Information, Belief, and Health Behavior: Evidence from China

Xiaoyan Lei* Guangxiang Song† Xuejuan Su‡

October 17, 2021

Abstract

Individuals with imperfect information may make suboptimal choices, but providing more information may not effectively improve decision making if the information is not turned into updated belief. We build a Bayesian updating model to illustrate this phenomenon and use a unique Chinese survey that provides data on information shock, belief updating, and corresponding behaviors to test it. We find that when individuals receive signals about their hypertension status, behavioral changes, such as quitting smoking and take medication, are more likely if the new information leads to updated belief. Furthermore, we find heterogeneous effects across subgroups of individuals: Males are more likely to quit smoking and taking medication after belief updating; rural people are more likely to quit smoking but less likely to take medication, possibly due to lack of affordability or accessibility to medical services. We find no significant impacts on drinking.

Keywords: Imperfect Information, Bayesian Updating, Belief, Health Behaviors

JEL codes: H12, D83, J14

*National School of Development, Peking University. Email: xylei@nsd.pku.edu.cn.
†Department of Economics, Pennsylvania State University. Email: gbs5325@psu.edu.
‡Department of Economics, University of Alberta. Email: xuejuan1@ualberta.ca.
We thank Rong Fu, Gordon Liu, Xuezheng Qin, Julie Shi and Ye Yuan for their insightful suggestions. We also thank the conference participants at Health and Labor workshop at Peking University, CEPAR at UNSW, and the Asian Workshop on Econometrics and Health Economics for their helpful comments. This project is supported by the National Key R&D Program of China (2018YFC2000400) , NSFC 71873006 and NSFC-UKRI_ESRC 72061137004. All remaining errors are our own.

1 Introduction

Individuals with imperfect information may make suboptimal decisions about their health, and this problem is particularly severe in developing countries and/or rural areas where resources are limited. To address this issue, a growing number of information programs have been designed to encourage behavioral changes, including on hypertension (Zhao et al., 2013), drinking water quality (Madajewicz et al., 2007; Jalan and Somanathan, 2008), HIV risk (Thornton, 2008; Dupas, 2011), and infant nutrition (Fitzsimons et al., 2016), among others. However, the effectiveness of such information programs depends critically on how uninformed individuals are to begin with, and to what extent they incorporate the received information into decision making (Bennear et al., 2013; Brown et al., 2017). All the above literature implicitly assumes that once receiving the information, individuals can thoroughly incorporate it and definitely update their beliefs about their health status, no matter whether they will change their behaviors accordingly or not. But when investigating the impacts of information about diabetes, Iizuka et al. (2021) find that health outcomes improve only for high-risk individuals. They explain that different individuals might have different belief-updating thresholds and sometimes the information received by an individual with a low threshold might be a false alarm and therefore have no substantial impact on them. That is, there exists observable and unobservable heterogeneity heterogeneity between individuals, which might lead to different cognition of information and thus different thresholds for updating their beliefs. This is the focus of our paper. In the context of hypertension, we examine how informing individuals of their blood pressure levels affects their beliefs about their hypertensive status, and how changes in their beliefs lead to subsequent behavioral changes.

To model belief updating explicitly as the channel through which information engenders behavioral changes, we consider a simple problem of choice under uncertainty via Bayesian updating. In particular, we highlight the importance of individual heterogeneity, namely differences in their prior beliefs as well as the perceived relevance of signals, in both belief updating and subsequent optimal choices. The key takeaway from the theoretical model is that, in empirical studies, if such individual heterogeneity is not adequately controlled, cross-sectional analyses may suffer the omitted variable problem and lead to biased estimates. We then estimate a corresponding two-stage regression model using the China Health and Retirement Longitudinal Study (CHARLS), with individual fixed effects to control for unobserved heterogeneity in the belief updating process.

CHARLS is a nationally representative, longitudinal survey of middle-aged and elderly individuals in China. It started in 2011 and had been carried out followed every two years since then. We use the three waves from 2011, 2013, and 2015 for the current study. We are interested in data from three aspects. First, in each wave, CHARLS provided a free physical examination, in which a sphygmomanometer automatically reported whether the respondent was hypertensive on the spot. A written report of the physical examination result was mailed to all the participants after the exam. In particular, individuals were informed of their blood pressure level and whether it fell in the hypertensive range. This constitutes a signal (information shock) in our model.[1] Second, prior to the physical examination, CHARLS asked participants whether they knew if they had hypertension or not. With such timing, individual awareness constitutes both the prior belief before receiving a signal in the current wave and, more importantly, the updated belief after receiving a signal in the previous wave. Third, in each wave, CHARLS also asked the participants about their health-related behaviors such as drinking, smoking, and taking hypertension medication, which are the major behavioral outcomes that are likely to be adjusted in response to the hypertension belief. For the empirical analysis, we use lagged signals as an instrument for current updated beliefs in the first-stage regression, and the predicted beliefs as the explanatory variable for any behavioral change in the second-stage regression. A regression discontinuity design (RDD) framework is also employed as a robustness check, comparing those who are just above and below the cutoff points of the hypertension measure. Accordingly, for each participant, three waves of survey data yield two sets of observations for the two-stage regression model, allowing us to use individual fixed effects to control for unobserved heterogeneity.

CHARLS is uniquely suitable for our empirical analysis for two reasons. First, when it is costly to acquire information (including monetary and psychological cost), individuals may choose whether to receive a signal or avoid it (Köszegi, 2003; Oster et al., 2013; Okeke et al., 2013; Ganguly and Tasoff, 2017). Such an endogenous decision of signal acquisition would pose a challenge for identification if individuals who deem the information important are more likely to seek the information and act upon it. CHARLS circumvents this endogeneity problem because the arrival of the signal is exogenous: it is the result of a free medical examination to all participants. This exogenous signal arrival is similar in spirit to the

[1] We chose to focus on hypertension, a chronic disease, because of its high prevalence in the elderly population. In China, nearly half of adults ages 35-75 years have hypertension (Lu et al., 2017), resulting in major health and economic burdens at the community and national levels (Bloom et al., 2018).

randomized controlled trials (RCTs) of information programs cited earlier. Furthermore, randomized evaluation of information provision has been implemented in many other contexts, such as health plans (Scanlon et al., 2002; Jin and Sorensen, 2006; Kling et al., 2012), financial decisions (Duflo and Saez, 2003), calorie posting (Bollinger et al., 2011), takeup of social benefits (Bhargava and Manoli, 2015), water use (Ferraro and Price, 2013), electricity use (Byrne et al., 2018), and others.

Second, and more importantly, whether and how a signal is incorporated into one's belief depends on important but unobserved individual characteristics, including the prior belief, the perceived relevance of the signal, the individual's cognitive capacity, and so forth. While socioeconomic status (SES) such as education, income, and wealth may be correlated with unobserved characteristics (Auld and Sidhu, 2005; Lange, 2011; Brown et al., 2017; Galama and van Kippersluis, 2019), such SES proxies are by no means perfect. Given our focus on belief updating as the mechanism, cross-sectional variations alone are inadequate for identifying the belief channel when unobserved individual heterogeneity leads to omitted variable bias. The panel data structure of CHARLS enables us to use individual fixed effects to control for unobserved heterogeneity and estimate the two-stage regression model without bias. Unlike most RCTs where information is found to have an impact on behaviors but the mechanism remains a black box, our two-stage results further shed light on the channel, namely belief updating, linking information treatment to subsequent behaviors.

What we find is interesting. For belief updating, the first-stage regression results show that while some individuals became aware of their hypertension status after receiving the signal, a larger percentage of people continued to remain unaware despite receiving the hypertension reading from the physical examination. This might suggest a phenomenon that it is not enough to give a signal or new health information, which should be considered carefully. For behavioral changes, we find that the respondents who received a signal were more likely to change their behaviors, such as quitting smoking and taking medication, and such behavioral changes were mostly driven by individuals who updated their belief compared with those who did not.

Furthermore, we also detect heterogeneous effects of the information treatment. We find that males and rural respondents were more likely to update their belief after receiving a signal than their female and urban counterparts. Compared with individuals who were unaware of their hypertension status, males tended to quit smoking after becoming aware that they were hypertensive. The impacts on taking medication were larger in urban areas, probably because public health amenities are less accessible in rural areas. But the impacts on quitting smoking changed their lifestyle, because medical care was less accessible or affordable. These results suggest that in addition to help with physical examinations and information updating, more actions are needed to help elderly people, especially women and rural people, to control chronic diseases including hypertension.

The rest of the paper is organized as follows. Section 2 builds a simple model of choice under uncertainty via Bayesian updating, and highlights the importance of individual heterogeneity. Section 3 presents the corresponding two-stage regression model and discusses our identification strategy. Section 4 describes the CHARLS data set used for estimation. The empirical results are reported in Section 5. Section 6 draws the conclusion.

2 Bayesian Model

In medical science, hypertension is a long-term medical condition in which the blood pressure in the arteries is persistently elevated. Consider the case when there are two states of nature, $\theta \in \Theta = \{0, 1\}$, indicating whether an individual has hypertension ($\theta = 1$) or not ($\theta = 0$). An individual's prior belief is $P(\theta = 1) = \lambda$, where we leave out the individual-specific subscript i to economize on notation.

Each individual receives a binary signal $s \in \{0, 1\}$, a one-time blood pressure measurement, with the signal precision $P(s = \theta|\theta) = q_\theta$.[2] It is possible for individuals without hypertension to have blood pressure that is occasionally above the normal range, for example, when they feel stressed. It is also possible for individuals with hypertension to have blood pressure that occasionally falls within the normal range, for example, after fluid loss from sweating. We assume that the signal is informative of the true state, namely individuals with hypertension are more likely to have high blood pressure measurements, and those without hypertension are more likely to have normal blood pressure measurements.

Assumption 1. Let $q_0 \in (1/2, 1)$ and $q_1 \in (1/2, 1)$.

An immediate implication of this assumption is that $q_0 + q_1 > 1$, as commonly seen in the literature.

Without loss of generality, consider the case when the signal is $s = 1$, that is, the blood pressure level for an individual is above the normal range. Using the Bayesian rule to for belief updating, we have $P(\theta = t|s = 1) = \frac{P(s=1|\theta=t)P(\theta=t)}{P(s=1)}$ for

[2]Although we consider a discrete signal here for tractability, similar results can be easily obtained when the signal follows a continuous distribution.

$t = 0, 1$. Taking the ratio of the two equations, the Bayesian rule can be expressed in likelihood ratios (LRs):

$$\underbrace{\frac{P(\theta=1|s=1)}{P(\theta=0|s=1)}}_{posterior LR} = \underbrace{\frac{P(s=1|\theta=1)}{P(s=1|\theta=0)}}_{signal factor} \times \underbrace{\frac{P(\theta=1)}{P(\theta=0)}}_{prior LR} = \frac{q_1}{1-q_0} \times \frac{\lambda}{1-\lambda} \quad (1)$$

Under Assumption 1, $\frac{q_1}{1-q_0} > 1$, so a signal $s = 1$ increases the odds that an individual has hypertension (the posterior LR is larger than the prior LR).

From (1), it is easy to see how individual heterogeneity matters in the belief updating process. First, for any given signal factor, individuals with strong prior belief that they have no hypertension (i.e., $P(\theta = 1) = \lambda$ close to 0) tend to maintain strong posterior belief (i.e., $P(\theta = 1|s = 1)$ also close to 0), despite the signal pointing otherwise ($s = 1$). Second, and more subtly, although our Bayesian rule is cast in the rational individual framework, the signal factor can nonetheless capture behavioral patterns that are typically associated with bounded rationality, such as *status quo* bias or the behavior of impressionable individuals. More specifically, in one limiting case when $q_0 = q_1 = \frac{1}{2}$, an individual would view the signal as a purely random noise and hence irrelevant, and his updated belief would remain identical to the prior belief regardless of the signal. This is an extreme example of status quo bias. In the other limiting case when $q_0 = q_1 = 1$, an individual would view the signal as purely deterministic, so his updated belief would become perfectly aligned with the signal regardless of the prior belief. This is an extreme example of an impressionable individual. In between, the larger an individual perceives the signal factor to be, the more relevant he regards the signal, and the larger is the signal's impact on the updated belief. Overall, individual heterogeneity in both the prior belief and the perceived signal factor will influence the belief updating process.

With the updated belief, an individual makes a binary choice $x \in \{0, 1\}$ on a health-related problem. On the extensive margin, the binary choice captures the individual's decision on whether to quit smoking, to quit drinking, to take medication, and so forth.[3] Let $NB(x, \theta)$ denote the net benefit of x when the state of nature is θ. When receiving a signal $s \in \{0, 1\}$, an individual chooses x to maximize the expected net benefit:

$$\max_x ENB(x) = P(\theta = 0|s)NB(x, 0) + P(\theta = 1|s)NB(x, 1).$$

[3]Again, although we consider a binary choice here for tractability, similar results can be easily obtained when the choice is continuous and hence on the intensive margin.

This optimization problem would be trivial if $NB(x, \theta)$ could be ordered independently of θ. More specifically, if $NB(1,1) \geq NB(0,1)$ and $NB(1,0) \geq NB(0,0)$, the solution is $x^* = 1$; similarly, if $NB(1,1) \leq NB(0,1)$ and $NB(1,0) \leq NB(0,0)$, the solution is $x^* = 0$. Individuals with such preferences do not contribute to identification because their optimal choices are invariant to their beliefs. The more interesting case is when the ordering of $NB(x, \theta)$ depends on θ.

Assumption 2. Suppose $NB(1,1) > NB(0,1)$ and $NB(1,0) < NB(0,0)$, that is, x is more valuable when it matches the state θ.

When this is the case, individuals may change their behaviors as a result of belief updating.[4]

Proposition 1. *There exists a cutoff level $\hat{P}$ such that if $P(\theta = 1|s) > \hat{P}$, $x^* = 1$; if $P(\theta = 1|s) < \hat{P}$, $x^* = 0$; and if $P(\theta = 1|s) = \hat{P}$, the individual is indifferent, so $x^* \in [0,1]$.*

Proof. Let $k \equiv \frac{NB(1,1)-NB(0,1)}{NB(0,0)-NB(1,0)} > 0$, and $\hat{P} = \frac{1}{1+k} \in (0,1)$. It is straightforward to verify that when $P(\theta = 1|s) > \hat{P}$, $ENB(1) = (1 - P(\theta = 1|s))NB(1,0) + P(\theta = 1|s)NB(1,1) > (1 - P(\theta = 1|s))NB(0,0) + P(\theta = 1|s)NB(0,1) = ENB(0)$, $x^* = 1$; when $P(\theta = 1|s) < \hat{P}$, $ENB(1) < ENB(0)$, $x^* = 0$; and when $P(\theta = 1|s) = \hat{P}$, $ENB(1) = ENB(0)$, $x^* \in [0,1]$. $\square$

Proposition 1 establishes the comparative static result linking behaviors to beliefs. Together with equation (1), it highlights belief updating as the channel through which information shock engenders behavioral changes. In particular, whether the posterior belief exceeds the cutoff level or not depends on not only the signal, but also individual heterogeneity. Even with the same signal $s = 1$, two individuals can maintain different posterior beliefs and hence exhibit different behaviors, if they hold different prior beliefs and/or different perceptions of the signal factor.

3 Regression Model

Given our focus on belief updating as the mechanism to link information to behaviors, we first consider a two-stage regression model with individual fixed effects that can be directly tied to the theoretical model.

[4] In the other case where the two inequalities are reversed, this assumption will be satisfied when x is replaced with $1 - x$, i.e., a simple relabeling exercise.

The first-stage regression links an individual's updated belief to both the signal he has received previously and an individual-specific component meant to capture differences in prior beliefs and/or signal factor perceptions:

$$Belief_{it} = \alpha_i^1 + \beta_t^1 + \gamma^1 Signal_{i,t-1} + \epsilon_{it}^1, \tag{2}$$

where $Belief_{it}$ is the updated belief for individual i in period t, and $Signal_{i,t-1}$ is the signal individual i received in period $t-1$. The superscript 1 denotes the first-stage regression, with individual fixed effects α_i^1, time fixed effects β_t^1, and the error term ϵ_{it}^1.

The second-stage regression links an individual's behavior to his updated belief, using the predicted value from the first-stage regression on the right-hand side:

$$y_{it} = \alpha_i^2 + \beta_t^2 + \gamma^2 \widehat{Belief}_{it} + \epsilon_{it}^2, \tag{3}$$

where superscript 2 denotes the second-stage regression, with individual fixed effects α_i^2, time fixed effects β_t^2, and the error term ϵ_{it}^2. The individual fixed effects in the behavior regression need not be the same as those in the belief updating regression, as α_i^2 is meant to capture differences in $NB(x, \theta)$ across individuals, that is, their underlying preferences.

In the two-stage regression model, essentially $Signal_{i,t-1}$ is used as an instrument for $Belief_{it}$ to estimate belief updating as the channel through which information affects behaviors. However, we could also pursue the more straightforward approach and estimate a reduced-form regression by regressing Y_{it} on $Signal_{i,t-1}$ directly, as is commonly done in the RCT literature. But this approach remains silent on the mechanism behind such an effect; thus, we need the above two-stage least squares (2SLS) estimations.

The use of the instrumental variable method here implies that we hope to estimate the local rather than global effects of the provided information. In other words, our 2SLS estimator consistently estimates the average impact of the information on the behaviors of individuals who are affected in their behavioral choices by the updated beliefs.

In the two-stage regression model, although the key variable of interest, $Belief_{it}$, is a dummy variable, we use the linear probability model (LPM) for estimation instead of the logit or probit model. Despite the obvious caveat that the predicted probability $\widehat{Belief}_{it}$ may fall outside the interval $[0, 1]$, the LPM offers a notable advantage over the nonlinear models. More specifically, individual fixed effects can be easily handled in the LPM but would pose a significant estimation challenge in the nonlinear models. This is critical to control for unobserved individual heterogeneity in the belief updating process, as highlighted in the theoretical model.

4 Data and Variables

CHARLS is a nationally representative longitudinal survey of people over age 45 along with their spouses, and collects comprehensive information including demographics, SES, health status, health behaviors, and so forth. We are interested in hypertension, which is the most prevalent chronic disease among middle-aged and elderly people in China. CHARLS not only records respondents' beliefs about their hypertension status (self-reported), but also gives all respondents a free physical examination and informs them of their blood pressure results and hypertension implications. The panel structure of CHARLS allows us to link previous signals to current beliefs and behaviors, thus identifying the causal effect of exogenously given signals on behavioral changes via belief updating. For example, the respondents who were hypertensive but did not realize the fact before the physical examination would be diagnosed and informed of their status. In the follow-up survey we can trace whether the respondents updated their belief or, in other words, became aware of their hypertension status and changed their behaviors correspondingly.

The baseline survey was conducted by face-to-face, computer-aided personal interviews in 2011 and followed up in 2013 and 2015. To construct the panel data, we first restricted the sample to respondents ages 45 or older with valid information on their beliefs about their hypertension status and their behaviors. Second, we kept respondents who participated in all three waves over 2011-2015 and physical examinations in 2011 and 2013, to construct the information shock. Finally, we dropped the respondents who were aware that they were hypertensive throughout the three surveys. And we dropped the limited number of respondents who were unreasonable defiers, that is, those who updated their beliefs if they were informed of a negative signal. With these restrictions, there are 5,926 respondents in our sample.

4.1 Belief and Signal

An individual's belief is given by their answers to two questions: "Have you been diagnosed with hypertension by a doctor?" and "Do you know if you have hypertension?" The respondent's beliefs about their hypertension status, denoted $Belief_{it}$, equals 1 if the respondent answered yes to either of the above two questions. This awareness of hypertension status forms the respondent's belief, which is a relatively longer and persistent understanding of their health status. The CHARLS follow-up questionnaire asked the respondents again the same two questions. These follow-up records help verify whether the respondents updated their beliefs, that is, whether they became aware of their hypertension status after receiving the information shock provided by the CHARLS physical examination in the previous wave.

The CHARLS physical examination was conducted by a professional nurse and measured the respondents' systolic and diastolic blood pressures three times, with a time span between each measurement being at least 1 minute. We use the average of the second and third blood pressure readings to avoid using the first reading, which may be high due to anxiety or the "white coat" effect. Then the signal received by the respondent, denoted $Signal_{i,t-1}$, equals 1 if the average systolic pressure of the last two measurements is 140 mmHg or greater, or the average diastolic pressure is 90 mmHg or greater. This definition is consistent with that of Lei et al. (2012).

The CHARLS physical examination is conducted after asking the respondents for their self-reported health status and related behaviors, so the information shock is exogenous and enables us to identify the causal relationship between belief updating and behavioral changes by an instrumental variable approach. Meanwhile, there may be a concern that the respondents did not receive the health report due to some unknown delivery problems and thus they did not receive the information shock. We argue that the respondents received the signal not only by the mailed health report, but also the sphygmomanometer, which automatically reports whether the respondents were hypertensive during the physical examination.

Panel A in Table 1 shows that the proportion of respondents who received a positive signal about their hypertension was 22.7%. However, only 7.7% of the respondents updated their belief that they were truly hypertensive. This unfolds the fact that only a small percentage of respondents who received a positive signal had updated their beliefs. As a result, if we regress behaviors on $Signal_{i,t-1}$, the estimate is the impact of the "intention to update" rather than the impact of those who updated their beliefs. Thus, the true impact of the provided information in the CHARLS physical examination may be biased toward zero. To identify the local average treatment effect on those who truly received and valued the signal, we can use $Signal_{i,t-1}$ as the instrument for $Belief_{it}$.

4.2 Behaviors

Supposing that the exogenous health information is valuable for the respondent, then they would be more likely to update their beliefs and change their behaviors accordingly. In this paper, the principal outcome variables include smoking, drinking, and taking anti-hypertension medication. The variable for smoking equals 1 if the respondent reported to be smoking.[5] The variable for drinking equals 1 if the respondent had any alcohol more than once a month. The variable for medication equals 1 if the respondent was taking anti-hypertension medication. Panel B in Table 1 shows that 5.1% of the respondents were taking medication, 29.9% were smoking, and 26.1% were drinking.

Table 1: Summary Statistics

VARIABLES	**Mean**	**SD**	**Min**	**Max**
Panel A: Key Variables				
Signal_{t-1}	0.227	0.419	0	1
Belief	0.077	0.266	0	1
Panel B: Health Behaviors				
Medication	0.051	0.221	0	1
Smoking	0.299	0.458	0	1
Drinking	0.261	0.439	0	1
Panel C: Demographics				
Age	61.40	9.371	45	102
Male	0.471	0.499	0	1
High School+	0.101	0.302	0	1
Rural Hukou	0.841	0.365	0	1
# of Individuals	5,926			
# of Observations	11,852			

[5] In the 2013 follow-up survey, information about smoking was missing for over 20% of the respondents, so the CHARLS recollected the information in the 2015 follow-up survey by asking the respondents about their smoking status in the previous wave. We combined information from the two waves and obtained the full information for the 2013 wave.

5 Results

5.1 Belief Updating

The Bayesian model indicates that the respondents update their beliefs after receiving the new information. Thus, we begin by examining the impact of providing information on the respondents' beliefs and estimate Equation (2). Table 2 presents the coefficient estimates of $Signal_{i,t-1}$ for the ordinary least square (OLS) model and the fixed effects model, which both control for body mass index (BMI) and year fixed effects to absorb the effects of physical health and unobserved time effects.

Column (1) reports the estimates of the OLS model, which controlled for some individual demographics including age, gender, education, and hukou type. The positive coefficient of $Signal_{i,t-1}$ is on average 28.3 percentage points and significant at the 1% level. It depicts that after controlling some individual demographics, the respondents who initially were unaware of their hypertension status are 28.3 percentage points more likely to become aware after receiving the signal, that is, the CHARLS physical examination diagnosis of hypertension.

However, as our Bayesian model shows, the time invariant individual heterogeneity plays a role in the belief updating process. Thus, we further control the individual fixed effects in our regression model and the results are shown in column (2). The coefficient of $Signal_{i,t-1}$, 9.9 percentage points, is still significant and the magnitude becomes much smaller relative to column (1). This means that although we can control for some observable demographics, there are still some unobservable heterogeneities that matter when people are updating their beliefs. In summary, the first-stage result proves that the respondents do update their beliefs according to the Bayesian rule as is shown in Section 2. But the magnitude is relatively low and indicates that only a small share of the individuals updated their beliefs after receiving the information.

Table 2: Belief Updating: First Stage

D.V. : Belief	(1) OLS	(2) FE
Signal_{t-1}	0.283***	0.099***
	(0.010)	(0.009)
Age	0.000	
	(0.000)	
Male	-0.005	
	(0.006)	
High School+	0.000	
	(0.008)	
Rural Hukou	0.015**	
	(0.007)	
Individual FE	N	Y
Year FE	Y	Y
# of Individuals	5,926	5,926
# of Observations	11,852	11,852

All regressions include BMI.
Standard errors in parentheses are clustered at the community level.
* p<0.1, ** p<0.05, *** p<0.01

5.2 Behavioral Changes

Based on the belief updating process, we further investigate whether behaviors respond to the signal and Table 3 presents the 2SLS estimates. Bear in mind that the first-stage regression results shown in Table 2 suggest that $Signal_{i,t-1}$ and $Belief_{it}$ are positively highly correlated and we do not need to worry about the weak instrument problem. In Table 3, we find that the respondents who became aware that they were hypertensive were 51.8 percentage points more likely to take medication and 13.1 percentage points more likely to quit smoking. We find a consistently negative impact on drinking, although the coefficient is not statistically significant. Table 3 shows that after receiving the signal and updating their belief, the respondents are more likely to adopt a healthier lifestyle: taking medication and quitting smoking.

Table 3: Beliefs and Behaviors : Second Stage

D.V.	(1) Medication	(2) Smoking	(3) Drinking
FE:			
Belief	0.518***	-0.131**	-0.085
	(0.069)	(0.063)	(0.108)
OLS:			
Belief	0.658***	0.014	0.025
	(0.018)	(0.022)	(0.018)
# of Individuals	5926	5926	5926
# of Observations	11852	11852	11852

All regressions include BMI and year fixed effects.
The FE model includes individual fixed effect additionally.
Standard errors in parentheses are clustered at community level.
* p<0.1, ** p<0.05, *** p<0.01

5.3 Robustness Check

5.3.1 Hypertension Rank

The above analyses all use the signal, a dummy variable to indicate whether the individual is hypertensive, as the instrument. Actually we know the exact blood pressure measures of each respondent and can specify the severeness of their hypertension. According to *The Guidelines for the Treatment of Hypertension in China*, we divide hypertension severeness into four ranks: 0-3, which correspond to no hypertension, minor hypertension, medium hypertension, and severe hypertension. The exact definitions are presented in Table 4.

Table 4: Hypertension Ranks

Hypertension Rank	Definition (mmHg)		
0	SBP<140	and	DBP<90
1	140≤SBP<160	or	90≤DBP<100
2	160≤SBP<180	or	100≤DBP<110
3	SBP≥180	or	DBP≥110

The basic idea is that severer hypertension may imply stronger signals. Individuals who are informed that they have severer hypertension may be more likely to update their beliefs and become aware of their hypertension status. In a new first-stage regression, we test this hypothesis with a similar specification to that in Table 3 and use three dummy variables that indicate whether the respondent has minor, medium, or severe hypertension. The results are presented in Table 5. For the first-stage regression, all the coefficients of the hypertension ranks are significantly positive and the magnitudes increase with hypertension rank. This indicates that individuals who are informed about their severer hypertension status are more likely to update their beliefs and become aware that they are hypertensive. The second-stage regression results show that those with updated beliefs are more likely to take medication and quit smoking. Although the impact on drinking is insignificant, the sign of the coefficient of $Belief_{it}$ is negative. All the results are consistent with those in Table 3. Thus, we can robustly conclude that those receiving the signal and updating their beliefs are more likely to take medication and quit smoking.

Table 5: Hypertension Rank as IV

D.V.	**(1) Medication**	**(2) Smoking**	**(3) Drinking**
Belief	0.525***	-0.124**	-0.085
	(0.072)	(0.060)	(0.103)
First Stage D.V.: Belief			
Hypertension Rank 1	0.094***	0.094***	0.094***
	(0.009)	(0.009)	(0.009)
Hypertension Rank 2	0.116***	0.116***	0.116***
	(0.021)	(0.021)	(0.021)
Hypertension Rank 3	0.149***	0.149***	0.149***
	(0.041)	(0.041)	(0.041)
# of Individuals	5,926	5,926	5,926
# of Observations	11,852	11,852	11,852

All regressions include BMI, individual fixed effects, and year fixed effects.
Standard errors in parentheses are clustered at the community level.
* p<0.1, ** p<0.05, *** p<0.01

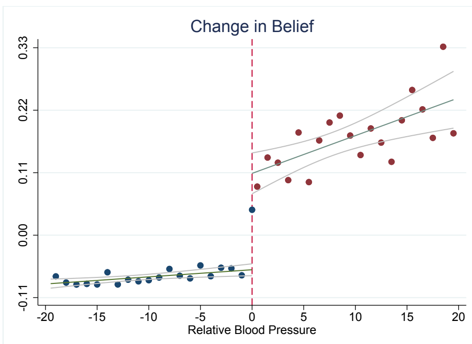
5.3.2 Regression Discontinuity Design

A major concern is that those who receive a positive hypertension diagnosis, that is, actual hypertension equals 1, are incomparable with those who have normal blood pressure. In our definition of hypertension in Table 4, we can naturally exploit a regression discontinuity design (RDD) and compare the outcomes of people with blood pressure just above and below the critical value to investigate the possible causality. However, unlike the ordinary RDD, there are two forcing variables here, systolic and diastolic blood pressures, to define whether the respondent is hypertensive, and their critical values are 140 mmHg and 90 mmHg, respectively. For the study sample, only 1.5% of individuals are diagnosed as hypertensive only by diastolic blood pressure. This means that the majority of the hypertensive individuals are diagnosed just because their systolic blood pressures is above the threshold of 140 mmHg. Thus, for simplicity, we exclude the hypertensive patients who are diagnosed only by diastolic blood pressure and the the only threshold of 140 mmHg can be used as the cutoff point for the RDD design.

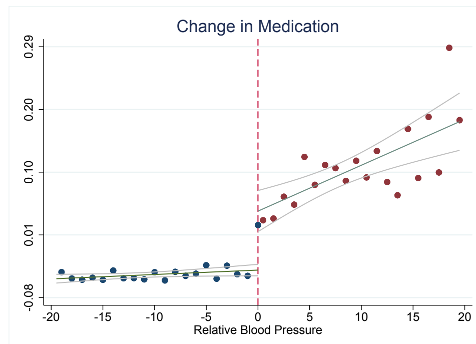
Furthermore, we construct a measure of relative blood pressure (RBP) by centering the systolic blood pressure relative to the critical values. With this construction, the respondent is actually hypertensive if RBP ≥ 0; otherwise, the respondent is normal. As stated in Sections 2 and 4, there are some respondents who ignore the information and do not update their beliefs, so here we use fuzzy RDD to investigate the causality, which is similar to the instrumental variable approach by using the sample around the threshold from an econometric perspective. Figure 1(a) shows the first-stage result with RBP in $[-20, 20]$. It shows a positive upward jump for the change of belief around the threshold RBP=0. This means that for individuals whose RBP is close to the threshold, those who receive a positive signal are more likely to update their beliefs and become aware that they are actually hypertensive.

We further draw the second-stage results with RBP in $[-20, 20]$ and Figure 1(b) through Figure 1(d) show the impacts on medication, smoking, and drinking, respectively. Figure 1(b) shows a significant positive impact of belief updating on taking medication and Figures 1(c) and 1(d) present a downward jump for smoking and drinking, which means that individuals with updated beliefs are more likely to quit smoking and drinking, although here the impacts are not significant.

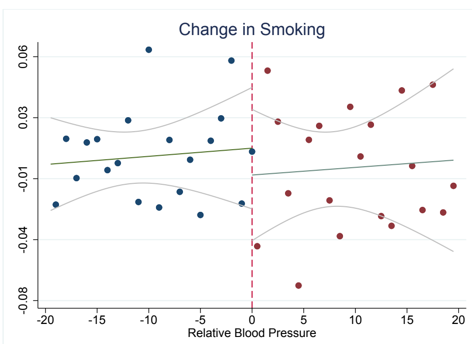
We can similarly run the 2SLS regressions within different bandwidths and the results are presented in Table 6. For taking medication, the impacts are significantly positive across different bandwidths, $[-10, 10]$, $[-20, 20]$, and $[-40, 40]$. For smoking, the impact is negative and significant across bandwidth $[-10, 10]$, which means that respondents who received positive signals are 30.5 percentage points less likely to smoke compared with respondents who did not receive signals when their reported SBP was in $[130, 150]$. As the bandwidth becomes larger, the coef-



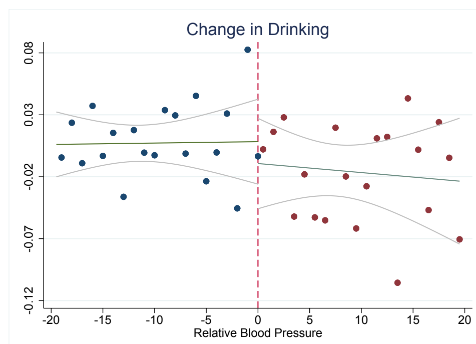
(a) Change in Belief



(b) Change in Medication



(c) Change in Smoking



(d) Change in Drinking

Figure 1: RDD Figures

ficient of $Belief_{it}$ is still negative but no longer significant, and we do not find any significant impact on drinking. In summary, the RDD results imply that people tend to take medication and quit smoking after they receive the signal and update their beliefs.

Table 6: RDD Results

	(1) [-10,10]	(2) [-20,20]	(3) [-40,40]
D.V. : Medication			
Belief	0.481***	0.599***	0.473***
	(0.185)	(0.146)	(0.118)
D.V. : Smoking			
Belief	-0.305**	-0.226	-0.099
	(0.149)	(0.149)	(0.135)
D.V. : Drinking			
Belief	0.245	-0.006	-0.286
	(0.261)	(0.233)	(0.213)
First Stage D.V.: Belief			
RBP	0.008***	0.003***	0.001***
	(0.002)	(0.001)	(0.000)
# of Individuals	2,090	3,706	5,549
# of Observations	2,591	5,516	10,498

All regressions include BMI, individual fixed effects, and year fixed effects.
Standard errors in parentheses are clustered at the community level.
* p<0.1, ** p<0.05, *** p<0.01

5.3.3 Spousal Effect?

There may be a worry that the respondents' beliefs may be affected not only by their own signals but also by their spouses'. We investigate this possibility in this subsection. We first keep respondents who have a spouse living with them. Then we run the respondents' beliefs on their spouses' signals, with and without own signal included. The results are presented in Table 7. Column 1 shows that respondents' spouses' signals have no significant impact on their own belief updating. By adding their own signal, column 2 shows that the coefficient of the spouses' signals remains insignificant and the number slumps to near zero, but the coefficient of the respondents' own signals is economically and statistically significant. Therefore, we can conclude that it is the respondents' own signals, not their spouses', that play a significant role in their belief updating.

Table 7: Spousal Effect

D.V. : Belief	**(1)** **FE**	**(2)** **FE**
Signal_{t-1}		0.112***
		(0.015)
Spouse's Signal_{t-1}	0.015	0.001
	(0.011)	(0.010)
Individual FE	Y	Y
Year FE	Y	Y
# of Individuals	2,754	2,754
# of Observations	5,508	5,508

All regressions include BMI.
Standard errors in parentheses are clustered at the community level.
* p<0.1, ** p<0.05, *** p<0.01

5.4 Heterogeneous Effect

We notice the facts that males account for a majority of smokers and drinkers, and that people in rural China have fewer economic resources and less access to health-related infrastructure compared with people in urban China. These differences may lead to different types of behavioral responses across different groups. To identify the source of the behavioral changes, we employ the same 2SLS method and carry out heterogeneity analysis by gender and residence type. The estimates are shown in Table 8, where columns (1) and (2) are divided by gender, columns (3) and (4) are by residence type. For gender, both males and females are significantly more likely to take medication and the difference between them is slight. The main impact on quitting smoking comes solely from the males, probably because smokers are mainly males (89.9%). In addition, rural people are more likely to quit smoking but less likely to take medication compared with urban people. This is probably due to gaps in health care accessibility and economic resources between rural and urban areas. In rural areas, public health amenities are less accessible than those in urban areas, and people living in rural areas are on average poorer than those in urban areas. Thus, after receiving a positive signal and updating their beliefs about their hypertension status, rural people have greater difficulties buying anti-hypertension medicine compared with urban people, so rural people tend to turn to the more economical response of smoking less. For drinking, again, we do not see any significant difference in the effect across different groups.

Table 8: Heterogenous Effects

	(1) Male	(2) Female	(3) Rural	(4) Urban
D.V. : Medication				
Belief	0.531***	0.521***	0.502***	0.543***
	(0.088)	(0.104)	(0.088)	(0.112)
D.V. : Smoking				
Belief	-0.203*	-0.000	-0.132*	-0.125
	(0.115)	(0.037)	(0.080)	(0.102)
D.V. : Drinking				
Belief	-0.116	-0.044	-0.009	-0.218
	(0.183)	(0.119)	(0.138)	(0.173)
First Stage D.V.: Belief				
Signal_{t-1}	0.102***	0.096***	0.094***	0.110***
	(0.012)	(0.013)	(0.011)	(0.016)
# of Individuals	2,802	3,149	4,055	1,871
# of Observations	5,579	6,273	8,110	3,742

All regressions include BMI, individual fixed effects, and year fixed effects.
Standard errors in parentheses are clustered at the community level.
* p<0.1, ** p<0.05, *** p<0.01

6 Conclusion

There is growing concern about the effects of information on health behaviors in the developing world, where the increasing proportion of people with chronic diseases and less access to public health facilities is colliding with high levels of harmful behaviors and lifestyles. However, the effectiveness of information on behaviors not only depends on provision of information to the individuals, but also whether the information can be successfully turned into their updated beliefs. This article sheds light on the importance of health information in the efforts to curtail risky behaviors, highlighting the importance of belief updating in the process.

We built a Bayesian updating model to illustrate how people update their beliefs based on a Bayesian rule and accordingly change their behaviors. Then we used a nationally representative longitudinal survey in China to investigate empirically the predictions from the model. Consistent with the model predictions, we found that only a part of the respondents updated their beliefs after receiving a signal. Statistically significant effects of information on quitting smoking and taking medication were observed for people who actually updated their beliefs, that is, become aware of their hypertension status. Moreover, heterogeneity analysis showed that the impact on quitting smoking came from males and rural people, while the impact on taking medication was larger for males and urban people. Nevertheless, we did not find any significant evidence on drinking. Our findings illustrate that eliminating information asymmetry through a prior physical examination greatly helps people to reduce risky behaviors and live a healthier lifestyle. Policy makers should focus not only on health information provision, but also respondents' belief updating. Heterogeneity across regions should also be carefully considered.

References

[1] Christopher Auld, M., & Sidhu, N. (2005). "Schooling, cognitive ability and health." *Health Economics*, 14(10), 1019–1034.

[2] Bennear, L., Tarozzi, A., Pfaff, A., Balasubramanya, S., Ahmed, K. M., & Van Geen, A. (2013). "Impact of a randomized controlled trial in arsenic risk communication on household water-source choices in Bangladesh." *Journal of Environmental Economics and Management*, 65(2), 225–240.

[3] Bhargava, S., & Manoli, D. (2015). "Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment." *American Economic Review*, 105(11), 3489–3529.

[4] Bloom, D. E., Chen, S., Kuhn, M., McGovern, M. E., Oxley, L., & Prettner, K. (2018). 11The economic burden of chronic diseases: estimates and projections for China, Japan, and South Korea." *Journal of the Economics of Ageing*, 100163.

[5] Bollinger, B., Leslie, P., & Sorensen, A. (2011). "Calorie posting in chain restaurants." *American Economic Journal: Economic Policy*, 3(1), 91–128.

[6] Brown, J., Hamoudi, A., Jeuland, M., & Turrini, G. (2017). "Seeing, believing, and behaving: Heterogeneous effects of an information intervention on household water treatment." *Journal of Environmental Economics and Management*, 86, 141–159.

[7] Byrne, D. P., Nauze, A. L., & Martin, L. A. (2018). "Tell me something I don't already know: Informedness and the impact of information programs." *Review of Economics and Statistics*, 100(3), 510–527.

[8] Duflo, E., & Saez, E. (2003). "The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment." *Quarterly Journal of Economics*, 118(3), 815–842.

[9] Dupas, P. (2011). "Do teenagers respond to HIV risk information? Evidence from a field experiment in Kenya." *American Economic Journal: Applied Economics*, 3(1), 1–34.

[10] Ferraro, P. J., & Price, M. K. (2013). "Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment." *Review of Economics and Statistics*, 95(1), 64–73.

[11] Fitzsimons, E., Malde, B., Mesnard, A., & Vera-Hernandez, M. (2016). "Nutrition, information and household behavior: Experimental evidence from Malawi." *Journal of Development Economics*, 122, 113–126.

[12] Galama, T. J., & Van Kippersluis, H. (2019). "A theory of socio-economic disparities in health over the life cycle." *The Economic Journal*, 129(617), 338–374.

[13] Ganguly, A., & Tasoff, J. (2017). "Fantasy and dread: The demand for information and the consumption utility of the future." *Management Science*, 63(12), 4037–4060.

[14] Jalan, J., & Somanathan, E. (2008). "The importance of being informed: Experimental evidence on demand for environmental quality." *Journal of Development Economics*, 87(1), 14–28.

[15] Jin, G. Z., & Sorensen, A. T. (2006). "Information and consumer choice: The value of publicized health plan ratings." *Journal of Health Economics*, 25(2), 248–275.

[16] Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C., & Wrobel, M. V. (2012). "Comparison friction: Experimental evidence from Medicare drug plans." *Quarterly Journal of Economics*, 127(1), 199–235.

[17] Köszegi, B. (2003). "Health anxiety and patient behavior." *Journal of Health Economics*, 22(6), 1073–1084.

[18] Lange, F. (2011). "The role of education in complex health decisions: Evidence from cancer screening." *Journal of Health Economics*, 30(1), 43–54.

[19] Lei, X., Yin, N., & Zhao, Y. (2012). "Socioeconomic status and chronic diseases: The case of hypertension in China." *China Economic Review*, 23(1), 105-121.

[20] Lu, J., Lu, Y., Wang, X., Li, X., Linderman, G. C., Wu, C., ... & Su, M. (2017). "Prevalence, awareness, treatment, and control of hypertension in China: data from 1.7 million adults in a population-based screening study (China PEACE Million Persons Project)." *The Lancet*, 390(10112), 2549–2558.

[21] Madajewicz, M., Pfaff, A., Van Geen, A., Graziano, J., Hussein, I., Momotaj, H., & Ahsan, H. (2007). "Can information alone change behavior? Response

to arsenic contamination of groundwater in Bangladesh." *Journal of development Economics*, 84(2), 731–754.

[22] Okeke, E. N., Adepiti, C. A., & Ajenifuja, K. O. (2013). "What is the price of prevention? New evidence from a field experiment." *Journal of Health Economics*, 32(1), 207–218.

[23] Oster, E., Shoulson, I., & Dorsey, E. (2013). "Optimal expectations and limited medical testing: Evidence from Huntington disease." *American Economic Review*, 103(2), 804–30.

[24] Scanlon, D. P., Chernew, M., McLaughlin, C., & Solon, G. (2002). "The impact of health plan report cards on managed care enrollment." *Journal of Health Economics*, 21(1), 19–41.

[25] Thornton, R. L. (2008). "The demand for, and impact of, learning HIV status." *American Economic Review*, 98(5), 1829–63.

[26] Iizuka, T., Nishiyama, K., Chen, B., & Eggleston, K . (2021). "False alarm? Estimating the marginal value of health signals." *Journal of Public Economics*, 195.

[27] Zhao, M., Konishi, Y., & Glewwe, P. (2013). "Does information on health status lead to a healthier lifestyle? Evidence from China on the effect of hypertension diagnosis on food consumption." *Journal of Health Economics*, 32(2), 367–85.