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**Effects of Chronic Disease Diagnoses on Alcohol Consumption among Elderly
Individuals—Longitudinal Evidence from China**

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Effects of Chronic Disease Diagnoses on Alcohol Consumption among Elderly Individuals—Longitudinal Evidence from China

Abstract

This study estimates the effect of chronic disease diagnoses on elderly Chinese individuals' alcohol consumption. A Chamberlain-Mundlak correlated random-effect Tobit model is adopted to analyze a longitudinal dataset on 5,724 individuals aged 50 or above. Our estimation suggests that, on average, an additional chronic disease diagnosed by medical doctors (among myocardial infarction, diabetes, hypertension, and stroke) reduced an individual's weekly consumption of beer, red wine, and Chinese spirits, respectively, by 1.49, 0.93, and 0.89 ounces. These effects translate into a reduction of 0.95 ounces in total weekly alcohol consumption and a reduction of 24% in the incidence of excessive drinking. While chronic disease diagnoses reduced alcohol consumption among elderly Chinese individuals, they failed to stop all heavy drinkers from excessive drinking. Relevant policies and measures are thus needed to urge heavy drinking patients to quit excessive drinking.

Keywords: Chronic conditions; Diagnosis; Alcohol consumption; Correlated random-effects Tobit; China

1. Introduction

Whereas alcohol consumption has important social and cultural functions, heavy drinking is considered one of the world's largest public health threats (WHO, 2019). Not only may heavy drinking lead to devastating incidents such as car crashes and domestic violence (Carpenter & Dobkin, 2009, 2017; Kennedy et al., 1996; Leonard, 2005; Kaysen et al., 2007), but it is also strongly associated with the incidences of many chronic diseases, including heart disease, diabetes, hypertension, and strokes, among others (Briasoulis et al., 2012; Cahill & Redmond, 2012; Holmes et al., 2014; Lee & Hashibe, 2014; Shankar et al., 2006). Globally, alcohol consumption contributes to more than three million deaths each year and accounts for over 5% of the global burden of diseases and injuries (WHO, 2019).

However, despite the increasing awareness of the adverse effects of heavy drinking and the considerable effort devoted by governments worldwide to curbing heavy drinking, alcohol consumption has been rising in many countries. China is no exception. Chinese residents' per capita alcohol consumption increased rapidly from 4.1 liters in 2005 to 7.2 liters in 2016 (WHO, 2019), leading many scholars to call for actions to control excessive drinking in China (Jiang et al., 2015). In such a context, an adequate understanding of who consumes alcohol (heavily) in China, what affects Chinese residents' alcohol consumption, and more importantly, what may reduce (excessive) drinking, will undoubtedly help inform China's public health policy.

One important factor is consumer health. Unfortunately, while there have been numerous studies on the impacts of alcohol consumption on health (Briasoulis et al., 2012; Cahill & Redmond, 2012; Carpenter & Dobkin, 2009; 2017; Holmes et al., 2014; Lee & Hashibe, 2014; Shankar et al., 2006), studies that examine the effects of health on alcohol consumption have been limited, especially in China. The present study attempts to fill this gap by examining how chronic disease diagnoses (CDD) affect elderly Chinese individuals' alcohol consumption. The role CDD plays is of particular interest, given the rapidly increasing incidences of chronic diseases in China (National Center for Cardiovascular Disease, 2018; Wang et al., 2017).¹ If CDD fails to serve as a wake-up call for drinkers to stop (heavy) drinking, effective early interventions may be carefully designed (to stop heavy drinking) before one develops chronic conditions. One might argue that early interventions should always be implemented. Yet the fact that there are still many heavy drinkers and the widespread of chronic diseases suggest that early interventions targeting the general population are either very costly or not very effective. The addictive nature of alcohol consumption adds a layer of complexity to this issue. If drinkers keep on drinking even after developing chronic diseases, then special treatments may be needed to reduce the harmful effects of alcohol consumption on the patients' health, which will certainly increase the costs of healthcare.

Our analysis draws on data from the China Health and Nutrition Survey (CHNS), a longitudinal household survey covering more than ten provinces in China. To account for the fact that many respondents do not consume alcohol, which may lead to a “zero-inflation” issue, and to allow for the correlation between unobserved individual fixed factors (e.g., genetic traits) and observed explanatory variables, we adopt a Chamberlain-Mundlak correlated random-effect (CRE) Tobit model in the analysis.² The longitudinal structure of the CHNS data also helped address identification issues such as reverse causality and omitted variables to a large extent.

Our estimation, focusing on 5,724 respondents aged 50 and above, suggests that CDD reduces elderly individuals' alcohol consumption in a statistically significant manner. Specifically, an additional chronic disease (among myocardial infarction, diabetes, hypertension, and stroke) diagnosed by medical professionals reduces one's weekly consumption of beer, red wine, and Chinese spirits (“*baijiu*”) by 1.49, 0.93, and 0.89 ounces. These effects translate into a reduction of 0.95 ounces in total weekly alcohol consumption and a reduction in the likelihood of excessive drinking—defined as consuming more than 25g/15g of pure alcohol daily for an adult male/female—by 24%. These results are robust to a series of checks. Further analysis reveals that diabetes

¹ From 2015 to 2020, the prevalence of hypertension among Chinese people aged 18 and above increased from 25.2 % to 28 %, and that of diabetes from 9.75% to 12.2% (National Health Commission of the People's Republic of China, 2020).

² As pointed out by Greene (2018), “there are no firm theoretical results on the behavior of the MLE of” the fixed-effects Tobit model. As such, the Chamberlain-Mundlak CRE Tobit remains the state-of-the-art model in Tobit settings.

diagnosis has the largest impact on elderly Chinese individuals' beer and red wine consumption, while stroke diagnosis has the largest impact on their spirits consumption.

Our study contributes to the literature in two ways. First, to the best of our knowledge, this study is among the few that attempt to estimate the effect of chronic disease diagnoses on elderly individuals' alcohol consumption in developing countries. Second, it complements previous studies of the impact of CDD on Chinese individuals' food intake behavior (e.g., Hu et al., 2021; Zhao et al., 2013), helping to depict a fuller picture of CDD's behavioral impacts.

2. Data

2.1. Survey

Our analysis draws on data from the China Health and Nutrition Survey (CHNS: <https://www.cpc.unc.edu/projects/china>), a longitudinal survey project jointly designed, implemented, and managed by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Health at the Chinese Center for Disease Control and Prevention. Based on a stratified random sampling framework, the first wave of the CHNS, conducted in 1989, selected a sample of over 16,000 individuals from approximately 3,800 households in nine provinces that vary substantially in geographical features, economic conditions, public resources, and health indicators.³ Follow-up waves were conducted in 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. Three municipal cities (Beijing, Shanghai, and Chongqing) joined the project in 2011.

The CHNS collected rich information on sample individuals' sociodemographic characteristics, food consumption, nutrition intakes, health status, and livelihoods, as well as infrastructure and healthcare conditions of their residing communities (i.e., rural villages and urban districts).⁴ Most important for our study, the CHNS started to collect information on respondents' alcohol consumption in 1993 and that on CDD in 1997.⁵

2.2. Sample

Given the purpose of our study, we applied several restrictions to form the analytical sample. First, we excluded data collected before 2000 to ensure that all observations have information on alcohol consumption and CDD lagged for one time period (—lagged values are used for robustness checks). Second, to exploit as much longitudinal information as possible, we kept only observations from the nine original

³ These nine provinces are Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou.

⁴ Since the present study was conducted based on a de-identified, publicly available dataset (CHNS: <https://www.cpc.unc.edu/projects/china>), it does not constitute human-subject research. Since there was no interaction with any individual, and no identifiable private information was used, its institutional review board review was waived.

⁵ The CHNS started to collect information on alcohol consumption in 1991, but only on individuals' drinking frequency. Information on the amounts of beer, red wine, and spirits consumption was not collected until 1993. The CHNS started to collect information on hypertension diagnosis in 1993 and that on diabetes, stroke, and myocardial infarction in 1997.

project provinces. Finally, we excluded respondents under the age of 50 in 2000 because the incidences of chronic diseases are very low for individuals under 50 in the data. The above procedures yielded an unbalanced panel of 21,013 individual-year observations for 5,724 individuals residing in 228 communities, appearing at least in one wave (out of six in total) between 2000 and 2015.

2.3. Variables

Outcome variables. The outcome variables of primary interest are measures of elderly individuals' weekly consumption of alcoholic beverages in the previous year: beer, red wine, Chinese spirits ("baijiu"), and total alcohol intake. The first three, reported directly by the respondents, are readily available in the CHNS data. However, beer and red wine intakes were measured in bottles and Chinese spirits in *liang* (one *liang*=1/20 kg). For ease of comparison, we converted all three alcohol-intake variables into multiples of (international standard) ounces (one international ounce=30 ml). The last variable, total weekly alcohol consumption, is constructed based on the first three: beer and red wine consumption were first converted into their spirits equivalents; then, all three sum to yield total alcohol intake.

Key explanatory variables. The explanatory variable of primary interest is the number of chronic diseases diagnosed. Given data availability, we focus on four chronic diseases: hypertension, diabetes, stroke, and myocardial infarction. It would be desirable to include other chronic conditions, such as gastritis and hepatitis, in the analysis. Unfortunately, information on other chronic diseases is not available in the CHNS data (except that on cancer, which became available in 2011). In some analyses, separate indicators of the diagnoses of specific chronic conditions are used to gain more insights into the CDD-alcohol consumption relationship.

Other covariates. Other covariates in our empirical models developed below were chosen based on standard theory and previous empirical findings. The first set of covariates concerns sample individuals' demographic characteristics. A male dummy is included to capture potential gender differences in alcohol consumption behavior. Also included are age and age-squared to capture life-cycle patterns. Since marital status is found to affect alcohol consumption (Falba & Sindelar, 2008; Fletcher & Marksteiner, 2017; Meyler et al., 2007), we also include a dummy for having a spouse in the model. The second set concerns sample individuals' socioeconomic status. Since both standard economic theory and previous empirical studies (Arcidiacono et al., 2007; Kim & Sambou, 2019; Yen & Jensen, 1996) suggest that income is an essential determinant of alcohol consumption, we include individuals' annual household income per capita in the analysis. Also included are years of education (Cutler et al., 2010; Yen, 2005), work status (Kim & Sambou, 2019; Ren et al., 2020), and a dummy for rural residents (Yen & Lin, 2008), to capture potential differences in lifestyles associated with these factors. The final set of covariates is health-related. Height is included since individuals with larger

body sizes naturally consume more food and beverages. We also include sample individuals' self-reported health status, a dummy for feeling “good” or “very good”,⁶ to measure their subjective health (Kim & Baik, 2004; Gronbak et al., 1999). Since health insurance coverage has been found to affect health behavior (Cheng et al., 2015), we also include a dummy for health insurance coverage in the analysis. Moreover, many studies have found that drinking and smoking are closely related (Arcidiacono et al., 2007; Feng et al., 2020; Yen & Lin, 2008); we follow this strand of literature and include a dummy for smokers in the analysis. Finally, we include a dummy for whether other household members drink to capture within-household peer pressure and family culture.

2.4. Descriptive statistics

Table 1 presents the profile of the individuals in the analytical sample by their drinking status at the time of the survey—a survey wave-individual observation is defined as a “drinker” if non-zero alcohol consumption is reported for this observation. Consistent with the spatial distribution of survey sites, about two-thirds of the observations came from rural areas. Despite the average age of 68, nearly one-third of the observations reported “working” during the survey period. Presumably because of their relatively old age, only 75% of the observations reported “having a spouse.” The average respondent has about five years of education, living in a household with an annual income of slightly less than 27,000 yuan (\approx 3,913 U.S. Dollars in the 2000 price). As a result of the rapid expansion of China’s health insurance sector since the early 2000s (Cheng et al., 2015; Yip & Hsiao, 2009), 71% of the observations had health insurance coverage at the time of the survey.

Regarding alcohol consumption, 28% of the wave-individual observations reported drinking. The average respondent consumed 5 ounces of beer, 0.8 ounces of red wine, and 4.7 ounces of Chinese spirits per week, which amounted to a liquor content equivalent to 5.5 international unit ounces. Nearly 44% of the drinkers were heavy drinkers—heavy drinking is defined as consuming more than 25g of pure alcohol per day for adult males and 15g for adult females (Chinese Nutrition Association, 2016). The average number of chronic diseases diagnosed (hypertension, diabetes, myocardial infarction, and stroke combined) is 0.44 among sample individuals. Hypertension has the highest prevalence (34%), followed by diabetes (8%), stroke (6%), and myocardial infarction (4%).

A quick comparison between drinkers and non-drinkers suggests that the incidences of chronic diseases are in general higher among non-drinkers, which seems counterintuitive at first glance. However, this observation may suggest that CDD causes the patients to reduce alcohol consumption. To sort out the direction of causality, one needs to control for potential confounding factors in the analysis. The next section develops a method for this purpose.

⁶ Other values of self-reported health status include “very poor”, “poor”, and “fair”.

[Table 1 about here]

3. Method

To guide empirical modeling, consider first a standard statistical model that links one's alcohol consumption and its determinants:

$$A_{it} = \beta_0 + \beta_1 D_{it} + \mathbf{z}_{it} \boldsymbol{\beta}_2 + u_{it}, \quad (1)$$

where the outcome variable, A_{it} (“alcohol”), is the amount of alcoholic content individual i consumes per week in year t (—in some analyses below, A_{it} is replaced with weekly intakes of specific alcoholic beverages). The explanatory variable of primary interest, D_{it} (“diagnosis”), is the total number of chronic conditions (diabetes, hypertension, myocardial infarction, and stroke combined) that individual i had ever been diagnosed with by medical professionals by time t , i.e., $D_{it} = \sum_{j=1}^4 d_{jit}$, where d_{jit} is a dummy for the diagnosis of the j th chronic disease mentioned above (—in some analyses, D_{it} is replaced with d_{jit}).⁷ The vector \mathbf{z}_{it} represents a set of other observed determinants of one's drinking behavior (discussed in section 2.3). The error term u_{it} captures the influence of unobserved factors.

If equation (1) is correctly specified, the effect of CDD, captured by β_1 , can be consistently estimated by least-squares techniques. However, several potential estimation issues may lead to misleading estimates of β_1 . First, many sample individuals do not consume alcoholic beverages, which applies to 68% of all individual-wave cases in the analytical sample. Failing to account for the clustering of “zeros” in the outcome variable may bias the estimates of the β 's. A natural approach to handling this issue is to recast the above model into a Type-I Tobit (corner-solution) framework (Wooldridge, 2010):

$$A_{it} = \max(0, \mathbf{x}_{it} \boldsymbol{\beta} + \varepsilon_{it}), t = 1, 2, \dots, T, \quad (2)$$

where $\mathbf{x}_{it} = (1, D_{it}, \mathbf{z}_{it})$ denotes the set of observed variables in equation (1), $\boldsymbol{\beta}$ is the corresponding coefficient vector, and $\varepsilon_{it} | \mathbf{x}_{it} \sim \text{Normal}(0, \sigma_\varepsilon^2)$. The parameters in equation (2), $\boldsymbol{\beta}$ and σ_ε , can be estimated by maximum likelihood estimation (MLE). Given our main aim to test whether CDD urges elderly individuals to reduce alcohol intake, our interest centers on estimating the marginal effect for the *uncensored* population:

$$\partial E(A_{it} | A_{it} > 0, \mathbf{x}_{it}) / \partial D_{it} = \beta_1 [1 + \frac{d\lambda}{dc} (\frac{\mathbf{x}_{it} \boldsymbol{\beta}}{\sigma_\varepsilon^2})], \quad (3)$$

⁷ As noted in section 2.3, the choice of chronic diseases to study is constrained by data availability.

where $\lambda = \frac{\phi(c)}{\Phi(c)}$, $c = \frac{\mathbf{x}_{it}\boldsymbol{\beta}}{\sigma_\varepsilon^2}$, and ϕ and Φ are the probability density function and cumulative distribution of the standard normal distribution. Since the marginal effect of interest (3) is a function of $\boldsymbol{\beta}$ and σ_ε , consistent estimates of these parameters are needed to recover this effect.

The second issue is the potential existence of unobserved individual-specific fixed factors (e.g., genetic fitness) that simultaneously affect one's alcohol consumption and health status, causing a spurious correlation between A_{it} and D_{it} . With the presence of such fixed factors (denoted f_i), equation (2) becomes:

$$A_{it} = \max(0, \mathbf{x}_{it}\boldsymbol{\beta} + f_i + \varepsilon_{it}), t = 1, 2, \dots, T, \quad (4)$$

where $\varepsilon_{it}|\mathbf{x}_i, f_i \sim \text{Normal}(0, \sigma_\varepsilon^2)$, with \mathbf{x}_i containing \mathbf{x}_{it} for all t . The possible correlation between f_i and D_{it} (part of \mathbf{x}_{it}) may generate biased estimates of $\boldsymbol{\beta}$ and (thus) the marginal effects of interest (3).

In the linear case (equation 1), the individual-specific fixed effects f_i can be easily controlled for by applying the standard fixed-effects (FE) approach. In a Tobit setup, however, the standard FE approach will yield inconsistent MLE estimates of σ_ε^2 , even if it can consistently estimate $\boldsymbol{\beta}$ (Greene, 2018).⁸ This is unfortunate because a consistent estimate of σ_ε^2 is needed to compute the marginal effects of interest (3). As an alternative, we follow Wooldridge (2010) and adopt a Chamberlain-Mundlak correlated random-effects (CRE) specification, which allows f_i and \mathbf{x}_i to be correlated and seeks to capture the former explicitly in the model. Formally, the Chamberlain-Mundlak CRE Tobit model assumes that

$$f_i|\mathbf{x}_i \sim \text{Normal}(\psi + \bar{\mathbf{x}}_i\boldsymbol{\eta}, \sigma_r^2), \quad (5)$$

where $\bar{\mathbf{x}}_i$ is the average of \mathbf{x}_{it} across all T periods, and σ_r^2 is the variance of r_i in the equation $f_i = \psi + \bar{\mathbf{x}}_i\boldsymbol{\eta} + r_i$.⁹

Given the Chamberlain-Mundlak formulation (5), equation (4) becomes

$$A_{it} = \max(0, \psi + \mathbf{x}_{it}\boldsymbol{\beta} + \bar{\mathbf{x}}_i\boldsymbol{\eta} + r_i + \varepsilon_{it}), t = 1, 2, \dots, T, \quad (6)$$

where $\varepsilon_{it}|\mathbf{x}_i, r_i \sim \text{Normal}(0, \sigma_\varepsilon^2)$ and $r_i|\mathbf{x}_i \sim \text{Normal}(0, \sigma_r^2)$. The “trick” here is that the equation $f_i = \psi + \bar{\mathbf{x}}_i\boldsymbol{\eta} + r_i$ translates the individual-level *fixed effect* (f_i) into a *random effect* (r_i). Now, equation (6), combined with the two normality assumptions immediately

⁸ As pointed out in Greene (2018), the behavior of MLE of the FE Tobit is unclear thus far. One way to see the problem here is through the analogue with a linear FE model. The MLE of the error variance in linear FE model is $\frac{\mathbf{e}_{fe}'\mathbf{e}_{fe}}{nT}$, where \mathbf{e}_{fe} is the residual vector of a linear FE model, n is the number of observations in each time period, and T is the number of time periods involved. This estimate is biased downward by a factor of $(T-1)/T$.

⁹ Note that \mathbf{x}_{it} may include time-invariant variables, which play the role of $\bar{\mathbf{x}}_i$ in the CRE specification.

below it, is a standard random-effects (RE) Tobit model with a set of observed covariates ($\bar{\mathbf{x}}_i$) added. As such, the parameters in equation (6), ψ , β , η , σ_ε^2 and σ_r^2 , as well as the marginal effects defined based on these parameters (3), can be consistently estimated by MLE. Note also that, conditional on $\bar{\mathbf{x}}_i$, the variation in \mathbf{x}_{it} exploited to identify β is the time-varying part of it. Since $\bar{\mathbf{x}}_i$ is held fixed, the time-varying variation in \mathbf{x}_{it} plays a role analogous to that of “deviations from means” resulting from a “within transformation” in linear FE models.

The third issue concerns the potential reverse causality from alcohol consumption (A_{it}) to chronic disease diagnosis (D_{it}). As is widely documented in the literature, excessive drinking can cause serious harm to one’s health. With the presence of such reverse causality, the statistical relationship between individuals’ alcohol consumption and their diagnosed chronic conditions observed in the same period t may reflect this reverse causality rather than the actual effect of CDD on alcohol consumption. To address this issue, we replace D_{it} with its lagged values observed in the previous period, $D_{i,t-1}$, in some analyses. Since whether a person drinks in a given period should not affect his/her health status in the previous period, this strategy effectively circumvents the reverse-causality problem.¹⁰ Since the reverse-causality issue may also apply to one’s subjective health status, we also replace this variable with its lagged values in the model as a robustness check.

The final issue is the potential existence of other omitted determinants of alcohol consumption. While the Chamberlain-Mundlak CRE specification helps take care of unobserved fixed factors (f_i), there is no guarantee that it captures the influence of all unobserved confounders. One (partial) solution is to add lagged values of the outcome variable, $A_{i,t-1}$, as an additional control variable in the model. Since $A_{i,t-1}$ is a function of all relevant factors, observed or unobserved, in period $t-1$, it should reasonably capture the influence of all omitted factors. It is worth noting that $A_{i,t-1}$ is also a “corner-solution” outcome at $t-1$, which suggests that the censored and uncensored parts of it may have different effects on A_{it} . Thus, following Wooldridge’s (2010) recommendation, we include a dummy for censored observations at $t-1$, $c_{i,t-1}$ (“censored”) and a term $(1 - c_{i,t-1}) \times A_{i,t-1}$ in the model to capture both effects.¹¹ Note also that conditional on $A_{i,t-1}$, which summarizes one’s disease-diagnosis and drinking histories up to $t-1$, identification of the CDD effect comes from the variation in D_{it} between periods $t-1$ and t . Admittedly, this identification mechanism is not immune to confounding factors varying between $t-1$ and t . Yet unlike acute diseases, which are usually driven by short-time shocks, chronic diseases are more likely to be caused by factors accumulated for a long period.¹² Thus, it seems safe to assume that D_{it} is uncorrelated with factors varying between $t-1$ and t .

¹⁰ Of course, if the duration from $t-1$ to t is long, this approach may lead to some notable changes in the estimates and the related interpretation.

¹¹ A more general approach, detailed in Wooldridge (2010), is to include both $A_{i,t-1}$ and A_{i0} , the initial value of A_{it} in the model, which yields very similar results (not reported but available upon request).

¹² This argument also alleviates concerns about reverse causality from alcohol consumption to chronic disease

Finally, the above framework can be easily adapted to estimate the effect of CDD on the likelihood of (stopping) excessive drinking (E_{it})— $E_{it}=1$ if the daily intake of pure alcohol exceeded 25g for an adult male or 15g for an adult female and 0 otherwise—and the likelihood of (quitting) alcohol drinking altogether. A Probit model with the Chamberlain-Mundlak CRE specification can be applied to the analytical sample:

$$Prob(E_{it} = 1|x_i) = \Phi(\psi^0 + x_{it}\beta^0 + \bar{x}_i\eta^0). \quad (7)$$

Again, we are interested in estimating the marginal effect of an additional CDD on the probability of heaving drinking: $\partial Prob(E_{it} = 1|x_i, r_i)/\partial D_{it} = \beta_1 \phi(\frac{\psi^0 + x_{it}\beta^0 + \bar{x}_i\eta^0}{1 + \sigma_r^2})]$.

All estimations discussed above were performed in Stata SE 14.0.

4. Results

4.1. Main results

Table 2, panel B, presents the main results of estimating the Chamberlain-Mundlak CRE Tobit model (equation 6) for elderly Chinese individuals' weekly consumption of three alcoholic beverages (beer, red wine, and Chinese spirits) and weekly total alcohol intake, based on all available observations (an unbalanced panel). For comparison purposes, results of traditional RE Tobit models are presented in panel A. All columns report the marginal effects for the uncensored population ($\partial \hat{E}(A_{it}|A_{it} > 0, z_{it}, \bar{x}_i)/\partial x_k$, for a given variable x_k).

[Table 2 about here]

Three notable findings emerge from the table. First, many \bar{x}_i variables (i.e., within-individual means) in the Chamberlain-Mundlak CRE Tobit specification (Table 2, panel B) have statistically significant predictive power for elderly Chinese individuals' alcohol consumption, suggesting that the individual-specific unobserved effects (f_i) are indeed correlated with observed variables (x_{it}), at least through some \bar{x}_i 's. As such, the Chamberlain-Mundlak CRE Tobit specification represents a more suitable modeling device than the traditional RE Tobit (Table 2, panel A).¹³ Comparisons between panels A and B suggest that the traditional RE Tobit underestimates the effects of CDD.

Second, all columns in Table 2 suggest that the number of chronic conditions diagnosed has a statistically significant and negative effect on elderly individuals' alcohol consumption, but the effect is modest. CRE Tobit estimates (panel B) suggest that, on average, an additional chronic condition diagnosed reduces a drinker's weekly beer

diagnosis.

¹³ The traditional RE tobit models reported in Table 2 control for province dummy variables. Traditional RE tobit models that control for community dummy variables yield quite similar estimates of the effects of chronic disease diagnoses, but are less significant. Results are not reported but are available upon request.

intake, red wine intake, and spirits intake, respectively, by 1.49, 0.93, and 0.89 ounces. It appears that the reduction in red wine intake is modest in absolute terms. But given the very small amount of red wine intake (2.86 ounces) among drinkers (Table 1), the estimate in column (2) implies a sizable reduction in red wine intake in proportional terms (32.5%), much larger than those in beer (8.1%) and spirits intakes (5.1%). Yet, in any case, the estimated effect of CDD is small in practical terms. Since the average drinker consumes more than 20 ounces of alcoholic beverages per week (Table 1), the reduction in total weekly alcohol consumption (0.95 ounces) induced by one additional CDD amounts to a mere 4.7% reduction.

Nevertheless, CDD has a sizable effect on the likelihood of stopping excessive drinking and quitting drinking. Table 3 reports Chamberlain-Mundlak CRE Probit estimates of the effects of CDD (equation 7). The results indicate that an additional CDD is associated with a reduction in the likelihood of quitting excessive drinking by 24.3% (column 2) and a reduction in the likelihood of quitting drinking by 19.7% (column 4). Again, the standard RE specification (columns 1 and 3) yields estimates of smaller sizes.

[Table 3 about here]

Finally, the effects of many other explanatory variables differ greatly across alcoholic beverages, depicting different demands for different products. Specifically, CRE Tobit estimates (Table 2, panel B) show that males consume substantially more of all three beverages than females, but the gender gap in beer intake (15.8 ounces) is much wider than those in red wine (2.6 ounces) and spirits (8.1 ounces) intakes. For all three beverages, the age profile has an inverted-U shape, but that for beer is the steepest among the three. Smokers drink significantly more beer (by 4.4 ounces) and spirits (by 2.3 ounces), but not red wine, than non-smokers. The presence of other drinkers in the household induces more consumption of all three beverages, but the effect is larger for beer than for red wine and spirits. Rural residents consume more spirits but less beer and red wine than urban residents. Interestingly, health insurance coverage encourages beer consumption but discourages spirits consumption.

4.2. Robustness checks

The above findings are convincing only to the extent that the Chamberlain-Mundlak CRE specifications are valid. This section performs several checks to assess the performance of CRE Tobit in addressing the estimation issues discussed above. To keep the discussion focused, we only report results based on the model for total weekly alcohol consumption.¹⁴

Column (1) of Table 4 reproduces column (8) of Table 2, providing the basis for comparisons. To address potential reverse causality from alcohol consumption to health,

¹⁴ Results for the three specific alcoholic beverages are available upon request.

column (2) of Table 4 replaces the number of chronic diseases diagnosed and (self-reported) health status with their respective one-period lagged measures. The estimate remains quite comparable, greatly alleviating the concern about reverse causality.

[Table 4 about here]

To address the potential concern of omitted variables, column (3) includes the lagged outcome measure ($A_{i,t-1}$) in the model, allowing the censored ($A_{i,t-1} = 0$) and uncensored ($A_{i,t-1} > 0$) parts to have different effects. The estimate becomes slightly smaller but still indicates a significantly negative impact of CDD on alcohol consumption. The similarity in the estimates across these columns suggests that the benchmark CRE Tobit model (Table 3, column 1) depicts the CDD-alcohol consumption relationship reasonably well.

The third concern is that some of the control variables, such as smoking and working status, might be endogenous. To see how the inclusion of such variables affects our estimation results, we drop all potentially endogenous explanatory variables from the model in column (4). Reassuringly, the estimated effect of CDD in this column remains very similar to the benchmark estimate in column (1).

The final concern is over the use of an unbalanced panel. Identification of parameters using an unbalanced panel exploits partly cross-individual variations in CDD, which may be contaminated with unobserved individual-specific factors if the Chamberlain-Mundlak CRE specification fails to capture such factors. As a test, panel B restricts the sample to be a balanced panel, ensuring that identification relies entirely on time-varying variations. Reassuringly, the results are comparable to their counterparts reported in panel A, again suggesting that the benchmark CRE Tobit model (Table 4, column 1) performs reasonably well. Therefore, we base most of the analyses below on this specification.

4.3. Further exploration: effects of the diagnoses of specific chronic diseases

Diagnoses of different chronic diseases may have different effects on alcohol consumption; thus, pooling different chronic conditions together in the analysis may mask important patterns. This section explores how the effects of the diagnoses of different chronic conditions might differ. Based on the benchmark CRE Tobit model, we replace the number of chronic diseases diagnosed (D_{it}) with dummies for the diagnoses of specific chronic conditions (d_{it}) and re-estimate the models.

Table 5 reports the main results—to avoid cluttering the table, we omitted results on the control variables. Two findings are informative. First, in the aggregate, the diagnoses of all four specific chronic conditions help reduce elderly Chinese individuals' alcohol consumption, although not all effects are statistically significant (panel A). Second, elderly Chinese individuals' alcohol consumption is most responsive to diabetes

and stroke diagnoses, but the effects vary across different beverages. More specifically, diabetes diagnosis has the largest (negative) effect on beer (Panel B) and red wine consumption (panel C), while strokes diagnosis has the biggest effect on spirits consumption (panel D). In comparison, the diagnosis of myocardial infarction exerts a significant effect only on spirits consumption but not on the consumption of other beverages (panel D). In fact, the effect of myocardial infarction diagnosis is very imprecisely estimated in general, presumably due to the very few cases with myocardial infarction diagnosis (4%) in the sample.

[Table 5 about here]

4.4. Further exploration: subgroup analyses

To further examine whether our findings are driven by certain subgroups, this section performs a series of subgroup analyses. We divide the sample into subsamples defined based on characteristics that significantly influence one's drinking behavior (Table 2): gender, age, residential area (urban versus rural areas), whether one smokes, whether there are other drinkers in the household, health insurance coverage, and subjective health status. The Chamberlain-Mundlak CRE Tobit model is then applied to each subsample.

The results, reported in Table 6, again, reveal a robust and statistically significant link between CDD and alcohol consumption, suggesting that our findings discussed above reflect a general pattern rather than a pattern driven by some specific subgroups. There appears to be heterogeneity in the CDD effect across subgroups, although the differences are all statistically insignificant. For example, elderly males (panel A) respond to CDD more strongly than elderly females (panel B). Since elderly males and elderly females have similar numbers of chronic conditions (0.42 for males and 0.46 for females), the difference in their responses is presumably due to the fact that males consume much more alcohol than females (Tables 2-3), thereby having more room for reductions in alcohol consumption. Compared to urban residents (panel F), rural residents are more responsive to CDD (panel E), with might reflect the higher level of vulnerability of rural residents' livelihood against health risks. This is also consistent with the pattern revealed in panels G and H—individuals' responses are stronger without health insurance. Smokers' alcohol consumption is also more responsive to CDD, possibly reflecting the fact that smokers are more prone to chronic diseases. This is, in fact, consistent with the pattern shown in panels O and P, where individuals with different numbers of chronic diseases diagnosed are compared. Finally, those living with other drinkers are less likely to cut back on drinking when diagnosed with a chronic disease, possibly due to within-family peer pressure.

[Table 6 about here]

5. Discussion

Many studies have examined the effect of alcohol consumption on health, but research on the effects of health (especially chronic diseases) on drinking has been limited. To our knowledge, only a few studies have been conducted on this topic, and essentially no related research has been done in China. Our study fills the gap by estimating the impacts of chronic disease diagnoses on elderly individuals' alcohol consumption in China. Analyzing a longitudinal dataset on 5,724 Chinese individuals over age 50, we discovered that CDD helped reduce their alcohol consumption (by 0.95 ounces per week). More importantly, CDD reduced the likelihood of excessive drinking by 24%. Since chronic conditions affect an individual's health status for an extended period of time, the effects of CDD are presumably informational. Given our findings, regular health checks should aid in reducing alcohol consumption among elderly Chinese individuals. Yet our findings also suggest that many elderly Chinese individuals continued to drink (heavily) even after being diagnosed with certain chronic diseases. Relevant policies and measures (e.g., heavier tax on alcoholic beverages consumption) are thus needed to urge the patients to stop excessive drinking.

The patterns found in this study are consistent with those found in existing studies. For example, Kim and Sambou (2019), also using panel data, found that the odds of drinking and heavy drinking decreased as the number of chronic diseases increased among Korean individuals. Yet, our study discovered more heterogeneity in the effect of CDD. First, while the effect of CDD on elderly Chinese individuals' total alcohol consumption is modest, they have a notable effect on the likelihood of stopping excessive drinking. Second, CDD exerts different effects on elderly Chinese individuals' consumption of different alcoholic beverages. Specifically, diabetes diagnosis has the largest impact on beer and red wine consumption, while stroke diagnosis has the largest impact on spirits consumption.

Although we have performed a series of robustness checks to verify our findings, we note several limitations in the study. The first concerns recall bias. Respondents were asked to report their weekly alcohol intake over the last 12 months rather than over the past week or month. As such, the amount of alcohol consumption reported may not be perfectly accurate. Yet, such a survey strategy helped smooth out fluctuations in alcohol consumption due to short-time shocks such as drinking at social events. Also, recall errors are likely to be random errors (with mean zero), which may not introduce serious biases in our estimates. In the Tobit setup, such random errors become part of the disturbance term ε and thus increase its variance (σ_ε^2). But since σ_ε^2 are jointly estimated with the coefficient parameters, the influence of these errors will be accounted for in our estimates of marginal effects.

Secondly, due to data limitations, we do not include the diagnoses of other chronic diseases such as gastritis and hepatitis in the analysis. This lack of information

may impact our estimates, yet to the extent that CDD exerts a negative effect on elderly individuals' alcohol consumption in general, our findings (obtained without including the diagnoses of other chronic diseases) still provide lower-bound estimates of the effects of CDD. Future studies with more information on other chronic diseases are undoubtedly desirable, which may help obtain a more precise picture of the CDD-alcohol consumption relationship.

Despite these limitations, we believe that our analysis still adds new and valuable information to the literature, thereby helping to inform China's healthcare policy.

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Table 1: Summary statistics

Variable	Full sample		Drinkers		Non-drinkers	
	Mean	SD	Mean	SD	Mean	SD
Whether drinking (dummy, =1 if yes)	0.28	0.45	1	0	0	0
Weekly beer intake (oz) (current)	4.93	29.69	18.43	55.51	0	0
Weekly red wine intake (oz) (current)	0.77	7.88	2.86	15.09	0	0
Weekly Chinese spirits intake (oz) (current)	4.70	14.74	17.32	24.44	0	0
Total alcohol consumption (oz)(current)	5.54	15.88	20.29	25.29	0	0
Total alcohol consumption (oz)(lagged)	6.27	16.99	18.34	25.74	1.82	8.80
Excessive drinking (dummy, =1 if consuming ≥ 25 g (15g) pure alcohol daily for males (females))	0.15	0.36	0.44	0.50	0	0
Hypertension (current)	0.34	0.48	0.29	0.45	0.36	0.48
Diabetes (current)	0.08	0.27	0.05	0.22	0.09	0.29
Stroke (current)	0.06	0.24	0.04	0.19	0.06	0.24
Myocardial infarction (current)	0.04	0.19	0.02	0.15	0.04	0.19
Hypertension diagnosed (lagged)	0.26	0.44	0.21	0.41	0.28	0.45
Diabetes diagnosed (lagged)	0.06	0.23	0.04	0.19	0.06	0.24
Stroke diagnosed (lagged)	0.04	0.19	0.02	0.15	0.04	0.20
Myocardial infarction (lagged)	0.02	0.15	0.01	0.12	0.03	0.16
Number of chronic diseases diagnosed (current)	0.44	0.69	0.36	0.60	0.49	0.73
Number of chronic diseases diagnosed (lagged)	0.33	0.61	0.26	0.53	0.37	0.65
Male (dummy, =1 if yes)	0.48	0.50	0.84	0.36	0.34	0.47
Self-reported health status (current) (dummy, =1 if self-reported health is “good” or “very good”)	0.45	0.50	0.52	0.50	0.41	0.49
Self-reported health status (lagged)	0.49	0.50	0.56	0.50	0.46	0.50
Whether smoking (dummy, =1 if yes)	0.26	0.44	0.53	0.50	0.16	0.37
Other drinkers in the household (dummy, =1 if yes)	0.46	0.50	0.44	0.50	0.46	0.50
Age (years)	67.75	9.31	65.18	8.42	68.04	8.96
Age ² /100	46.77	13.08	43.19	11.34	47.09	12.51
Education (years)	4.82	4.35	6.04	4.34	4.43	4.32
Annual income (yuan)	26,626	41,910	26,238	41,378	26,496	41,116
Spouse (dummy, =1 if having a spouse)	0.75	0.43	0.84	0.36	0.72	0.45
Health insurance (dummy, =1 if having medical insurance coverage)	0.71	0.45	0.70	0.46	0.71	0.45
Working (dummy, =1 if currently working)	0.31	0.46	0.44	0.50	0.25	0.44
Rural (dummy, =1 if a respondent resides in a rural area)	0.64	0.48	0.63	0.48	0.64	0.48
Minority (dummy, =1 if a respondent is a minority)	0.13	0.33	0.14	0.35	0.12	0.33
Height (cm)	158.00	9.12	162.49	7.99	156.26	8.93
Number of individuals	5,724		2,249		4,591	
Number of individual-wave observations	21,012		5,510		14,364	

Source: Author’s calculation using CHNS data.

Table 2: Tobit estimates of associations between the number of chronic diseases diagnosed and weekly alcohol consumption (age ≥ 50 , unbalanced panel)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome variables (unit: ounces/week)	Beer	Red wine	Chinese spirits	Total	Beer	Red wine	Chinese spirits	Total
Estimator	A. Standard random-effects Tobit				B. Correlated random-effects Tobit			
Number of chronic diseases diagnosed	-1.273*** (0.465)	-0.639*** (0.243)	-0.765*** (0.134)	-0.754*** (0.134)	-1.488** (0.694)	-0.927*** (0.357)	-0.886*** (0.174)	-0.946*** (0.177)
Male (=1 if yes)	17.409*** (1.049)	2.969*** (0.530)	8.668*** (0.313)	8.701*** (0.309)	15.784*** (1.106)	2.592*** (0.566)	8.133*** (0.341)	8.094*** (0.338)
Self-reported health status	1.237** (0.523)	0.359 (0.267)	0.713*** (0.134)	0.779*** (0.137)	0.496 (0.584)	-0.242 (0.296)	0.471*** (0.144)	0.501*** (0.147)
Smoking (=1 if yes)	4.216*** (0.629)	0.173 (0.354)	2.903*** (0.174)	2.984*** (0.180)	4.440*** (0.867)	0.113 (0.492)	2.342*** (0.213)	2.524*** (0.222)
Other drinkers in the household (=1 if yes)	1.531*** (0.586)	0.931*** (0.301)	1.011*** (0.156)	1.186*** (0.159)	1.895*** (0.731)	0.991*** (0.374)	0.787*** (0.179)	0.992*** (0.183)
Age (years)	0.318 (0.484)	0.415* (0.224)	0.254** (0.118)	0.242** (0.119)	0.979* (0.591)	0.553** (0.274)	0.299** (0.139)	0.365*** (0.141)
Age ² /100	-0.555 (0.359)	-0.317* (0.163)	-0.243*** (0.086)	-0.238*** (0.087)	-0.940** (0.442)	-0.421** (0.199)	-0.298*** (0.101)	-0.339*** (0.102)
Years of education (years)	0.122 (0.083)	0.128*** (0.043)	-0.024 (0.025)	0.013 (0.025)	0.096 (0.086)	0.099** (0.044)	-0.016 (0.025)	0.014 (0.026)
Annual income (yuan) in log	0.458* (0.264)	0.307** (0.141)	0.018 (0.068)	0.045 (0.069)	0.377 (0.311)	0.262 (0.165)	0.009 (0.075)	0.023 (0.077)
Has spouse (=1 if yes)	-1.104 (0.863)	-0.334 (0.427)	-0.426* (0.234)	-0.250 (0.237)	-2.320* (1.351)	-0.585 (0.630)	0.075 (0.328)	0.063 (0.333)
Insurance coverage (=1 if yes)	3.174*** (0.766)	1.245*** (0.419)	-0.651*** (0.195)	-0.449** (0.200)	2.732*** (0.944)	0.509 (0.524)	-0.471** (0.228)	-0.436* (0.234)
Working (=1 if yes)	2.029*** (0.651)	0.146 (0.357)	0.459*** (0.170)	0.627*** (0.175)	-0.466 (0.765)	-0.337 (0.420)	0.133 (0.189)	0.150 (0.195)
Rural (=1 if yes)	-2.053*** (0.738)	-2.696*** (0.389)	0.740*** (0.234)	0.111 (0.234)	-3.103*** (0.771)	-2.784*** (0.409)	0.493** (0.246)	-0.186 (0.246)
Minority (=1 if yes)	-1.704 (1.326)	0.476 (0.728)	0.876** (0.374)	0.781** (0.385)	-1.897 (1.316)	0.460 (0.727)	0.681* (0.374)	0.593 (0.384)
Height (cm)	0.091* (0.052)	0.027 (0.028)	0.006 (0.015)	0.017 (0.015)	0.104** (0.052)	0.023 (0.028)	0.012 (0.015)	0.022 (0.015)
<i>Within-individual means (\bar{x}_i)</i>								
Number of chronic diseases diagnosed					0.930 (0.969)	0.793 (0.487)	0.605** (0.278)	0.795*** (0.278)
Self-reported health status					3.582*** (1.298)	2.913*** (0.684)	1.831*** (0.393)	2.002*** (0.395)
Smoking					-0.540	0.178	1.535***	1.257***

Other drinkers in the household					(1.271)	(0.715)	(0.367)	(0.378)
					-1.343	-0.253	0.767**	0.590
Age					(1.238)	(0.643)	(0.367)	(0.370)
					-0.902	-0.178	-0.089	-0.230
Age ² /100					(0.842)	(0.397)	(0.228)	(0.228)
					0.684	0.158	0.113	0.216
Annual income (yuan) in log					(0.645)	(0.297)	(0.171)	(0.171)
					0.411	0.007	0.031	0.085
Has spouse					(0.593)	(0.310)	(0.171)	(0.173)
					1.997	0.417	-0.930*	-0.596
Has insurance coverage					(1.813)	(0.881)	(0.478)	(0.483)
					1.160	1.844**	-0.579	0.045
Working in the labor market					(1.556)	(0.849)	(0.437)	(0.444)
					8.756***	1.790**	1.625***	2.434***
					(1.471)	(0.815)	(0.444)	(0.450)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. individual-wave observations	18,707	18,705	18,707	18,707	18,707	18,705	18,707	18,707
Log pseudolikelihood	-13160.66	-4693.10	-24091.19	-27933.96	-13133.40	-4677.08	-24054.45	-27890.94

Notes: Marginal effects for the non-censored population ($\partial \hat{E}(A_{it}|A_{it} > 0, \mathbf{x}_{it})/\partial x_k$) are reported.

Standard errors, adjusted for intra-individual clustering, are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Probit estimates of associations between the number of chronic diseases diagnosed and incidences of drinking or excessive drinking (age ≥ 50 , unbalanced panel)

Outcome variables Estimator	(1)	(2)	(3)	(4)
	Drinking Probit	Drinking CRE Probit	Excessive drinking Probit	Excessive drinking CRE Probit
Number of chronic diseases diagnosed	-0.162*** (0.031)	-0.197*** (0.043)	-0.132*** (0.039)	-0.243*** (0.053)
Male (=1 if yes)	1.930*** (0.077)	1.810*** (0.083)	1.604*** (0.093)	1.471*** (0.098)
Self-reported health status (=1 if “good/very good”)	0.107*** (0.033)	0.020 (0.036)	0.184*** (0.039)	0.108** (0.043)
Smoking (=1 if yes)	0.802*** (0.044)	0.757*** (0.055)	0.680*** (0.050)	0.553*** (0.064)
Other drinkers in the household (=1 if yes)	0.374*** (0.039)	0.361*** (0.045)	0.153*** (0.045)	0.124** (0.054)
Age (years)	0.045 (0.028)	0.099*** (0.034)	0.069** (0.035)	0.125*** (0.043)
Age (years) squared/100	-0.047** (0.021)	-0.082*** (0.024)	-0.060** (0.025)	-0.095*** (0.031)
Years of education (years)	0.007 (0.006)	0.003 (0.006)	-0.010 (0.007)	-0.011 (0.007)
Annual income (yuan) in log	0.009 (0.016)	-0.003 (0.019)	0.018 (0.020)	0.007 (0.023)
Has spouse (=1 if yes)	-0.088 (0.055)	-0.053 (0.079)	-0.074 (0.067)	-0.013 (0.098)
Insurance coverage (=1 if yes)	-0.023 (0.048)	-0.066 (0.057)	-0.065 (0.056)	-0.045 (0.068)
Working (=1 if yes)	0.157*** (0.042)	0.047 (0.047)	0.144*** (0.049)	0.046 (0.057)
Rural (=1 if yes)	-0.146*** (0.055)	-0.203*** (0.058)	0.129** (0.064)	0.088 (0.068)
Minority (=1 if yes)	0.144 (0.092)	0.117 (0.092)	0.225** (0.100)	0.190* (0.101)
Height (cm)	0.005 (0.004)	0.006* (0.004)	0.001 (0.004)	0.002 (0.004)
<i>Within-individual means (\bar{x}_i)</i>				
Number of chronic diseases diagnosed		0.156** (0.066)		0.314*** (0.078)
Self-reported health status		0.588*** (0.094)		0.522*** (0.110)
Smoking		0.139 (0.092)		0.345*** (0.104)
Other drinkers in the household		0.001 (0.089)		0.067 (0.103)
Age		-0.100* (0.054)		-0.103 (0.064)
Age ² /100		0.077* (0.040)		0.075 (0.048)
Annual income (yuan) in log		0.044 (0.041)		0.047 (0.048)
Has spouse		-0.070 (0.114)		-0.104 (0.138)
Insurance coverage		0.129 (0.106)		-0.096 (0.124)
Working		0.570*** (0.108)		0.443*** (0.124)
Province fixed effects	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes
No. individual-wave observations	18,703	18,703	18,707	18,707
Log pseudolikelihood	-7230.34	-7185.58	-4815.00	-4779.93

Notes: Marginal effects are reported. Standard errors, adjusted for intra-individual clustering, are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Correlated random-effects Tobit estimates of associations between the number of chronic diseases diagnosed and weekly total alcohol consumption (aged 50 or above)

Outcome variable = total weekly alcohol intake (ounce)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Unbalanced panel				B. Balanced panel			
Number of chronic diseases diagnosed	-0.946*** (0.177)		-0.761*** (0.215)	-0.979*** (0.176)	-0.957*** (0.248)		-0.816*** (0.276)	-1.013*** (0.254)
Number of chronic diseases diagnosed; 1-period lagged		-0.820*** (0.238)				-1.016*** (0.297)		
Total alcohol consumption, 1-period lagged ($A_{i,t-1}$)			0.078*** (0.005)				0.073*** (0.007)	
Did not consume alcohol, 1-period lagged (dummy, $A_{i,t-1}=0$)			-5.170*** (0.213)				-4.943*** (0.303)	
Male (dummy)	8.094*** (0.338)	7.407*** (0.391)	3.755*** (0.262)	10.118*** (0.309)	8.248*** (0.559)	7.928*** (0.543)	4.166*** (0.367)	11.031*** (0.494)
Self-reported health status “good/very good” (dummy)	0.501*** (0.147)		0.358** (0.174)		0.554*** (0.202)		0.428** (0.215)	
Self-reported health status, 1-period lagged		-0.000 (0.173)				0.008 (0.216)		
Smoking (dummy)	2.524*** (0.222)	2.717*** (0.270)	2.594*** (0.268)		2.314*** (0.309)	2.769*** (0.340)	2.621*** (0.335)	
Other drinkers in the household (dummy)	0.992*** (0.183)	1.029*** (0.224)	0.888*** (0.219)		1.115*** (0.247)	1.015*** (0.274)	0.854*** (0.267)	
Age (years)	0.365*** (0.141)	0.495** (0.218)	0.213 (0.216)	0.283** (0.139)	-0.590 (0.384)	-0.307 (0.320)	-0.299 (0.279)	-0.567 (0.399)
Age (years) squared/100	-0.339*** (0.102)	-0.480*** (0.156)	-0.238 (0.157)	-0.339*** (0.102)	-0.204 (0.138)	-0.365* (0.188)	-0.105 (0.189)	-0.163 (0.141)
Years of education (years)	0.014 (0.026)	0.010 (0.029)	0.009 (0.021)	-0.016 (0.026)	0.010 (0.040)	-0.030 (0.040)	-0.015 (0.029)	-0.026 (0.041)
Annual income (yuan) in log	0.023 (0.077)	-0.048 (0.092)	0.027 (0.092)	0.071 (0.077)	-0.043 (0.106)	-0.108 (0.115)	-0.073 (0.114)	0.007 (0.108)
Has spouse (dummy)	0.063 (0.333)	-0.397 (0.431)	-0.419 (0.412)	0.168 (0.336)	-0.439 (0.478)	-0.699 (0.554)	-0.685 (0.529)	-0.358 (0.489)
Has insurance coverage (dummy)	-0.436* (0.234)	-0.271 (0.281)	-0.080 (0.279)		-0.186 (0.314)	0.045 (0.346)	0.160 (0.340)	
Working (dummy)	0.150 (0.195)	0.239 (0.230)	0.312 (0.229)		-0.095 (0.260)	0.089 (0.280)	0.201 (0.277)	
Rural (dummy)	-0.186 (0.246)	-0.268 (0.292)	-0.075 (0.175)	0.372 (0.245)	-0.886** (0.433)	-1.072** (0.422)	-0.405 (0.247)	-0.293 (0.440)
Minority (dummy)	0.593 (0.384)	0.546 (0.436)	0.239 (0.254)	1.059*** (0.399)	0.432 (0.595)	0.290 (0.573)	0.288 (0.331)	1.060* (0.640)
Height(cm)	0.022 (0.015)	0.035** (0.018)	0.025** (0.012)	0.012 (0.016)	0.025 (0.024)	0.019 (0.023)	0.022 (0.016)	0.020 (0.024)
<i>Within-individual means (\bar{x}_i):</i>								

Number of chronic diseases diagnosed	0.795*** (0.278)		0.572** (0.290)	0.112 (0.282)	0.957** (0.451)		0.764** (0.386)	0.020 (0.470)
Number of chronic diseases diagnosed; 1-period lagged		0.615 (0.423)				1.194** (0.554)		
Self-reported health status	2.002*** (0.395)		1.222*** (0.337)		2.803*** (0.795)		1.584*** (0.477)	
Self-reported health status, 1-period lagged		2.437*** (0.458)				2.933*** (0.723)		
Smoking	1.257*** (0.378)	1.251*** (0.449)	-0.779** (0.351)		2.098*** (0.619)	1.377** (0.621)	-0.565 (0.464)	
Other drinkers in household	0.590 (0.370)	0.435 (0.446)	-0.266 (0.322)		1.611** (0.638)	1.312** (0.632)	0.084 (0.430)	
Age	-0.230 (0.228)	-0.330 (0.306)	-0.025 (0.242)	-0.647*** (0.227)	0.252 (0.556)	0.318 (0.478)	0.360 (0.335)	-0.363 (0.586)
Age ² /100	0.216 (0.171)	0.361 (0.229)	0.097 (0.184)	0.510*** (0.172)	0.454 (0.328)	0.361 (0.343)	0.056 (0.248)	0.756** (0.352)
Annual income (yuan) in log	0.085 (0.173)	0.141 (0.212)	0.015 (0.152)	0.164 (0.168)	0.032 (0.315)	0.135 (0.310)	0.137 (0.209)	0.301 (0.308)
Has spouse	-0.596 (0.483)	-0.179 (0.613)	0.044 (0.506)	-0.851* (0.494)	-0.344 (0.792)	-0.031 (0.850)	0.298 (0.675)	-0.408 (0.834)
Has insurance coverage	0.045 (0.444)	0.294 (0.549)	0.094 (0.387)		1.321 (0.901)	1.027 (0.887)	0.556 (0.557)	
Working	2.434*** (0.450)	2.852*** (0.536)	1.409*** (0.374)		4.317*** (0.777)	4.197*** (0.753)	2.174*** (0.505)	
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of individual-wave observations	18,707	12,925	13,554	19,107	9,242	7,900	8,318	9,265
Log pseudolikelihood	-27890.94	-18407.45	-18999.74	-28651.79	-14475.23	-11885.32	-12430.07	-14643.35

Notes: Marginal effects for the non-censored population ($\partial \hat{E}(A_{it}|A_{it} > 0, \mathbf{x}_{it})/\partial x_k$) reported.

Standard errors adjusted for intra-individual clustering are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Correlated Random-Effects Tobit estimates of effects of the diagnosis of specific chronic disease on alcoholic beverages consumption (aged 50 or above)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Weekly total alcohol consumption (ounces)				B. Weekly beer consumption (ounces)			
Hypertension diagnosis (= 1 if yes)	-0.624** (0.279)				0.292 (1.092)			
Diabetes diagnosis (= 1 if yes)		-1.536*** (0.546)				-8.290*** (2.229)		
Strokes diagnosis (= 1 if yes)			-3.334*** (0.513)				-6.628*** (1.977)	
Myocardial infarction diagnosis (= 1 if yes)				-1.047 (0.679)				1.397 (2.573)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-individual means of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of individual-wave observations	18,262	18,040	18,056	18,026	18,262	18,040	18,056	18,026
Log pseudolikelihood	-27250.703	-26963.902	-26956.218	-26975.486	-12817.085	-12679.990	-12713.691	-12713.433
	C. Weekly red wine consumption (ounces)				D. Weekly Chinese spirits consumption (ounces)			
Hypertension diagnosis (= 1 if yes)	-1.096** (0.547)				-0.592** (0.273)			
Diabetes diagnosis (= 1 if yes)		-2.028** (0.980)				-1.129** (0.541)		
Strokes diagnosis (= 1 if yes)			-1.167 (1.099)				-3.154*** (0.504)	
Myocardial infarction diagnosis (= 1 if yes)				-1.472 (1.406)				-1.393** (0.698)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-individual means of control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of individual-wave observations	18,260	18,039	18,054	18,025	18,262	18,040	18,056	18,026
Log pseudolikelihood	-4557.902	-4525.322	-4501.226	-4520.112	-23519.825	-23255.391	-23249.379	-23261.866

Notes: “Control variables” include those reported in columns (8) in Table 2. Marginal effects for the non-censored population ($\partial \hat{E}(A_{it}|A_{it} > 0, \mathbf{x}_{it})/\partial x_k$) are reported. Standard errors adjusted for intra-individual clustering are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Heterogenous impacts of chronic diseases diagnoses on total weekly alcohol consumption

	(1)	(2)	(3)	(4)
	A. Male	B. Female	C. Age < median	D. Age ≥ median
Number of chronic diseases diagnosed (current)	-1.653*** (0.317)	-0.302 (0.192)	-1.250*** (0.318)	-0.696*** (0.213)
Control variables	Yes	Yes	Yes	Yes
Within-individual means of controls	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes
Number of individual-wave observations	8,917	9,790	9,473	9,234
Log pseudolikelihood	-23080.043	-4678.1720	-16460.664	-11566.023
	E. Rural residents	F. Urban residents	G. No health insurance	H. With health insurance
Number of chronic diseases diagnosed (current)	-1.223*** (0.247)	-0.502** (0.227)	-1.045** (0.506)	-0.689*** (0.189)
Control variables	Yes	Yes	Yes	Yes
Within-individual means of controls	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes
Number of individual-wave observations	11,859	6,848	5,365	13,342
Log pseudolikelihood	-18006.406	-9735.883	-8331.663	-19601.007
	I. Not smoking	J. Smoking	K. No other drinkers in household	L. Other drinkers in household
Number of chronic diseases diagnosed (current)	-0.709*** (0.179)	-1.372*** (0.494)	-1.218*** (0.256)	-0.632** (0.257)
Control variables	Yes	Yes	Yes	Yes
Within-individual means of controls	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes
Number of individual-wave observations	13,803	4,904	10,317	8,390
Log pseudolikelihood	-13653.346	-14228.689	-16099.332	-11961.540
	M. Health status = “Fair” or below	N. Health status = “good” or above	O. < 2 chronic diseases diagnosed	P. ≥ 2 chronic diseases diagnosed
Number of chronic diseases diagnosed (current)	0.750*** (0.232)	-0.960*** (0.290)	-0.437* (0.245)	-1.461*** (0.512)
Control variables	Yes	Yes	Yes	Yes
Within-individual means of controls	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Survey-wave fixed effects	Yes	Yes	Yes	Yes
Number of individual-wave observations	10,290	8,417	17,091	1,616
Log pseudolikelihood	-13510.42	-14658.393	-26329.010	-1558.112

Notes: “Control variables” include those reported in columns (8) of Table 2. Marginal effects for the non-censored population ($\partial \hat{E}(A_{it}|A_{it} > 0, \mathbf{x}_{it})/\partial \mathbf{x}_k$) reported. Standard errors in parentheses, adjusted for intra-individual clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$