Skip all front matter: Jump to Page 1

DISSERTATION

Three Essays on Economics of Health Behavior in China

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Abstracts

This dissertation consists of three essays, each focusing on one topic in economics of health behaviors in China. The first essay attempts to examine the determinants of alcohol demand with concentration on impact of alcohol price among Chinese adult population. Although literature in developed countries context has indicated that average alcohol demand is price responsive, evidences from developing countries are limited and few work studied the heterogeneity in price elasticities. This paper estimates the price elasticity of demand for alcohol consumption using China Health and Nutrition Survey (CNHS), a representative panel data interviewed during 1993-2006. Specifically, three sources of heterogeneities in alcohol use are explored: differential responses across socio-economic characteristics, drinking levels, and types of drinks. Focusing on public health perspective, we define alcohol consumption in this study as milliliters of total pure alcohol usage in past week. Results of average price elasticity for pure alcohol consumption in China yield estimates ranging between -.07 to -.11 for males and -.07 for females in pooled data, and getting smaller (-.03) or even becoming insignificantly positive in panel data. Examination in heterogeneous demand suggests that alcohol price responsiveness varies substantially across residence, age groups, gender, income level, and labor force status; people who drink alcohol above median level are as sensitive as median level drinkers, and more sensitive than drinkers who drink below median level; beer and liquor are substitutes, drinkers are significantly responsive to liquor price but not beer price. This study suggests that individual unobserved heterogeneity plays an important role in the relationship between alcohol demand and alcohol price. The effect of alcohol price on alcohol consumption is much smaller than western countries. Taxation on alcohol may be not an efficient instrument to improve alcohol related health, although it is efficient in increasing government revenues. Non-monetary policy levers should be considered in China.

The second essay estimates healthcare expenditure in China and evaluates the performance of econometric models. The heavy skewness and non-normal distribution have made ordinary least squares (OLS) biased and inefficient in estimating individual healthcare expenditure. I compare a set of alternative methods including log-normal density maximum likelihood, generalized linear model, quantile regression and finite mixture model using CNHS individual healthcare expenditure data among Chinese adult healthcare users. The comparisons of statistical model selection criteria suggest that finite mixture model is preferred overall in terms of information criteria, goodness of fit, and cross sample validation. The in-sample prediction indicates that finite mixture model overestimates mean value of expenditure, but gives the most precise median prediction, and performs the best in both lower and upper tail predictions.

The objective of the third essay is to examine the time trend of obesity disparities across sociodemographic groups in school-aged youth population from 1991 to 2006 in mainland China. I estimate mean body mass index age- and gender- specific percentiles for sociodemographic subgroups defined by gender, nationality, residence, relative household per capita income, and parental education, using multivariate regression to adjust for changes in sample/population composition. Six waves of CNHS were analyzed, including 14 204 school-aged youth (age 6-18) observations between 1991 and 2006. The findings suggest that all sociodemographic subgroups experienced substantial weight gain during study period, but the gap in mean BMI between population subgroups is widening in many cases. Boys gained more than girls; Han Chinese gained more than minorities; youth in high income families gained more than youth in low-income families; youth whose parents (for both mother and father) had little education (only primary school diploma or less) gained less weight than youth whose parents had more education. In contrast, there was no strong evidence for a widening BMI gap between urban and rural residents. There appears to be a widening in BMI (and obesity rates) across sociodemographic groups in mainland China, yet it is the wealthier, more educated, ethnic majority that becomes more obese. In contrast, it is poorer, less educated, and minority groups in the United States and other developed countries that are at higher risk for obesity.

Table of Contents

List of Figures

List of Tables

Essay 1. Is Price Elasticity in Alcohol Demand Homogeneous? Evidence from Chinese Adult Population

1.1 Introduction

Over recent decades there has been evidence of striking increase in alcohol consumption in China (Cochrane et al. 2003; Pan, Fang, and Malaga 2006). According to 2000/2001 global data (WHO 2004), the recorded adult (age 15 and above) per capita pure alcohol consumption has reached 4.45 liters, above the median level in the world. At the same time, China is lack of comprehensive public health policy on alcohol (Hao et al. 1995). Although alcohol taxation has been traditionally and globally employed as a major policy lever to discourage alcohol consumption as well as to raise government revenue, alcohol taxation in China is still perceived as revenue raising tool rather than instrument to control drinking behavior (Hao 2005). The efficacy of alcohol taxation policy instrument, be it revenue raising or behavior control purpose, depends heavily on how responsive consumers are to alcohol price variations. However, there have been very few studies on alcohol consumption in China context in existing literature. Determinants of alcohol use received very little attention and even fewer studies investigated the price elasticity of alcohol demand. As a result, the decision makers in China are not well informed of the impacts of tax policy changes on alcohol demand and lack of support for an alcohol tax policy design.

Using household micro survey data covering more than ten years (1993-2006), a period that China experienced dramatic changes in its economy and society, this paper estimates price elasticity for alcohol use in China. Recent evidences based on western country population have indicated that understanding the average responsiveness to alcohol price changes is not adequate. Policy makers are also, if not more, interested in understanding the price responsiveness in particular socioeconomic subgroups and in different consumption level of drinkers. It is worthwhile from both welfare and public health point of view to realize whether a policy design targeting on alcohol consumption causes unintended consequences among specific subgroups, or affects subgroups disproportionally. We suggest that underlying heterogeneous effects of price variations stem from three distinct sources: socioeconomic characteristics, drinking levels, and types of drinks. This study, therefore, further investigate whether heterogeneity in elasticity is present in these three potential sources.

The study is expected to contribute to alcohol demand literature in three folds: it is the first and most comprehensive alcohol demand study in China. Utilizing household level panel surveys with a rich set of individual and community characteristics variables, we are able to estimate individual price elasticities as well as determinants of alcohol use, providing evidences on effectiveness of alcohol taxation in revenue generation or alcohol consumption control. Secondly, addictive behaviors are conventionally seen more sensitive to price when income level is low. China is the world largest developing country, and it has a huge market for alcohol consumption. We make possible the comparison of price elasticity of alcohol demand between developed countries and developing countries. Last, we extend limited literature on the heterogeneity of price responses. The study adds empirical evidence of heterogeneous alcohol demand in developing country setting based on micro surveys and goes beyond studying heterogeneity of single source to a comprehensive exploration of heterogeneity from all possible sources.

The remaining sections are organized as follows: section 2 briefly elaborates three possible sources of heterogeneity in alcohol demand in China; section 3 synthesizes enormous literature on alcohol demand and sporadic literature on heterogeneity of alcohol demand; analytical framework and empirical estimation methods are presented in section 4; section 5 reports descriptive statistics, estimation results of average price elasticity, and the heterogeneous responsiveness coming from three distinct sources; section 6 concludes and discusses the paper.

1.2 Three Sources of Heterogeneity in Alcohol Demand

Alcohol taxation has been traditionally and globally employed as a major policy lever to discourage alcohol consumption as well as to raise government revenue. No matter what purpose alcohol tax aims to achieve, the efficacy of policy instrument depends heavily on how responsive consumers are to alcohol price variations. However, understanding the average responsiveness to alcohol price changes is not adequate. Optimally, revenue raising taxes should be levied to population with an inelastic demand in alcohol consumption, whose drinking behaviors are not substantially varied in response to price. While behavior altering taxes should be levied where alcohol demand is sensitive and/or where drinking behavior yields largest harmful consequences (Baumol and Bradford 1970). Therefore, it is not only the estimate of average price elasticity in general population matters, policy makers are also, if not more, interested in understanding the price responsiveness in particular socioeconomic subgroups and in different consumption level of drinkers. Even though practically taxation may be necessarily universal across all types of customers, it is still worthwhile from a welfare and public health point of view to realize whether a policy design targeting on alcohol consumption causes unintended consequences among specific subgroups, or affects subgroups disproportionally. Additional heterogeneity in price responsiveness comes from the fact that alcohol itself is not homogeneous commodity. However, there has been little effort devoted to exploring the detailed underlying heterogeneous effects of price variations stemming from differences in socioeconomic characteristics, in alcohol consumption levels, or the types of alcoholic beverages consumed , with only a few exceptions, all of which focused on population in western countries (Manning, Blumberg, and Moulton 1995; Kenkel 1996; Ayyagari et al. 2010; Dave and Saffer 2008; Meier, Purshouse, and Brennan 2010; Gruenewald et al. 2006; Ramful and Zhao 2008).

China has the largest population in the world with immense geographic, cultural, and economic diversities. It is reasonable to hypothesize that the responses to price among various socioeconomic subgroups are not homogeneous. For example, discrepancy of alcohol price responsiveness between genders is likely present. Traditionally, Chinese culture has encouraged alcohol consumption, particularly among males. Men capable of consuming a large quantity of alcohol are perceived as masculine (Hao 2005; Zhang et al. 2004; Cochrane et al. 2003), while females were less likely to be encouraged drinking by family and peers (Hao et al. 1995). Therefore, females are possibly less addictive to alcohol and more sensitive to alcohol price than males are. Another example is differential responses to alcohol among occupations. Occupations have been suggested to significantly associated with excessive drinking in China (Hao et al. 1999). Alcohol is commonly used in business meetings and at social events to initiate business partnerships, maintain good relationships with supervisors, employees, relatives and families, and promote camaraderie among colleagues and friends (Hao 2005; Cochrane et al. 2003). Alcohol is also perceived as relief of tension and worry, and relief of craving and withdrawal symptoms (Hao et al. 1995). As a result, workers and non-workers may exhibit different response to alcohol price change since workers require social networking or take constant pressure, making them less sensitive to price variations. In addition, government civil servants in China are often invited to official banquets where rounds of spirits are consumed to the bottoms-up toast. Expenditure on meals and alcoholic beverages in such occasions are usually paid by junior staff, businessmen or government money. We therefore may expect employees in public sectors are less elastic to alcohol price changes relative to employees in private sectors.

The second possible source of heterogeneity of alcohol demand in China has to do with potential differential response across levels of alcohol consumption. The optimal tax from public health perspective usually encourages taxation on heavy drinkers since they generate harmful social and health consequences to themselves as well as to the society. However, such strategy is only efficient when heavy drinkers are sensitive to alcohol price, otherwise taxation on heavy drinkers would only have positive effect on revenue collection but not much impact on behavior change. Literatures from western countries (Manning, Blumberg, and Moulton 1995) have suggested that price elasticity among heavy drinkers is smaller than moderate drinkers but about the same level with light drinker. We hypothesize that differential responses to alcohol price variation also exist in China. By estimating price responsiveness across level of drinking, we aim to provide new evidence on optimal tax design in developing countries.

The third source of heterogeneity relies on the fact that alcohol itself is not homogeneous, although beer, wine and liquor are commonly considered as combinable commodities and usually jointly studied as one commodity. Estimates of cross price elasticities test whether the different types of alcoholic beverages are substitutes, complements, or unrelated commodities in consumption. The tax increase in one type of alcoholic beverage is expected to shift the consumption from this beverage to others if different types of alcohol are substitutes, and reduce consumption of all types if they are complements instead. The understanding of heterogeneous price elasticity to different alcoholic beverages in China will shed light on recent taxation policy change in China. On August 1, 2009, a State consumption tax policy on liquor took effect in China. It changes the tax base on liquor, expected to result in a substantial increase in the amount paid by liquor distillers and therefore an increase in final prices to consumers[1]. By treating alcohol as a heterogeneous commodity, this study is able to evaluate the impact of liquor tax increase on liquor consumption through own price elasticity estimates, and also assess the impact of policy on other types of alcohol beverages through cross price elasticity estimates.

1.3 Literature Review

Three strands of literature are relevant to this study. There has been vast literature estimating price elasticity for alcohol demand, which varies by data source (aggregate or household/individual level), data time frame (longitudinal or cross-sectional), measure of alcohol consumption (alcohol expenditure, drinking frequency or drinking quantity, ethanol equivalent or not), measure of price (beer, wine, liquor or average, price or tax), and econometric techniques employed. We concisely summarize existing knowledge about alcohol demand by abstracting two meta-analysis studies. The second source is a series of small but growing literature examining heterogeneity in alcohol price elasticity estimates. The last source is sporadic alcohol demand studies focusing on Chinese population.

[1] Alcohol taxation is one of the highest taxed commodities and one of the major sources of government revenue in China, particularly in less developed regions. China's alcohol consumption taxation system consists of two different components: a low level flat tax on liquor, and an additional ad valorem tax levied on the price of the drink rather than on its content. China State administration in 2009 introduced a new liquor consumption tax collection policy that took effect from August 1 2009. The biggest difference between the new policy and the previous standard of liquor consumption tax is that the new regulations have a significant tax base calculation in accordance with the sell unit charge of external sales price. This ad valorem tax was raised to 50 to 70 percent of the alcohol prices, up from 20 percent. Large liquor companies would face particularly high tax rate as high as 60 to 70 percent. Since distillers usually pass the tax increase to customers, the new regulation has been expected to raise the final price by roughly 20 percent for some brands (Source: official online news of Xinhua News Agency. http://news.xinhuanet.com/english/2009-08/03/content_11816403.htm)

The empirical literature on the responsiveness of consumers to changes in alcohol price has sporadically emerged in 1970s and increasingly expanded in recent forty years. Two most recent studies synthesized literature that estimated elasticities of alcohol demand: Gallet (Gallet 2007) and Wagenaar (Wagenaar, Salois, and Komro 2009). Each paper identified over a hundred studies and provided more than a thousand estimates of price elasticities. Because most of studies they included in the systematic review are overlapped, the conclusions drawn in two papers are quite similar. We highlight key findings of the two papers in the table below (**Table 1**).

Table 1: Summary of Systematic Review on Alcohol Price Elasticity Estimates

Factor	Category	**Gallet 2007 (median)**	**Wagenaar 2009 (mean)**
Number of studies		132	112
Number of estimates		1172	1003
Total estimate		-0.535	-0.615
Beverage category	Beer	-0.360	-0.46
	Wine	-0.700	-0.69
	Spirits	-0.679	-0.80
	Alcohol	-0.497	-0.51
Aggregate level	Alcohol	-0.490 /-0.671*	
Individual level	Alcohol	-0.640	
Heavy alcohol use			-0.28
Time frame[2]	Short run	-0.518	
	Long run	-0.816	
Alcohol consumption measure	Per capita	-0.519	
	Total	-0.680	
	Ethanol	-0.390	
Data	Time-series	-0.540	
	Cross-sectional	-0.683	
	Panel	-0.474	

*-0.490 at country level and -0.671 at state or province level

[2] The short-term price elasticity holds past consumption constant, while the long-term price elasticity allows past consumption to vary.

Both studies agree that price elasticity estimates of alcohol use are very much sensitive to a variety of factors. Some highlights are noteworthy. First, elasticities of spirits and wine consumption are significantly larger than that of beer. Second, studies relying on aggregate level data source generally yield much higher price elasticities than that using micro-level data. Third, studies using ethanol as outcome measure has smaller estimates of price elasticities than other measures. Fourth, estimates from panel data are on average smaller than those based on time-series data or cross-sectional data. Last, although several studies generating estimates insignificantly different from zero, alcohol price elasticity overall is not negligible: people are responsive to price or tax variations with average elasticity at about -0.5 or -0.6.

While nearly thousand studies provide useful estimates of alcohol price elasticities and have insightful policy implications, the implicit assumption of homogeneous response to price change in most of studies ignore the possible heterogeneity in price elasticities. There have been very few empirical evidences systematically examining the heterogeneity in consumer responsiveness to alcohol. The first formal analysis that examined the dispersion alcohol price elasticity is Manning (Manning, Blumberg, and Moulton 1995). The study was interested in whether price responsiveness of the demand for alcohol is differential across drinking levels (light, moderate, or heavy drinking). Cross-sectional Alcohol and Health Practices Supplement to 1983 National Health Interview Survey was the primary data source. Utilizing quantile regression techniques, they found that both light and heavy drinkers are much less price elastic than moderate drinkers with an estimated elasticity of -1.19 for moderate drinkers. Another recent study by Ayyagari (Ayyagari et al. 2010) also focused on the heterogeneous effect of alcohol price on light and heavy alcohol users. Based on HRS (Health and Retirement Study) data, Ayyagari employed finite mixture model to identify two latent groups, one was responsive to price who were disadvantaged in many characteristics such as health, financial resources, education; another was not responsive to price and drank heavily.

Several other studies are interested in understanding alcohol price responsiveness across different socioeconomic subgroups. Kenkel (Kenkel 1996) used same data source as Manning did and showed that alcohol price responsiveness varied with drinking associated health information (responses for whether heavy drinking causes a list of three illness). Results suggested that female's heavy drinking was more price responsive than males counterpart, and more informed consumers were suggested to respond more to changes in price. Dave (Dave and Saffer 2008) examined the alcohol consumption elasticity by individual risk preference. Panel Study of Income Dynamics (PSID) and Health and Retirement Study

(HRS) were utilized that allowed for age-specific models and measure of risk preferences. Empirical results indicated that alcohol tax elasticity did not differ significantly between risk-averse and risk-tolerant individuals. Other example studies include Saffer (Saffer and Chaloupka 1999; Saffer and Dave 2006) and Meier (Meier, Purshouse, and Brennan 2010), showing that substantial differential responsiveness to alcohol price exists across gender, age, racial and ethnic groups.

Different alcoholic beverages are often combined into one single outcome in literature when quantity of drinking includes more than one type of alcohol (Manning, Blumberg, and Moulton 1995; Ayyagari et al. 2010; Farrell, Manning, and Finch 2003; Nelson 2003; Markowitz 2000; Saffer and Chaloupka 1999; Atkinson, Gomulka, and Stern 1990). Differential responsiveness across type of drinking is rarely discussed in literature with only a few exceptions. Blake (Blake and Nied 1997) studied the time-series expenditure shares on beer, cider, spirits and wine in UK between 1952 and 1991, and suggested that demand in each type of alcoholic drinks are not homogeneous. The relationship between individual drinks could be substitutes or complements depending on model specifications. Based on micro Australia 1991-2001 data, participating decisions for beer, wine and spirits are jointly modeled in Ramful (Ramful and Zhao 2008) accounting for correlation via unobservables. Results indicated that drinkers of three types present heterogeneous characteristics. Gruenewald (Gruenewald et al. 2006) defined alcohol in terms of beverage type (beer, wine and spirits) and quality brands (high, medium and low). Using Swedish price and sales aggregate data, the study showed quality classes are substitutes and consumers respond to price increase by altering consumption as well as varying brand choices.

There have been very few studies on alcohol consumption in China context, and majority of recent research focused on health impacts and clinical treatment of alcohol use. Determinants of alcohol use received very little attention and even fewer studies investigated the price elasticity of alcohol demand, not to explore heterogeneity in price responses. To author's knowledge, only three studies are relevant and two of them relied on aggregate data source. All of these three studies focused on outcome of alcohol expenditure. One study by Yu (Yu and Abler 2010) used provincial level aggregate data that was collected by National Statistics Bureau of China (NSBC) and covered 10 years between 1994 and 2003 in rural areas of 26 Chinese provinces. The estimated alcohol expenditure price elasticity was about -1.53 and demand of cigarettes was very sensitive to alcohol price as well. Another study by Fan (Fan, Wailes, and Cramer 1995) utilized pooled time series and provincial level aggregate data covering period of 1982-1990. The average expenditure data comes from rural household survey by each province and price is also provincial or national level. Estimated alcohol price elasticity was much smaller than Yu (Yu and Abler 2010), at roughly -0.3 (in range of -0.31 and -0.36). Such aggregate demand studies have common limitations associated with aggregate type of analysis: first, it is limited in price variations at national or provincial level; second, commercial alcohol sales data is not precise in that they ignore possible smuggling across provinces and usually underestimate the actual consumption of alcohol use; third, use of aggregate data inherently assumes population are homogenous in price response and the estimates by socioeconomic subgroups are usually not possible; forth, they are subject to possible variable colinearity issues; finally, sample size is much smaller in aggregate analysis compared to micro-data that may lack of statistical power. The only study based on micro-level survey data is by Pan (Pan, Fang, and Malaga 2006) that sampled households in 1993 and 1998 in Beijing, Taijin, Shanghai and Jiangsu provinces. The estimate of alcohol expenditure price elasticity from two-stage Almost Ideal Demand System (LA/AIDS) suggested that beer and wine cooler had total price elasticity less than 1 (ranging between -0.51 and -0.85), and wine was larger than 1 (-1.39). People were more responsive to price of wine or wine cooler than price of beer. The study sample is primarily urban population.

Reported average price elasticities are quite wide in the sparse demand analysis of alcohol use in China as reviewed above, ranging from as low as -0.3 to as high as -1.53. The assumption of homogeneous response to price elasticity across socioeconomic groups and different level of drinking is common. Studies either utilized data from urban or from rural regions, providing an incomplete picture of China alcohol consumption.

1.4 Estimation Strategies

1.4.1 Framework

The function of alcohol demand can be constructed as:

$alcohol_i = f(price_i, X_i)$

Where $alcohol_i$ is the outcome variable alcohol consumption for individual i, $price_i$ is the alcohol price, the focus of the study; and X_i denote a set of individual, household and community characteristics variables. Outcome, price and control variables are discussed in detail in section 1.5 (Data). f is the functional form of $alcohol_i$ that are specified as follows.

1.4.2 Log Transformation

Log transformation is commonly used in alcohol demand literature and other health economics literature to deal with consumption skewness (for example (Manning, Blumberg, and Moulton 1995)). It makes highly right skewed distribution (positive alcohol demand in this case) approach normal distribution after log transformation, which is critical in some parametric models requiring normality assumption. We therefore transform positive outcome variable, pure alcohol consumed per week, into log terms. Such transformation also eases the interpretation of the coefficient values for log transformed price in linear models, which is simply price elasticity of alcohol demand.

Zero outcomes are kept as zeros. Such arrangement can be seen as deviating zeros by a very small positive amount (1 millimeter pure alcohol/week in this case) in order to get meaningful log transformation. Since the mean of positive pure alcohol consumption in general population is much bigger than zeros (around 236ml/wk), adding 1millimeter pure alcohol consumption to those who do not consume alcohol should not have big impact on the elasticity estimate[3].

1.4.3 Average Price Elasticity Estimators

The econometric models below are constructed to estimate average price elasticity in the general population. Pooled data estimators include Ordinary Least Squares (OLS), Tobit Model, and Two-part model. In order to utilize repeated measure information for a given individual and account for potential unobserved heterogeneities, we also perform separate panel models for male and female samples. Tobit random effect and Tobit fixed effect are used to estimate male alcohol consumption levels, and random effect Logit is used to model female participation decisions.

1.4.3.1 Ordinary Least Squares (OLS)

We start our analysis from simple OLS model in pooled data. Assuming log transformed alcohol consumption level among drinkers follows normal distribution, the benchmark OLS is given by:

$$logalcohol_i|price_i, X_i = \alpha logprice_i + X_i'\beta + \varepsilon_i$$

Where $logalcohol_i$ is individual i's quantity of drinking in log terms, $logprice_i$ is log transformed alcohol price that individual i faces in his/her community. Error term ε_i is assumed to follow normal distribution with mean 0 and variance σ_ε^2. While we assume alcohol price is exogenous[4], α is the key coefficient of interest estimating the average price elasticity for the whole research population. Observations are clustered at individual level to account for intra-person variation.

1.4.3.2 Tobit Model in Pooled Data

Considering that substantial fraction (40% adult male and 90% adult female) of population in China do not drink, OLS estimator is subject to impreciseness and inconsistency issues which have posed

[3] Two-part model is not affected by zero arrangement. We did sensitivity tests on zero arrangements, such as treating zeros as 0.1, 0.01, in Tobit model. The estimation results are not significantly different from the current estimates.

[4] Given that individual drinking and purchasing decision is unlikely affecting local market, this assumption is reasonable.

econometric challenges to researchers. The common strategy to cope with large fraction of zerost is Tobit model with left censoring at zero. It is given by:

$$logalcohol_i = \begin{cases} logalcohol_i^* \; if \; alcohol_i^* > 0 \\ 0 \; if \; alcohol_i^* \leq 0 \end{cases}$$

Where $alcohol_i^*$ is a latent variable taking linear functional form:

$$logalcohol_i^* | price_i, X_i = \alpha logprice_i + X_i' \beta + \varepsilon_i$$

Error term ε_i is assumed to follow normal distribution with mean 0 and variance σ_ε^2.

Tobit model assumes a single decision for individual's alcohol demand. The individual chooses the level of pure alcohol consumption, with positive demand corresponding to desired level of drinking and zero demand representing a corner solution in which the preferences of drinking or capability of purchase is too low to spend anything on alcohol. Tobit maximum likelihood estimator is consistent under the assumptions of normally distributed and homoskedastic error terms. However, Tobit maximum likelihood estimator becomes nonrobust when these strong assumptions are violated.

Price elasticity in Tobit model can be computed based on McDonald and Moffitt 1980 (McDonald and Moffitt 1980). The total change in outcome variable $logalcohol_i$ can be disaggregated into two parts: the change in $logalcohol_i$ above the threshold, weighted by the probability of being above the threshold 0, and the change in the probability of being above the threshold 0, weighted by the expected value of $logalcohol_i$.

The expected value $E(logalcohol_i)$ is given by:

$$E(logalcohol_i) = [\alpha logprice_i + X_i' \beta] * \Phi \left[\frac{(\alpha logprice_i + X_i' \beta)}{\sigma_\varepsilon} \right] + \sigma_\varepsilon * \phi [\frac{(\alpha logprice_i + X_i' \beta)}{\sigma_\varepsilon}]$$

The elasticity from Tobit model therefore can be computed from the expected value, simply be:

$$\alpha \Phi [\frac{(\alpha logprice_i + X_i' \beta)}{\sigma_\varepsilon}]$$

1.4.3.3 Two-part model in Pooled Data

The Tobit model makes strong assumption that the same probability mechanism generates both the zero observations and positive observations. It is more flexible to allow for the possibility that zeros and positives are generated by different mechanisms. The alternative model often applied in health economics is Two-part model that relax the Tobit model assumptions. Unlike Tobit model, Two-part model also does not require homoskedasticity and normality for consistency of estimators. The first part estimates the probability of participating drinking by Probit model (or Logit):

$Prob(alcohol_i > 0|price_i, X_i) = \Phi(\alpha_1 logprice_i + X_i'\beta_1 + \varepsilon_{1i})$

Where Φ is normal cumulative distribution function.

The second part of the OLS model predicts the drinking consumption levels among drinkers who consume positive quantity in observed period:

$logalcohol_i|price_i, X_i, alcohol_i > 0 = \alpha_2 logprice_i + X_i'\beta_2 + \varepsilon_{2i}$

The error term in second equation ε_{2i} is conditionally independent of covariates and need not be normally distributed for consistent estimates.

The unconditional expected value of drinking consumption quantity in log term is given by:

$E(logalcohol_i|price_i, X_i) = Prob(alcohol_i > 0|price_i, X_i) * E(logalcohol_i|price_i, X_i, alcohol_i > 0)$

Where $Prob(alcohol_i > 0|price_i, X_i)$ is the predicted probability of individual i participate in drinking, and $E(logalcohol_i|price_i, X_i, alcohol_i > 0)$ is the level of drinking estimated from second part OLS in log term.

The price elasticity of alcohol demand is a combination of two parts:

$Prob(alcohol_i > 0) * \alpha_2 + E(logalcohol_i|price_i, X_i, alcohol_i > 0) * \phi(\alpha_1 logprice_i + X_i'\beta_1) * \alpha_1$

where α_1 the price coefficient estimated in first part of probit model, and α_2 is the price coefficient estimated in second part of linear model.

The Two-part model has the advantage in its flexibility and easy interpretation. But the assumption that the two parts – the decision to drink alcohol and amount drink – are independent is a potential restriction on the model. If drinkers who drink positive amount of alcohol are not randomly drawn from population after controlling for regressors, the estimates from second part would be subject to selection bias.

1.4.3.4.Tobit Model in Panel Data

The models specified above provide consistent estimates of price elasticities in cross-sectional data if the model assumptions are valid. However, such estimators in data pooling from longitudinal panels (which this study relies on) are subject to bias that is caused by individual unobserved heterogeneity. In addition, pooled data is not able to utilized individual variations across time. Tobit models in Panel data are therefore performed to model male drinking level decisions.

In a random effect Tobit:

$$logalcohol_{it} = \begin{cases} logalcohol_{it}^{*} \; if \; alcohol_{it}^{*} > 0 \\ 0 \; if \; alcohol_{it}^{*} \leq 0 \end{cases}$$

Where $alcohol_{it}^{*}$ is a latent variable:

$$logalcohol_{it}^{*}|price_{it}, X_{it} = \alpha logprice_{it} + X_{it}'\beta + a_i + \varepsilon_{it}$$

With $a_i \sim N(0, \sigma_a^2)$, and $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$. a_i is random individual specific error term to capture unobserved heterogeneity.

Random effect Tobit model has its advantage to utilize repeated measures for a given individual, and to some extent address unobserved heterogeneity problem by incorporating a pure random individual specific error. At the same time, the reliance on distributional assumption in cross-sectional case becomes much greater in censored panels, and the assumption of pure random effect independent of covariates may be too strong.

Fixed effect Tobit model in panel data is first formulated by Honoré (Honoré 1992) but not widely used in health economic literature. The model is specified similarly with random effect Tobit, but unobserved individual specific effect a_i is permitted correlated with time-variant explanatory variables $price_{it}$, X_{it}'. The distribution of error term ε_{it} in Honoré's model is unspecified. The estimation is semiparametric: data are artificially trimmed so fixed effect is subsequently eliminated by apropriate diffrencing. Although the fixed effects maximum likelihood estimator is inconsistent in short panels because of the incidental parameters problem, Honoré's semiparametric estimator is shown to be $\sqrt{N}$ consistent and asymptoticall normal. Very few studies provide support to the performance of fixed effect Tobit to date (Chay and Honore 1998; Honore 2004; Honoré 1992).

1.4.3.5 Logit Model in Panel Data

Because 90% of female population are non-drinkers, Tobit model is obviously not appropriate in this large zero sample. We instead use random effect Logit model to utilize repeated measures in panel data for drinking participation decisions among females.

The Logit model in panel data specifies that:

$$Pr\left(drink_i^t\right) = \Lambda(logprice_{it}, X_{it}', a_i)$$

Where $drink_{it} = \begin{cases} 1 \; if \; alcohol_{it} > 0 \\ 0 \; if \; alcohol_{it} = 0 \end{cases}$ and Λ is the Logit function. When a_i is independent with covariates, the model is random effect Logit. Because female's drinking participation decisions do not have necessary variation over time, fixed effect Logit model is not employed here.

1.4.4 Heterogeneous Price Elasticity Estimators

If the homogeneous responsiveness to alcohol price assumption is violated, the estimated price elasticity α will vary across subgroups, different consumption level of drinkers, or different types of drinking, and the differential effect of alcohol price will be masked. Three sources of heterogeneity are analyzed separately. Subsample analysis is used to model heterogeneity in price elasticity across socioeconomic subgroups. Quantile regression is performed to model heterogeneity in drinking levels, and joint equation estimation is the technique to model self and cross price elasticity across different drink types.

1.4.4.1 Socioeconomic Subsample Analysis to model heterogeneity in socioeconomic characteristics

We group individuals based on their basic socioeconomic characteristics, including region of residence (urban or rural), age group (younger adult 18-45, older adult 46-59, and seniors 60+), income quartiles (lowest 25% quartile and highest 25 quartile in household per capita income distribution), labor force status (not in labor force, self employed, employed in public sector and employed in private sector). Price elasticity in each subsample is estimated using tools for average price elasticity, including two-part model and Tobit model.

1.4.4.2 Quantile Regression to model heterogeneity in drinking level

While heterogeneity across various socio-economic subgroups can be simply addressed by performing subgroups analysis or adding interaction terms, the different responses at different levels of alcohol consumption cannot be directly estimated in the models discussed above since all of them estimate the conditional mean of outcome variables.

Quantile regression is a natural candidate to solve heterogeneous response in level of drinking. It approximates median or quantile of the outcome variable, providing a more complete picture about the relationship between the outcome variable and independent variable at different points in the distribution of drinking quantity. Because Quantile regression is appropriate for continuously distributed positive observations, we focus on subsample of drinkers only.

If $alcohol_i$ is a random variable with distribution function log normal, $F(alcohol_i) = \Phi(\log(alcohol_i))$, the qth quantile estimator $\widehat{\beta_q}$ minimizes over β_q the objective function:

$$Q(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q\left|logalcohol_i - \alpha logprice_{it} - X_i'\beta_q\right| + \sum_{i:y_i < x_i'\beta}^{N} (1-q)\left|logalcohol_i - \alpha logprice_{it} - X_i'\beta_q\right|$$

Where 0< q <1, and β_q denotes estimates of β from different choice of q.

Quantile regression was first used in Manning (Manning, Blumberg, and Moulton 1995) to estimate differential price responsiveness at different drinking levels. It is well behaved in the context of continuous quantity data. Quantile regression has several advantages: median regression is more robust to outliers than mean regression; Quantile regression offers a richer understanding of the data by examining the impact of independent variable at different points of outcome variable; and Quantile regression is semiparametric, in the sense that it avoids assumption about parametric distribution of regression errors, making it especially suitable for heteroskedastic data. At the same time, Quantile regression is not able to incorporate large zeros that general population is featured with.

1.4.4.3 Joint Equation Regression to model heterogeneity in drink type

To examine the heterogeneity in price response to different alcoholic beverage types, joint equation regression (multi-equation regression) techniques are used to model multiple choices decisions of the same individual. Although estimates can be conducted separately for each type of beverage, joint equation regression is more efficient when errors of each type are correlated because it models the joint distribution of the errors. We model participating probability for beer and liquor only, since wine accounts for negligible share of alcohol market (3.5%) and price of wine is not available in the dataset.

Considering beer and liquor participating decisions, they are potentially related after conditional on regressors. Specifically, the two participating outcomes are determined by two unobserved latent variables:

$$drinkbeer_i^* = a_1 logprice_i + X_i'\beta_1 + Z_i'\gamma_1 + \varepsilon_{1i}$$

$$drinkliquor_i^* = a_2 logprice_i + X_i'\beta_2 + Z_i'\gamma_2 + \varepsilon_{2i}$$

Where ε_{1i} and ε_{2i} are jointly normally distributed with means of 0, variance of 1, and correlations of ρ, and we observe the two binary outcomes:

$$drinkbeer_i = \begin{cases} 1 \; if \; drinkbeer_i^* > 0 \\ 0 \; if \; drinkbeer_i^* \leq 0 \end{cases} \text{ and}$$

$$drinkliquor_i = \begin{cases} 1 \; if \; drinkliquor_i^* > 0 \\ 0 \; if \; drinkliquor_i^* \leq 0 \end{cases}$$

The model reduces to two separate Probit models if ρ=0.

The advantage of joint equation regression is that it allows us estimate joint and conditional probabilities across drink types for the same individual.

1.5 Data

1.5.1 Sample

On-going individual-level longitudinal data from the China Health and Nutrition Survey (CHNS) was the data source for statistical analysis. CHNS is a collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. This interviewer-administered survey used multistage, random cluster sampling approach and sampled around 4000 households from over 200 communities in nine provinces [5] which are fairly representative of mainland China's central and eastern area and vary substantially in population sociodemographic characteristics, economic development levels, food and physical activity environments, and health indicators. It also provides detailed information drinking behavior of the respondents. Community-facility survey provides detailed community data in which respondents reside including food market, health facilities, local environment, and more relevant to this research, price of certain product in local community such as alcohol. Five current available waves (1993, 1997, 2000, 2004, and 2006) were analyzed in this study. The first wave 1989 data was not used because of incomplete information on labor drinking behaviors. 1991 was also dropped since price data was not collected until 1993 survey.

This paper restricts the analysis within adult (18 years or older) sample only because drinking behavior questions were not collected among youth. The effective sample with complete information therefore included 47,685 observations of 18,266 individuals.

1.5.2 Dependent Variables: Alcohol Consumption Quantity

This paper focuses on the impact of alcohol prices on individual alcohol consumption. The primary outcome of concern is milliliters of pure alcohol (ethanol) consumed each week. Although quantity of alcohol, such as total bottles or total liters of alcoholic beverage consumed in a certain period, is also frequently studied in the literature, pure alcohol is of more interest from a public health perspective. Expenditure on alcohol is not analyzed either, because expenditure data is not directly reported by individuals.

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[5] The nine provinces include LiaoNing, HeiLongJiang, and ShanDong in Northeast, Jiangsu in East, HeNan, HuBei, and HuNan in Middle, GuiZhou in Southwest, and GuangXi in South. HeiLongJiang participated in the survey from 1997, and LiaoNing was not surveyed in 1997. Source: http://www.cpc.unc.edu/projects/china

Drinking behaviors of three alcoholic beverages were documented in the survey, including liquor (30%-50% ethanol), grape wine/colored wine/yellow wine (12-18% ethanol) and beer (4-6% ethanol). Each survey asked whether respondents ever drink any alcoholic beverage last year. Those who were identified as current drinker were then asked the frequency of drinking in a week or a month reference period. The following question asked the quantity (in bottle, or liang) of each type of alcoholic beverages per week if individual drinks. Utilizing such information, the pure alcohol consumption quantity (ml) per week can be constructed. It should be noted that the use of self-report drinking behavior is likely subject to underreporting problem. The estimates of price elasticity would be unbiased if underreporting is proportional in general population. However, if underreporting is disproportional across different types of drinkers, for example, higher level drinkers may be more likely to deny heavy drinking, estimates of price elasticity would be biased (Manning, Blumberg, and Moulton 1995).

Table 2 illustrates the pattern of drinking behavior in the study sample. About one third (34.25%) people reported participation in alcohol drinking in general population. While two thirds of males drink, only less than 10% of females are current drinkers. By type of alcoholic beverage consumed, liquor drinking accounts for the largest share among people who drink (48% males and 5% females). Beer drinking is also prevalent (30% in general population), but wine is far less common (5% in general population) compared with western countries. By age bands, beer is less popular than liquor for seniors (age 60+) but more prevalent among younger adults (age 18-45). With respect to level of drinking among drinkers, liquor is prominent across gender and age groups, while wine and beer ethanol consumption are about the same magnitude for both genders and all age groups. Drinking participation and level of drinking also exhibit substantial difference across labor force status. Those being not active in labor market are less likely to be drinkers (22.80%), and drink less beer than others. Participation of drinking is more prevalent among employed people (in public or private sector), and level of drinking is highest among employees in private sector and self-employed.

Table 2: Alcohol drinking pattern across basic socioeconomic groups

Consumption	Total population	Male	Female	18-45	46-59	60+	Not active in labor force	Employed in public sector	Employed in private sector	Self-employed
Participate drinking (%)										
Any alcohol	34.25	60.57	9.62	35.11	37.17	28.13	22.80	46.27	41.68	35.65
	(47.45)	(48.87)	(29.49)	(47.73)	(48.32)	(44.96)	(41.96)	(49.86)	(49.30)	(47.89)
Beer	16.73	30.13	4.20	21.18	15.30	6.83	9.96	29.11	24.76	14.93

	(37.33)	(45.88)	(20.06)	(40.86)	(36.00)	(25.24)	(29.95)	(45.43)	(43.16)	(35.64)
Liquor	26.32	48.80	5.29	25.10	30.78	23.69	16.97	32.48	29.61	29.36
	(44.04)	(49.98)	(22.39)	(43.36)	(46.16)	(42.52)	(37.53)	(46.83)	(45.66)	(45.54)
Wine	3.53	5.13	2.04	3.56	3.72	3.24	3.42	6.08	5.95	2.22
	(18.47)	(22.07)	(14.15)	(18.53)	(18.93)	(17.71)	(18.19)	(23.90)	(23.66)	(14.73)
Total pure alcohol (ml) consumed/wk in each type of alcohol beverage if drinker (mean)										
Any alcohol	227.81	249.17	97.69	205.22	265.92	235.61	221.20	206.28	239.14	237.23
	(280.40)	(290.92)	(149.43)	(257.13)	(314.97)	(282.26)	(274.22)	(251.48)	(275.44)	(295.39)
Beer	51.03	54.90	27.43	63.57	44.45	21.74	42.28	70.38	64.37	42.42
	(108.64)	(112.88)	(73.65)	(116.54)	(108.06)	(69.42)	(92.72)	(122.62)	(108.41)	(106.35)
Liquor	166.46	185.28	55.79	132.92	211.02	199.73	161.66	124.40	162.67	188.21
	(251.69)	(263.75)	(111.67)	(212.84)	(294.22)	(272.66)	(251.45)	(192.89)	(248.45)	(272.53)
Wine	7.87	7.28	11.45	6.01	8.76	12.47	12.06	8.83	9.96	5.33
	(48.20)	(47.29)	(53.17)	(38.07)	(53.04)	(65.70)	(62.83)	(49.78)	(49.14)	(39.99)

Sometimes heavy drinking (alcohol abuse, problem drinking or binge drinking) is of more research interest since they are associated with most risky behavior and generate most harmful health effects and external cost to society. To define such group of drinkers, we need to know number of drinks people consumed in each occasion. Unfortunately, the survey only asked number of days and quantity of drinking in reference period of a week. Lack of information on drinking behavior in a single occasion, the analysis is not able to categorize population into light, moderate and heavy drinkers as conventional literature does. Instead, we use quantile of pure alcohol quantity consumed in a week as a proxy to analyze differential responses to alcohol across level of drinking.

The structure of drinking patterns by alcohol type has changed noticeably since 1980s (Pan, Fang, and Malaga 2006). Chinese drink liquor traditionally, but beer consumption increased rapidly. The joint distribution of beer and liquor participation for sampled males is illustrated in **Table 3.** A third of male population consume beer, and among beer drinkers 43% consume liquor as well. Among a half of males who drink liquor, a larger proportion (70%) of them also drink beer. We see a high correlation between demand of beer and liquor.

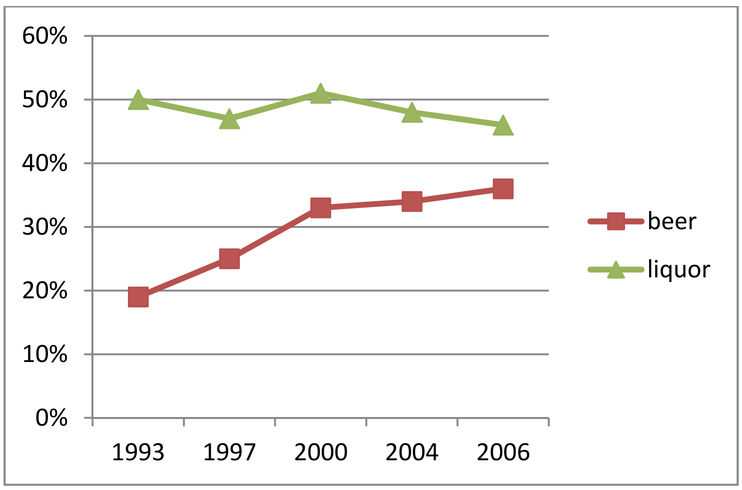
Table 3: Drinking Pattern by Type of Drinks, Adult Male Population (%)

probability	Probability	Conditional on drinking liquor	Conditional on drinking beer
Beer only	9.05%	/	/
Liquor only	27.72%	/	/
Beer	30.14%	43.20%	100%

Liquor	48.80%	100%	69.96%

Looking at the time trend of drinking across types, the proportion of beer consumers has been rapidly increased between 1993 (19%) and 2006 (36%), almost double within 13 years. The proportion of liquor drinkers dropped slightly in contrast, from 50% in 1993 to 46% in 2006. The considerable changes of beer and liquor participation are in accordance to price variations at the same period (discussed in next section).

Figure 1: Beer and Liquor Drinking Participation across Waves, Adult Male Population (%)



1.5.3 Key Explanatory Variable: Alcohol Price

We rely on community-level alcohol prices reported by community head or collected by survey teams at local markets in the communities, then merge the price data with individual information. Community-level price were presumably more accurate and provided more variations as opposed to national or provincial price data. At the same time, community reported alcohol price has its own disadvantage. Albeit community alcohol price is relatively reliable in that it was reported by community head or collected by survey staff at local markets, it only represents the most common local brand which is usually cheaper than top brand. We may expect high-income consumers are more likely to choose high-end brand, the price of which is not fully represented by local brands. In addition, price of alcohol at local market is a valid measure only when consumers obtain product from local market. The use of local price may ignore the purchase from nearby communities. Although there is no accurate estimate of smuggling for alcohol products in China, we suggest smuggling does not substantially affect our results in that few of the provinces we sampled are located near the country borders where smuggling is likely an issue.

Prices of local beer (per bottle, 640ml) and local liquor (per bottle, or 500ml) were reported, but price of wine was not. Considering that wine consumption in China is very small, we assume price of wine will not have a significant impact on individual drinking behavior. To capture price information from various types of alcoholic drinks, the combined price variable is often constructed in literature. For example, Manning (Manning, Blumberg, and Moulton 1995) and Farrell (Farrell, Manning, and Finch 2003) weighted price by drinking quantity in ounces, while Markowitz (Markowitz 2000) and Saffer (Saffer and Chaloupka 1999) weighted price by pure alcohol consumption. We choose to weight our price variable by relative pure alcohol consumed in each community in accordance with the combined pure alcohol outcome variable, and use price weighted by consumption quantity as a sensitivity check. When community reported alcohol price is missing (11.3% community did not report local beer price, and 7.8% did not report local liquor price), we fill in the average of the province in which the community belongs to.

The study period 1993-2006 is an era in which China experienced huge changes in its economic development, and such process is uneven across geographic areas. The price measures have large variations across communities as well as over time. The between community standard deviation of alcohol ethanol weighted price is 4.10 Chinese Yuan, and within community standard deviation of alcohol ethanol weighted price is 3.96 Yuan. **Figure 2** presents the trend of price variation between study period (1993-2006) and **Figure 3** shows average price across provinces. All monetary values were inflation adjusted to 2006 Chinese Yuan using Consumer Price Index provided by CHNS. Over time, local beer price was considerably reduced, from 3.17 Yuan in 1993 to 2.14 yuan in 2006; while local liquor price almost doubled from 4.13 yuan to 8.39 yuan during 13 years. Because pure alcohol in liquor accounts for approximately 80% of the total ethanol a typical person drinks, the ethanol weighted alcohol price is showing an upward trend as well. Price of alcohol, especially for local liquor, varies a lot across provinces, with highest price in Shandong, Henan and Hunan, and lowest price in Heilongjiang, Guangxi, and Guizhou.

Figure 2: Trend of price variation between study period (1993-2006), 2006 Chinese yuan

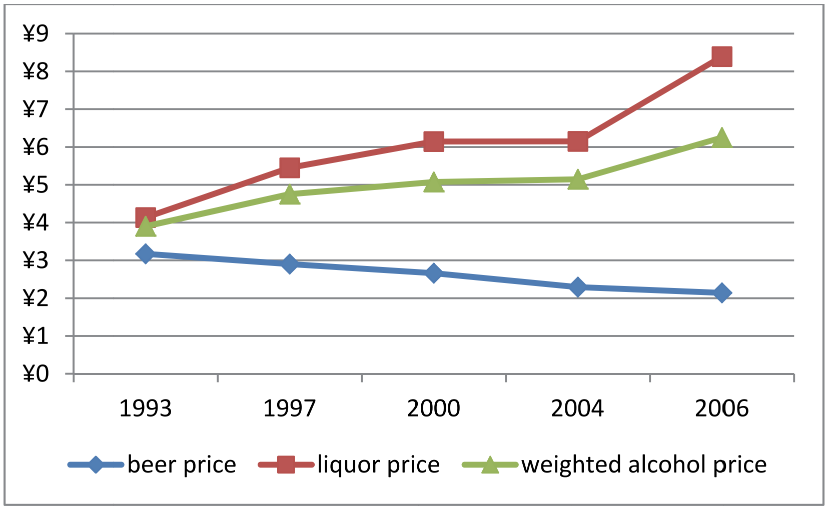
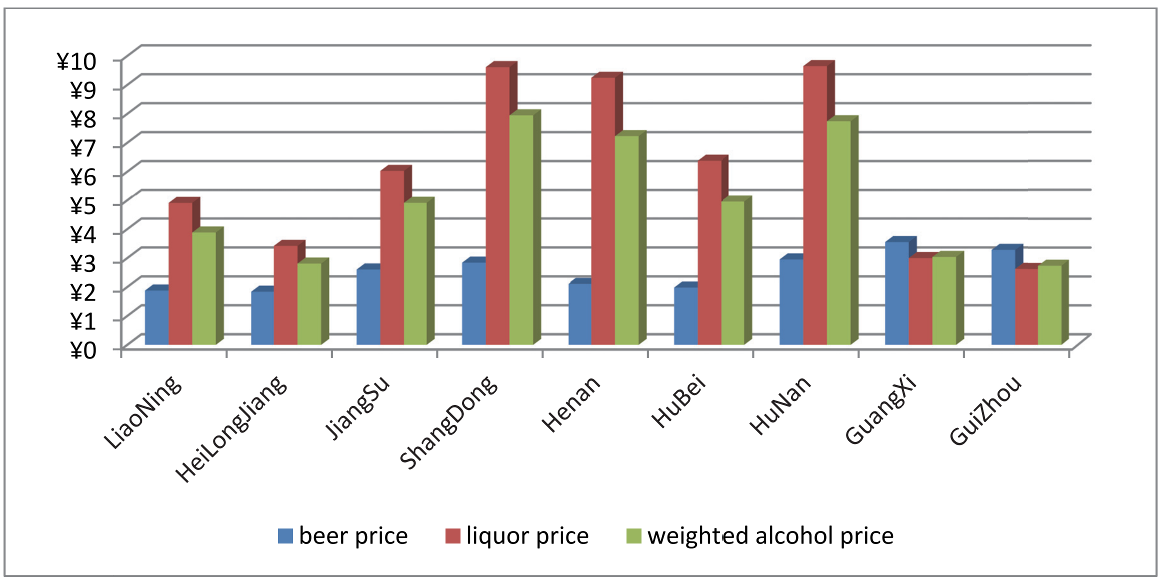


Figure 3: Average price across provinces, 2006 Chinese yuan



The anecdotal evidence from newspaper suggests that the diverging trend between liquor and beer price in recent decade is most driven by monopoly in liquor market and over-competition in beer market. Alcohol factories in China are located throughout the country, and local brand usually dominates the alcohol market share. Local alcohol price is substantially affected by many factors from both supply side and demand side, such as transportation cost, labor cost, local economic development level, price of raw materials, industry competitions, price regulations and policy interventions, and consumer taste. Top grade liquor market, featured with high taxes and high profit, is mostly monopolized by such brand as Maotai, Guojiao, Luzhou Aged Liquor and Shuijangfang. The top grade liquor brands have spread the operating network broadly across the nation. Beer, in contrast, has no nationally recognized brands. Local brands are widely dominating the regional markets, featured with intensive competition and poor profitability.

Furthermore, we did not find noticeable outliers that are primarily driving the time and geographic price variations. To check the robustness of inclusion of price outliers, we conduct separate analysis with alcohol price in the lowest 1% and highest 1% distribution trimmed. The results are not sensitive to this arrangement (see section 1.6). The time and geographic variation for alcohol price is not exceptional; it is also seen on other goods such as cigarettes (Lance et al. 2004).

1.5.4 Other Determinants of Alcohol Use

Besides alcohol price, other determinants of alcohol use can be grouped into the following three categories: individual socio-demographic characteristics that are associated with his/her preference drink, individual socio-economic characteristics that are associated with his/her ability to drink, and community environment that are associated with alcohol provision.

1.5.4.1Individual Characteristics Associated with Preference of Drink

Certain individual demographics are associated with preference of alcohol drink, including age, gender, ethnic groups (Han or minority), and marital status. Education has shown to be significantly correlated with alcohol consumption in numerous studies. It is measured by indicators for never completing primary school, for lower middle school degree, and upper middle school degree or above. Variable "number of meals eating at home in past 3 days" is constructed to measure whether dining out frequently is associated with alcohol demand. This variable is of particular interest because social drinking in China is a common phenomenon. Self-reported health status was used as a proxy for health measure. People in north part of China tend to have heavier drinking habits than those living in south part. Province indicators are therefore introduced to control for geographic variations.

1.5.4.2 Individual Characteristics Associated with Ability to Drink

Urban and rural dummy variable represents individual residency status, that is presumably associated with access of alcohol drinks. Income is a significant indicator of individual financial capability to purchase alcohol drinks. Log of deflated household per capita income is therefore used to control for individual financial status. Labor force status in China, categorized as employed in public sector, employed in private sector, self-employed, and not active in labor force, is assumed to be correlated with alcohol consumption. For example, working people are more likely to be provided with alcohol drinks at social drinking occasions relative to people who are not active in labor force.

1.5.4.3 Community Environment Associated with Alcohol Provision

The community environment variables represent community economic development level and cost of living (community population density, percentage workforce engaged in agriculture, ordinary male worker wage, percentage workforce working outside of town, education facilities, healthcare facilities), access to alcohol and related food commodities (number of restaurant, market access), and transportation infrastructure that are associated with alcohol provisions in the community. Some of these variables have been previously used in CHNS-based literature (Ng, Norton, and Popkin 2009; Zimmer, Kaneda, and Spess 2007). Year dummies are also included to account for possible time effect.

1.5.5 Summary Statistics

Descriptive summary statistics are illustrated in **Table 4**.

Table 4: Dependent, Independent Variable and Descriptive Statistics

Variable	Description	mean	std	min	max
Dependent Variable: Alcohol consumption					
Participate drinking	Drink any alcoholic beverages last year	.34	.47	0	1
drinking quantity	Total pure alcohol (ml) consumed/week	75.07	193.31	0	2511
Alcohol Price Variable					
Weighted alcohol price	Community pure alcohol weighted local alcohol price in 2006 Chinese yuan	5.19	5.65	.46	51.55
Local beer price	Local beer price in 2006 Chinese yuan	2.59	2.01	.47	31.59
Local liquor price	Local liquor price in 2006 Chinese yuan	6.15	7.16	.12	55.96
Individual Characteristics Associated with Preference of Drink					
Age	Age in years	45.13	15.95	18	101
Gender	Gender (male=1, female=0)	.48	.49	0	1
Ethnicity	Ethnic group (Han=1, minority=0)	.87	.33	0	1
Marital Status	Marital status (married=1, other=0)	.78	.40	0	1
Education					
	Primary school or below (base)	.47	.49	0	1
	Lower middle school	.30	.46	0	1
	Upper middle school or above	.22	.41	0	1
Meal at home	3-day total times eating at home including breakfast, lunch and dinner (score ranging from 0 to 9)	7.95	1.78	0	9
Good health	Self-reported health status. Excellent or good=1, fair or poor=0	.65	.47	0	1
Individual Characteristics Associated with Ability to Drink					
Region	Region (urban=1, rural=0)	.33	.47	0	1

HH per capita income	Household per capita annual income in 2006 Chinese thousand yuan	18206	20676	-25934	744328
Labor force status	Not active in labor force (base)	.28	.45	0	1
	Work in public sector	.097	.29	0	1
	Work in private sector	.15	.36	0	1
	Self-employed	.46	.49	0	1
Education					
	Primary school or below (base)	.47	.49	0	1
	Lower middle school	.30	.46	0	1
	Upper middle school or above	.22	.41	0	1
Meal at home	3-day total times eating at home including breakfast, lunch and dinner (score ranging from 0 to 9)	7.95	1.78	0	9
Good health	Self-reported health status. Excellent or good=1, fair or poor=0	.65	.47	0	1
Community Environment Associated with Alcohol Provision					
Population density	Population density of the neighborhood = population/square kilometers	3847	9641	.16	162500
Agriculture share	% workforce engaged in agriculture	37.86	33.86	0	100
Male worker wage	Ordinary make worker daily wage in the neighborhood in 2006 Chinese yuan	23.57	13.78	0	233.93
Work outside share	% workforce working outside of town longer than one month	25.65	23.65	0	100
Education facilities	Sum score of primary, lower middle, upper middle and vocational school accessibility. Community was assigned two points if each of the school was located within the community boundary and one point if the school was not in the community but located < 5 km outside of the community (score ranging from 0 to 8)	4.25	1.69	0	8
Health facilities	Health facilities available within the community were given 1 point for each village or work unit clinic, 2 points for neighborhood or maternal child health (MCH) clinics, 3 points for town hospital, 4 points for district hospital, 5 points for county, work unit or army hospital, 6 points for private for city hospital, and 7 points for university hospital. Facilities available outside the community but <10 km away were given half of the listed points (score ranging from 0 to 33)	5.53	3.84	0	33
Restaurant	Total number of indoor restaurants	10.26	20.56	0	400
Market access	Sum score of seven food accessibility in the market (grains, oil, vegetable, meat, fish, bean curd, and fuel), with one point assigned for each good available within the community and half point assigned for each good available in a neighbor community < 1 km away (score ranging from 0 to 7)	2.74	2.29	0	7
Transportation infrastructures	Sum score of bus stop and train station accessibility. Community was assigned two points if their leaders reported a bus stop or train station	1.83	1.24	0	4

	within their community boundaries and assigned one point if there was a bus stop or train station in a neighbor community <1 km away) (score ranging from 0 to 4)				
Total #obs		47685 (18266 individuals, 234 communities)			

1.6 Results

In this section, we first assume alcohol demand is homogeneous and illustrate estimations from alternative specifications. After performing robustness check for outcome and price variables, we further explore the heterogeneity of price elasticity stemming from three different sources: socioeconomic characteristics, level of drinking, and type of drinks. Statistical software Stata 11 is used for econometric analysis[6].

1.6.1 Average price elasticity estimate

Before exploring heterogeneity of price responsiveness for alcohol consumption, we report coefficient estimates for homogeneous demand based on alternative model specifications. **Table 5** and **Table 7** contain results for adult male and female sample, respectively. We start with benchmark OLS model with community variables and wave province interactions, which yield inconsistent results because of censoring issues in alcohol consumption. OLS model gives us estimate of alcohol price elasticity among male adult population at -.088, and among female adult population at -.050.

We then focus on two-part model with participating decision and conditional consumption level equations separately estimated. In Two-part model, the increase of pure alcohol weighted price is significantly associated with a non-negligible drop in pure alcohol consumption per week for both adult male and female sample. The participation decision and consumption level combined price elasticity in all models for both genders is about -0.07. The price elasticity for being a drinker (first part) among males is -0.013, and the conditional response (second part) is slightly higher (-0.034). Among females, the price elasticity with respect to level of drinking (second part) among females is much larger (-0.11), and price elasticity for being a drinker (first part) is smaller (-0.015).

Tobit model results are reported for male sample only in **Table 5**. The estimated price elasticity in pooled Tobit model is slightly larger than that estimated in two-part model for males, which is -.11. Random effect Tobit model utilizes the nature of longitudinal data and provides a smaller estimate (-.034) relative to pooled Tobit model. The difference between pooled Tobit and random effect Tobit in panel data is

[6] Stata command "pantob" is borrowed from Honoré (Honoré 1992).

mostly driven by panel nature of the dataset.The unobserved heterogeneity across individuals explains a large fraction of alcohol demand variation over time (44% in random effect Tobit). This suggests that pooled Tobit is not appropriate if individual unobserved heterogeneity is not controlled for in panel data. The results are not surprising, however, as we see estimates from panel data are in general smaller than those estimated from cross-sectional data (Gallet 2007)[7]. Fixed effect Tobit model generates an insignificant positive price elasticity .046, again suggesting that unobserved heterogeneity plays a significant role on the relationship between alcohol price and alcohol demand over time. Compared with pooled data estimators (Two-part model and pooled Tobit model), random effect Tobit and fixed effect Tobit is probably closer to the "true" price elasticity in that they are able to account for unobserved heterogeneities and utilize repeated measures for a given individual over time. Although panel Tobit has its own limitations, we suggest that the real responsiveness to alcohol price in China approaches zero.

Tobit model is not appropriate for female sample considering over 90% sample do not drink. We instead employ random effect Tobit to capture participating decisions over time. The estimation results suggest similar coefficient estimate with first part of two-part model: price coefficient is estimated at -.12. Again, unobserved individual heterogeneity explains large fraction of variations in alcohol demand (rho=0.44).

In sum, the estimated price elasticity among China adult population is much smaller than estimates from western country population (-0.50 to -0.60), ranging between .046 to -.11 for males and -.05 to -.07 for females depending on model specification. Unobserved heterogeneity plays a significant role in the relationship between alcohol price and alcohol demand.

The conclusions we draw across different model specifications are consistent with respect to the relationship between other explanatory variables and alcohol demand, several of which are noteworthy. Taking income as an example, response to income is elastic in all models, with combined elasticity estimated among males at about 0.11 in two-part model, and 0.5 in Tobit random effect model. Region of residence, labor force status, and education are significantly associated with pure alcohol consumption: urban residence, currently employed and educated population are more likely to be drinkers or drink more. Number of meals eating at home gives expected result: the more frequently males have meals at home, the less they drink. This is in line with China drinking culture: social drinking accounts for large fraction of drinking occasions (Hao 2005). Coefficients of most of community variables representing economic development levels are not significant, possibly because individual characteristics have partly captured

[7] Estimates from (Gallet 2007) are primarily based aggregate data sources though.

this information. Transportation infrastructures have positive effect on alcohol demand as expected since it is directly associated with alcohol provision at communities.

Table 5: Coefficient Estimates among Adult Male Population Assuming Homogeneous Demand

Outcome variable: Pure alcohol consumed/week (ml), log transformed	**OLS**	**Two-Part**		**Tobit**		
		Participating Decision	**Conditional Consumption Level**	**Pooled Data**	**Random Effect**	**Fixed Effect**
Log pure alcohol weighted price	-.088 (-2.69)***	-.027 (-1.70)*	-.034 (-1.95)**	-.14 (-2.54)***	-.042 (-1.85)*	.046 (0.91)
Age	.0060 (3.26)***	.0031 (0.35)	.0062 (6.46)***	.0092 (2.88)***	.0070 (2.39)**	-.0076 (-1.03)
Han	-.33 (-3.97)***	-.16 (-4.03)***	-.083 (-2.09)**	-.56 (-4.00)***	-.58 (-4.22)***	
Married	.83 (15.15)***	.41 (15.34)***	.18 (6.00)***	1.50 (14.78)***	1.27 (14.88)***	
Urban	.11 (1.95)**	.12 (4.34)***	-.11 (-4.30)***	.23 (2.47)**	.24 (2.68)***	
Log HH per capita income	.039 (2.96)***	.0091 (1.35)	.024 (3.43)***	.062 (2.66)***	.057 (2.80)***	.080 (3.21)***
Work in public sector	.85 (12.52)***	.44 (12.87)***	.078 (2.11)**	1.57 (13.01)***	1.35 (13.05)***	
Work in private sector	.83 (11.27)***	.40 (10.91)***	.12 (3.20)***	1.52 (11.68)***	1.34 (12.29)***	
Self-employed	.78 (12.73)***	.38 (12.82)***	.11 (3.31)***	1.46 (13.01)***	1.21 (13.31)***	
Lower middle school diploma	.095 (1.61)*	.066 (2.33)**	-.029 (-5.69)***	.19 (1.98)**	.20 (2.22)**	
Upper middle school or above diploma	.025 (0.36)	.043 (1.29)	.13 (5.98)***	.069 (0.59)	.066 (0.61)	
Meal at home	-.053 (-5.00)***	-.020 (-3.93)***	-2.40e-06 (-1.75)*	-.082 (-4.69)***	-.069 (-4.52)***	-.067 (-4.10)***
Good health	.42 (9.97)***	.18 (8.77)***	.0013 (3.10)***	.69 (9.47)***	.43 (6.99)***	.19 (2.86)***
Population density	-5.27e-06 (-2.06)**	-1.50e-06 (-1.27)	.0010 (1.24)	-7.82e-06 (-1.76)*	-7.41e-06 (-2.00)**	-1.37e-06 (-0.27)
Agriculture share	.0015 (1.86)*	.00036 (0.88)	.00085 (1.92)*	.0020 (1.41)	-.000014 (-0.01)	-.0021 (-1.25)
Male worker wage	.0021 (1.39)	.00027 (0.37)	.0010 (1.24)	.0032 (1.31)	.0029 (1.32)	.0019 (0.89)

Work outside share	-.00055 (-0.66)	-.00031 (-0.74)	.00085 (1.92)*	-.0013 (-0.93)	-.00062 (-0.50)	.00077 (0.54)
Restaurant	-.00035 (-0.32)	-.00015 (-0.27)	-.000046 (-0.08)	-.00071 (-0.38)	.00028 (0.17)	.0024 (1.32)
Market access	-.0045 (-0.50)	-.00041 (-0.09)	.0060 (1.28)	-.0094 (-0.62)	-.0073 (-0.55)	.0062 (0.45)
Education facilities	.043 (3.26)***	.018 (2.86)***	.010 (1.45)	.073 (3.21)***	.051 (2.61)***	.026 (1.10)
Health facilities	.00030 (0.06)	-.0016 (-0.60)	.0031 (1.05)	.00018 (0.02)	.0070 (0.85)	.021 (2.36)**
Transportation infrastructures	.087 (4.90)***	.036 (4.22)***	.020 (2.28)**	.14 (4.75)***	.069 (2.65)***	
Wave dummies	Y	Y	Y	Y	Y	N
Province dummies	Y	Y	Y	Y	Y	N
Wave and province interactions	Y	Y	Y	Y	Y	N
R-Squared	.068		.074			
Log Likelihood		-14351.79		-42935.91	-41531.19	
Rho					0.44	
Obs	21757	22466	12554	21757	21757	21848

***denotes significance level at 0.001, ** denotes significance level at 0.05, and * denotes significance level at 0.1.

Table 6: Price Elasticity Estimates among Adult Male Population Assuming Homogeneous Demand

Outcome variable: Pure alcohol consumed/week (ml), log transformed	OLS	Two-Part			Tobit		
		Participating Decision	Conditional Consumption Level	Combined Elasticity	Pooled Data	Random Effect	Fixed Effect
Log pure alcohol weighted price	-.088 (-2.69***)	-.013 (-1.70)*	-.034 (-1.95)**	-.070	-.11 (-2.54)***	-.034 (-1.85)*	.046 (0.91)

Note: Elasticity calculated at population mean

Table 7: Coefficient Estimates among Adult Female Population Assuming Homogeneous Demand

Outcome variable: Pure alcohol consumed/week (ml), log transformed	OLS	Two-Part in Pooled Data		Logit Model in Panel Data
		Participating Decision	Consumption Level	Random Effect
Log pure alcohol	-.050	-.075	-.11	-.12

weighted price	(-3.76)***	(-3.47)***	(-2.70)***	(-2.38)**
Age	.0050 (7.10)***	.0056 (5.29)***	.0088 (4.40)***	.012 (4.67)***
Han	-.16 (-5.10)***	-.19 (-4.36)***	-.16 (-1.79)*	-.44 (-3.59)***
Married	.045 (2.08)**	.056 (1.66)*	.16 (2.85)***	.18 (2.37)**
Urban	.22 (8.41)***	.35 (10.94)***	-.095 (-1.75)*	.85 (10.95)***
Log HH per capita income	.017 (3.81)***	.035 (3.61)***	.012 (0.63)	.087 (3.64)***
Work in public sector	.17 (5.32)***	.27 (6.28)***	.17 (2.21)**	.60 (5.70)***
Work in private sector	.11 (3.73)***	.21 (4.32)***	.20 (2.14)**	.51 (4.37)***
Self-employed	.094 (4.34)***	.17 (4.94)***	.10 (1.51)	.40 (4.75)***
Lower middle school diploma	-.047 (-2.12)**	-.063 (-1.72)*	-.072 (-1.02)	-.15 (-1.63)*
Upper middle school or above diploma	-.00015 (-0.01)	.063 (1.44)	-.12 (-1.46)	.14 (1.33)
Meal at home	-.012 (-2.25)**	-.014 (-1.99)**	-.017 (-1.29)	-.033 (-1.94)**
Good health	.019 (1.11)	-.019 (-0.72)	.029 (0.62)	-.093 (-1.52)
Population density	-2.41e-06 (-2.54)***	-1.06e-06 (-0.73)	-4.12e-07 (-0.20)	-4.43e-06 (-1.34)
Agriculture share	.00029 (0.82)	-.00060 (-1.17)	.0026 (2.58)***	-.0027 (-2.24)**
Male worker wage	-.00075 (-1.12)	-.0018 (-1.73)*	.0024 (1.07)	-.0046 (-1.82)*
Work outside share	.00030 (0.78)	.00084 (1.56)	.00087 (0.85)	.0013 (1.12)
Restaurant	.00073 (1.41)	.00079 (1.24)	.0011 (1.02)	.0031 (2.14)**
Market access	-.0078 (-2.02)**	-.0060 (-1.04)	-.00068 (-0.06)	-.024 (-1.74)*
Education facilities	.0093 (1.70)	.0097 (1.17)	.0012 (0.08)	.020 (1.03)
Health facilities	-.0012 (-0.49)	-.0013 (-0.36)	.0015 (0.26)	.0037 (0.46)

Transportation infrastructures	.025 (3.41)***	.035 (3.14)***	.035 (1.74)*	.068 (2.58)***
Wave dummies	Y	Y	Y	Y
Province dummies	Y	Y	Y	Y
Wave and province interactions	Y	Y	Y	Y
R-Squared	.034		.16	
Log Likelihood		-7276.58		-6929.12
Rho				.44
Obs	23925	24121	1998	24121

***denotes significance level at 0.001, ** denotes significance level at 0.05, and * denotes significance level at 0.1.

Table 8: Price Elasticity Estimates among Adult Feale Population Assuming Homogeneous Demand

Outcome variable: Pure alcohol consumed/week (ml), log transformed	OLS	Two-Part in Pooled Data			Logit Model in Panel Data
		Participating Decision	Consumption Level	Combined Elasticity	Random Effect
Log pure alcohol weighted price	-.050 (-3.76)***	-.015 (-3.46)***	-.11 (-2.70)***	-.07	-.16 (-2.38)***

Note: Elasticity calculated at population mean

1.6.2 Robustness check

Several robustness checks are conducted. To minimize the impact of outliers on estimation, we remove extreme pure alcohol weighted prices (lowest 1% and highest 1% in price distribution) and repeat same average price elasticity estimates. The difference of price elasticity between full sample and trimmed sample based on same estimation strategy is very small and not significant, indicating that our estimates are quite robust.

Alcohol consumption quantity, measured by total bottles/liters of alcoholic beverages, is also of great research interest especially in consumer demand literature. We therefore replace pure alcohol outcome variable with level of alcoholic beverage consumed (ml/week), and replace pure alcohol weighted price with alcoholic beverage drinking level weighted price. We find the estimated elasticity is slightly higher than estimations using pure alcohol consumption as outcome variable (estimation results are available upon request). Recall that pure alcohol weighted price is heavily weighted towards to liquor, while more weight is given to beer in constructing total alcoholic beverage consumption level weighted price, the results indicate that taking alcohol as a single commodity may mask the heterogeneity across type of drinks.

1.6.3 Heterogeneity in price elasticity among socioeconomic subgroups

To detect heterogeneity in price responsiveness by individual basic socioeconomic characteristics, we perform separate regression for each subgroup. Two-part model, pooled Tobit and panel Tobit estimates of price elasticities are presented in **Table 9**. Although the magnitude of price elasticity estimates vary with model specifications, the general patterns across residence, age groups, income categories, and labor force status are true. Taking male population as an example, male urban residents are far less sensitive to alcohol price than male rural ones. Younger male adults (age 18-45) and older male adults (46-59) are much more sensitive to price than senior males (age 60+). Males having highest household income (in fourth quartile of income distribution) are far less sensitive to alcohol price relative to males in poorest households (in first quartile of income distribution). The differences in price elasticities across different female subgroups are as large as male counterparts. Although female sample does not show substantial difference across labor force status, males who are employed in public sector or who are not working are not responsive to price, with combined price elasticity approaching to zero. This evidence supports our previous hypothesis that public sector employees have smaller price elasticity relative to private sector employees or self-employed because their drinking behavior involves more social drinking and their consumption is usually not paid by themselves. All the differences in price elasticities across socioeconomic subgroups are statistically significant.

Table 9: Elasticity Estimates across Basic Socioeconomic Characteristics

Outcome variable= Pure alcohol consumed/week (ml) Price measure=community pure alcohol weighted price	Elasticity in Two-Part Model			Tobit Model		
	Participating Decision	Consumption Level	Combined Elasticity*	Pooled data	Random Effect	Fixed Effect
Adult male population						
Urban residents	-.024 (-2.23)**	.047 (1.47)	-.084	-.12 (-1.32)	.0073 (0.09)	.10 (1.21)
Rural residents	-.017 (-2.15)**	-.078 (-3.52)***	-.13	-.25 (-3.40)***	-.13 (-2.11)**	.026 (0.42)
Age 18-45	-.021 (-2.40)**	-.0082 (-0.35)	-.10	-.14 (-2.02)*	-.10 (-1.49)	.0010 (0.01)
Age 46-59	-.0094 (-0.99)	-.052 (-1.64)*	-.088	-.18 (-1.99)**	-.063 (-0.76)	.070 (0.79)
Age 60+	.0067	-.082	-.0068	-.10	.030	.12

	(0.46)	(-1.88)*		(-0.64)	(0.23)	(1.02)
Poorest (household income in first quartile)	-.030 (2.53)**	-.098 (-2.72)***	-.49	-.45 (-3.71)***	-.35 (-3.14)***	.0079 (0.06)
Richest (household income in fourth quartile)	-.019 (-1.51)	-.0017 (-0.05)	-.015	-.15 (-1.41)	-.080 (-0.81)	.24 (1.94)*
Not active in labor force	.0028 (0.23)	.0097 (0.25)	.019	-.079 (-0.58)	-.029 (-0.24)	.062 (0.42)
Employed in public sector	.0062 (0.48)	.046 (1.12)	.062	.14 (1.24)	.12 (1.21)	.034 (0.27)
Employed in private sector	-.021 (-1.25)	.0066 (0.14)	-.10	-.11 (-0.80)	-.064 (-0.48)	.077 (0.39)
Self-employed	-.027 (-2.83)***	-.092 (-3.51)***	-.19	-.34 (-4.11)***	-.19 (-2.57)***	.088 (1.12)

Outcome variable= Pure alcohol consumed/week (ml) Price measure=community pure alcohol weighted price	**Elasticity in Two-Part Model**		
	Participating Decision	**Consumption Level**	**Combined elasticity***
Adult female population			
Urban residents	-.010 (-2.12)**	-.12 (-1.89)*	-.045
Rural residents	-.016 (-3.17)***	-.043 (-0.64)	-.073
Age 18-45	-.0096 (-2.92)***	-.10 (-1.62)*	-.040
Age 46-59	-.010 (-1.80)*	-.10 (-1.43)	-.056
Age 60+	-.0030 (-0.52)	-.054 (-0.57)	-.017
Poorest (household income in first quartile)	-.0078 (-1.64)*	-.15 (-1.52)	-.69
Richest (household income in fourth quartile)	-.0060 (-1.48)	-.068 (-0.69)	-.24
Not active in labor force	-.0057 (-0.94)	-.064 (-0.84)	-.030
Employed in public sector	-.0052 (-0.35)	-.10 (-0.85)	-.035
Self-employed	-.013 (-2.77)***	-.026 (-0.36)	-.059

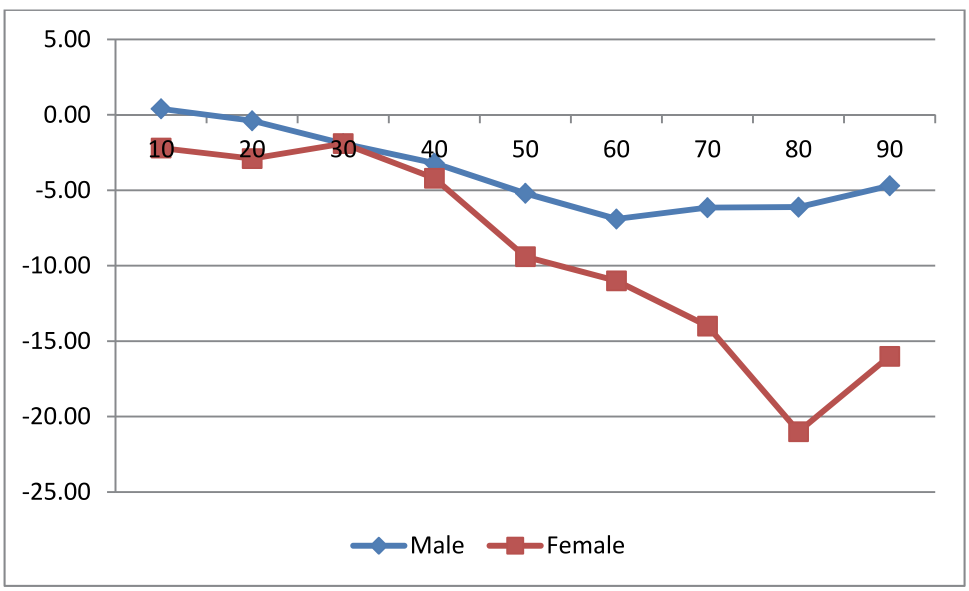
* Combined elasticity standard errors calculated from 50 bootstrap replications

Note" Results for female employed in private sector are not reported due to limited observations (drinkers<200)

1.6.4 Heterogeneity in price elasticity across level of drinking

Relaxing the assumption that alcohol demand is the same for all level of drinkers, we estimate conditional price elasticity at different quantiles among drinkers. **Figure 4** illustrates the relationship between level of drinking (pure alcohol per week) and price elasticity for male and female sample respectively. We see the general pattern is U-shape curve: higher quantile of drinking is significantly associated with higher price responsiveness before certain percentile points (60th percentile for male and 90th percentile for female); however, the price elasticity starts to go up as drinking level further increases. For example, adult male drinkers have an estimated price responsiveness about -0.032 at 40th percentile, getting highest at 60th percentile (-0.069), and getting slightly lower at 80th percentile (-0.0612). Although higher percentile of drinking is correlated with smaller price elasticity than medians, it is still bigger than low level of drinking. This suggests that same alcohol tax will lead to larger reductions among heavier drinkers who drink below the median level relative to lighter drinkers who drink below median level. From public health perspective, we may expect alcohol tax has biggest impact on those who consume most alcohol and who yield most severe health adverse effects to society.

Figure 4: Price Elasticity across Quantiles of Drinking Level among Drinkers (%)



Note: Price elasticity estimated from quantile regressions. Outcome variable= Pure alcohol consumed/week (ml), Price measure=community pure alcohol weighted price

1.6.5 Heterogeneity in response to beer and liquor price

Table 10 reports joint equation regression results for participation decisions and level of pure alcohol consumption among male and female adult sample. The coefficient estimates and price elasticity are both presented. The correlation of beer and liquor participation is high and significant (ρ =0.51 for males and ρ =0.71 for females), indicating that joint equation regression is appropriate and supposed to superior than two separate regressions. To interpret the results, we take male population as an example. With respect to price responsiveness in general male population, the effect of beer price on both beer and liquor participation is insignificantly positive after controlling for individual and community characteristics (own price elasticity=1.2%, cross price elasticity=0.39%). The cross price elasticity of liquor price on beer participation is insignificant and negligible (0.55%), while own price elasticity of liquor is significant (-1.0%). The cross price effects suggest that beer and liquor are substitutes. Conditional participation elasticity indicates that among male drinkers who already consume liquor has 1.7% responsiveness in beer participation to beer price, 1.1% to liquor price; while among male drinkers who already consume beer, conditional beer price elasticity is -0.3% and conditional liquor price elasticity is -1.3% for liquor participation. As we have observed in general male population, the impact of beer price on conditional participation is not significant, while liquor price is significantly affecting both conditional beer and liquor participation. Although the coefficient and elasticity estimates based on female sample are different from male sample, the key fact still holds: beer price in general does not significantly affect participating decision of either beer or liquor, while the impact of liquor price on conditional and unconditional liquor participating decision is significant. This implies that the liquor tax in China would have larger policy impact than beer tax.

Table 10: Own and Cross Price Elasticity Estimates by Drinks

	Beer consumption			**Liquor consumption**		
	Coefficient	**Price Elasticity in General Population**	**Price elasticity conditional on liquor drinker**	**Coefficient**	**Price Elasticity in General Population**	**Price elasticity conditional on beer drinker**
Participating probabilities for males						
Log local beer price	.046 (1.36)	.012 (1.36)	.017 (1.33)	.010 (0.32)	.0039 (0.32)	-.003 (-0.29)
Log local liquor price	.020 (1.38)	.0055 (1.37)	.011 (2.12)**	-.027 (-1.95)**	-.010 (-1.96)**	-.013 (-2.64)***
ρ	.51, chi2=1511.56					
Participating probabilities for females						

Log local beer price	-.0091 (-0.17)	-.00049 (-0.17)	-.026 (-0.99)	.065 (1.33)	.0022 (1.24)	.028 (1.46)
Log local liquor price	-.027 (-1.20)	-.0015 (-1.19)	.0089 (0.76)	-.070 (-3.30)***	-.0023 (-2.37)**	-.021 (-2.43)**
ρ	.71, chi2=730.62					

Note: Elasticity calculated at population median if variable is continuous, and calculated as discrete change as dummy variable changes from 0 to 1.

1.7 Conclusion and Discussion

The estimates of average alcohol price elasticity range between -.07 to -.11 for males and -.07 for females in pooled data, and get smaller (-.03) or even becoming insignificantly positive in panel data. Compared with estimates based on western country population (-0.53 or -0.61) (Gallet 2007; Wagenaar, Salois, and Komro 2009), we suggest the argument that consumers in developing countries are more sensitive to price is not supported in our study. Actually similar small elasticity has also seen in other addictive products, such as cigarettes, using same data source in China (Lance et al. 2004). The smaller or even positive alcohol price elasticity estimated from panel data indicates that unobserved heterogeneity plays a significant role on the relationship between alcohol price variations and alcohol demand over time.

At the same time, we find that the price responsiveness is not homogeneous: it varies substantially across socioeconomic subgroups, across level of drinking, and across type of drinks. Considerably variations in alcohol price responsiveness are seen across gender, residence, age groups, and labor force status. For both genders, urban residents are less sensitive to alcohol price than rural residents; younger adults (age 18-45) and older adults (46-59) are much more sensitive to price than seniors (age 60+). People with highest household income are far less sensitive to alcohol price compared with people with lowest household income. Although female sample does not show substantial difference across labor force status, males who are employed in public sector are very insensitive to alcohol price (price elasticity about 0) supporting the hypothesis that public sector employees have smaller price elasticity relative to private sector employees or self-employed because their drinking behavior involves more social drinking and their consumption is usually not paid by themselves.

Heavy drinkers impose more externalities than light or moderate drinkers. The evidences from western countries (Ayyagari et al. 2010; Manning, Blumberg, and Moulton 1995) however suggest that heavy drinker are less sensitive to price, and higher taxation would not have expected reduction in harmful drinking behavior. Although our measure of drinking level in China is not perfect, it indicates that higher quantile of drinking is as sensitive as median quantile, and even more sensitive than lower quantile of drinking. This suggests that same alcohol tax will lead to larger reductions among heavier drinkers who drink below the median level relative to lighter drinkers who drink below median level. From public health perspective, we may expect alcohol tax has biggest impact on those who consume most alcohol and who yield most severe health adverse effects to society.

Alcohol is not a single commodity. The participation and drinking levels of different types of drinks are associated with different responses to price. The joint analysis for beer and liquor among males suggests that they are substitutes. Evidence from conditional price elasticity show that liquor price is not only significantly associated with reduction of participation in liquor among beer drinkers, but also encourages more participation in beer drinking among liquor drinkers. Beer price, however, has no significant impact on any of the following: own participation, cross participation, and conditional participation among liquor drinkers. Our finding with respect to beer and liquor price elasticity is in line with evidences based on western country population: Gallet (Gallet 2007) and Wagenaar (Wagenaar, Salois, and Komro 2009) also suggest that elasticity of liquor (spirits) is much larger than beer. This indicates that taxation on beer is a more efficient instrument for revenue raising purpose, and taxation on liquor is more effective to control drinking behavior and generate health benefits.

This study has profound policy implications. There has been growing concern on increasing liquor price in recent years in China, especially after the new taxation policy taking effect on August 1, 2009. If we assume conservatively that the taxation on liquor will result in a 10% corresponding increase in final liquor product price, the average pure alcohol weighted price will go up by 7%. Even using the largest price elasticity estimate from pooled Tobit model (-.11), this will still result in a very marginal reduction in pure alcohol consumption by 0.7% in general male population. From government revenue raising perspective, alcohol taxation is efficient in that taxation does not substantially change individual consumption levels. On the other hand, alcohol taxation, as an important instrument to control alcohol consumption in western countries, will not generate substantial alcohol related health benefits. Non-monetary policy instruments should be considered in China for public health improvement purpose. China currently lacks of comprehensive public health policy on alcohol (Hao 2005). More efforts have to be made by the government and researchers to evaluate alternative policies or interventions to control individual drinking behaviors.

This paper has several limitations. First, the use of self-report drinking behavior is likely subject to underreporting problem. The estimates of price elasticity would be unbiased if underreporting is proportional in general population. However, if underreporting is disproportional across different types of drinkers, for example, higher level drinkers may be more likely to deny heavy drinking, estimates of price elasticity would be biased (Manning, Blumberg, and Moulton 1995). Second, albeit community alcohol price is relatively reliable in that it was reported by community head or collected by survey staff at local markets, it only represents the most common local brand which is usually cheaper than top brand. We may expect high-income consumers are more likely to choose high-end brand, the price of which is not fully represented by local ones. Third, price of alcohol at local market is a valid measure only when consumers obtain product from local market. The use of local price may ignore the purchase from nearby communities. Although there is no accurate estimate of smuggling for alcohol products in China, we suggest smuggling does not substantially affect our results in that few of the provinces we sampled are located near the country borders where smuggling is likely an issue. Fourth, the construction of drinking levels is based on number of drinks and quantity of drinks in a week, which does not tell us consumption in each occasion. A drinker may drink a little every day or drink a lot in a single occasion, the total pure alcohol for whom maybe same. Therefore, the price responsiveness estimated in different quantile should not be interpreted as comparisons across light, moderate, or heavy drinkers. Last, we are not able to fully interpret the difference between pooled data estimates and panel data estimates. Unobserved heterogeneities account for large share of individual alcohol consumption over time. Future research should be directed to understand the sources of such heterogeneities.

Despite these limitations, this study provides new and unique estimates of alcohol demand in a developing country context, and adds to our understanding of differential responses of alcohol demand across socioeconomic subgroups, across level of drinking, and across type of alcoholic drinks.

Appendix: Community Level Aggregate Data Analysis

Although this essay focuses on individual level alcohol consumption outcomes, community level aggregate data analysis is also of research interest, because: 1) majority of current literature estimating alcohol price elasticities rely on national or state level aggregate data; 2) aggregate data is potentially able to average out individual heterogeneities, which is the major driver of the difference between pooled data and panel data estimates at individual level. We therefore conduct average price elasticity estimates using community aggregate data from CHNS.

The data is constructed as follows. We keep all adult male and female in the study sample. Individual pure alcohol consumption is then collapsed by community and wave to compute community per capita pure alcohol consumption (millimeters/week) in a given wave. Total of 1031 community-wave observations are kept in the final analysis, with 234 communities in 5 waves between 1993 and 2006. Control variables are community environment, including community economic development level and cost of living (community population density, percentage workforce engaged in agriculture, ordinary male worker wage, percentage workforce working outside of town, education facilities, healthcare facilities), access to alcohol and related food commodities (number of restaurant, market access), and transportation infrastructure that are associated with alcohol provisions in the community.

Since the outcome variable, community per capita pure alcohol consumption (millimeters/week), is continuous and non-censored, ordinary least squares (OLS) in pooled data and panel data are used. The coefficient estimates are shown in the table below.

Outcome variable: community per capita pure alcohol consumption in log (millimeters/week)	**OLS in pooled data**	**Random effect**	**Fixed effect**
Log pure alcohol weighted price	-.14 (-4.05)***	-.099 (-2.96)***	-.070 (-1.97)**
Population density	-3.77e-06 (-1.66)*	-3.07e-06 (-1.30)	-1.31e-06 (-0.47)
Agriculture share	.0027 (3.70)***	.0015 (1.89)**	-.0012 (-1.11)
Male worker wage	.0032 (1.90)**	.0016 (1.05)	.00035 (0.22)
Work outside share	-.00	-.00	-.0016

	(-0.10)	(-0.80)	(-1.81)*
Restaurant	-.00 (-0.60)	-.00 (-0.07)	.00097 (0.77)
Market access	-.0075 (-0.76)	-.010 (-1.16)	-.014 (-1.46)
Education facilities	.020 (1.48)	.020 (1.53)	.022 (1.45)
Health facilities	.0036 (0.59)	.0063 (1.10)	.010 (1.66)*
Transportation infrastructures	.066 (3.69)***	.026 (1.44)	-.0096 (-0.45)
Wave dummies	Y	Y	Y
Province dummies	Y	Y	Y
Wave and province interactions	Y	Y	Y
R-Squared	0.15	0.14	0.05
rho		.29	.47
Obs	1031	1031	1031

***denotes significance level at 0.001, ** denotes significance level at 0.05, and * denotes significance level at 0.1.

We find that price elasticities estimated from aggregate data is larger than that estimated from individual data. Pooled OLS yields average price elasticity at community level at -.14. Panel data estimates are again smaller but not substantially different from pooled OLS, with random effect estimate at -.099 and fixed effect estimate at -.070. This suggests that unobserved community heterogeneities play a less significant role in formulating alcohol consumption and alcohol price relationship at community level.

Essay 2. Estimating Health Expenditure in China: A Comparison of Models

2.1 Introduction

Estimating individual healthcare expenditure has continued to be a fundamental issue in health policy research. It helps government, healthcare providers, and insurers understand the determinants of healthcare expenditure, predict future economic burden from healthcare, and determine actuarially fair rate of medical insurance copayment. Healthcare expenditure in general population is featured with large fraction of non-users who do not consume any healthcare, and alternative estimators have been employed to cope with censored distribution problem. Conditional positive healthcare expenditure among healthcare users, however, also poses econometric challenges to researchers: it has right-hand tail skewness with rare exceptionally high cost users (Buntin and Zaslavsky 2004), the distribution of which is not easily characterized by known parametric forms (Jones 2001). In addition, unobserved heterogeneity in healthcare expenditures may exist across different types of healthcare users (Deb and Holmes 2000; Manning 1998). These issues have made ordinary least squares (OLS) biased and inefficient in estimating healthcare expenditure.

There are sporadic literatures attempting to address the unique characteristics of healthcare expenditure data, the estimates of which are shown to be relied on empirical model specifications. Buntin (Buntin and Zaslavsky 2004) found that OLS, generalized linear model (GLM), and one- and Two-part models behave similarly satisfactorily in addressing large fraction of zeros and predicting Medicare reimbursed health care costs. Based on Health Insurance Experiment (HIE), Manning (Manning 1998) emphasized the issue of heteroskedasticity by treatment groups and suggested that GLM estimator and Huber/White correction should be considered in log transformed dependent variable estimates. Deb (Deb and Holmes 2000; Deb and Burgess 2003; Deb and Trivedi 1997) conducted a body of work comparing finite mixture model (FMM) with standard estimators including log normal and GLM for positive expenditure data using National Medical Expenditure Survey or Monte Carlo simulation. Results showed that FMM provided a much better fit and a better description of the unobserved heterogeneity for healthcare expenditure data than standard econometric methods.

The selection among alternative econometric models in estimating healthcare expenditure data is still in debate. Specifically, there is no study to author's knowledge formally comparing the performance of alternative estimators that are only applicable to positive healthcare expenditure data, such as Quantile Regression and FMM. In this paper, I focus on positive healthcare expenditure among healthcare users and aim to model expected healthcare expenditure among adults in China as a function of their sociodemographic and economic characteristics and self-reported health status. The performances of four alternative estimators are evaluated, including commonly used lognormal density maximum likelihood (ML-lognormal), generalized linear model (GLM), and less commonly used quantile regression (QR), finite mixture model (FMM). Heteroskedasticity problem is specifically paid attention.

2.2 Econometric Models and Model Selection

2.2.1 Alternative estimators

Healthcare demand here is specified as individual total healthcare expenditure if any. Therefore, dependent variable is positive and continuous. Log transformation is often used to deal with right hand tail skewness issue in health economics literature. We have the following four alternative estimators for comparisons.

(1) Normal Density Maximum likelihood (ML-lognormal)

Assuming expenditure data follows lognormal distribution[8], the estimation can be performed using maximum likelihood method:

$$f(logy|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp(-((\log(y)-\mu)^2/2\sigma^2)$$

Where μ is the distribution mean, and σ^2 is the variance.

To address heteroskedasticity issue, Huber/White is used to get consistent inference statistics. Manning (Manning 1998) also suggested that regression model should include a term that captures any heteroskedasticity in the error term on the log scale to improve the estimates. Therefore, I also model σ as a function of a set of independent variables based on White test for heteroskedasticity.

(2) Generalized Linear Model (GLM)

Mean μ and variance σ^2 are modeled in raw scale in GLM model. In GLM model, each outcome of y is assumed to be generated from a particular distribution in the exponential family. The mean μ of the distribution depends on the independent variable x, through:

$$E(y) = \mu = g^{-1}(x\beta)$$

Where $E(y)$ is the expected value of y, $x\beta$ is the linear predictor g is the link function, which is chosen to be log link in this study, or $\mu = exp(x\beta)$.

[8] Box-cox test supports the log relationship between $x\beta$ and y, with χ^2 likelihood ratio test for θ=0 being the smallest compared with alternative θ values.

Under this framework, the variance of σ^2 is typically a family function of the mean μ:

$\sigma^2 = Var(\mu) = \kappa\mu^\lambda$

Park test (GLM family test)[9] suggests gamma family variance structure in the empirical dataset of this study, where $\lambda = 2$, the variance is proportional to the mean squared.

GLM is appealing because it avoids retransformation problem by directly modeling outcome variable in raw scale and at the same time accommodates distribution skewness by variance weighting. At the same time, however, if the mean function is not correctly specified, GLM estimator becomes inconsistent and predicts unequally across the sample. Particularly in heavy skewed log-scale data, GLM may result in imprecise estimates (Manning and Mullahy 2001).

(3) Quantile regression (QR)

While OLS estimates the conditional mean of the outcome variable y, QR results in estimates that approximates median or quantile of the outcome variable, providing a more complete picture about the relationship between the outcome variable y and independent variable x a different points in the distribution of y.

If y is a random variable with distribution function log normal, $F(y) = \Phi(\log(y))$, the qth quantile estimator $\widehat{\beta_q}$ minimizes over β_q the objective function:

$Q(\beta_q) = \sum_{i:y_i \geq x_i'\beta}^{N} q\left|logy_i - x_i'\beta_q\right| + \sum_{i:y_i<x_i'\beta}^{N}(1-q)\left|logy_i - x_i'\beta_q\right|$

Where 0< q <1, and β_q denotes estimates of β from different choice of q

Quantile regression has several advantages over OLS: median regression is more robust to outliers than mean regression, making it especially appropriate in heavily tailed healthcare expenditure data; QR offers us a richer understanding of the data by examining the impact of independent variable x at noncentral locations of y, which is often the research interest in healthcare expenditure studies that concern about upper tail of the data distribution; and QR is semiparametric, in the sense that it avoids assumption about parametric distribution of regression errors, making it especially suitable for heteroskedastic data. Huber/White is used to get consistent inference statistics.

(4) Finite mixture model (FMM)

[9] Park test regresses log transformed squared residuals from GLM on predicted values from the same model to obtain coefficient λ, which is 1.92 in the dataset (std=.060).

The density function for a finite mixture model is an additive mixture of C-component distributions with weight $\pi_1, \pi_2, \dots, \pi_c$:

$f(logy|x; \theta_1, \theta_2, \dots., \theta_c; \pi_1, \pi_2, \dots, \pi_c) = \sum_{j=1}^{C} \pi_j f_j(logy|x; \theta_j)$

Where $0 < \pi_j < 1$, and $\sum_{j=1}^{C} \pi_j = 1$. π_j could be a function of control variables.

In the case of positive health expenditure and j =2,

$f(logy|x) = \pi f_1(logy|\mu_1, \sigma_1) + (1-\pi) f_2(logy|\mu_2, \sigma_2)$

Where $f_1(logy|\theta_1)$ and $f_2(logy|\theta_2)$ are lognormal distributions with different mean and variance.

$f_j(logy|\mu_j, \sigma_j) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp(-((\log(y) - \mu_j)^2/2\sigma_j^2)$

Although less commonly used in health economics literature, FMM approach has been gradually adopted and become popular in recent years in estimating healthcare demand literature (Deb and Holmes 2000; Deb and Trivedi 1997; Deb and Burgess 2003). FMM has the advantage of distinguishing healthcare demand by latent subgroup users and accommodating their heterogeneities. For example, healthcare users may be categorized into two latent subgroups by their consumption intensity: severely ill, who have high demand for healthcare, and relatively healthy, who consume moderate or marginal healthcare. The heterogeneity in healthcare demand of these two subgroups is represented by two distinct distributions in FMM. Compared with standard specifications, FMM usually provides more accurate predictions of average use and reflect true distribution of the costs since it is more flexible. Moreover, FMM is more able to predict healthcare utilization and costs for minority high demand consumers, whose consumption account for a large share of total healthcare resources (Deb and Holmes 2000).

2.2.2 Log retransformation

After log transformation of expenditure variables, the predicted values need be transformed back to raw scale. Simple retransformation without adjustment is subject to biasness in the presence of heteroskedasticity. Duan's smearing factor (Duan et al. 1983) is often used to provide consistent expected values, defined as:

$S = \frac{1}{N} \sum_{i=1}^{N} \exp(logy_i - x_i' \hat{\beta})$

The adjusted prediction of outcome variable y in raw scale is:

$E(y|x) = Sexp(x'\hat{\beta})$

2.3 Data

2.3.1 Sample

On-going individual-level longitudinal data from the China Health and Nutrition Survey (CHNS) is the data source for statistical analysis. CHNS is a collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. This interviewer-administered survey used multistage, random cluster sampling approach and sampled around 4000 households from over 200 communities in nine provinces[10] which are fairly representative of mainland China's central and eastern area and vary substantially in population sociodemographic characteristics, economic development levels, health indictors, healthcare utilization and healthcare expenditures. Latest wave 2006 was analyzed in this study to provide a most recent representative healthcare users sample.

I limit the model comparisons in positive continuous observations by restricting the sample of analysis to healthcare service consumers who spent any positive healthcare cost in the reference period (past 4 weeks). Age restriction (age>=18) is further applied to the sample since health utilization behavior for adults and children is presumably distinct. Total of 986 individual observations with complete information are therefore kept in the analysis, which accounts for approximately 10% of the general adult population.

2.3.2 Dependent Variables

Dependent variable of interest is total healthcare expenditure from all sources (paid by both individuals and insurers) in past 4 weeks, including expenditure not associated with provider visit, expenditures associated with visit to first visit to providers, expenditures associated with visit to second visit to providers, and additional healthcare expenditures. No observations are trimmed from analysis because one goal of this study is to compare model fits, especially for right tail extreme values. Monetary values are inflation adjusted to 2006 Chinese Yuan.

2.3.3 Individual Control Variables

Control variables are those believed to be associated with expenditure structure and observed by providers or insurers. Individual demographic and economic conditions: age, age square, gender (male=1), ethnicity (Han=1), marital status (married==1), region of residence (urban=1), household per capita

[10] The nine provinces include LiaoNing, HeiLongJiang, and ShanDong in Northeast, Jiangsu in East, HeNan, HuBei, and HuNan in Middle, GuiZhou in Southwest, and GuangXi in South. HeiLongJiang participated in the survey from 1997, and LiaoNing was not surveyed in 1997. Source: http://www.cpc.unc.edu/projects/china

income in log terms in 2006 Chinese Yuan, schooling years, and labor force status; individual health associated status: self report health status (good or excellent health=1), insurance coverage (covered by any type of insurance=1), disease diagnosis (suffering from typical chronic disease[11]=1), limitation of usual activity (unable to conduct usual activity due to illness=1). The main purpose is to examine model performances instead of establishing causal relationship between health expenditures and explanatory variables. Therefore, the potential coefficient bias caused by endogeneity of certain variables is not discussed in this study[12]. Province dummies are added to control for geographic variation of healthcare cost.

2.4 Results

2.4.1 Descriptive statistics

Descriptive summary statistics for total of 984 healthcare users are illustrated in **Table 11**. The mean age of the sample is 54.80, 40% of them are males and 80% are married. 29% individuals are residing in urban regions. Average household per capita annual income in 2006 is 19,644 Chinese Yuan. Average person completed 6.84 years of schooling. 51% sample are not active in labor market; 34% are self employed; and the rest of 13% are either employed in public sector or private sector. With regard to individual health status, 27% reported themselves as in excellent or good health; roughly half are covered by medical insurance of any type; 45% are suffering from major chronic disease conditions and 38% are unable to perform usual activity due to illness.

Table 11. Adult Healthcare Users Characteristics

Variable	Description	mean	std	min	max
Age	Age in years	54.80	15.42	18	91
Gender	Gender (male=1, female=0)	.40	.49	0	1
Ethnicity	Ethnic group (Han=1, minority=0)	.89	.31	0	1
Marital Status	Marital status (married=1, other=0)	.80	.39	0	1
Region of residence	Region (urban=1, rural=0)	.29	.45	0	1
Income	Household per capita annual income in 2006 Chinese Yuan	19644.11	22345.96	0	221965.4
Education	Years of schooling	6.84	4.50	0	18
Labor force status					
	Not active in labor force (base)	.51	.49	0	1
	Employed in public owned enterprise	.046	.21	0	1

[11] Including heart disease, tumor, respiratory disease, mental/psychiatric disorder, mental retardation, dermatological disease, muscular/rheumatological disease, and old age/mid-life syndrome.
[12] For example, health insurance coverage is likely to be a non-random selection that is correlated with error terms in the model estimates. Various studies in China setting have attempted to address this issue, for example, (Wagstaff and Lindelow 2008).

	Employed in private enterprise	.089	.28	0	1
	Self employed	.34	.47	0	1
Good health	Self-reported health status (excellent or good=1, fair or poor=0)	.27	.44	0	1
Insurance coverage	Covered by any type of insurance[13] = 1, no insurance=0	.51	.49	0	1
Disease diagnosis	Chronic disease=1, non-chronic disease=0	.45	.49	0	1
limitation of usual activity	Unable to conduct usual activity due to illness=1	.39	.48	0	1
Total #obs		984			

The distribution of empirical total healthcare expenditures for 984 healthcare users is illustrated in **Table 12**. The mean of healthcare expenditure incurred in past 4 weeks is 1108 Chinese Yuan, with standard deviation at 4917.57. The skewness value 9.52 and the huge discrepancy between median (127) and mean (1108) indicates a heavy right tail. Percentiles values are also reported.

Table 12. Healthcare Expenditure Distribution Statistics

Statistics	Expenditure (2006 Yuan)
Mean	1108.91
S.d	4917.57
Skewness	9.52
Minimum	2.15
5%	8.98
10%	13.77
25%	30.09
Median	127.00
75%	407.52
90%	1777.46
95%	4053.44
Maximum	77069.64

2.4.2 Coefficient estimates

The estimation results are reported in **Table 13**. The second column and third column show ML estimates with Huber/white adjustment and heterogeneous error terms, respectively. GLM estimates are presented in column 3. The following columns list results for QR at median, QR at 90 percentile, and two components estimates of FMM.

[13] Insurance type includes commercial insurance, free medical insurance, urban employee medical insurance, cooperative insurance, and other.

Estimation results show that most of individual control variables give reasonable face validity, and the parameter estimates are pretty consistent across models in terms of coefficient sign and magnitude. For example, all models show that urban residents generally pay more on healthcare than rural residents, representing the geographic difference in healthcare cost. Household income is significantly associated with health spending, the elasticity of which is ranging between 5% and 14%. Healthcare spending is also significantly associated with labor force status, suggesting that employed people (including public employed, private employed and self-employed) on average paid less than unemployed people. Diagnosed chronic ill patients spent less than acute diseases. Limitation in usual activity is associated with larger healthcare expenditure, and such association is statistically significant.

Some variables estimated in FMM for component 2 heavy healthcare users (about 10% of the entire study sample) have opposite signs compared with others. This is not a surprising result because the observations in this subgroup presumably behave differently as opposed to general patient population or low intensity healthcare users. We take medical insurance coverage as an example. Insurance coverage, albeit insignificant, affects health expenditure positively in all alternative models except FMM component 2. The positive relationship have been supported in Wagstaff (Wagstaff and Lindelow 2008), which established causal interpretation using fixed effect in panel data and instrumental variable techniques. This unique phenomenon that insurance induces higher healthcare expenditure was explained in Wagstaff by overprovision of high-tech care that is encouraged by insurance: insured people are more likely to move up the provider "ladder" from village clinics to township health centers, and from township health centers to hospitals. The negative relationship indicated by FMM component 2 estimation, however, may be explained by the fact that severely ill patients in China generally go to higher ladder of healthcare providers for better care regardless of their insurance coverage. As a result, health insurance improves financial protection in health when high-tech care are equally provided to severely ill subgroup. This hypothesis lacks of empirical support due to data limitations, and needs further investigation in future research. Other variables that show different sign of parameter estimates between FMM component 2 estimation and other models include Han nationality, marital status, and gender, suggesting that sociodemographic characteristics are associated with latent low intensity and high intensity usage of healthcare expenditures. Tentative explanations for the sociodemographic disparity are that male and Han in China are much more likely to be household heads than male and minority. They are the primary income source in the family and usually make final consumption decisions. When such people are severely ill, households are inclined to spend more for them. While married patients generally have more income than single ones, they tend to spend less than singles when severely ill in order to leave necessary savings to their spouse and next generation.

Table 13. Estimation Results and Model Selection Criteria (#984)

Total healthcare expenditure in past 4 weeks in log terms

	ML-Lognormal (Huber/white)	**ML-Lognormal (heteroskedastic error term[1])**	**GLM**	**QR (median)**	**QR (90th percentile)**	**FMM-component1 (low-intensity)**	**FMM-component2 (high-intensity)**
Age	.026	.036	.018	.029	.0065	.029	.11
	(1.17)	(1.78)*	(0.54)	(1.52)	(0.11)	(1.39)	(1.05)
Age square	-.00029	-.00026	-.00019	-.00023	3.77e-06	-.00021	-.0011
	(-0.96)	(-1.38)	(-0.62)	(-1.28)	(0.01)	(-1.05)	(-1.21)
Male	-.12	-.15	.38	-.17	.24	-.23	.83
	(-1.01)	(-1.45)	(2.07)**	(-1.78)*	(0.79)	(-2.06)**	(2.83)***
Han	-.17	-.077	-.084	-.037	-.056	-.22	.92
	(-0.95)	(-0.45)	(-0.32)	(-0.24)	(-0.11)	(-1.29)	(1.39)
Married	.34	.23	.35	.23	.39	.24	-.35
	(2.43)**	(1.63)*	(1.74)*	(1.89)*	(1.00)	(1.69)*	(-0.47)
Urban	.40	.38	.65	.45	.55	.32	.89
	(3.01)***	(3.12)***	(3.32)***	(4.40)***	(1.63)*	(2.59)***	(2.51)**
Log Income	.071	.070	.13	.051	.14	.069	.33
	(2.55)**	(2.60)***	(3.81)***	(1.90)*	(1.83)*	(2.39)**	(6.62)***
Schooling years	.029	.036	.017	.035	.030	.033	.019
	(1.94)*	(2.56)***	(0.71)	(2.74)***	(0.77)	(2.25)**	(0.31)
Public employed	-.22	-.17	-1.11	-.34	-.34	-.0073	-2.69
	(-0.82)	(-0.66)	(-3.56)***	(-1.53)	(-0.49)	(-0.03)	(-3.05)***
Private employed	-.35	-.30	-.82	-.39	-.20	-.024	-3.68
	(-1.67)*	(-1.57)	(-2.97)***	(-2.21)**	(-0.35)	(-0.10)	(-3.46)***
Self employed	-.59	-.49	-.69	-.64	-.60	-.44	-.59
	(-4.24)***	(-3.71)***	(-3.53)***	(-5.70)***	(-1.60)*	(-3.34)***	(-1.28)
Good health	-.81	-.77	-1.51	-.83	-1.42	-.66	-1.65
	(-7.12)***	(-7.05)***	(-8.70)***	(-8.01)***	(-4.48)***	(-6.07)***	(-3.34)***
Insurance covered	.11	.096	.25	.078	.45	.0010	-.34
	(0.98)	(0.89)	(1.48)	(0.81)	(1.44)	(0.01)	(-1.34)
Chronic disease	-.25	-.22	-.56	-.30	-.71	-.21	-1.54
	(-2.49)***	(-2.29)**	(-3.60)***	(-3.47)***	(-2.56)***	(-2.06)**	(-2.94)***
Unable activity	.94	.92	.86	.99	.88	.89	.67
	(8.47)***	(8.91)***	(5.19)***	(10.90)***	(3.03)***	(8.45)***	(2.42)**
Province dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.03	3.80	5.65	4.11	6.46	3.72	3.87
	(5.79)***	(6.00)***	(5.56)***	(6.90)***	(3.60)***	(5.58)***	(1.16)

pi						.905	.094
Log Likelihood	-1865.57	-1834.59	-7240.80			-1815.77$^{\#}$	
AIC	3781.14	3727.19$^{\#}$	14529.62			3733.55	
BIC	3903.43	3869.04$^{\#}$	14647.02			3983.02	
Degree of freedom	25	29	24	23	23	51	
Chi-square goodness of fit	518.3	535.63	1066.18	536.14	1185.96	453.95$^{\#}$	
Modified Hosmer-Lemeshow test	353.34	385.07	327.12$^{\#}$	361.77	339.75	422.90	
Copas test[2]	.84	.87	.57	.85	.52	.95$^{\#}$	
	(-17.14)	(-13.34)	(-58.26)	(-16.49)	(-60.63)	(-1.17)	
Predicted mean	1022.61	1046.38	1192.22	1068.88$^{\#}$	1445.63	1811.31	
s.d	1085.69	1157.86	1947.64	1245.88	2999.57$^{\#}$	9533.93	
Skewness	3.04	3.47	6.16	3.57	7.40	10.28$^{\#}$	
10 percentile	202.01	210.36	117.41	191.49	121.35	75.56$^{\#}$	
Median	687.73	678.53	615.01	679.22	629.33	236.62$^{\#}$	
75 percentile	1279.32	1292.41	1390.79	1291.75	1532.35	495.16$^{\#}$	
90 percentile	2201.26$^{\#}$	2281.36	2725.37	2348.45	3104.41	1085.89	
95 percentile	2923.30	2909.93	3884.07$^{\#}$	3109.97	4845.90	5132.91	

1. White test shows that gender, region, health status and diagnostic disease type account for heteroskedasticity in error terms. So σ is modeled as a function of these four variables.
2. Coefficient is obtained by regressing half sample true outcome values on the other half sample predicted values. T-test statistic (in bracket) for coefficient =1 is obtained from 100 iterations.
3. # denotes preferred model in specific criterion.

2.4.3 Model selection criteria

To evaluate model performance, the following criteria are conducted for comparisons and reported after parameter estimation in **Table 13**.

(1) Information criteria

Akaike information criteria (AIC) and Bayesian information criteria (BIC) are used to assess efficiency of estimators, which are maximum likelihood based.

$AIC = -2logL + 2K$

$$BIC = -2logL + Klog(N)$$

Where log L is the maximized value of the likelihood function for the estimated model, K is the number of parameters, and N is the number of observations in the sample. The preferred model is the one with the minimum AIC and BIC value. These two criteria include a penalty that is an increasing function of the number of parameters K, in other words, they balance model accuracy and complexity.

The estimation results from models suggest that ML-log normal account for heteroskedasticity behaves best in terms of information criteria, with lowest AIC at 3727.19 and BIC at 3869.04. Meanwhile, Log-normal (Huber/White) and FMM estimation yield similar AIC and BIC in same magnitude with ML-log normal (heteroskedastic error term). We find that GLM has the highest AIC (14529) and BIC (14647), primarily driven by model complexity. QR model does not yield AIC and BIC statistics for comparison because it is not based on maximum likelihood estimation.

(2) Goodness of fit

The Pearsons's chi-square goodness of fit test indicates how well a model fits observed distributions. It tests whether the discrepancy in frequencies between observed values and the predicted values from estimated models is significantly different. Smaller values of the test imply a better fit and are preferred. Although it is usually used to test goodness of fit for categorical variables, continuous variables can be grouped into ten categories based on decile cutoff values.

Another test, modified Hosmer-Lemeshow test, also check model fit for systematic bias. It identifies sample subgroups as the deciles of fitted values. If the mean residuals among subgroups are not significantly from zero from F-test, the null hypothesis that there is no systematic pattern in expected and observed residuals is not rejected.

In terms of Pearson's chi-square goodness of fit test, the discrepancy between observed and predicted values from all models is statistically significant, but FMM has lowest Chi-square statistics 453 suggesting that FMM fits the observed data relatively better when healthcare expenditure values are grouped into categories. Chi-Square statistics in ML-Lognormal (Huber/White), ML-Lognormal (heteroskedastic error term), QR median are approximately at the same level around 500. GLM again does not behave well, so does QR (90th percentile), Chi-Square value of both exceeding 1000.

Modified Hosmer-Lemeshow test indicate that all models behave similarly when difference between observed and predicted residuals are tested. GLM maybe perform the best, but the hypothesis that the difference in residuals is systematic is rejected in all models.

Goodness of fit test does not yield meaningful comparison here since predicted distribution and observed distribution are statistically different based on both Chi-Square test and Modified Hosmer-Lemeshow test results in all models. A higher statistics does not necessarily indicate a worse fit, given that all models have rejected the null hypothesis.

(3) Cross-validation

Overfitting becomes a concern when the model overemphasizes the fit for a few outliers. Complex models usually fits the data better at the expense of out of sample forecasting. Copas test assesses the overfitting problem by splitting sample for cross validation, which estimates model on randomly split one part of sample, uses estimated coefficients to do prediction for the other part of the sample, and finally tests whether the observed and predicted value in the other part are significantly different. I repeat such experiment 100 times for all alternative models to obtain t-statistic for the null hypothesis that the estimated coefficient by regressing the observed outcome value on predicted value in the random split sample is equal to 1.

Results from Copas test suggest that FMM is superior over other alternative models. The coefficient estimate (0.95) from FMM Copas test indicates that the observed values in half split sample are not significantly different from the predicted values form the other half of split sample, a strong support for outstanding performance in out-of-sample prediction. Copas test coefficient estimates in other models are all statistically different from 1, such as GLM (0.57), and QR (90^{th} percentile) (0.52), suggesting poor performance in out-of-sample prediction when split sample strategy is used.

(4) Point Estimation

Various statistics are also computed to compare the fitted distributions, including outcome mean, median, lower percentile such as 10, and right-tail upper percentiles such as percentile 75, 90, and 95.

The actual mean in the entire study sample is 1108.91 Chinese Yuan. ML-lognormal (Huber/White), ML-lognormal (heteroskedastic error term), QR(median), and GLM are all not too far off from the actual mean values, with predicted mean ranging between 1085 to 1192 Chinese Yuan. QR (90^{th} percentile) and FMM are higher than actual mean health expenditures by hundreds of Chinese Yuan.

In terms of standard deviation estimation, QR (90^{th} percentile) reports closest estimates (3000 Chinese Yuan) compared with actual statistics (4917 Chinese Yuan). The dispersion of predicted values from FMM is much bigger, since we model the sample as two distinct subgroups. Predicted standard deviation from the other models are between 1085 and 1947 Chinese Yuan.

The skewness of observed data is 9.52, and the estimated skewness for FMM is 10.28, making FMM the best fit in terms of data skewness. This is reasonable because we pay particularly attention to extremely high values in FMM. For the same reason, QR (90^{th} percentile) also performs satisfactory, with estimated skewness at 7.40. Other models, including ML-Lognormal, GLM, and QR (median) have much smaller right tail skewness compared with actual data.

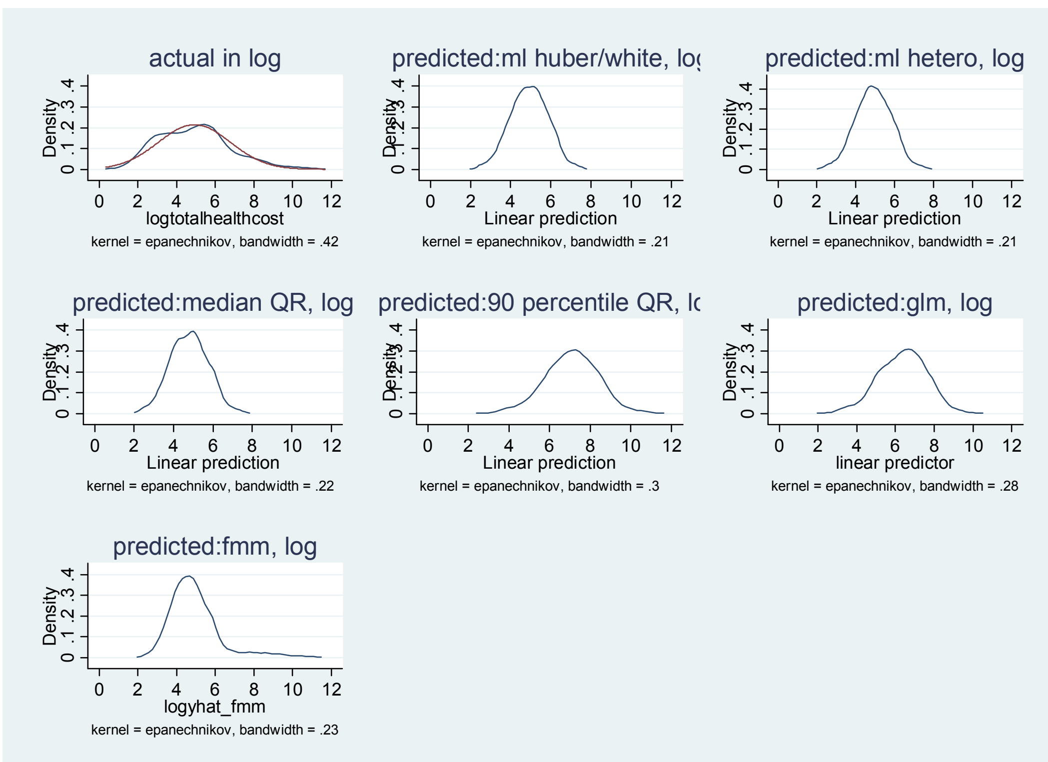
When looking at point estimates at different percentiles, all of the estimators tend to over-predict the lower percentiles (10 percentile and below) but the gap between actual and predictions from FMM is the smallest. FMM also predicts the median and 75^{th} percentile value very well, with the closest predicted estimates to the actual. Upper tail percentile (90^{th} and 95^{th} percentile) predictions are overall satisfactory in FMM.

In sum, FMM estimator is superior or not noticeably worse in information criteria, goodness of fit test and cross sample validation. Log likelihood, chi-square goodness of fit test, and copas test support two component FMM over other specifications. The high coefficient (0.95) in Copas test, which is not statistically different from 1, particularly indicates that FMM has an outstanding performance in out-of-sample prediction. Other criteria, namely AIC, BIC, and modified Hosmer-Lemeshow test, also give FMM satisfactory results that are not substantially different from the criterion-preferred model. The second-best estimator is ML-log normal that accounts for heterogeneity in error terms. GLM does not perform well in Copas test, confirming the results from literature (Buntin and Zaslavsky 2004; Manning and Mullahy 2001) that GLM does not predict equally across samples. QR at 90 percentile also fails to provide accurate prediction in split sample due to heavy weight given to the upper tail.

The in-sample prediction also suggest that FMM gives the most precise median prediction after log retransformation, and performs well in both lower and upper tail predictions. Upper tail percentile predictions are overall satisfactory in ML-lognormal, GLM, and QR. FMM performs the worst in terms of in-sample mean prediction because it overestimates values over 95 percentile, while QR at median and ML-lognormal perform well in terms of calibration of in-sample mean predictions. All of the estimators tend to over-predict the lower percentiles (10 percentile and below) but the gap between actual and predictions from FMM is the smallest.

Figure 5 graphically compare actual and predicted expenditure values in log scale for all alternative models. The actual healthcare expenditure in log scale is distributed roughly normally (red curve shows normal distribution), supporting the log transformation for expenditure outcome variables. As indicated in lower percentile in-sample prediction, all the models do not predict very well for lowest percentile (left hand tail) distribution. The graphs show that FMM fits the actual distribution best in terms of central density and flat right tail. The reason that FMM successfully predicts the extremely high values in observed data is FMM pays particular attention to model heavy healthcare user group, which generate outliers at right hand tail.

Figure 5. Actual and Predicted Expenditure (in log) Comparisons



2.5 Conclusion and Discussion

This study estimates demand for healthcare in China and evaluates the performance of econometric models. The skewness, non-normal distribution, and differential response by level of consumption have made ordinary least squares (OLS) biased and inefficient in estimating individual healthcare expenditure.

A set of alternative methods are compared, including log-normal density maximum likelihood, generalized linear model, quantile regression and finite mixture model.

Literature has suggested that finite mixture model has the advantages of distinguishing healthcare demand by latent subgroup users and accommodating their heterogeneities (Deb and Holmes 2000). For example, healthcare users may be categorized into two latent subgroups by their consumption intensity: severely ill, who have high demand for healthcare, and relatively healthy, who consume moderate or marginal healthcare. The heterogeneity in healthcare demand of these two subgroups is represented by two distinct distributions in Finite mixture model. Compared with standard specifications, finite mixture model usually provides more accurate predictions of average use and reflect true distribution of the costs since it is more flexible.

The empirical performance of finite mixture model against alternative estimators is evaluated using CNHS individual healthcare expenditure data among Chinese adult population. Similar with evidences from western countries (e.g., (Deb and Holmes 2000; Deb and Trivedi 1997), the results based on finites mixture model suggest that two groups of healthcare users exist among Chinese adults. The high intensity user group has much higher expected expenditures (19,728 yuan) than low intensity user group (311 yuan). Although only accounting for 10% of study population, high intensity group consume majority (82.2%) of total expenditures in the entire healthcare users. Empirical results also suggest that health status, income, and occupations are strong predictors of healthcare expenditure. The model also finds that behavioral responses differ across the high intensity and low intensity group, particularly with respect to health insurance coverage, gender, nationality and marital status.

The comparisons of statistical model selection criteria support the evidences from western country that finite mixture model is preferred overall in terms of model estimation efficiency (information criteria), fit of actual distribution (goodness of fit), and not-overfitting outliers (cross sample validation). With respect to in-sample prediction, most of estimators (ML-log normal, GLM, QR-median) give reasonably good mean estimation. Finite mixture model does not predict in-sample mean very well because it overestimates values over 95 percentile which represent consumption of high-intensity user group. This finding is in accordance with Deb's study (Deb and Holmes 2000) which suggests that high intensity user group exhibit not only high expected expenditures, but less predictable expenditure as well. However, finite mixture model gives the most precise median prediction after log retransformation, and performs very well in both lower and upper tail predictions. In-sample predictions from finite mixture model in general fits the actual distribution the best. Moreover, finite mixture model has the distinct advantage to predict subgroup average cost that other estimators are not capable of.

This study has several limitations. First, we do not utilize panel nature of CNHS longitudinal data and focus on only cross-sectional observations. The performance of alternative estimators in repeated measures needs further examination. Second, finite mixture model, as well as quantile regression model, is not appropriate in estimating healthcare expenditure distribution in general population where a large fraction of zero (non-users) exist. In that case, other alternative estimators may be superior, for example, Two-part model or sample-selection model. Third, we restrict our analysis to two-component finite mixture model which implies two distinct users in study population, high intensity and low intensity users. While two-component may be not adequate to fits the data when sample size is large (Deb and Holmes 2000). Fourth, finite mixture model has been suggested to be also superior in count data, but we are not able to do the evaluation due to survey data limitations. Last, the analysis is based on self-reported data that is subject to reporting bias.

In conclusion, it appears that finite mixture model may be a superior estimator of healthcare consumption relative to alternative specifications. It has the advantage of providing more accurate median and upper tail estimates of the distribution of healthcare cost, fitting the actual overall distribution, and estimating cost in two distinct user groups that behave very differently in healthcare consumption.

Essay 3. Trend of Body Mass Index across Sociodemographic Groups among School-aged Youth in Mainland China

3.1 Introduction

For at least 2 decades, obesity rates in mainland China have been increasing among youth and adults (Luo and Hu 2002; Dearth-Wesley, Wang, and Popkin 2008; Li et al. 2008; Zhang et al. 2008; Wang, Du, and Popkin 2006), although China started at a very low level and undernutrition remained a bigger concern. Obesity rates differed by sociodemographic status and in mainland China were generally higher among groups with higher education, income, and urbanization (Li et al. 2008; WHO 1999; Molarius et al. 2000; Ji and Cheng 2009). In contrast, in developed countries, it is typically found that lower income, less educated, and minority groups have higher obesity rates (WHO 1999; Molarius et al. 2000; Ogden et al. 2006).

But changes in nutritional patterns in mainland China have been very rapid and weight gain may have been even more dramatic than in developed countries (Drewnowski and Popkin 1997). Indeed, it has been estimated that the BMI at the 95th percentile of the country-specific weight distribution for 6-year old youth is now higher in China than in the US (Popkin 2009). This raises the question of whether disparities in BMI or obesity in China are changing and becoming more similar to other countries. In that case, we should see much faster BMI gain among lower income and education groups in recent years, but it could also be that weight gain is similar across group or even that there are widening disparities. In the US, most sociodemographic groups were experiencing very similar weight gain, rather than either a widening or narrowing of the disparities that exist at every point in time (Truong and Sturm 2005). This study examines how weight gain, as measured by average body mass index (BMI) age- and gender- specific percentile, differed across sociodemographic groups over time in Chinese school-aged youth population through 1991 to 2006.

3.2 Methods

3.2.1 Data

We use individual level longitudinal data from the China Health and Nutrition Survey (CHNS), a collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. CHNS used multistage, random cluster sampling approach, conducted in nine provinces which are fairly representative of mainland China's central and eastern area and vary substantially in population sociodemographic characteristics, economic development levels, food and physical activity environments, and health indicators. Counties in the nine provinces were stratified by income and a weighted sampling scheme was used to randomly select four counties in each province. While not designed to be nationally representative, statistics on diet and BMI, CHNS tend to be very similar to national data (Popkin 2008). Study details are available at University of North Carolina website http://www.cpc.unc.edu/projects/china. Six waves (1991, 1993, 1997, 2000, 2004, and 2006) were analyzed in this study, sample including all school-aged youth (age 6-18). **Table 14** presents descriptive statistics for sampled youth and their parents.

Table 14. Sample Characteristics: school-aged youth, CHNS 1991-2006

	% in sample (SD)		
	All waves, (N=14 204)	1991	2006
Age, mean	11.86(3.55)	11.89(3.67)	11.80(3.61)
Income†, mean	3 418(3 793)	2 156(1 593)	5 665(7 096)
Male	52.66(49.93)	51.07(49.99)	53.40(49.90)
Han	84.85(35.84)	83.18(37.41)	83.91(36.76)
Urban	27.65(44.72)	25.77(43.74)	30.01(45.87)
Father smoking	68.87(46.30)	74.58(43.54)	60.57(48.89)
Mother smoking	2.30(14.99)	2.75(16.37)	1.61(12.56)
Father drinking	70.12(45.77)	71.91(44.95)	61.97(48.56)
Mother drinking	11.68(32.12)	14.98(35.69)	9.09(28.71)
Father working	93.29(25.01)	96.97(17.16)	86.48(34.20)
Mother working	85.10(35.60)	92.57(26.21)	73.79(43.99)
Father education			
Primary sch & below	36.28(48.08)	53.16(49.90)	19.14(39.35)
Middle sch	40.28(49.05)	30.91(46.22)	50.31(50.01)
High sch & above	23.43(42.35)	15.92(36.59)	30.54(46.07)
Mother education			
Primary sch & below	53.66(49.86)	71.16(45.31)	31.56(46.49)
Middle sch	30.21(45.91)	18.86(39.12)	47.38(49.95)
High sch & above	16.13(36.78)	9.97(29.97)	21.04(40.77)

Note: BMI (body mass index) percentile was age- and gender specific, generated based on CDC 2000 youth growth charts. See "Independent variables" subsection for explanation.

† Household per capita Income was derived by CHNS, and CPI adjusted into 2006 Chinese Yuan.

3.2.2 Dependent Variable

The primary variable of interest was individual BMI, calculated in kg/m^2 and converted to age- and gender-specific BMI percentiles. One advantage of CHNS data is that individual height and weight data were objectively collected by trained health workers, rather than self-report as in many large population studies. Body weight was measured in light indoor clothing to the nearest 0.1kg with a beam balance scale; height was measured by a portable stadiometer without shoes to the nearest 0.1cm (Popkin 2008). Specific age- and sex-specific percentiles were generated based on the Centers for Disease Control (CDC) youth BMI 2000 growth charts, using computerized SAS program provided by CDC (available at http://www.cdc.gov/nccdphp/dnpao/growthcharts/resources/sas.htm). CDC 2000 growth charts were developed from U.S. National Health Examination Surveys and National Health and Nutrition Examination Surveys (Kuczmarski et al. 2002). This makes our percentile measures directly comparable to US measures. Other studies have used Chinese population-specific percentiles and also suggest other cut-off points, which might be more appropriate for obesity screening purpose in this particular population (Ma et al. 2006; Wang et al. 2004; Xu and Ji 2008).

3.2.3 Independent Variable

We want to investigate the time trend by specific characteristics net of other demographic changes the Chinese population or the study sample, paralleling the approach used in a US study for adults (Truong and Sturm 2005). We therefore show adjusted trends based on a regression model and weighted to correspond to the 2006 study population. The regression model includes calendar year, age splines (age knot at 12 to allow differences between youth in primary school and middle-school), gender, nationality (Han or minority), region of residence (urban or rural), household per capita income category (income above median or not), parental education category (primary school diploma and below, middle school diploma, high school diploma and above), parental working status (currently in labor force or not), parental smoking status (currently a smoker or not), and parental alcohol consumption status (whether any alcohol consumption last year). Information on both biological mother and father were linked to youth through CHNS household identifier and included as parental characteristics. Time trend was specified as year linear splines with one knot at year 2000 to present nonlinear time changes allowing different amounts of weight gain for the periods of 1991-1997, and 2000-2006. As a sensitivity test to this functional form, we also conducted the analysis regression replacing the spline function with quadratic function (results not shown), but findings were similar. Time trend of weight gain by key sociodemographic groups were captured as interactions between year and gender, year and nationality, year and residence, year and father/mother education, year and household income category. These interactions terms examined changes of weight gain among different subgroups across time, which are the focus of our study. Two interaction terms were generated between any sociodemographic variable and two year splines. For example, region of residence (urban = 1, rural = 0) is a dummy variable, and year1, year2 represents two periods before and after year 2000. The two interaction terms between residence and time would thus be residence with year1 and residence with year2. If rural residence was reference group and if both interactions terms simultaneously equals to 0, this indicates that, in each and every period, weight gain was the same for urban and rural residence, no difference in time trend of weight gain between these two subgroups.

3.2.4 Statistical Methods

We performed ordinary least squares regression to estimate time trend of BMI percentiles among school-aged youth. Joint tests of interaction terms were conducted for the null hypothesis that no differences in weight gain exist across sociodemographic groups. Statistical significance level was defined as $p<0.05$.

We first estimate ordinary least squares model using 1991-2006 school-aged youth full sample and predicted BMI percentile for respondents of 2006. Predicted BMI percentiles in all other years were generated based on 2006 sample characteristics and full model coefficients except for the time value replaced with that particular year. For instance, to predict conditional mean BMI percentile in year 1989, we retained all observations from 2006 but changed year value from 2006 to year 1989. Average annual conditional mean BMI percentiles were then plotted each wave from 1991 to 2006 by sociodemographic groups.

3.3 Results

3.3.1 Trends by parental education

Time trend of body mass index age- and gender-specific percentiles across maternal education attainment is shown in **Figure 6**. On average, youth with mother in lowest education (primary school diploma or below) group had a significantly lower BMI compared to the other two (mother with middle school diploma and mother with high school diploma and above), and the weight gain in three categories were increasingly diverged over time. Although the general difference over paternal education groups was as not significant, it showed the same pattern, while here the main gap is between the high school and above group versus the other two groups (**Table 15**). The total weight gain difference by mother's education was large (and statistically significant): 14.13 BMI percentile increase in high-school-diploma mother group vs. 12.60 units in middle-school-diploma mother group vs. 3.11 units in mother with primary school diploma and below group.

Figure 6.Trends in average BMI percentile, by maternal education attainment

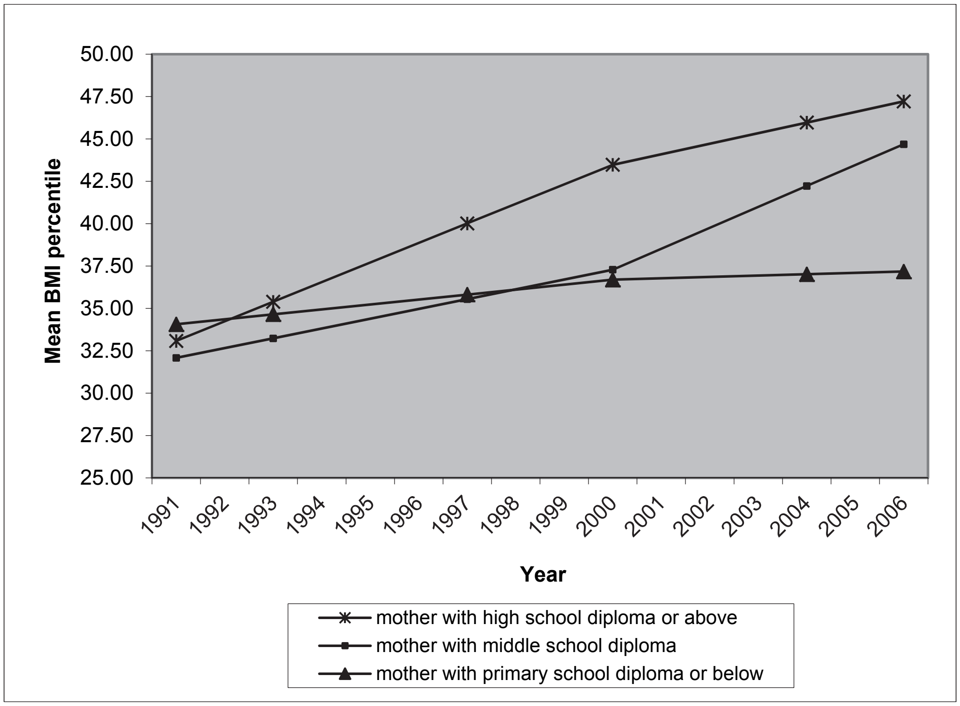


Table 15.Increase in BMI percentile and overweight fraction by sociodemographic groups

Sociodemographic Groups	Total increase in BMI percentile 1991-2006	
	Mean difference	SE
Gender		
Male	12.83*	0.32
Female(reference)	6.81*	0.36
Nationality		
Han	11.05*	0.25
Minority(reference)	3.81*	0.66
Residence		
Urban	10.25*	0.44
Rural(reference)	10.04*	0.28
Income		

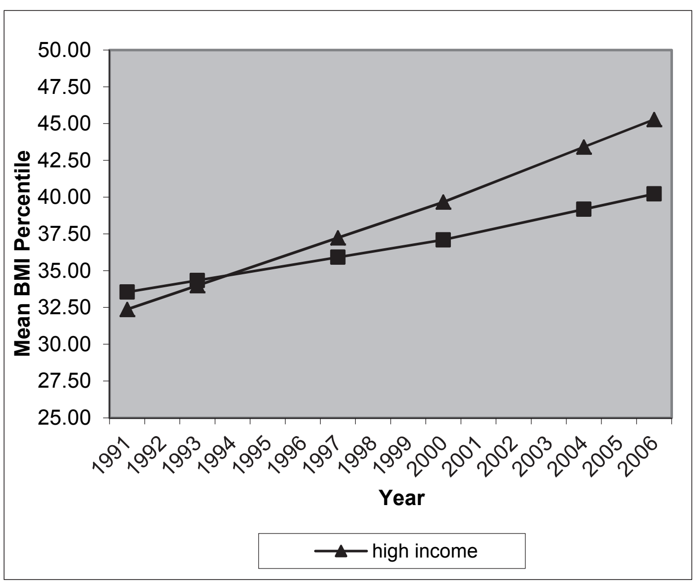
Above median	12.91*	0.31
Below median(reference)	6.67*	0.36
Father education attainment		
Primary sch & below	7.08*	0.48
Middle sch	7.44*	0.33
High sch & above(reference)	15.55*	0.37
Mother education attainment		
Primary sch & below	3.11*	0.35
Middle sch	12.60*	0.31
High sch & above(reference)	14.13*	0.46

*p<0.001

3.3.2 Trends by income

Figure 7 shows there is a widening gap by family income. The higher income group witnessed a more rapid weight gain than low-income groups (12.91 BMI percentile increase in high income group over 15 years compared to 6.67 percentile increase in below median income group).

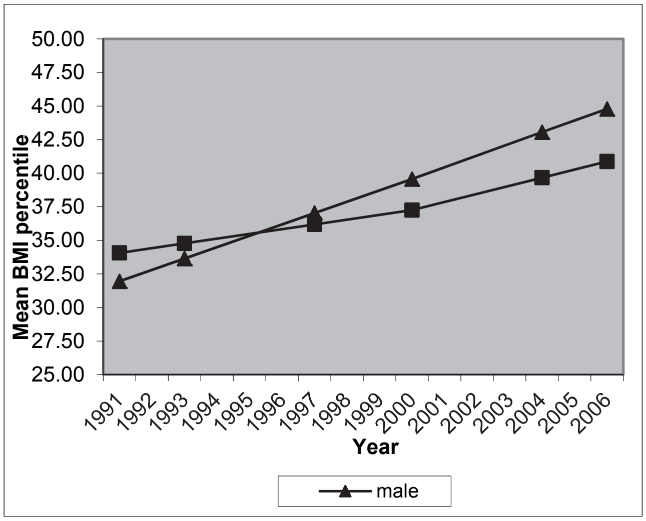
Figure 7. Trends in average BMI percentile, by household income



3.3.3 Trends by nationality and sex

Male youth increased BMI more than female during the study period of 15 years (**Figure 8**). Female gained 6.81 additional BMI percentile, in contrast with male who gained 12.83 units (**Table 15**). Han nationality group essentially did not differ from non-Han minority in terms of average BMI, but gap of weight gain emerged and became significantly larger during the most recent decade with Han Chinese youth increasing BMI percentiles significantly faster.

Figure 8.Trends in average BMI percentile, by gender



3.3.4 Results from Other Explanatory Variables

Residence subgroups exhibited parallel weight gain trends from 1991 and 2006, and joint test of two time interactions was not significant. The BMI percentile gap between rural and urban population is very small compared to other sociodemographic groups: roughly 10.25 units increase for urban residence and 10.04 for rural residence. Besides BMI disparity explained by basic sociodemographic groups, youth with a smoking mother, father currently not in labor force or mother currently not in labor force are in generally more likely gaining weight. Father addictive behavior status turned out not significantly associated with youth BMI percentile increases.

3.4 Discussion

(Li et al. 2008)Rapid increase in BMI was observed in all sociodemographic groups of school-age youth in mainland China during 15 years between 1991 and 2006. Adjusting for demographic changes in the population and study samples, we found diverging trends by several sociodemographic characteristics. The finding was not affected by our choice of functional forms to estimate the time trends (quadratic function of year yielded same results) or model specifications. Even though Chinese youth may have caught up to the obesity levels (and for 6-year olds even exceed) of the US (Popkin 2009), the patterns are very different. The largest increases in China were among youth in higher income families, youth with more highly educated parents, Han (i.e. majority) nationality, and among males. That these gaps exist is not surprising, they have been reported in recent studies (Li et al. 2008; Ji and Cheng 2009; Johnson et al. 2006). What is surprising, however, is that we see no evidence that the trends are narrowing or that China becomes more similar to developed countries in terms of the sociodemographic patterns. Instead, obesity disparities in China seem to be widening in a direction that is opposite to cross-sectional disparities found in developed countries. One area where our longitudinal analysis differs from cross-sectional findings is urbanicity. Previous studies reported higher obesity rates for urban areas, but we do not find that the rural-urban gap is changing (Luo and Hu 2002; Li et al. 2008; Ji and Cheng 2009). Our study differs from these studies in another aspect, namely that we are focusing on the mean of the BMI distribution, rather than obesity indicators (which is what percentile cut points, e.g. 95th percentile) do. We capture the dynamic of weight gain on the population, which may differ from the dynamic of the very high weight group (Sturm 2003, 2007).

There some limitation of the analysis. The CHNS is not a national-representative sample data (although patterns in diet and BMI were found to be identical to those from national surveys) (Popkin 2008). Nevertheless, results may not extend to other regions such as western area. In addition, sampling weights were not provided by CHNS, restricting us from controlling sampling probabilities that may differ across sociodemographic groups and time. We use US BMI percentiles, but it may also be interesting to have age- and gender- adjusted BMI percentiles from Chinese population-specific BMI distributions. Finally, the surveys were not conducted annually and sample sizes were not large. Despite the limitations, the analysis is unique in modeling the time trend of weight gain, defined as age- and gender- specific BMI percentile, across sociodemographic groups among school-aged youth and using longitudinal data in a relatively long period.

In summary, we see large divergence in average youth BMI percentile across sociodemographic groups in China, in a way that is opposite to patterns observed in developed countries. While BMI gain was substantial across all groups, the largest increases were among Chinese male youth in higher income families with more educated parents and Han nationality.

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