariate test. We use a star to indicate whether variables in the cancer treatment are significantly different from those in the diabetes treatment.

[Table 1]

Panel A is the key decision variable: the take-up rate of tests in the treatment. Not surprisingly, as the price of the diabetes test rises, the take-up rate of the test declines significantly, from 0.66 (T0) to 0.37 (T10) and then 0.20 (T30). However, the take-up rates in the disease treatments are 0.86 and 0.89 for diabetes and cancer tests, respectively—which not significantly different from each other—and are much higher than in the price treatments. This is expected, because in the disease treatments both tests were free and individuals were asked whether they would like to take the test *after*

their blood samples were collected; as a result, the cost of taking the test are much lower.

Panel B reports demographic information. The mean values show some significant difference across price treatments in age, education, and household size, suggesting that the assignment to price treatment has some nonrandom component in the dimension of demographic background. We include all of the variables in this category in the regressions to address this issue. However, in the disease treatments the randomization is notably successful in this dimension, since none of the variables in Panel B is significantly different.

Panel C reports health conditions and health behavior, including information on height, weight, BMI ratio, smoking, drinking, and frequency of sleeping and exercise. Importantly, we construct measures of subjective and objective knowledge about diabetes from survey questions 52-57. We are also interested in people's subjective evaluation of how hard it is for them to follow the requirements of treating diabetes ("ability to follow treatment"), including adhering to diet and excise recommendations, since this reflects the potential cost of learning about their diabetes status.

Finally, the key control variable is the subjective assessment of disease risk. This measure is constructed from survey question 67, and serves as the key variation in our analysis. People generally believe that they are about 0.10-0.13 likely to have the corresponding disease, and this number is not statistically significant across all five treatments.[8] In general, the randomization is relatively successful in this category, as most variables do not show significant differences.

Panel D summarizes the key preference variables constructed from survey questions 71 to 78. We use hypothetical questions to elicit participants' degree of risk aversion, loss aversion, time preferences, and present bias using survey questions 71 to 73. We use a series of survey questions to construct psychological measures of the tendency to keep monitoring, the Big Five Inventory (Neuroticism), and openness.

[8] One may wonder whether the self-reported subjective risks contain any real information. We show via regression that people who have better knowledge of diabetes, who are less able to follow treatment requirements, and who are more anxious in general have higher reported subjective risk on diabetes. Conditional on taking the diabetes test, the correlation between subjective beliefs and the test outcome is 0.2188. Both types of evidence suggest that our self-reported beliefs are not purely errors and have real information content.

Again, none of the variables shows significant difference across all five treatments.

Overall, seven out of 72 contrasts from Panel B to Panel D are significant, which is expected under random assignment.

3.2. Price Treatments

3.2.1. Within-treatment results

It is interesting to explore how the take-up rate changes with subjective risk within treatment. A simple neoclassical model that assumes that individuals cannot take the best treatment action before being formally diagnosed predicts that the take-up rate is monotonically increasing in subjective risk—i.e., that high-risk individuals are more incentivized to take the test. We test this prediction first.

Figure 2 graphs the relationship between subjective risk and the take-up rate for T0, T10, and T30. Individuals are divided into five groups based on their subjective risk of diabetes: group 1 if subjective risk is 0; group 2 if subjective risk is between 0 and 0.2; and group 3, 4, or 5 if subjective risk is between 0.2 and 0.4; 0.4 and 0.6; and above 0.6, respectively. The x-axis indicates the group, while the y-axis is the average take-up rate within the group.

We can see that for treatments T0 and T10, the relationship is mostly monotonic; however, T30 shows a non-monotonic pattern in which the take-up rate is low when subjective risk is either low or high, and reaches the peak for the median-level risk group.

[Figure 2]

Equation (1) presents the OLS regression on the within-treatment pattern. The outcome variable Y_i is the dummy that indicates whether to take the diabetes test. The key explanatory variable is subjective risk s_i and its square term s_i^2. We control for six demographic variables—gender, age, education, marriage, household size, and monthly income—and 10 variables on health conditions and behaviors: height, weight, BMI, sleeping hours, drinking behavior, smoking behavior, exercise frequency, subjective/objective knowledge of diabetes, and the ability to comply with diabetes

treatment.

$$Y_i = \alpha + \beta_1 s_i + \beta_2 s_i^2 + \gamma X_i + \varepsilon_i$$

(1)

Table 2 reports regression results. For T0 and T10, both the estimates of the subjective risk and its square term are not significantly different from zero, suggesting that subjective risk shows no significant effect on take-up rate. However, there is a significant non-monotonic relationship in T30, in which the take-up rate first increases significantly with subjective risk, then drops significantly after subjective risk reaches a subjective risk level of 0.37—i.e., both the low and high-risk groups are less likely to take the test.

[Table 2]

Finding 1: Both the low- and high-risk groups tend to refuse the diabetes test in T30.

In general, these results are not consistent with the simple neoclassical intuition that assumes no best treatment can be taken before being diagnosed: The non-monotonic relationship in T30 is obviously inconsistent with the neoclassical perspective, and the estimates in T0 and T10 also do not show that take-up rate will be significant higher for the high-risk group. But the non-monotonic pattern in T30 conforms to the intuition of information avoidance: Those who with high risk tend to refuse the test, because refusing allows them to maintain optimistic beliefs, which generate high anticipatory utility.

3.2.2. Cross-treatment results

In this section we analyze the cross-treatment pattern in the price treatment. We begin by providing summary information for the diabetes tests. We asked individuals to fast before coming to our study. For those who were in a fasting state, the fasting plasma glucose (FPG) test was preformed. Ninety-two individuals took the FPG, and

were diagnosed as having diabetes if the outcome level exceeded 7 mmol/L.[9] For those who were not fasting, the random plasma glucose (RPG) test was performed. Forty individuals who took the RPG, and the standard for diagnosis is 11 mmol/L.

Figure 3 displays the take-up rate of the diabetes test across treatments. Not surprisingly, the take-up rate steadily declines as the price of the test increases. More than 60% of participants take the test when it is free, but this rate drops to about 40% when the price is 10, and to 20% when the price increases to 30. These changes are all statistically significant.

[Figure 3]

The simple neoclassical intuition predicts that high-risk individuals are more likely to take the test. As a result, when the test price increases, high-risk individuals remain as test takers, while individuals with lower risk tend to select out of the test. Therefore, the average test outcome of those who take the test should demonstrate more diabetes risk as the price increases from T0 to T30. We now investigate this pattern.

We start by looking at how test price affects the average outcome among those who took the test. We investigate both average subjective diabetes risk and test outcome conditional on taking the test. If the test takers who remain are indeed the high-risk group, these outcomes should be significantly different across treatments.

Figure 4 displays cross-treatment results. The left figure reports the mean value of subjective risk across treatments, together with the 90% confidence interval. The right figure displays the average diabetes test outcome in terms of blood glucose level across different treatments. For simplicity, we pool FPG and RPG outcomes and use GLU to denote the pooled outcome.[10] Despite a significant decline in the take-up rate as price increases, both figures suggest *no* significant difference across treatments either in

[9] Of the 92 individuals, 33 were willing to wait for two hours and take the OGTT, which requires two blood tests. The first is exactly the same as the fasting plasma glucose test, and the second test is taken two hours after drinking a mixture of glucose and water. We use the first test results for these 33 individuals for analysis, which yields exactly the same diagnosis outcome as using the results from both tests.

[10] The right figure reports results for the overall sample, including the fasting and non-fasting samples. For individuals in the fasting state, GLU indicates fasting blood glucose level. For individuals in the non-fasting state, GLU indicates random blood glucose level. For simplicity, we pool the outcomes of the two tests here; however, results remain the same if the two tests are analyzed separately.

terms of subjective diabetes risk or the actual outcome. This result is in contrast to the simple neoclassical prediction.

[Figure 4]

Table 3 reports formal regression results on how price increase affects subjective risk and test outcome conditional on taking the test. Consistent with Figure 6, we see no significant difference across treatments on these variables after controlling for demographic information and health background.

[Table 3]

There are several possible explanations for why the mean test outcome does not change across treatments: Either the low- and high-risk groups select out of the test, both groups take the test and the median-risk group selects out of the test, or individuals select out of the test independent of their disease risk. In the first case we expect to see a reduced dispersion of the test outcome, because the test takers are more concentrated on the medial-risk level. In the second case the distribution should have more dispersion, while in the third case the dispersion remains the same.

Figure 5 presents the distribution of test outcome across treatments. As the price increases from 0 to 10 and 30, there is a clear concentration of test outcomes toward the median level. It is also evident that the dispersion in test outcomes is reduced as test price increases. The standard deviation of blood glucose level is 1.455 for T0, 1.205 for T10, and 0.560 for T30. Bartlett's test for equal variances shows that the difference in standard deviations is significant across treatments at the 1% level.

[Figure 5]

We provide more evidence from the perspective of the diabetes prevalence rate—i.e., the proportion of people being diagnosed with diabetes conditional on taking the test. While the average outcome in terms of blood glucose level measures the continuous risk level, the diabetes prevalence rate measures the proportion of high-risk individuals. The prevalence rate is 4.00% (3/75) for T0, 2.44% (1/41) for T10, and 0.00% (0/16) for T30. If high-risk individuals continue to take the test as the price increases, as predicted by simple neoclassical intuition, the prevalence rate should increase as the

test price increases. However, if high-risk individuals select out of the test as the price increases, the prevalence rate will naturally decline from T0 to T30, consistent with the above finding.

Finding 2: As the test price increases, both low- and high-risk groups select out of the test.

To summarize, we find that as the test price increases, test takers' average subjective risk and blood glucose level do not significantly differ across treatments, but the prevalence rate and standard deviations of the blood glucose level steadily decline. All results suggest that both the high-risk and low-risk groups tend to select out of the test as the price increases.

3.3. Disease Treatment

This section reports the results for the disease treatment, in which the take-up decisions for diabetes and cancer tests are compared. Figure 6 displays the take-up rate across treatments by different levels of subjective risk of having the corresponding disease. The y-axis is the take-up rate, and the x-axis denotes groups representing percentiles of subjective risk: group 1 if subjective risk is 0; group 2 if subjective risk is between 0 and 0.2; and group 3, 4, or 5 if subjective risk is between 0.2 and 0.4; 0.4 and 0.6; and above 0.6, respectively.

We can see that the take-up pattern is quite different for diabetes and cancer treatments. Both treatments start with a high take-up rate—around 0.8 to 0.9—when subjective risk is zero. This is because both tests are free and have no additional transaction cost, as the blood has already been taken for other purposes. In the diabetes treatment, despite a slight drop when subjective risk is in the middle range, the take-up rate generally increases with subjective risk, and reaches about 1 when the subjective risk is above 0.6. The pattern is consistent with group T0 in Figure 2 in the price treatments. In the cancer treatment, however, there is an obvious non-monotonic

relationship, in which the take-up rate is highest when subjective risk is between 0 and 0.2, then steadily drops as subjective risk increases. When subjective risk is above 0.6, the take-up rate becomes 0.8—lower than when subjective risk is zero.

[Figure 6]

Table 4 tests whether there is a non-monotonic effect of subjective risk on the take-up rate within each treatment. The first column represents the diabetes treatment. The estimate of the effect of subjective risk suggests that for each 10% increase in subjective risk, the take-up rate will increase by 7.9%. The square term is negative, which suggests some evidence of drop in the take-up rate for a high level of subjective risk, but this square term is not significant. The estimated turning point at which the high-risk group starts to avoid the test is at the subjective risk level of 0.57. The second column represents the cancer treatment. We see a strong and significant non-monotonic effect in this case: The take-up rate first increases and then decreases with subjective risk. The estimated turning point is at a subjective risk level of 0.27, which is lower than the turning point for the diabetes treatment.

Finding 3: The non-monotonic pattern between the subjective probability of having the corresponding disease and the take-up decision is stronger in the cancer treatment than the diabetes treatment.

[Table 4]

We would like to further investigate whether subjects' evaluations of the severity of the disease would affect the take-up pattern. We add the variable "controllable" constructed from Q55 and Q69 in the survey. Q55 asks whether subjects believe that diabetes is curable, and Q69 asks whether subjects believe that cancer can be controlled to some degree. The variable "controllable" takes the value 1 if the answer to Q55 is "Yes" and 0 otherwise in the diabetes treatment; it takes the value 1 if the answer to Q69 is "Yes" and 0 otherwise in the cancer treatment.

In columns (3) and (4) of Table 4, we add the variable "controllable" and interact

it with subjective risk for the two disease treatments. Column (3) reports results for the diabetes treatment. Those who believe that diabetes is *less* controllable tend to have a significant non-monotonic pattern: The probability of taking the test first increases and then decreases with subjective risk, with the turning point around the subjective risk level of 0.51. When subjects believe that diabetes is more controllable, this tendency is weakened, despite the nonsignificant estimates of the interaction between controllable and the risk terms, and the estimated turning point rises to 0.72. Column (4) reports results for cancer. Similar to the case with diabetes, when subjects believe that cancer is less controllable, they tend to demonstrate a stronger non-monotonic pattern, with the turning point of for subjective risk level being 0.22. For those believe that cancer can be controlled, however, this pattern is significantly weakened, and the estimating turning point increases to 0.31.

Finding 4: In both the diabetes and cancer treatments, those who believe that the disease is less controllable demonstrate a stronger pattern for a non-monotonic relationship, and the estimated turning point for the high-risk group to avoid taking the test is also lower.

In general, the key message from the disease treatment is that when the disease is more serious or believed to be less controllable or curable, high-risk individuals are more likely to avoid the test.

3.4. Alternative Explanations

We would argue that high-risk individuals tend to avoid the test based on information avoidance. Before presenting a formal model of this phenomenon, we will discuss alternative explanations. The high-risk group may have less health knowledge of the benefits of testing and subsequent medical treatment; they may also have higher compliance costs for undergoing treatment, or are financially constrained from undergoing treatment if diagnosed as having diabetes. All of these factors may

contribute to test avoidance behavior.

To test these alternatives, we directly test whether subjective risk is correlated with these variables. We measure health knowledge by whether they answer the knowledge questions correctly on the survey. These include subjective and objective knowledge of diabetes (the construction method is specified in Appendix Table A1). We measure treatment compliance cost based on questions about how difficult it would be to comply with diabetes treatment (Q58 and Q59). We measure their financial status based on their self-reported income (Q18 and Q19) and expenditure levels (Q12-14). For this analysis, we use observations from only the price treatment.

[Table 5]

Table 5 reports regression results. We can see that higher subjective risk is significantly correlated with better rather than worse subjective knowledge of diabetes. All other factors are not significantly related to subjective risk. Therefore, the above alternatives do not seem to explain the estimated non-monotonic pattern.

4. Theoretical Explanation: The Optimal Expectations Model

4.1. The model

To provide a formal explanation for our empirical findings, we apply the theoretical model from Oster et al. (2013) to study take-up decisions in our setting. Their model is based on an optimal expectation model from Brunnermeier and Parker (2005). The idea of the model is that belief about future health status generates utility, which we call anticipatory utility. If individuals take the medical tests, their beliefs on health status must update in a Bayesian way; i.e., their beliefs will be rational. They will also choose the correct actions based on their health status. However, if individuals do not take the test, they are allowed to choose their own beliefs based on the trade-off between the anticipation utility of feeling healthy today and the cost of wrong actions if they remain ignorant. The influence of anticipatory utility based on current beliefs creates the value of choosing overly optimistic beliefs, and this is only possible when one avoids taking the test.

Specifically, there is a binary state $s \in \{0, 1\}$ where $s = 1$ indicates that the

individual has the disease (diabetes or cancer) and $s = 0$ otherwise. Individuals have some exogenous $p = E(s)$, which measures the true probability of having the disease. At time 0, individuals choose whether or not to learn the true state through medical testing with cost C. At time 1, individuals choose a binary action $a \in \{0, 1\}$, which can be understood as treatment related to the disease, and experience utility associated with their expectations of time 2 consumption. Ex post individual consumption utility is maximized when action is matched to state. At time 2, the true state is revealed, and individuals receive consumption utility.

The key assumption in the model is that individuals experience anticipation utility over future health status. Individuals form beliefs about their probability of having the disease, π, and π can be different from the true probability p. Let $u(a, s)$ be the consumption utility given action a and health state s. Let δ be the weight on anticipation utility. Equation (2) gives the utility function at time 0, which is a weighted average of anticipation utility based on π and consumption utility based on p.

$$U(\pi|p) = \delta E[u(\hat{a}, s|\pi)] + E[u(\hat{a}, s|p)] \tag{2}$$

The optimal choices are derived in a backward-induction manner. At time 1, individuals decide on the optimal action given belief π to maximize anticipatory utility. At time 0, individuals maximize $U(\pi|p)$ by choosing whether to take the test, and if not, what is the optimal belief π. If individuals take the test, their beliefs become rational, so π=p. If they remain untested, they also choose the optimal π to maximize total utility $U(\pi|p)$.

When individuals do not learn the true state at time 0, they choose action $\hat{a}(\pi) = argmax_a E[u(a, s|\pi)]$. In this case, the anticipation utility at time 1 is $\delta E[u(\hat{a}, s|\pi)] = \delta(\pi u(\hat{a}, 1) + (1 - \pi)u(\hat{a}, 0))$, and the expected consumption utility at time 2 is $E[u(\hat{a}, s|p)] = pu(\hat{a}, 1) + (1 - p)u(\hat{a}, 0)$. Thus, the utility of not testing is

$$U_{untest} = \delta\big(\pi u(\hat{a}, 1) + (1 - \pi)u(\hat{a}, 0)\big) + pu(\hat{a}, 1) + (1 - p)u(\hat{a}, 0) \tag{3}$$

If they learn the true state at time 0, they will adopt ex post optimal action $a = s$. The utility of testing is

$$U_{test} = (1+\delta)[pu(1,1) + (1-p)u(0,0)] \quad (4)$$

When individuals decide whether to take the test, they compare the utility of testing to the utility of not testing given their optimal choices.

We follow Oster et al. (2013) and define utility function u as follows. Being healthy and taking the state-matched action has a value of 1 ($u(0, 0) = 1$). Taking the wrong action in the healthy state leads to the utility loss of Φ compared to taking the right action ($u(1, 0) = 1 - \Phi$). Being sick and taking the state-matched action has a value of 0 ($u(1, 1) = 0$). Taking the wrong action in the sick state leads to a utility loss of Ω compared to taking the right action ($u(0, 1) = -\Omega$). Therefore Φ measures the cost of taking any action when healthy and Ω measures the cost of not taking any action when sick. We assume that $\Phi, \Omega < 1$, implying that individuals value health more than they value the correct action.

The optimal solution takes the following form. At time 1, according to Lemma 1 in Oster et al. (2013), $\hat{a}(\pi) = 0$ if $\pi \leq \frac{\Phi}{\Phi+\Omega}$ and $\hat{a}(\pi) = 1$ if $\pi > \frac{\Phi}{\Phi+\Omega}$. Define $p^* = \frac{\Phi}{\Phi+\Omega} + \frac{\delta\Phi(1+\Omega)}{(\Phi+\Omega)^2}$. At time 0, according to Propositions 1 and 2 in Oster et al. (2013), when individuals remain untested the manipulation of beliefs goes as follows: When $p \leq p^*$, $\pi = 0$ and $a = 0$. When $p > p^*$, $\pi = \frac{\Phi}{\Phi+\Omega}$ and $a = 1$. The intuition is as follows. Since action is binary, there is a range in which changing π does not change the optimal actions, and hence consumption utility. To maximize anticipation utility, individuals will choose the lowest π in that range, leading to the corner solution of π.

When individuals decide whether to take the test, they face the following trade-offs. The benefit of not testing is to hold biased beliefs (low π), which generate high anticipation utility. The benefit of testing is to avoid the utility loss from the wrong state-matched action (Φ, Ω). If the former consideration outweighs the latter, individuals will choose not to be tested.

[Figure 7]

Figure 7 shows the total value of testing when the test is free and there is low value of anticipation ($\delta < \Omega$). The horizontal axis is p. The vertical axis is the total value of

testing, which equals the benefit of testing minus the benefit of not testing. Positive values imply that individuals will choose to take the test. We can see that when the test is free, those with low p will take the test and those with high p will avoid the test. The positive value of testing in low p is driven by $\delta < \Omega$. When there is low value of anticipation, the benefit of testing outweighs the benefit of not testing and holding biased beliefs. The negative value of testing in high p is mainly driven by two factors. First, the benefit of not testing in terms of anticipatory utility is increasing in p when $p > p^*$. In this case, not testing will allow individuals to hold biased beliefs $\pi = \frac{\Phi}{\Phi+\Omega}$ (when $p > p^*$), but testing forces them to form rational beliefs $\pi = p$. The difference in the anticipatory utility generated by the two beliefs is increasing in p. Second, the benefit of testing in terms of consumption utility is decreasing in p when $p > p^*$. This is because in this case, individuals are taking proper action regardless of whether they test or not. This non-monotonic relationship also appears in Figure 6 of Oster et al. (2013), but is not formally discussed in that paper. However, this prediction is very important for our study, since we find that high-risk individuals tend to avoid the test—a pattern that is consistent with this omitted prediction in Oster et al. (2013).

4.2. Model predictions

This section obtains several new predictions of the model not explicitly derived in Oster et al. (2013), based on the non-monotonic relationship between disease risk and the value of testing. To make the utility function general enough to facilitate comparison between cancer and diabetes, we extend the model from Oster et al. (2013) and assume two changes in utility for cancer compared to that of diabetes. First, having cancer and taking the state-matched action has a value of -v instead of 0; i.e. $\mathrm{u}(1,1) = -v$. We assume v>0, since the utility of cancer patients after taking cancer treatment is likely to be lower than that of diabetes patients after taking diabetes treatment. Second, the utility loss of the wrong action relative to the right action given cancer, represented by Ω_c, is higher than when individuals have diabetes, represented by Ω. Therefore we define the utility level of taking the wrong action given cancer as $\mathrm{u}(0,1) = -v - \Omega_c$,

assuming that $\Omega_c > \Omega$.

Since the total value of testing is non-monotonic, there are two potential cutoff points at which the total value of testing is zero. We define p_{low} and p_{high} to be the low and high cutoff points, respectively. Individuals with probability of having the disease lower than p_{low} and higher than p_{high} will avoid the test. We can solve the closed form based on Proposition 3 in Oster et al. (2013). Proposition 1 below summarizes model predictions.

Proposition 1 (Price Treatment). When $0 < \delta + \delta v < \Omega$, $p_{low} = \frac{C}{\Omega - \delta - \delta v}$, and $p_{high} = \frac{\delta\Phi(1+\Omega+v)}{(\Phi+\Omega)(\delta+\delta v+\Phi)} + \frac{\Phi - C}{\delta+\delta v+\Phi}$, we show that $\frac{\partial p_{low}}{\partial C} > 0$, and $\frac{\partial p_{high}}{\partial C} < 0$.

Proof: see Appendix A.2

Proposition 1 explores how the cutoff level for low- and high-risk individuals to avoid taking the test varies with test price (C). We focus on p_{high}, since this is more relevant for our purpose. Proposition 1 suggests that the higher the test price, the lower the high cutoff point, and the more likely we will observe information avoidance in the high-risk group, given that observations at the extreme right tail may be scarce empirically. The intuition is that given the non-monotonic relationship in Figure 7, an increase in the test price will reduce the value of testing, and thus marginal individuals around high cutoffs will avoid the information.

In the price treatment, we randomize the price of diabetes testing, which is the cost of test C in the model. In the disease treatment, since cancer is more serious than diabetes, it is reasonable to assume that individuals would incur more loss from cancer if they do not treat the disease when they have it.

Figure 8, Panel A illustrates the predictions from the price treatment when we vary the cost of testing based on Proposition 1. The horizontal axis is *p*, the vertical axis is the total value of testing, and C is the cost of testing. When C=0, the total value of testing is an inverse V-shape over *p*, which is the same as Figure 7. In this case, those

with low p are likely to take the test and those with high p will not take the test. When C>0, the total value of testing moves downward. In this case, those with very low p and very high p are predicted to not take the test. The model, therefore, makes the following two predictions for the price treatment.

[Figure 8]

Prediction 1: When the test price is positive, the relationship between beliefs about disease probability and test take-up is non-monotonic: The take-up rate should be lower for low- and high-risk groups.

The take-up for the high-risk group is likely to be low due to the benefit of holding biased beliefs. For the low-risk group the take-up is low, since the benefit of testing to avoid utility loss is also low. This prediction provides a reasonable explanation for the observed non-monotonic pattern in T30 (finding 1). However, the patterns in T0 and T10 are not fully consistent with this prediction. One possible reason is the following: Proposition 1 suggests that the predicted cutoff point for the high-risk group to avoid the test decreases with test cost. For very low test cost, such as our T0 and T10, the cutoff point for the high-risk group to avoid the test is very high. In reality. there may be few observations with subjective risk beyond this high cutoff point. With the higher price in T30, however, the cutoff point is not that high, so we have observations beyond that point to demonstrate the non-monotonic pattern empirically. The pattern for T30 is also more informative, because it is the most comparable to the market price, and hence this non-monotonic pattern is more relevant.

Prediction 2: In the price treatment, increasing the test price will reduce take-up for both the low-risk and the high-risk groups. Thus, conditioning on taking the tests, increasing the test price will not change the average test outcomes but reduce the dispersion of test outcomes.

Increasing the test price will reduce the total value of testing. Following prediction 1, when the take-up for tests is an inverse V-shape over p, marginal individuals who take the tests in high p would not choose to take the test. Marginal individuals who take the test in low p would not choose to take the test, either. Therefore, increasing the test price will not change average test outcomes, but rather reduce the dispersion of test outcomes. This is also fully consistent with our finding 2.

Proposition 2 (Disease Treatment). When $0 < \delta + \delta v < \Omega$, $p_{low} = \frac{c}{\Omega - \delta - \delta v}$, and $p_{high} = \frac{\delta\Phi(1+\Omega+\mathrm{v})}{(\Phi+\Omega)(\delta+\delta v+\Phi)} + \frac{\Phi - c}{\delta+\delta v+\Phi}$, We show that $\frac{\partial p_{low}}{\partial \Omega} < 0$, $\frac{\partial p_{low}}{\partial \mathrm{v}} > 0$, $\frac{\partial p_{high}}{\partial \Omega} < 0$, and $\frac{\partial p_{high}}{\partial \mathrm{v}} < 0$ when C is small.

Proof: see Appendix A.2

Proposition 2 explores how the cutoff level for low- and high-risk individuals to avoid taking the test varies with the utility loss of taking the wrong action when being sick (Ω) and how serious the disease is (v). Figure 8, Panel B illustrates the prediction from the disease treatment when the test is free. The horizontal axis is p. The vertical axis is the total value of testing. Given the two changes in v and Ω, we see that the non-monotonic relationship between p and the value of screening is stronger in the cancer group, i.e., the cut-off level of p beyond which high-risk individuals will choose not to take the test is lower in the case of cancer than diabetes. Proposition 2 shows that both changes in parameters contribute to the stronger non-monotonic relationship. Each change alone also has the same prediction. The intuition is as follows. First, since the health state with cancer is worse than with diabetes, even after the proper treatment ($v > 0$), the benefit of taking action when sick is lower for cancer. This reduces the benefit of taking the test. Second, since cancer has higher Ω, individuals will take the proper action ($\mathrm{a} = 1$) without taking the test even when π is lower, which allows these individuals to hold more optimistic beliefs (lower π) while still avoidin the cost of not taking action when sick. This increases the benefit of not taking the test, and thus marginal individuals around high cutoffs will avoid the information. (See Appendix A.2 for proof of comparative statics with respect to v and Ω in the disease treatment.) We therefore have the following predictions:

Prediction 3: In the disease treatment, since the cancer test has larger v and Ω than the diabetes test, the non-monotonic relationship between beliefs of disease risk and take-up for tests is stronger in the cancer treatment.

Note that Proposition 1 suggests that the high cutoff point is decreasing in Ω. In practice there might not be many people with extreme high beliefs about disease risk, so we might not observe the non-monotonic relationship due to lack of observations at the right tail. The cancer treatment strengthns the non-monotonic relationship, because the cutoff point for the high-risk group to avoid the test is lower and therefore we are likely to observe the right-tail pattern of not taking the test. This prediction can explain finding 3.

Regarding finding 4, the explanation depends on how we interpret "the disease is less controllable" in terms of the change in parameters in the model. There are three possibilities. Either "less controllable" means higher v—i.e., the health status is worse even after the treatment—or it means lower Ω, i.e., the utility cost from the wrong action (no treatment) when sick is low, or both. Higher v alone predicts that "less controllable" belief implies more salient information avoidance among the high-risk group, but lower Ω predicts the opposite. If both parameters change, our simulation suggests that as long as the change in v is not too drastic, the v effect dominates and the model prediction is consistent with our finding 4. Therefore, the model can still predict a reasonable explanation for finding 4.

In general, the optimal expectations model of Oster et al. (2013) provides a satisfactory explanation for our findings. We explore the non-monotonic relationship between the beliefs of probability risk and the take-up decision, a prediction of the model ignored in the original paper, and investigate how this pattern—as well as the associated cutoff risk level for the high-risk group to avoid the test—varies with test price and disease type. Our main findings are all consistent with model predictions.

4.3. The model without anticipatory utility

The evidence above suggests that the optimal expectation model of Oster et al. (2013) provides a satisfactory explanation for our findings. In this subsection, we discuss whether the model without anticipatory utility can explain our findings. Proposition 3 below summarizes model predictions under the assumption of no anticipation.

Proposition 3. When $\delta = 0$, $p_{low} = \frac{C}{\Omega - \delta}$, and $p_{high} = \frac{\delta\Phi(1+\Omega)}{(\Phi+\Omega)(\delta+\Phi)} + \frac{\Phi - C}{\delta+\Phi}$, we show that $\frac{\partial p_{low}}{\partial C} > 0$, $\frac{\partial p_{low}}{\partial \Omega} < 0$, $\frac{\partial p_{high}}{\partial C} < 0$, and $\frac{\partial p_{high}}{\partial \Omega} = 0$.

Proof: see Appendix A.2

From proposition 3, we can see that the model without anticipation in Oster et al.'s (2013) setting can also predict that both the low- and high-risk groups are more likely to avoid the test. This is because their model assumes that high-risk individuals will take the same proper treatment action as in the medical system, even without being formally diagnosed. As discussed before, if we relax this assumption by assuming that the treatment action one can take is not the best compared to the one after being diagnosed, the high-risk group is less likely to avoid the test in the neoclassical sense.

However, even within Oster et al.'s (2013) setting, models with and without anticipatory utility can be distinguished in the disease treatment. In particular, the model with anticipatory utility ($0 < \delta < \Omega$) predicts that the cutoff point for high-risk individuals to avoid the test is decreasing in the utility loss of taking the wrong action when sick ($\frac{\partial p_{high}}{\partial \Omega} < 0$), i.e., it is more likely to observe the non-monotonic relationship empirically in the cancer treatment than in the diabetes treatment. On the contrary, the model without anticipatory utility ($\delta = 0$) predicts that the cutoff point is independent of the utility loss of taking the wrong action when sick ($\frac{\partial p_{high}}{\partial \Omega} = 0$). The intuition is that without anticipatory utility, an individual should always take the test when it is free. Thus, changes in the disease type will not change testing behavior and, all will take the tests.

Figure 9 shows the predictions of the model with no anticipatory utility. Panel A illustrates the predictions from the price treatment when we vary the cost of testing based on Proposition 2. The prediction is similar to Figure 8, Panel A. Panel B illustrates the predictions from the disease treatment when the test is free. The prediction is different from Figure 8, Panel B. The model without anticipation predicts that changes in the disease type will not change testing behavior and all will take the tests.

In the disease treatment, we show that the cancer treatment strengthens the non-monotonic relationship, because the cutoff point for the high-risk group to avoid the test is lower and therefore we are likely to observe the right-tail pattern of not taking the test. This is consistent with the model of optimal expectations, but not consistent with the model without anticipatory utility.

5. Estimation, Simulation, and Welfare Analysis

5.1. Structural Estimation

We use the method of simulated moments (MSM) to estimate the three parameters of the model using data in the price treatment: the weight on anticipation utility, δ; the cost of taking any action when healthy, Φ; and the cost of not taking any action when sick, Ω. When $\delta = 0$, there is only consumption utility and the model reduces to the neoclassic model.

Let d be an indicator to measure the actual testing decision and $\hat{p}$ be the predicted probability of testing. The estimation is based on six moment conditions: testing decisions (d) in T0, T10, and T30 (Equation 5), and subjective beliefs (π) in T0, T10, and T30, respectively (Equation 6). The moment conditions minimize the predicted value with actual value to obtain optimal parameter estimates.

$$\frac{1}{N}\sum(\hat{p} - d) = 0 \tag{5}$$

$$\frac{1}{N}\sum(\hat{\pi} - \pi) = 0 \tag{6}$$

We use a random utility model to calculate the moments of testing decisions. Let $u(\delta, \Phi, \Omega)$ be the net value of testing, i.e., the utility of testing minus the utility of not

testing. We use a random-utility model:

$$\tilde{u}(\delta, \Phi, \Omega) = \frac{1}{\sigma} u(\delta, \Phi, \Omega) + \varepsilon \,, \tag{7}$$

where ε is assumed to be an i.i.d. error term and modeled as type I extreme value. The utility is scaled by 1/σ and the parameter σ is the scale parameter, because it scales the utility to reflect the variance of the unobserved portion of utility. The probability of diabetes testing is presented by the usual logit formula:

$$p(d = 1) = \frac{\exp(u(\delta, \Phi, \Omega))}{\exp(u(\delta, \Phi, \Omega)) + 1} \tag{8}$$

We use Propositions 1 and 2 in Oster et al. (2013) to calculate the moments of subjective beliefs. When $\mathrm{p} \leq p^*$, $\pi = 0$ and $a = 0$. When $\mathrm{p} > p^*$, $\pi = \frac{\Phi}{\Phi+\Omega}$ and $a = 1$. In our estimation, we do not observe diabetes risk p. We assume that p follows a truncated standard normal distribution, $\mathrm{p} \sim \mathrm{N}(0,1)$. We simulate objective risks and use MSM to estimate parameter δ, Φ, and Ω.

Table 6 reports the estimated coefficients. The estimated weight on anticipation utility is 0.48. The anticipation utility is about half as much as consumption utility. Recall that being healthy and taking the state-matched action has a value of 1. Being sick and taking the state-matched action has a value of 0. The estimated cost of not taking any action when sick is 0.61. The estimated cost of taking any action when healthy is 0.47. All the parameters are significantly different from zero at 1% the level. In our estimation, we find that $\delta < \Omega$. This is consistent with the condition in Proposition 1 and further supports our empirical predictions.

[Table 6]

5.2. Simulation and Welfare Analysis

We use our estimated parameters to conduct counterfactual welfare analysis under different screening policies. We have three types of screening policies: the status quo, the subsidy policy, and the mandate policy. The benchmark policy is the status quo when the cost of testing is 30 RMB. This is the case in our T30 group and close to the real-life situation. In the subsidy policy, we provide free diabetes tests and ask

individuals to decide whether to take the tests. We conduct simulations for several different subsidy policies. In the full subsidy policy, we provide free diabetes tests to everyone, which is the same as our T0 group. In the targeting subsidy policy (50), we only provide free tests to individuals with above-median risk and provide the status quo price to individuals with below-median risk. In real life, such targeted policies are often used by policy makers to reach risky individuals. In the full mandate policy, we provide free diabetes tests and require all individuals to take the tests. Similarly, in the targeted mandate policy (50), we only require individuals with above-median risk to take the tests and provide the status quo price to individuals with below-median risk. In real life, policy makers can use annual health screening as a condition for accessing health insurance to achieve mandates.

Our main purpose is to evaluate the welfare effect of different policies compared to the status quo policy, given certain model specification and policy maker's objective function. The model specification determines the optimal screening decision. We consider both the neoclassical model with only consumption utility ($\delta = 0$) and the optimal expectations model discussed in this paper, given the estimated δ. Other parameters are the same as in both models.

The policy maker's objective determines the welfare criterion. The policy maker might not understand that anticipation utility affect screening decisions. Even when the policy maker understands that the individuals make their screening choices based on the optimal expectations model, the policy maker may or may not want to incorporate the anticipatory utility into the objective function. Thus, we analyze three cases. In the first case, the policy maker does not understand the anticipation utility. They predict the screening decisions and calculate the welfare only based on consumption utility. In the second case, the policy maker only cares about maximizing consumption utility even when they are aware of the existence of anticipatory utility.[11] They predict the

[11] This approach follows the spirit of the literature of optimal policy in which agents have behavioral biases (Liebman and Zeckhauser 2008; Allcott and Taubinsky 2015; Beshears et al. 2017). In this literature, a policy maker considers behavioral biases as mistakes and calculates welfare only based on the neoclassical utility function. It is debatable whether anticipation can be considered a "mistake," since it influences an individual's feelings. One justification of the assumption is that many policy makers do not consider anxiety when designing screening subsidy policies, because they often value health benefit

screening decisions based on the overall utility— both consumption utility and anticipatory utility, but calculate the welfare only based on consumption utility. In the third case, the policy maker cares about the overall utility. They predict screening decisions and calculate the welfare based on both consumption utility and anticipatory utility.

Since the policy maker needs to pay the subsidy, we define the subsidy efficiency to be the welfare changes (depending on policy maker's objective) per person receiving the subsidy, and use it to measure the cost effectiveness of the policy. For example, if a policy increases the welfare from the status quo (T30) by ΔU in the population and the number of persons receiving the subsidy is ΔN, the subsidy efficiency is $\frac{\Delta U}{\Delta N}$.

Combining model specification with policy maker's welfare criterion, we end up with three cases, which is represented by Panel A, B and C in Table 7, respectively: neoclassical model with consumption utility as welfare criterion, optimal expectations model with consumption utility as welfare criterion and optimal expectations model with both the consumption utility and anticipatory utility as the welfare criterion. Within each case, we analyze the cost effectiveness of each policy mentioned above. We can compare the cost effectiveness of the first two cases because they are both under the same welfare criterion; but we can only make comparison within the third case.

[Table 7]

Panel A reports simulation results assuming individuals have neoclassical preferences (i.e., consumption utility only) under different policy environments. In all welfare calculations, we multiply the consumption utility by 1,000 to make presentation more convenient. Under the status quo policy, the neoclassical model predicts that about 62% of individuals take the diabetes test, and mean consumption utility is 730. The full subsidy policy increases take-up to 89% and mean consumption utility to 846. For the subsidy paid for each person, the utility increases by 0.20 relative to the status quo policy. So the subsidy efficiency for the full subsidy policy is 0.20. The targeting subsidy policy (50) increases take-up to 75% and mean consumption utility to 789. The

much more than anxiety or view anxiety as temporary.

subsidy efficiency is 0.20. Simulation results suggest that the targeted subsidy policy is similar to the full subsidy policy in terms of cost effectiveness.

The subsidy efficiency of the full mandate policy is 0.17, while that of the targeted mandate policy (50) is 0.16. These results suggest that the mandate policy is worse than the subsidy policy in general, both in terms of increase in consumption utility and cost effectiveness. The intuition is that the subsidy policy still allows individuals to make a welfare-improving choice based on the subsidy, and thus only changes the behavior of marginal individuals. In contrast, the mandate policy might force individuals with very low benefit to take the test.

Panel B reports simulation results for the anticipation utility model with only consumption utility as welfare criterion. We calculate welfare based on consumption utility only. Under the status quo policy, about 16% of individuals take the diabetes test. Take-up is lower than in the status quo under neoclassic utility due to information avoidance. Mean consumption utility in this case is 677. The full subsidy policy increases take-up to 62% and the mean consumption utility to 813. The subsidy efficiency for the full subsidy is 0.34, which is 70% greater than the one based on the neoclassic model in Panel A. The targeted subsidy policy (50) increases take-up to 39% and mean consumption utility to 746. The subsidy efficiency is 0.34, which is 68% greater than that based on the neoclassic model in Panel A. In the full mandate policy (50), the subsidy efficiency is 0.25, which is 50% greater than that based on the neoclassic utility. In the targeted mandate policy (50), the subsidy efficiency is 0.23, which is 39% greater than that based on neoclassic utility.[12]

Our results suggest that if individuals have anticipation utility that leads to information avoidance, the policy maker who views individuals as neoclassical utility maximizers underestimates the cost effectiveness of both the subsidy policy and mandate policy in terms of consumption utility change. The subsidy policy is in particular more cost effective hence being underestimated more.

[12] We also perform another version of the welfare analysis based on overall utility, including anticipatory utility. The results (not reported) are very similar: Subsidy policies are more effective in general than mandate policies. However, since the welfare standard is different, we cannot compare the results directly to that in Panel A.

We further simulate a perfect targeted subsidy policy in which we only provide free tests to information avoidant individuals. We define individuals to be information avoidant if they take the test in the neoclassic model but refuse to take the test in the anticipation utility model under the status quo policy. We find that such a policy is the most cost effective of all the policies, in which the subsidy efficiency is 0.43. This result shows that if individuals indeed have anticipatory utility, identifying and targeting individuals with information avoidant tendencies is a better policy than previous ones.[13] Panel C reports simulation results for the anticipation utility model with both consumption utility and anticipation utility as welfare criterion. We find that the mandate policy is worse than the subsidy policy in general. The pattern is similar to Panel A and B. We cannot compare the cost effectiveness to the first two cases because they are under the different welfare criterion.

6. Conclusion

This paper reports results from a randomized field experiment in rural China to investigate whether individuals have a tendency to avoid medical tests due to information avoidance. We randomly assigned individuals to different treatments that varied the price of a diabetes test, and different treatments to vary the type of the disease being tested, diabetes or cancer. We observe that both low- and high-risk individuals are less likely to take the test—a phenomenon not revealed before—by using a field experiment. Subsequently, we find that as the test price increases, the average test outcome remains the same but the dispersion of the outcome decreases, indicating that both low- and high-risk individuals select out of the test as price increase. We also find interesting heterogeneity: The pattern in which high-risk individuals avoid the test is more salient when the test price is higher and when the disease is more severe.

We apply the optimal expectations model of Oster et al. (2013) to explain our findings. The model predicts a non-monotonic relationship between beliefs on the probability of having the disease and the probability of taking the test—a prediction not

[13] How to identify such individuals remains a question for future research. We attempt to explore which factors in our sample can predict such individuals. It turns out that two factors have significant effects: when one has less frequent exercise and more self-control problems, as measured in the survey, they are more likely to demonstrate information avoidance as defined above.

explicitly derived or emphasized in Oster et al.—and explain our empirical findings. The model also predicts heterogeneity across test price and disease type consistent with our empirical findings. These results not only provide a satisfactory explanation for the empirical findings, but also help to distinguish the optimal expectations model from the anxiety model empirically.

Why do our findings differ from those of Oster et al. (2013) and Okeke et al. (2013)? Our Proposition 1 makes clear predictions about comparative statics with respect to C and Ω. It shows that high-risk individuals are more likely to avoid information when the test price is high and the utility loss of taking the wrong action when sick is high. Our finding 1 in the price treatments and finding 3 in the disease treatments are consistent with these predictions. Since Huntington's disease is not curable, Ω in Oster et al. (2013) is likely to be small, and thus high-risk individuals are less likely to avoid information. The test cost is also relatively low in Okeke et al. (2013) They state in section 5.2.1 that "even the highest price offered represented approximately a 90% subsidy". The fact that they do not observe that high-risk individuals are less likely to avoid information could be due to this low test price. Therefore, our propositions might help to reconcile mixed results in different settings and explain under what conditions high-risk individuals avoid information.

How the tendency to avoid information varies across the probability of having the disease has important policy implications. The test is more valuable for high-risk individuals. Under simple neoclassical intuition, they are more likely to take the test in any case; but according to our empirical results and under the optimal expectations model, they are less likely to take the test. If the latter is true, proper interventions that target the high-risk group create higher welfare gains than traditionally thought. Also, new policies that target the group that attaches higher weight to anticipatory utility can be more effective than traditional policies.

Reference

Allcott, Hunt, and Dmitry Taubinsky (2015). "Evaluating Behaviorally Motivated Policy: Experimental Evidence from the Lightbulb Market." *American Economic Review*, Vol 105, No. 8 (August), pages 2501-2538.

Beshears, John, James Choi, Christopher Clayton, Christopher Harris, David Laibson, Brigitte Madrian. 2017. "Optimal Illiquidity" Working paper.

Bénabou, Roland, and J. Tirole, " Self Confidence and Personal Motivation, " *Quarterly Journal of Economics*, 117 (2002), 871–915.

Brunnermeier, Markus K., and J. A. Parker. "Optimal Expectations." *American Economic Review* 95.4(2005):1092-1118.

Caplan, L. S. "Patient Delay in Seeking Help for Potential Breast Cancer. " *Public Health Reviews* 23.3(1995):263-74.

Caplin, Andrew, and J. Leahy. "Psychological Expected Utility Theory and Anticipatory Feelings." *Quarterly Journal of Economics* 116.1(2001):55-79.

Eliaz, Kfir, and R. Spiegler. "Can anticipatory feelings explain anomalous choices of information sources?" *Games & Economic Behavior* 56.1(2006):87-104.

Epstein, Larry G. "Living with Risk." *The Review of Economic Studies* 75.4(2008): 1121-1141

Golman, Russell, D. Hagmann, and G. Loewenstein. "Information Avoidance." *Journal of Economic Literature* 55(2017):96-135.

Ganguly, Ananda R, and J. Tasoff. "Fantasy and Dread: The Demand for Information and the Consumption Utility of the Future." *Management Science* 63(2016):4037-4060.

Holt, Charles A., and S. K. Laury. "Risk Aversion and Incentive Effects." *American Economic Review* 92.5(2002):1644-1655.

International Diabetes Federation, 2015. Brussels: International Diabetes Federation.

Kőszegi, Botond. "Health anxiety and patient behavior." *Journal of Health Economics* 22.6(2003):1073-1084.

Kőszegi, Botond and Matthew Rabin. "Reference-dependent consumption plans." *The American Economic Review*, 99(3):909-936, 2009.

Kőszegi, Botond, "Utility fromAnticipation andPersonal Equilibrium," *Economic Theory*, 44 (2010), 415–444.

Lerman, C, et al. "Genetic Testing in Families with Hereditary Nonpolyposis Colon Cancer. " *JAMA* 281.17(1999):1618.

Liebman, J. and R. Zeckhauser, "Simple Humans, Complex Insurance, Subtle Subsidies," Working Paper 14330, NBER 2008.

Lyter, D. W., et al. "The HIV antibody test: why gay and bisexual men want or do not want to know their results. " *Public Health Reports*102.5(1987):468.

Meechan, G, J. Collins, and K. Petrie. " Delay in Seeking Medical Care for Self-Detected Breast Symptoms in New Zealand Women." *New Zealand Medical Journal* 115 (1166):U257.

Miller, S. M. "Monitoring and blunting: validation of a questionnaire to assess styles of information seeking under threat." *Journal of Personality & Social Psychology* 52.2(1987):345-53.

Okeke, E. N., C. A. Adepiti, and K. O. Ajenifuja. "What is the price of prevention? New evidence from a field experiment." *Journal of Health Economics* 32.1(2013):207.

Oster, Emily, I. Shoulson, and E. R. Dorsey. "Optimal Expectations and Limited Medical Testing: Evidence from Huntington Disease." *American Economic Review* 103.2(2013):804-830.

Persoskie, Alexander, Rebecca A. Ferrer, and William M. P. Klein. 2014. "Association of Cancer Worry and Perceived Risk with Doctor Avoidance: An Analysis of Information Avoidance in a Nationally Representative US Sample." *Journal of Behavioral Medicine* 37 (5): 977–87.

Sullivan, Patrick S., Amy Lansky, and Amy Drake. 2004. "Failure to Return for HIV Test Results among Persons at High Risk for HIV Infection: Results from a Multistate Interview Project." *JAIDS Journal of Acquired Immune Deficiency Syndromes* 35 (5): 511–18.

Thornton, R. L. "The Demand for, and Impact of, Learning HIV Status." *American Economic Review* 98.5(2008):1829-1863.

World Health Organization (2016), *Global Report on Diabetes*. Geneva, 2016.

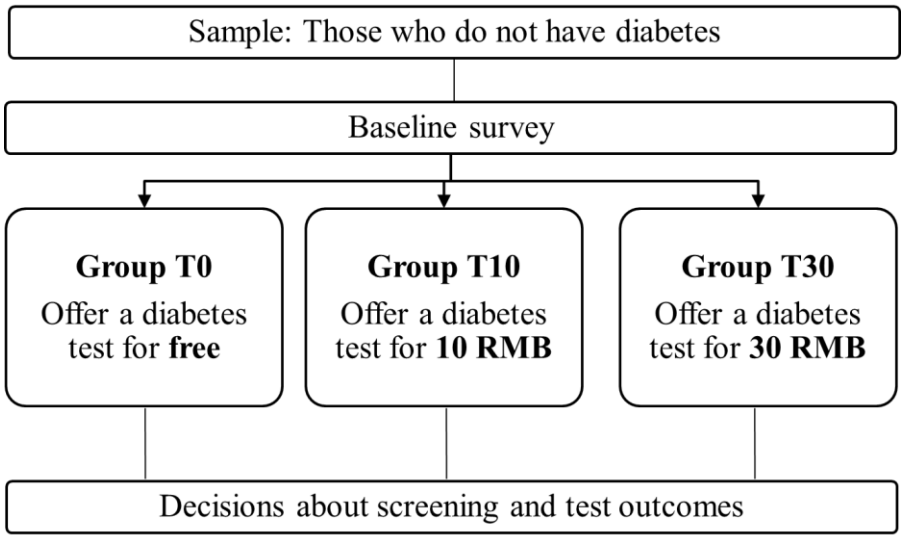
World Health Organization (2017), "The top 10 causes of death Fact sheet". *World*

Health Organization. Jan 2017.

Yang, W., et al. “Prevalence of diabetes among men and women in China.” *New England Journal of Medicine* 362.25(2010):2425.

Figure 1. Experimental Design

Panel A: Price Treatment



Panel B: Disease Treatment

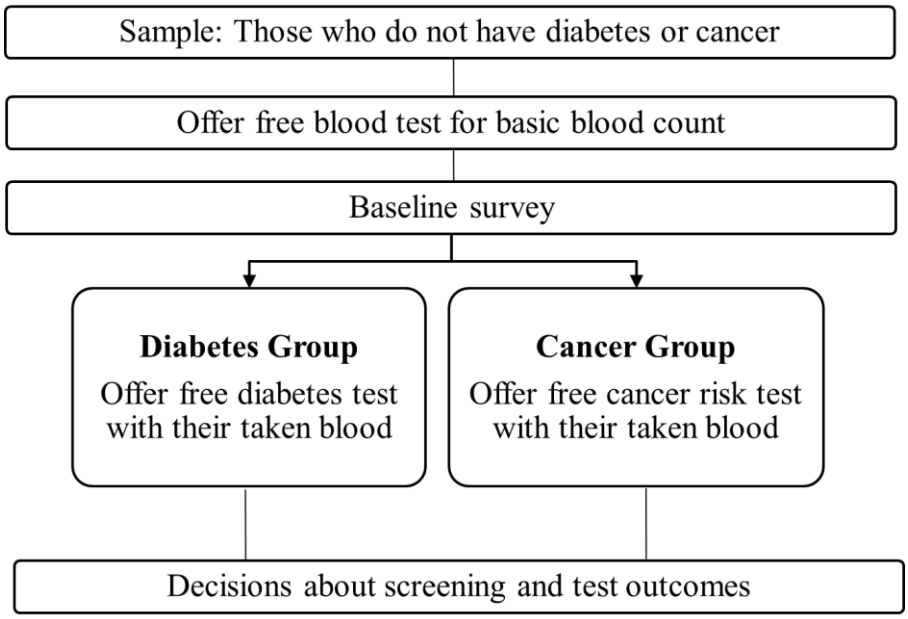
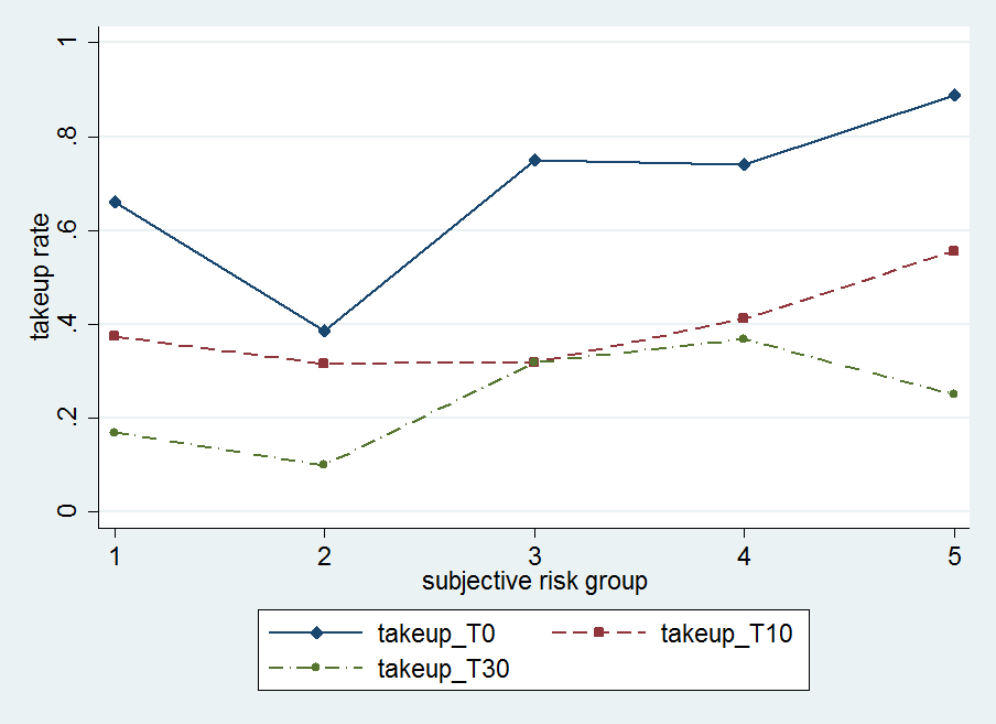
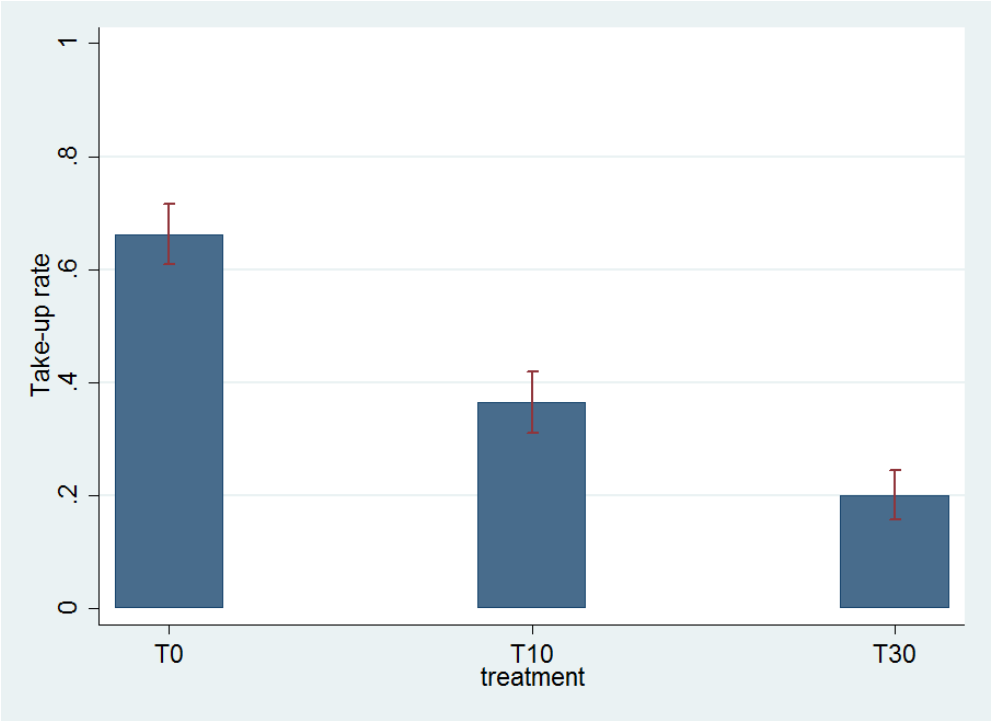


Figure 2. The Relationship between Subjective Risk and the Take-up Decisions



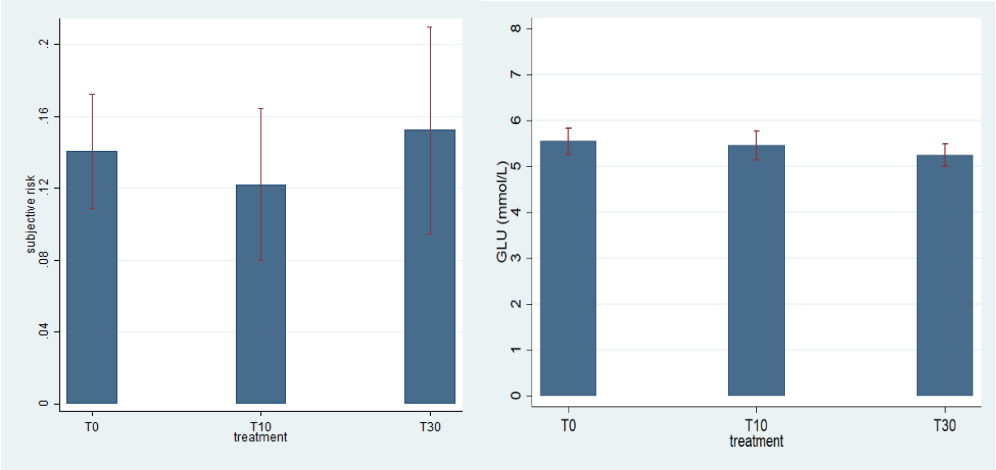
Note: Individuals are divided into 5 groups based on their subjective risks of diabetes. They are in group 1 if subjective risk is 0, group 2 if subjective risk is between 0 and 0.2, and group 3, 4, or 5 if subjective risk is between 0.2 and 0.4, 0.4 and 0.6, or above 0.6, respectively.

Figure 3. Take-up Rate across Treatments



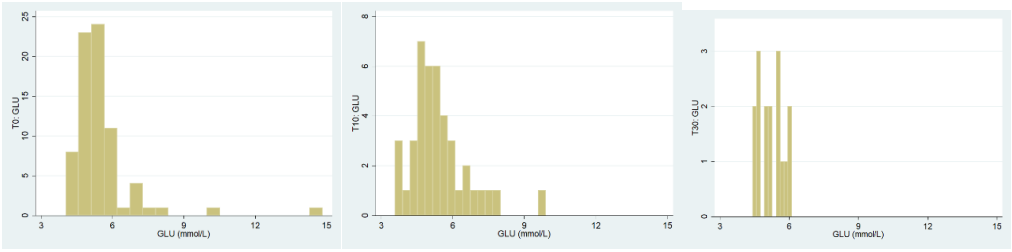
Note: This figure compares subjects' take-up rates of the diabetes test across different treatments with 90% confidence intervals.

Figure 4. Risk and Test Outcome Conditional on Taking the Test



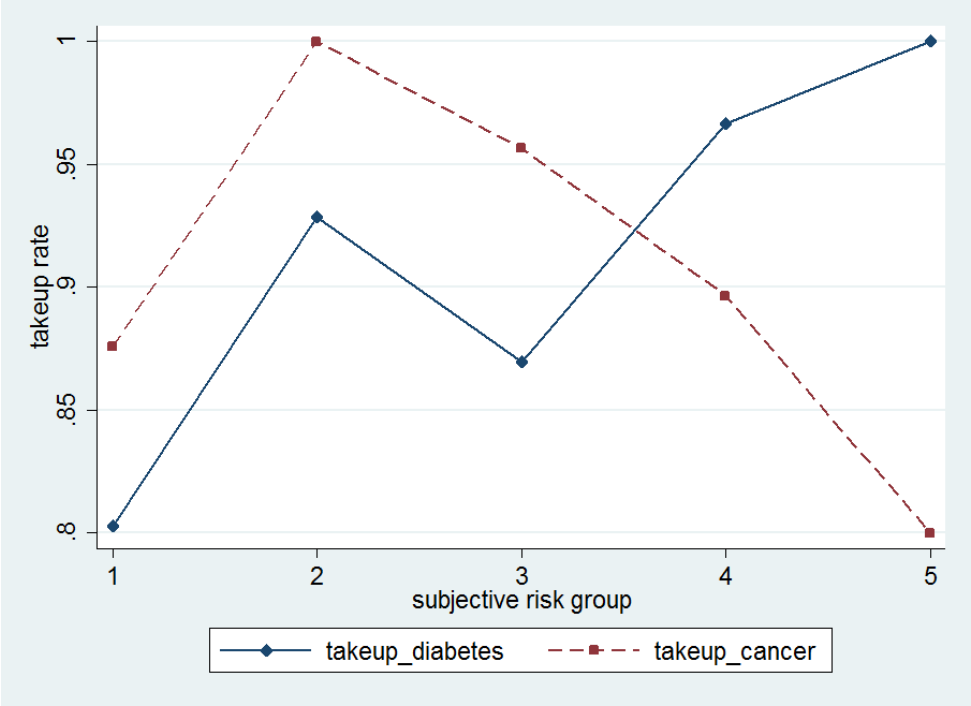
Note: The left figure displays the average subjective risk across different treatments with 90% confidence interval conditional on taking the test. Subjective risk is the chance that individuals think of themselves as having diabetes. The right figure displays the average blood glucose level (GLU) of the two diabetes tests across different treatments conditional on taking the test.

Figure 5. Distribution in Test Outcome across Treatments



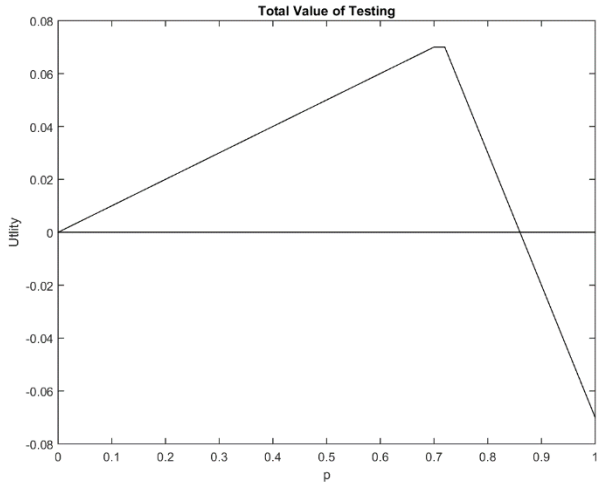
Note: This figure displays the frequency distributions of blood glucose level (GLU) of the two diabetes tests across different treatments conditional on taking the test.

Figure 6. Take-up Rate across Treatments by Percentiles of Subjective Risk of the Corresponding Diseases



Note: Individuals are divided into 5 groups based on their subjective risks of the corresponding disease. They are in group 1 if subjective risk is 0, group 2 if subjective risk is between 0 and 0.2, and group 3, 4, or 5 if subjective risk is between 0.2 and 0.4, 0.4 and 0.6, or above 0.6, respectively. For individuals in the diabetes treatment, subjective risk is defined as the chance that they believe they will develop diabetes. For individuals in cancer treatment, it is defined as the chance that they believe they will develop cancer.

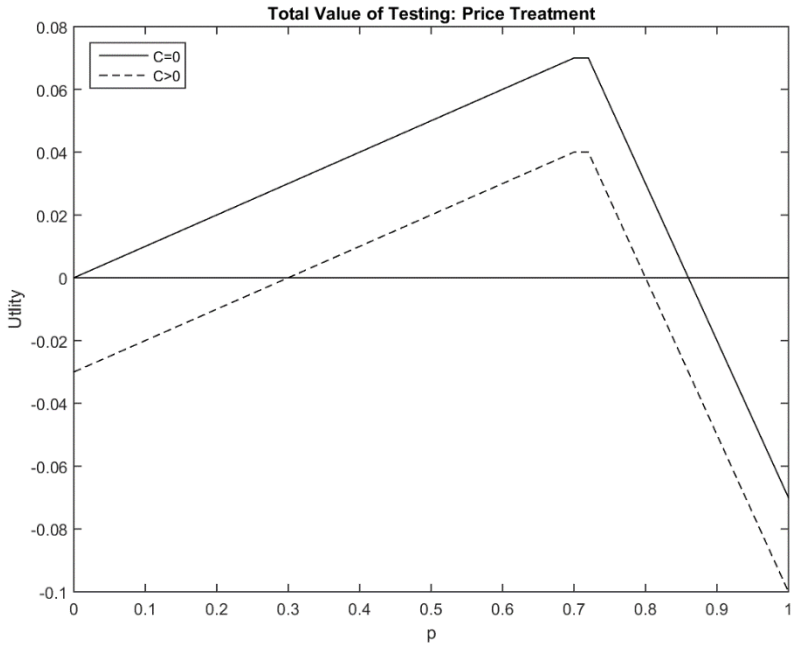
Figure 7. Total Value of Testing



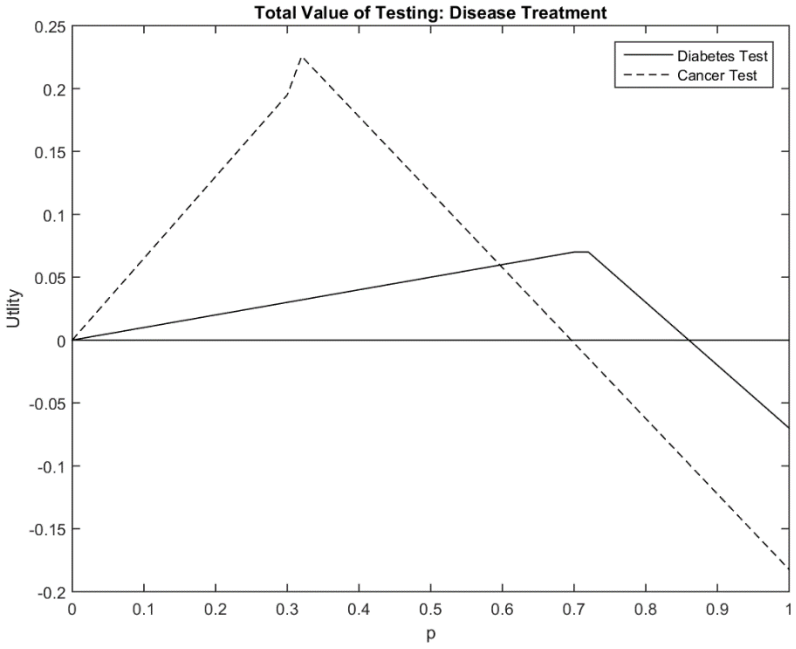
Note: This figure shows the total value of testing when the test is free and there is low value of anticipation ($\delta < \Omega$). The horizontal axis is p. The vertical axis is the total value of testing, which equals the benefit of testing minus the benefit of not testing.

Figure 8. Predictions for Price Treatment and Disease Treatment

Panel A. Price Treatment



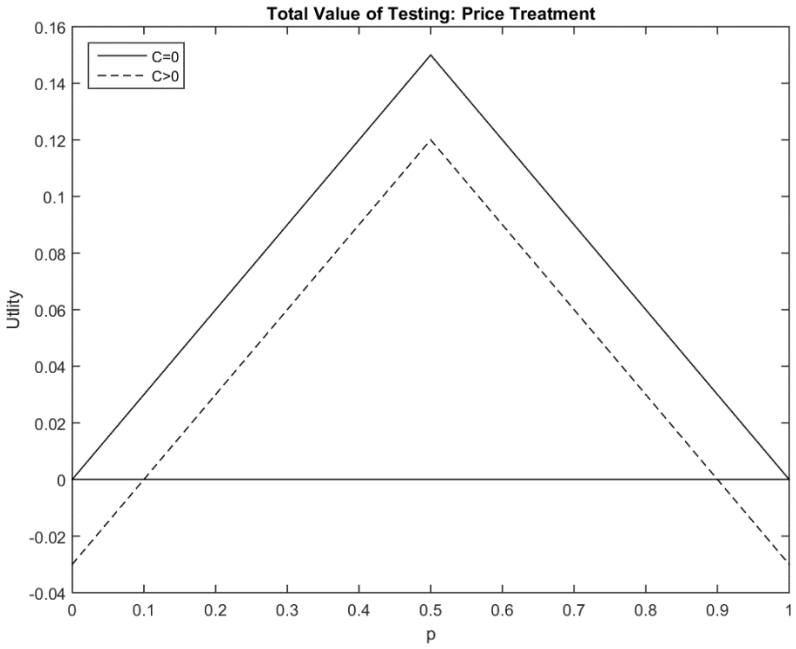
Panel B. Disease Treatment



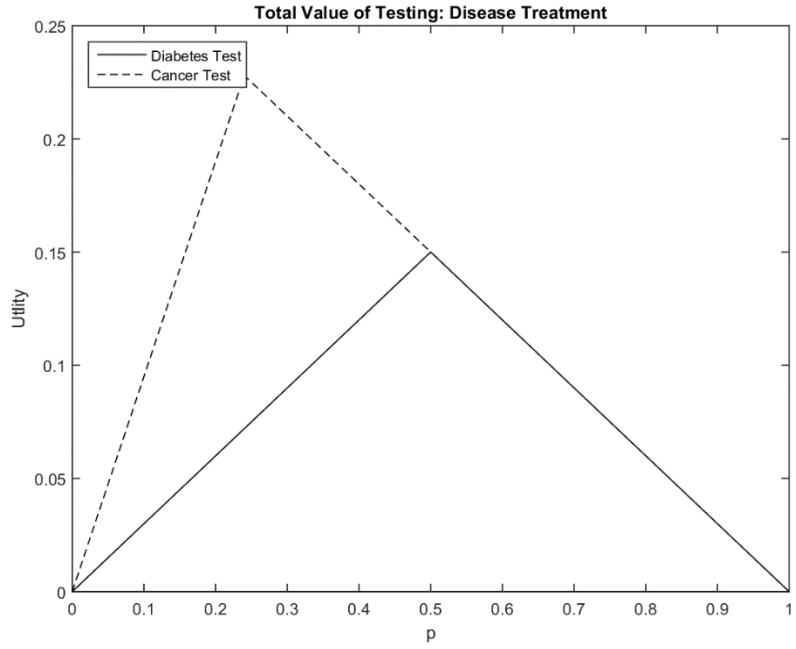
Note: Panel A illustrates the predictions from the price treatment when we vary the cost of testing based on Proposition 1. The horizontal axis is p. The vertical axis is the total value of testing. C is the cost of testing. Panel B illustrates the predictions from the disease treatment when the test is free.

Figure 9. Predictions for Price Treatment and Disease Treatment: No Anticipation

Panel A. Price Treatment



Panel B. Disease Treatment



Note: These figures show the predictions of the model with no anticipatory utility. Panel A illustrates the predictions from the price treatment when we vary the cost of testing based on Proposition 2. The horizontal axis is p. The vertical axis is the total value of testing. C is the cost of testing. Panel B illustrates the predictions from the disease treatment when the test is free.

Table 1. Summary Statistics and Randomization Check

	T0	T10	T30	Diabetes	Cancer
Panel A. Screening					
Take-up rate of the test	0.66	0.37	0.20	0.86	0.89
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Panel B. Demographics					
Gender (male)	0.37	0.38	0.43	0.45	0.39
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age	53.29	51.57	52.59	52.61	52.05
	(0.45)	(0.47)	(0.48)	(0.47)	(0.43)
Education years	7.28	7.90	6.67	7.04	7.09
	(0.21)	(0.19)	(0.22)	(0.21)	(0.19)
Marriage Status	0.94	0.98	0.94	0.90	0.93
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Household Size	3.18	3.54	3.27	3.29	3.35
	(0.09)	(0.10)	(0.09)	(0.09)	(0.09)
Whether monthly income is	0.48	0.55	0.48	0.54	0.45**
larger than 1000 RMB	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Panel C. Health Conditions and Behaviors					
Height (cm)	159.46	160.28	160.17	160.91	160.43
	(0.52)	(0.54)	(0.54)	(0.55)	(0.47)
Weight (kilogram)	67.13	65.57	68.39	67.36	66.79
	(0.74)	(0.80)	(0.82)	(0.78)	(0.66)
BMI ratio	26.44	25.49	26.63	25.98	25.96
	(0.29)	(0.27)	(0.28)	(0.27)	(0.24)
Smoking (percentage)	0.30	0.31	0.36	0.36	0.34
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Drinking (percentage)	0.35	0.31	0.33	0.42	0.41
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Sleeping hours	7.73	7.84	7.51	7.74	7.85
	(0.11)	(0.10)	(0.12)	(0.10)	(0.09)
Exercise frequency	2.63	2.74	2.80	2.76	2.75
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
Subjective knowledge of					
diabetes	0.31	0.30	0.28	0.30	0.29
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Objective knowledge of					
diabetes	0.47	0.48	0.46	0.46	0.44
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Ability to follow treatment	1.44	1.14	1.40	0.84	0.83
	(0.43)	(0.31)	(0.58)	(0.01)	(0.01)
	0.12	0.11	0.10	0.13	0.10

Subjective assessment of disease risk	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Panel D. Preference Coefficients					
Risk aversion	3.13	3.30	3.17	2.87	3.18
	(0.15)	(0.15)	(0.15)	(0.15)	(0.14)
Loss aversion	2.46	2.65	2.68	2.47	2.58
	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)
Patience (includes present bias)	3.28	3.15	3.50	3.28	3.51
	(0.18)	(0.18)	(0.17)	(0.17)	(0.16)
Patience (not includes present bias)	3.16	2.98	3.47	3.22	3.49
	(0.18)	(0.18)	(0.18)	(0.17)	(0.16)
Monitoring	0.13	0.13	0.13	0.13	0.13
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Neuroticism	2.52	2.62	2.58	2.63	2.69
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Openness	4.67	4.57	4.70	4.52	4.52
	(0.06)	(0.06)	(0.05)	(0.07)	(0.06)
Observations	219	216	229	255	276

Note: We use stars on the T30 variable to indicate whether the variables in T0, T10, and T30 are significantly different in the multivariate test. We use stars to indicate whether variables in the cancer treatment are significantly different from those in the diabetes treatment. For how to construct the variables in the table from survey answers, please refer to Table A1 in Appendix 3.

Table 2. Testing the Non-monotonic Effect of Subjective Risk on Take-up Decisions

	(1)	(2)	(3)
	T0	T10	T30
Subjective risk	-0.02	-0.39	0.82
	(0.41)	(0.46)	(0.43)
Subjective risk^2	0.55	0.94	-1.10
	(0.57)	(0.61)	(0.54)
Constant	8.77	3.62	-2.28
	(4.04)	(4.97)	(3.76)
Demographics (6)	Yes	Yes	Yes
Health Conditions and Behaviors (10)	Yes	Yes	Yes
Observations	204	197	209
R-squared	0.10	0.09	0.12

Note: The regressions in the table show non-monotonic effect of subjective risk on take-up decisions in different treatment groups. Results are not affected by adding different categories of controls gradually. We control for six demographic variables—gender, age, education, marriage, household size, and monthly income—and 10 variables on health conditions and behaviors: height, weight, BMI, sleeping hours, drinking behavior, smoking behavior, exercise frequency, subjective/objective knowledge of diabetes, and the ability to comply with diabetes treatment. Please refer to the online appendix for full regressios results. Robust standard errors in parentheses.

Table 3. Subjective Risk and Test Outcomes Conditional on Taking the Test

	(1)	(2)
	Subjective risk	GLU
T10	-0.03	-0.08
	(0.03)	(0.30)
T30	-0.02	-0.30
	(0.04)	(0.28)
Constant	-0.12	14.76
	(1.74)	(22.18)
Demographics (6)	Yes	Yes
Health Conditions and Behaviors (10)	Yes	Yes
Observations	254	127
R-squared	0.09	0.16
F-statistics: T10=T30	0.164	0.469

Note: Regressions in the table show average subjective risk and test outcomes across treatments conditional on taking the test. Please refer to the online appendix for full regression results. Robust standard errors in parentheses.

Table 4. Testing the Non-monotonic Effect of Subjective Risk on Take-up Decisions

	(1) Diabetes treatment	(2) Cancer treatment	(3) Diabetes treatment	(4) Cancer treatment
Subjective risk	0.79	0.74	1.06	1.84
	(0.33)	(0.39)	(0.39)	(0.37)
Subjective risk square	-0.69	-1.39	-1.03	-4.12
	(0.52)	(0.78)	(0.59)	(0.70)
Controllable×Subjective risk			-0.37	-1.23
			(0.75)	(0.46)
Controllable×Subjective risk square			0.55	3.15
			(1.27)	(0.97)
Constant	1.89	0.39	0.07	0.30
	(2.08)	(3.74)	(2.30)	(3.96)
Demographics (6)	Yes	Yes	Yes	Yes
Health Conditions and Behaviors (10)	Yes	Yes	Yes	Yes
Observations	211	239	176	207
R-squared	0.10	0.10	0.13	0.15

Note: This table reports the non-monotonic effect of subjective risk on take-up decisions in different treatment groups. Results are not affected by adding different categories of controls gradually. We control for six demographic variables—gender, age, education, marriage, household size, and monthly income—and 10 variables on health conditions and behaviors: height, weight, BMI, sleeping hours, drinking behavior, smoking behavior, exercise frequency, subjective/objective knowledge of diabetes, and the ability to comply with diabetes treatment. Please refer to the online appendix for full regression results. Robust standard errors in parentheses.

Table 5. Alternative Explanations

	(1)
	Subjective risk
Subjective Knowledge	0.10
	(0.04)
Objective Knowledge	0.05
	(0.04)
Treatment Compliance Cost	-0.01
	(0.01)
Income Level	-0.01
	(0.01)
Expenditure Level	0.02
	(0.02)
Constant	0.15
	(0.12)
Demographics (6)	Yes
Observations	620
R-squared	0.05

Note: The regression in the table shows the effect of subjective and objective knowledge of diabetes, treatment compliance cost, income, and expenditure level on subjective risk. We control for six demographic variables: gender, age, education, marriage, household size, and monthly income. Robust standard errors in parentheses.

Table 6. Structural Estimation

Parameter	Symbol	Value
Weight on anticipation utility	δ	0.48
		(0.12)
Cost of not taking any action when being sick	Ω	0.61
		(0.18)
Cost of taking any action when being healthy	Φ	0.47
		(0.12)
Observations	N	645

Note: This table use the method of simulated moments to estimate model parameters with the sample from the price treatment. Standard errors in parentheses.

Table 7. Simulation

	%Testing	Consumption Utility(U)	No of Subsidy (ΔN)	Utility change from Status quo (ΔU)	Subsidy Efficiency (ΔU/ΔN)	Increase in Subsidy Efficiency
Panel A: Neoclassical Model:welfare based on consumption utility						
Status quo (T30)	62%	730				
Full subsidy(T0)	89%	846	575	116	0.20	
Target subsidy (50)	75%	789	290	59	0.20	
Full mandate	100%	837	645	107	0.17	
Target mandate (50)	80%	779	298	49	0.16	
Panel B: Anticipation Model: welfare based on consumption utility						
Status quo (T30)	16%	677				
Full subsidy(T0)	62%	813	401	137	0.34	70%
Target subsidy (50)	39%	746	205	69	0.34	68%
Full mandate	100%	837	645	161	0.25	50%
Target mandate (50)	54%	745	298	68	0.23	39%
Target subsidy: Information avoidance	53%	779	238	102	0.43	
Panel C: Anticipation Model: welfare based on both consumption utility and anticipation utility						
Status quo (T30)	16%	815				
Full subsidy(T0)	62%	872	401	56	0.14	
Target subsidy (50)	39%	846	205	30	0.15	
Full mandate	100%	837	645	22	0.03	
Target mandate (50)	54%	826	298	10	0.03	

Note: This table reports simulation results for neoclassical model with consumption utility as welfare criterion (Panel A), optimal expectations model with consumption utility as welfare criterion (Panel B) and optimal expectations model with both the consumption utility and anticipatory utility as the welfare criterion (Panel C).In all welfare calculations, we scale the utility by 1,000 to avoid very small utilities and improve presentation. We define subsidy efficiency to be the consumption utility changes per person receiving the subsidy, and use this to measure the cost effectiveness of the policy. For example, if a policy increases the utility from the status quo (T30) by ΔU and the number of persons receiving the subsidy is ΔN, the subsidy efficiency is $\frac{\Delta U}{\Delta N}$.