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Depression Hurts, Depression Costs: The Medical Spending Attributable to Depression and Depressive Symptoms in China

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Abstract

Due to its fast economic growth and lifestyle changes, China is experiencing a rapid epidemiological transition from communicable to non-communicable diseases (NCDs). Mental disorder such as depression is an important yet often neglected NCD, and is becoming a growing cause of disability, suicides and disease burden. This paper provides the first nationally representative estimate of the medical cost attributable to depression and depressive symptoms among the adult population in China. Based on the 2012 China Family Panel Studies (CFPS) survey, our results indicate that these mental health conditions have significant impacts on the individual medical expenditure, and they jointly contribute to 14.7% of total personal expected medical spending in China, with depression and depressive symptoms accounting for 6.9% and 7.8%, respectively. Given that patients with mental illness face multiple psychological and institutional barriers in seeking appropriate treatment, the high depression-induced medical costs may be primarily driven by the cost-shifting effect from mental healthcare to general healthcare, as mental disorders often co-exist with other NCDs such as diabetes and hypertension. As an implication, our study calls for an urgent reform of China's mental health and insurance systems to remove the policy-induced obstacles for the access to mental healthcare resources.

Key words: Depression; Depressive Symptoms; Mental Healthcare System, Medical Cost; China

I. Introduction

It has been widely recognized that mental disorders such as depression have become a fast growing cause of disability and of the global burden of diseases (Patel, 2016). Around the world, more than 650 million people live with diagnosable mental disorders, which in turn imposes considerable costs on the individuals, their families, and the society as a whole (WHO, 2013). Depression is the most common type of mental disorder, with an estimated 350 million people affected, indicating that on average about 1 in every 20 people in the world are affected by depression according to the world's current population size (WHO 2016). Several studies have documented that the impact of depression not only lies in its detrimental effect on health (such as disability and mortality), but also on economic productivity (e.g. Greenberg et al., 2015; Chisholm et al., 2016). As a result, the rising prevalence of depression is not just a public health concern, but also a significant concern for economic development and social welfare. A recent policy recommendation initiated by the WHO and the World Bank Group even suggested to include mental health in the global development priority agenda (World Bank Group and WHO, 2016).

After enjoyed fast economic growth for several decades, China now also faces the challenge of increasing prevalence of depression, which has become one of the leading causes of disability-adjusted life years in this country (Phillips et al., 2009; Yang et al., 2013; Qin et al., 2016). Although the number of people with mental illness has increased in recent years, less research has been done on the mental health status in China compared to the developed countries, and little has been known about the impacts of depression on the overall healthcare costs. The purpose of this paper is to fill this gap by estimating the medical cost attributable to depression and depressive symptoms among the adult population in China.

An important challenge for this task is the under-diagnosis and under-treatment of mental depression. Unlike physical health conditions, mental health problems are more difficult to be detected and properly treated because of the added barriers to the access of mental healthcare services, especially in developing countries like China. Some of these barriers (such as stigma) are due to social factors[1], while other barriers are caused by country-specific institutional arrangement. For example, the available mental healthcare manpower in China is insufficient and unevenly distributed across regions (Liu et al., 2011), partially due to the government control of medical education and accreditation. The qualified personnel tend to be concentrated in urban-based specialty psychiatric hospitals, indicating that the mental health services are quite limited in the rural areas (Philips et al., 2009). Another example of the institutional barriers in China is the knowledge gap between the frontier of new medical technology and the local practice standards: due to the Essential Drug Policy and the regulated insurance reimbursement schedule, there may be a long delay in the launch of new mental healthcare drugs or treatment procedures in China[2]; as a result, physicians may not be able to prescribe what proves to be the most effective treatment regimes.

The above psychological, social and institutional hurdles in the access to mental healthcare in turn causes a delay in treatment or a "cost shift" towards the non-mental healthcare spending, as mental disorders such as depression often co-occur with other NCDs such as diabetes and hypertension (Patel and Chatterji, 2015), and many patients with mental illness may choose to seek general healthcare instead of mental healthcare. Thus, empirical estimation on the depression-induced medical costs can be biased if such estimation is based solely on the data of mental healthcare utilization. In this paper, we try to address this issue by (i) adopting the two-part and four-part models that overcome the problem of no-use or under-use of mental health services,

[1] Bharadwaj et al. (2015) provide strong evidence of stigma associated with mental illness: they find that more than one-third of survey respondents under-report mental health conditions, while the respondents are less likely to under-report other physical illnesses such as diabetes or hypertension.

[2] Between 2008 and 2012, there were 12 global new molecular entities available for treating mental illness. In 2013, only one of these 12 new drugs are available in China, indicating a long delay in the launch of new drugs (IMS Institute, 2014). For a more comprehensive study on the launch delay of new drugs in India, see Berndt and Cockburn (2014). One of the plausible explanations for the launch delay in China as well as other low- and middle-income countries is the lack of insurance coverage for these new drugs. In addition, the three social health insurance schemes in China are heterogeneous in terms of funding sources and benefit packages, which in turn leads to a disparity in access to new drugs across different insurance programs. For example, in 2013, the per-capita fund for the rural new cooperative medical scheme (NCMS) was only 61 USD, just around 15% of the per-capita fund of urban employee basic medical insurance (UEBMI) scheme (Meng et al., 2015).

and (ii) using a national household survey dataset that records more comprehensive information on personal medical spending than the utilization-based datasets. To the best of our knowledge, this paper is among the first in the health economic literature to use the hurdle models (such as the two-part and four-part models) to characterize the cost impact of mental depression, and it provides the first nationally representative estimates on the medical costs induced by depression and depressive symptoms among adults in China.

Our results indicate that depression and depressive symptoms have significant impacts on the individual expected medical expenditure. Specifically, we find that about 6.9% of total personal medical expenditure is attributable to depression. In addition, about 7.8% of total medical expenditure is attributable to the depressive symptoms. Putting together, our empirical study shows that about 14.7% of total personal medical expenditures in China are attributed to depression and depressive symptoms, which is almost three times as large as the impact of obesity and overweight on healthcare costs obtained from a previous study by Qin and Pan (2016). The significant impact of depression and depressive symptoms on healthcare costs indicate that reforming China's mental healthcare system to cope with the increase in the disease burden is an urgent need.

II. Background and Previous Research

The trend on the rising prevalence of depression has stimulated many studies to estimate the economic consequences of the mental health condition, which usually adopt a similar estimation approach as that for other NCDs. One of the important characteristics that distinguish mental disorders such as depression from the physical illnesses is its high likelihood of under-diagnosis and under-treatment. The World Health Organization (WHO) estimates that only 15% to 24% of people with severe mental disorders receive medical treatment in low- and middle-income countries. Although the treatment rate in high-income countries is higher, it is also in the range of 50 to 65% (WHO, 2013b), indicating that at least one third to one half of people with mental disorders go untreated. The consistent pattern of low treatment rate for mental disorders across countries highlights the importance to separate the estimation of depression-induced medical costs into two strands of research. The first strand includes the studies using patient-level data, which provides a conditional estimate on the depression-induced costs focusing on a sample of patients who received medical treatment. Given the pervasive evidence of under-treatment in mental disorders, this type of studies may suffer from the problem of underestimating the cost impact of mental depression. The second category of studies uses the population-level data, which provides an unconditional estimate on the medical costs based on a broader survey of general population including those with mental disorders but never receive medical treatment. The latter methodology hence has the advantage of avoiding the underestimation bias for the cost impact.

Most existing studies adopted the first approach, using a set of sampling criteria to recruit patients from the outpatient settings in mental health clinics. Two types of costs are associated with depression: the direct cost, or the outpatient and inpatient medical cost for the treatment of depression and its complications; the indirect cost, or the opportunity cost of depression, which includes the morbidity costs caused by absenteeism (missed work days due to depression) and presenteeism (reduced productivity while at work due to depression). Given the heterogeneity in their estimation methods and data sources, the results of these studies are difficult to compare directly. However, the existing studies did find several consistent patterns in the cost impact of mental depression.

First, the estimated cost of depression is quite high and increases over time. For example, Andlin-Sobocki et al. (2005) estimated the cost of depression in 28 European countries to be €118 billion in 2005, accounting for 13% of the total healthcare expenditure of these countries. Greenberg et al. (2015) report that the economic burden of depression in the United States was $210.5 billion in 2010, an increase of 21.5% as compared to the estimated figure in 2005.

Second, the estimated cost of depression is positively correlated with the disease severity. Based on data obtained from a retrospective, multi-center, non-interventional study in Switzerland, Tomonaga et al. (2013) report that the mean total direct costs per person per year, mainly due to hospitalization costs, were €3,561 for mild, €9,744 for moderate and €16,240 for severe depression; and the mean indirect costs per person per year, mainly due to workday losses, were €8,730 for mild, €12,675 for moderate and €16,669 for severe depression.

Third, the direct cost often accounts for a small portion of the total economic burden of depression, indicating that the major economic burden of depression arises from the indirect costs such as the labor productivity loss. This pattern is also quite consistent across countries: using data obtained from the United States, Greenberg et al. (2003) find that 31% of the estimated economic burden of depression was attributable to direct medical costs, 7% was suicide-related mortality costs, and 62% was workplace costs; Sobocki et al. (2007) also report a very similar result by using data from Sweden; based on data obtained from Spain, Salvador-Carulla et al. (2011) find that about 21% of the disease burden corresponded to direct costs, and 79% to indirect costs mainly due to productivity losses; in China, Hu et al. (2007) find that the direct cost accounts for about 16% of the total cost of depression, while the indirect costs contribute about 84%.

As noted, the stylized facts in the epidemiological studies indicate that many people with mental disorders go undiagnosed (Trivedi et al., 2004; Bor, 2015). This highlights the advantage of using population-level data to estimate the cost impact of depression. To our knowledge, there are virtually no studies applying this approach to provide an unconditional estimate of the health care costs attributable to depression at the population level. However, this approach is widely used to estimate the cost impact attributable to some other chronic diseases such as obesity. For example, based on the hurdle models and national medical expenditure survey data, Finkelstein et al. (2009) find that obesity accounts for an increasing share of annual medical spending in the United States, from 6.5% in 1998 to 9.1% in 2006. Their evidence suggests that the major driver of the cost growth is the increase in obesity prevalence instead of the per-capita cost inflation. By taking the endogeneity of weight into account, Cawley and Meyerhoefer (2012) show that obesity raises annual personal medical costs by $2,741 (in 2005 dollars), which is equivalent to 20.6% of the U.S. national health care expenditure. Based on a similar research method and data obtained from Spain, Mora et al. (2015) find that the obesity-induced cost varies with the severity of the condition: being severely obese is associated with 26% increase in medical costs, and this share reduces to 16% and 8.5% for moderate obesity and overweight respectively. Using longitudinal data obtained from China, Qin and Pan (2016) find that 5.29% of the total personal medical expenditures are attributable to obesity and overweight, which is equivalent to about 2.46% of China's national health expenditure.

In China, less than one tenth of individuals with mental disorders have ever received any types of mental health services (Philips et al. 2009). This extremely low treatment rate suggests that the medical costs of depression will be underestimated if we only use the patient-level data obtained from mental healthcare utilization. As a result, the survey data that report all medical spending of an individual in a given year provides an advantage over the existing studies, as they can take into account the cost-shifting effect as well as the comorbidity effects between mental health and physical health problems. Using the internationally comparable methods and survey instruments, we will estimate the impact of depression and depressive symptoms on the respondents' reported annual healthcare costs, and compute the expected personal medical spending attributable to these mental health conditions in China.

There are several advantages of using Chinese data to provide an unconditional estimate of health care costs attribute to depressive symptoms and depression. First, although the under-diagnosis and under-treatment of mental illness such as depression is very common in all countries, the diagnosis and treatment rate is particularly low in China, which in turn highlights the importance and the value-added of using population-based data to quantify the impact of increasing prevalence of mental illness on healthcare costs. Second, China has experienced both rapid economic growth and fast epidemiological transition (from communicable to non-communicable diseases) in recent years, thus how China copes with the rising challenges of increasing mental illness has important implications for many countries with the same development experience. Although our paper does not directly address the future path of reform in the mental health sector, our quantitative analysis sheds new light for the reform directions for both China and many low- and middle-income countries that face similar healthcare and economic challenges.

III. Data Source and Descriptive Analysis

CFPS (China Family Panel Studies) is a nationally representative longitudinal survey designed and implemented by the Institute of Social Science Surveys (ISSS) of Peking University. It was conducted in 25 Chinese provinces (these provinces jointly cover 95% of the Chinese population) in five years (2008, 2009, 2010, 2011, 2012). In each wave, the CFPS survey samples about 15,000 households nationwide using the multi-stage probability proportional to size (PPS) sampling method, and interviews all member of the family in each sample household. The questionnaire gathers individual-, family-, and community-level information on the demographic and socioeconomic variables, as well as information on the respondents' health outcomes. In the 2012 CFPS survey, a full 20-question version of the CES-D (Center for Epidemiologic Studies Depression) questionnaire (Radloff, 1977) is included to assess the respondents' mental health status.

The CES-D questionnaire is one of the most frequently used self-assessment tools for depression and depressive symptoms. An advantage of using this survey-based instrument is that the questions contained in CES-D are non-intrusive and related to everyday feelings[3], which makes it easier for the respondents to answer, leading to better detection of their depressive symptoms compared to other clinical instruments. This in turn may help to alleviate the underreporting problem commonly experienced among the mental illness patients (Bharadwaj et al., 2015). The CES-D questionnaire contains four subscales: somatic-retarded activity, interpersonal relations, depressed affect and positive affect. The former three measure negative emotions, while the latter measures positive ones. Respondents are asked to rate how often they experienced the specified emotions in the past week, with the options varying from 0 to 3 for each question (0 = rarely, 1 = little, 2 = occasionally, 3 = often). The CES-D score can thus be calculated based on the responses as follows:

$$CES-D = \sum_i Score_{i,somatic} + \sum_j Score_{j,interpersonal} + \sum_k Score_{k,depressed} + \sum_l (4 - Score_{l,positive}) \quad (1)$$

where $Score_{i,somatic}$, $Score_{j,interpersonal}$, $Score_{k,depressed}$ and $Score_{l,positive}$ represent the score for the i-th question on the somatic-retarded activity, the j-th question on interpersonal relations, the k-th question on the depressed affect and the l-th question on the positive affect, respectively.

Thus, the overall CES-D score ranges from 0 to 60, with a higher score indicating more frequent occurrence of depressive symptoms and higher likelihood of depression. According to Radloff (1977, 1991), the values of 16 and 28 approximately correspond to the 80th and 95th percentile of the CES-D distribution in the U.S.-based Community Mental Health Assessment (CMHA) survey, thus these two thresholds were commonly used to define the mental health conditions of depression and depressive symptoms among the U.S. population. Following this approach and considering the country difference in the mental health conditions between U.S. and China, we set our threshold values based on the 80th and 95th percentile of the CES-D distribution in the national sample of CFPS 2012, which correspond to the

[3] Examples of the CES-D questions include: "How often do you feel that everything I did was an effort?"; "How often do you feel not like eating (your appetite is poor)?"

CES-D scores of 20 and 28, i.e. a CES-D of 20~27 indicates that the person suffers from depressive symptoms, and a score of 28 or higher indicates depression[4]. Based on the above CES-D classification, the key explanatory variable in our study is the respondent's mental health status (*Mhs*), which takes on three possible values: 0 indicates being mentally healthy, 1 indicates depressive symptoms, and 2 indicates depression. The central outcome variable is the respondent's total annual medical expenditure as reported in the CFPS survey, which includes the inpatient and outpatient medical costs on the treatment of injuries and diseases (including mental health diseases) paid by the individuals and the insurance providers.

Based on the 2012 CFPS dataset, we drop the observations younger than 16 and older than 99, as well as the ones with missing information on key variables such as gender, age and the CES-D scores. In addition, we drop the observations with zero personal income (defined as the per capita annual household net income) for the reason that their medical costs are likely to be paid and decided by their family members[5]. The final study sample consists of 30,568 observations, among whom 81.2% are mentally healthy, 13.5% experience depressive symptoms, and 5.3% suffer from depression[6].

Table 1 provides the sample summary statistics of key variables, with column (1) to (4) representing the full sample and the subsamples in the three mental health categories (mentally healthy, depressive symptoms, depression), respectively. The table shows that the annual medical expenditure is strongly related to the status of individual mental health. On average, a mentally healthy person spends 1,561 *Yuan* on medical services per year, while for those who suffer from depressive symptoms,

[4] The "depression" identified by CES-D is different from the clinical definition, which is based on psychiatric diagnostic criteria, e.g. the DSM-IV or the ICD-10. Clinical depression, including major depression disorder (MDD) and major depression episodes (MDE), is usually diagnosed with 12-month occurrence of depressive events, while the "depression" in this paper is diagnosed with one-week occurrence of depressive events.
[5] From the original sample of 35,720 observations, 3 observations are dropped due to age restriction, 4,484 are dropped due to their missing information on key variables, and 665 are dropped due to zero income.
[6] Due to the discrete nature of the CES-D scores, the distributional percentiles corresponding to the CES-D cutoff values (20 and 28) differ slightly from the proposed percentiles (80th and 95th). In the Robustness Check section, we also use the alternative CES-D thresholds of 16 and 28 as originally proposed by Radloff (1977, 1991) for sensitivity check purpose.

the costs increase to 2,628 *Yuan*. Furthermore, the mean medical expenses of the group with depression are nearly 4,200 *Yuan*, almost three times higher than that of the mentally healthy group. There are three plausible explanations for this outcome. First, the treatment and control of depression and depressive symptoms, such as the use of antidepressants and cognitive-behavioral therapy, typically incur substantial medical costs (March et al., 2004). Second, depression not only causes a reduction in psychological well-being, but also damages people's physical health and hence create a comorbidity pattern in which depression often co-exists with other NCDs that require costly medical treatments (Penninx, et al., 1999). Third, the existence of the social and institutional barriers in access to mental health services often causes a delay in treatment or a cost shift to non-mental healthcare. Putting together, people suffering from depression and depressive symptoms are also likely to struggle under the financial burden of medical care, and the following sections intend to numerically estimate the medical cost induced by these conditions through econometric models.

[Insert Table 1 Here]

In our econometric analysis, the control variables include the respondent's demographic and socioeconomic characteristics, such as gender (*female*), age in years (*age*), education attainment ("primary school or below", "middle school", "high school" and "college or above"), residential status (*urban*), employment types ("not working", "household farming", "government employee", "employed by collective enterprise", "employed by private enterprise", "other types of employment"), marital status (*married*), household size (*familysize*) and annual personal income (*income*).

According to column (1) of Table 1, 51% of the respondents in our sample are female, and 31% live in the urban areas. 80% of the sample are married (including common-law marriage), with a sample average family size of 4.3 people. The average age of the full sample is 45.2, and the average annual personal income is 13,323 *Yuan*.

For education attainment, 50% of the full sample do not have formal schooling or only complete primary school education; 28% and 14% of the sample have middle school and high school education, respectively; only 8% of the sample have tertiary education. In terms of employment status, 25% of the respondents are not currently working (including retirees and students), while the rest of the sample is categorized into household farmers (24%), government employees (8%), collective enterprise employees (2%), private enterprise employees (28%) and other types of employment (13%). For healthcare utilization, 77.8% of the sample have incurred medical spending in the previous year, and 8.9% have inpatient spending. Among the medical users, the average annual medical cost is 2,371.35 *Yuan*, and the average inpatient spending is 11,643.19 *Yuan* among the inpatient users.

A comparison among the three mental health subsamples indicates considerable group differences in several key variables. For example, women are more likely to be depressive than men: 61% and 65% of the observations experiencing depressive symptoms and severe depression are female, which are higher than the female percentage in the full sample. According to the previous research (Nolen-Hoeksema, 2001; Simon, 2002; Tsang et al., 2008), both biological (or hormone) factors and social factors (e.g. sexual discrimination) may account for women's higher vulnerability to depression. The average ages of the three mental health groups are 44, 48 and 53, respectively, which demonstrates that the elderly are at higher risks of severe depression than the younger people. The conclusion is consistent with other studies that find higher depression prevalence rates among older people in both developed and developing countries (Vanltallie, 2005; Tsang et al., 2008). One plausible reason is that the socioeconomic status of the elderly are relatively low due to their poor health status, lack of social support, and the absence of financial support from adult children (see detailed discussions on the "empty nest" syndrome among China's elderly by Liu and Guo (2007) as well as Xie et al. (2010)).

Another conclusion drawn from the subsample comparison is that depression is more prevalent in rural than urban areas. The urban population accounts for 33% of the respondents who are mentally healthy, but the percentage of urban residents decreases to 23% and 20% in the depressive symptom and the severe depression groups, which is also consistent with the literature (Ma et al., 2009; Philips et al., 2009). Compared to their rural peers, urban residents in China have easier access to education and healthcare, and hence they generally enjoy higher income and better quality of life, which may in turn contribute to their better mental health status.

Socioeconomic status is highly correlated with people's tendency of depression, suggesting the strong socioeconomic gradient in mental health. For example, the severe depression group has the highest representation of the lowest education attainment (76%), much higher than the depressive symptom group (63%) and mentally healthy group (46%). On the other hand, the proportions of people completing middle school, high school and college (or above) are 30%, 15% and 9% in the mentally healthy group, while the proportions are 23%, 10% and 4% in the depressive symptom group, and they are 15%, 7% and 2% in the severe depression groups, respectively. Mirowsky and Ross (1998, 2003) show that education plays a critical role in helping people accumulate human capital and develop personal control over life events, which may explain why better-educated people are less vulnerable to depression. There is considerable income inequality among the three groups: the mentally healthy respondents earn an average of 14,009 *Yuan* per year, while the mean annual income of the depressive symptom group and depression group are only 10,778 *Yuan* and 9,260 *Yuan*, respectively. The results are consistent with the theoretical and empirical studies on the promoting effect of income on happiness (Zimmerman and Katon, 2005), which suggest that individuals in low income status may not be able to afford quality consumptions and comprehensive health services, leading to potential anxiety and disappointment that cause depression. Additionally, low-income people are also more likely to be exposed to violence and unstable living environment, which are risk factors for depression (Fitzpatrick, 1993).

IV. Estimation Method

4.1. The Two-part Model

We use a baseline two-part model (2PM) to characterize the determinants of an individual's annual medical expenditure, which can be expressed as follows:

$$\Pr(y_i > 0 \mid X_i) = G(\theta_1 D_{1i} + \theta_2 D_{2i} + \beta X_i + u_i) \qquad (2)$$

$$y_i = \exp(\delta_1 D_{1i} + \delta_2 D_{2i} + \gamma Z_i) + e_i, \quad \text{for } y_i > 0 \qquad (3)$$

where the outcome variable y_i is the total medical expenditure incurred in the previous year by individual i. The key explanatory variables are the two dummies – D_{1i} and D_{2i}, with the former indicating whether the person experiences depressive symptoms (Mhs=1) and the latter indicating whether the person suffers from depression (Mhs=2). The parameters θ_1, θ_2, δ_1 and δ_2 are the coefficients of interest, which represent the effects of depressive symptoms and depression on the probability of medical usage and the conditional medical expenditure among medical users, respectively. X_i is a vector of individual characteristics including gender, age, education, residential type, employment status, marriage status, household size, personal income and province dummies. Consistent with the literature convention, vector Z_i contains the same set of variables as X_i.

The above 2PM assumes that the individual medical spending is determined by two separate decision making processes: equation (2) is the "participation equation" and captures the systematic difference between medical users and non-users; equation (3) is the "intensity equation" and characterizes the determination mechanism of the amount of medical cost among medical users. Following the suggestion of prior studies (Jones, 2000; Manning and Mullahy, 2001), we estimate equation (2) with the

Logit model (specifying $G(\cdot)$ as the cumulative distribution function of the logistic distribution) and estimate equation (3) with the Gamma GLM model (generalized linear model with a Gamma distribution for e_i). The model specification is justified by the modified Park test[7], which shows that the conditional variance function of the medical expenditure distribution is consistent with the Gamma-class model. In addition, the result of the Hosmer-Lemeshow test[8] also confirms that our choice of log link function is consistent with the data generating process.

4.2. The Four-part Model

As an extension of the baseline 2PM, we follow Finkelstein et al. (2003) and use the four-part model (4PM) to characterize the medical spending of inpatient and outpatient users separately:

$$\Pr(y_i > 0 \mid X_i) = G(\theta_1 D_{1i} + \theta_2 D_{2i} + \beta X_i + u_i) \quad (4)$$

$$\Pr(g_i > 0 \mid y_i > 0, X_i) = G(\omega_1 D_{1i} + \omega_2 D_{2i} + \sigma Z_i + r_i) \quad (5)$$

$$y_i = \exp(\delta_1 D_{1i} + \delta_2 D_{2i} + \gamma Z_i) + e_i, \quad \text{for } g_i \le 0 \text{ and } y_i > 0 \quad (6)$$

$$y_i = \exp(\varphi_1 D_{1i} + \varphi_2 D_{2i} + \mu Z_i) + v_i, \quad \text{for } g_i > 0, y_i > 0 \quad (7)$$

where g_i is the inpatient expenditure incurred in the previous year by individual i. Compared to the baseline 2PM, 4PM adds another "participation" equation (equation (5)) and an "intensity" equation (equation (7)) to the model: equation (5) is a Logit regression that denotes whether a person with positive medical expenditure incurs any inpatient spending; equation (7) is a Gamma GLM regression on the determinants of medical expenditure based on the sample with positive inpatient spending.

Prior literature suggests that the determination mechanism of medical expenditure can be different between the medical users with and without inpatient utilization. First,

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[7] The modified Park test is used to identify the potential distribution of the dependent variable in GLM. The coefficient is 1.755, suggesting that variance is proportional to square of mean, which means that the assumption of Gamma distribution as the right variance function is broadly appropriate for the data.

[8] The Hosmer–Lemeshow test intends to verify the link function in GLM by regressing the prediction errors on the deciles of the predicted expenditure. Under the log-link assumption, the p-value is 0.702, which can't reject the null hypothesis that the decile coefficients are jointly non-significant and suggests that the regression model is fit.

the type of treatment differs with the severity of depression. Druss and Rosenheck (1999) find that the treatment for depressive symptoms includes both inpatient and outpatient services, but for people facing severe symptoms of depression, the inpatient treatment or hospitalization become one of the best solutions to the illness. Second, compared to the outpatient treatments, the inpatient treatments are more likely to be prescribed for chronic pains and physical diseases, which are strongly correlated with depression (Moussavi et al., 2007). To conclude, depression would cause an increase in both the inpatient and outpatient costs, especially the inpatient costs.

Thus, the above 4PM assumes a 3-stage determination process of an individual's medical spending: equations (4) estimates the systematic difference between medical users and non-users; equations (5) captures the difference between medical users with and without inpatient utilization; equation (6) and (7) then characterizes the total medical spending among users of outpatient services only and those of inpatient services, respectively. Accordingly, the parameters θ_1 and θ_2 indicate the impacts of depressive symptoms and depression on the probability of incurring positive medical spending, and the parameters ω_1 and ω_2 reflect the impacts on the probability of incurring inpatient spending among the medical users. The influences of depressive symptoms and depression on the amount of medical spending are represented by parameters δ_1 and δ_2 (on the outpatient users) and φ_1 and φ_2 (on the inpatient users).

4.3. Estimating the Cost of Depression and Depressive Symptoms

Following the method used by Finkelstein et al. (2003), Finkelstein et al. (2009), Wang et al. (2011) and Cawley and Meyerhoefer (2012) on estimating the medical cost induced by overweight and obesity, we can estimate the expected medical spending induced by depressive symptoms and depression through the following three-step approach based on the coefficients in 2PM and 4PM (similar methods are discussed in Buntin and Zaslavsky (2004), Deb et al. (2006) and Trogdon et al. (2008)),

First, we calculate the predicted medical cost of each sample individual using the fitted values in the "participation" equation(s) and "intensity" equation(s). Using 2PM as an example, the predicted individual medical spending can be specified as:

$$E(y_i \mid D_{1i}, D_{2i}, X_i, Z_i) = \Pr(y_i > 0 \mid D_{1i}, D_{2i}, X_i) \times E(y_i \mid y_i > 0, D_{1i}, D_{2i}, Z_i) \qquad (8)$$

where the first term on the right hand side is the predicted probability of having positive medical expenditure based on equation (2), and the second term is the expected medical costs of medical users according to equation (3). Since equation (3) is specified as Gamma GLM, the link function directly characterizes how the expectation of y_i is related to the regressors, avoiding the complication in a log-linked OLS model where a log dependent variable needs to be consistently retransformed back to its original scale (Buntin and Zaslavsky, 2004). The sample average of $E(y_i)$ thus becomes the expected medical spending of the population.

In case of 4PM, the predicted individual medical spending can be written as:

$$\begin{aligned} E(y_i \mid D_i, X_i, Z_i) = \Pr(y_i > 0 \mid D_i, X_i) \times \Big[& \Pr(g_i > 0 \mid y_i > 0, D_i, X_i) \times E(y_i \mid g_i > 0, y_i > 0, D_i, Z_i) \\ & + \big(1 - \Pr(g_i > 0 \mid y_i > 0, D_i, X_i)\big) \times E(y_i \mid g_i \leq 0, y_i > 0, D_i, Z_i) \Big] \end{aligned} \qquad (9)$$

In the second step, we calculate the counter-factual medical spending of an individual by setting his or her mental health indicators (D_{1i} and D_{2i}) to 0, while holding the other control variables at the original values. This counter-factual prediction can be specified as follows in the 2PM setting:

$$E(y_i \mid D_{1i} = 0, X_i, Z_i) = \Pr(y_i > 0 \mid D_{1i} = 0, X_i) \times E(y_i \mid y_i > 0, D_{1i} = 0, Z_i) \qquad (10)$$

$$E(y_i \mid D_{2i} = 0, X_i, Z_i) = \Pr(y_i > 0 \mid D_{2i} = 0, X_i) \times E(y_i \mid y_i > 0, D_{2i} = 0, Z_i) \qquad (11)$$

Thus, for individuals with depressive symptoms or depression, the above counter-factual spending is their expected medical cost if they were to become mentally healthy. The sample average of such counter-factual individual spending is thus the expected medical cost of a mentally healthy population with the same baseline characteristics except for the mental health status.

Similarly, the counter-factual medical spending in a 4PM can be written as:

$$E(y_i \mid D_{1i}=0, X_i, Z_i) = \Pr(y_i > 0 \mid D_{1i}=0, X_i) \times \Big[\Pr(g_i > 0 \mid y_i > 0, D_{1i}=0, X_i) \times E(y_i \mid g_i > 0, y_i > 0, D_{1i}=0, Z_i) + \big(1-\Pr(g_i > 0 \mid y_i > 0, D_{1i}=0, X_i)\big) \times E(y_i \mid g_i \leq 0, y_i > 0, D_{1i}=0, Z_i)\Big] \quad (12)$$

$$E(y_i \mid D_{2i}=0, X_i, Z_i) = \Pr(y_i > 0 \mid D_{2i}=0, X_i) \times \Big[\Pr(g_i > 0 \mid y_i > 0, D_{2i}=0, X_i) \times E(y_i \mid g_i > 0, y_i > 0, D_{2i}=0, Z_i) + \big(1-\Pr(g_i > 0 \mid y_i > 0, D_{2i}=0, X_i)\big) \times E(y_i \mid g_i \leq 0, y_i > 0, D_{2i}=0, Z_i)\Big] \quad (13)$$

In the third step, we calculate the expected personal medical costs attributable to depressive symptoms and depression, represented by ΔE_1 and ΔE_2 respectively, by taking the differences between the three expected medical costs (one from step 1 and the other two from step 2).

$$\Delta E_1 = E(y_i \mid D_{1i}, D_{2i}, X_i, Z_i) - E(y_i \mid D_{1i} = 0, X_i, Z_i) \quad (14)$$

$$\Delta E_2 = E(y_i \mid D_{1i}, D_{2i}, X_i, Z_i) - E(y_i \mid D_{2i} = 0, X_i, Z_i) \quad (15)$$

These cost estimates can be expressed in monetary values or as a percentage of the total expected medical expenditure, and their statistical significance can also be obtained using the t test on the difference between the two expected medical costs.

V. Empirical Results

5.1 Regression results

Table 2 reports the main results for the baseline 2PM, which contain information on the variable marginal effects for both the "participation" equation and "intensity" equation, with standard errors clustered at the county level[9]. The baseline model

[9] CFPS follows a multi-stage stratified sampling method, and the primary sampling unit (PSU) is either an administrative district (in urban areas) or a county (in rural areas). Thus, following the literature convention, standard errors are clustered at the county level in all regressions (see Xie and Hu (2014) for more details).

shows that the mental health status has a statistically significant impact on both the probability of using healthcare services and the amount of medical spending among the users of healthcare services. Specifically, the results indicate that individuals with depressive symptoms are 8.8% more likely to have non-zero medical expenditure and will spend 1,029.78 *Yuan* more on healthcare services in a year. For individuals with depression, the impacts of mental health status on healthcare costs are even stronger: they are 11% more likely to use healthcare services and will spend 1,836.52 *Yuan* more on healthcare. These results reinforce the findings obtained from previous studies that the cost impacts of mental illness such as depression are high.

[Insert Table 2 Here]

The coefficients of other control variables are generally consistent with the existing studies on the demand for healthcare. To be specific, we find that females are more likely to use healthcare services but spend less money on healthcare conditional on utilization. In addition, both the probability and the amount of healthcare spending increase with age. Income also has a significantly positive impact on the use of healthcare and the healthcare costs, indicating that healthcare services are normal goods in the sense that the demand for healthcare increases with income. Although marital status does not significantly influence the probability of healthcare usage, evidence shows that the single or divorced/widowed individuals tend to spend less on healthcare compared to their married counterparts.

We also find that working status has a significant impact on the demand for healthcare: compared to individuals who are not currently working, individuals who are active in the labor market are less likely to use healthcare services and spend less if they use healthcare. There are two possible explanations for this result. First, the labor market participants may face a higher time price in seeking healthcare as compared to non-participants. Since the full price of using health care service consists of both monetary cost and time cost, individuals with higher time price will have less demand for healthcare, holding other things constant (Sloan and Hsieh, 2017, p. 93). Second, the participation of labor market may serve as a proxy for being in good health, and hence labor market participants may use less healthcare services as compared to non-participants.

However, we find that education, residential status and family size do not have significant impacts on either the probability of using healthcare services or the amount of spending among healthcare users. The insignificant result may be contributed by the two offsetting effects working in opposite directions. For example, on the one hand, high-educated individuals tend to have better awareness of their health problems and hence are more likely to have higher healthcare demand. On the other hand, these individuals are more efficient in the production of their own health, and hence they will use less healthcare inputs to achieve the same health improvement as compared to low-educated people (Sloan and Hsieh, 2017, p. 54). Similarly, rural residents may need to pay a higher time price in seeking healthcare than urban residents due to the lower availability of healthcare resources, and thus rural residents may use less healthcare services than urban residents at one point in time. However, there is also evidence indicating that rural residents are in disadvantage to manage their health problems, so they tend to have poorer awareness and treatment for NCDs (Lei et al., 2012). The poor health management in turn forces the rural residents to use more health care services in the long run to restore their health status, such as the use of avoidable inpatient services.

Table 3 reports the regression results for the four-part model. The results are generally consistent with the two-part model with the additional information on the impact of mental health status on the probability of using inpatient services and the amount of spending on hospital care. Specifically, we find that individuals with depressive symptoms are 4% more likely to have non-zero inpatient expenditure and will spend 1,768.32 *Yuan* more on hospital care. For individuals with depression, the impact of their mental health status on their inpatient utilization is stronger too: they are 6.9% more likely to use inpatient services and will spend 3,773.92 *Yuan* more on hospital care. The estimated results on other control variables are similar to those reported in Table 2 with a few exceptions. For example, compared to the male group, the conditional healthcare expenditure for the female respondents is higher in the outpatient setting but lower in the inpatient setting, and this result suggests that the previous 2PM-based findings on the gender difference in medical expenditure are mainly driven by the inpatient spending in the data.

[Insert Table 3 Here]

5.2 Estimating the medical cost of depression and depressive symptoms

Based on the regression results of the two-part model, Table 4 presents the estimated personal medical cost attributed to depressive symptoms and depression for the full sample as well as the subsamples of different regions, genders, age groups and education levels. Following the three-step method described in Section 4.3, we report for each sample: (1) the predicted individual medical spending based on Equation (8); (2) the counter-factual medical expenditure when depressive symptoms/depression are set to healthy mental status; (3) the expected medical costs attributed to depressive symptoms and depression, which are expressed in level (*Yuan*) and percentage terms; (4) the t-statistics and p-values associated with the t-tests on the significance of cost estimates.

The upper part of Table 4 shows that the annual expected medical cost attributed to depressive symptoms is predicted to be 142.42 *Yuan*, or 7.8% of the total expected personal medical expenditure in a year. For the depression-induced medical cost, the estimate is 126.38 *Yuan* per annum, or 6.9% of total personal medical expenditure (lower part of Table 4). Putting together, we conclude that about 14.7% of the personal medical expenditure among Chinese adults can be attributed to depressive symptoms and depression[10]. In comparison to a recent study on the impact of overweight and obesity on healthcare costs (Qin and Pan, 2016), our results indicate that both depressive symptoms and depression are very costly to individuals and the society as a whole.

[Insert Table 4 Here]

A comparison among subsamples suggests that the personal medical expenditure attributable to depressive symptoms and depression are not evenly distributed across regions and subpopulations, with the female, the rural residents, the poorly-educated and the elderly people bearing a higher percentage of medical costs due to depression. For example, the share of total personal medical expenditure attributed to depression is larger in the rural areas (8.1%) than that in the urban areas (4.9%), and the cost impact of depressive symptoms has a similar pattern (8.7% vs. 6.2%). This result indicates that although mental health problems are major contributors to the increasing healthcare costs in both urban and rural China, the rural residents shoulder a bigger burden as they pay a higher share for severe depression and they also face larger barriers than their urban counterparts in seeking mental healthcare due to the low availability of mental health resources in the rural areas. Similarly, we also find that the depression-induced medical expenditure is higher for females and less educated people. For example, the expected medical cost attributable to depression (depressive symptoms) is 8.4% (8.7%) of total spending for female, which is much higher than male 5.2% (6.7%); likewise, the estimated cost of depression (depressive symptoms) is 9.3% (8.9%) among people with "primary school or below" education levels, while it is in the range of 2.0% to 4.0% (4.5% to 6.8%) for people with higher levels of educational attainment. The results suggest that these disadvantaged groups

[10] For clarification, the estimated medical costs attributable to depression and depressive symptoms are the population-based expected costs, which factor in both the probability and the conditional costs of incurring these mental health conditions. Thus, the expected cost of depression can be lower than that of the depressive symptoms due to its much lower prevalence rate within the population.

may have more difficulty in overcoming the accessibility hurdles of mental healthcare. For example, female and the less educated people may be subject to more social stigma when depressed; they may also be constrained by larger information gaps in seeking effective medical treatment for mental illness. A comparison among age groups indicates that the elderly people (over age 60) suffer the most from the depression-induced spending (about 8.4% of total medical spending), while the middle-aged individuals (aged between 40 and 60) are most affected by the medical cost related to depressive symptoms (accounting for 8.0% of total spending). A plausible explanation is that the elderly people in China (especially those living in the rural areas) tend to live away from their children and likely to suffer from the "empty nest" syndrome with insufficient social and emotional support, while the middle-aged group is more prone to work- and family-related stress, resulting in higher prevalence of mental health problems among these subpopulations.

Table 5 presents the estimated personal medical cost attributed to depressive symptoms and depression based on the regression results of the four-part model. The results and subsample patterns are similar to those reported in Table 4, indicating that our medical cost estimates and previous conclusions are not sensitive to alternative model specifications.

[Insert Table 5 Here]

5.3 Robustness Checks

In this section, we test the robustness of our main results by setting different cutoff scores of CES-D and using alternative model specifications for estimation. First, our main analysis uses the CFPS-based thresholds (20 and 28), which correspond to the 80th and 95th percentiles of the CES-D distribution in our study sample. In this section, we use the original CES-D classification thresholds (16 and 28) from Radloff (1977, 1991) in defining the mental health categories. In other words, a CES-D of 16~27 indicates depressive symptoms, while a score of 28 or higher indicates depression. The results associated with the new CES-D classification standard are reported in the first two columns of Table 6. These results are similar to those reported in Table 2, indicating that our basic results are not sensitive to the cut-off points of the CES-D classification.

[Insert Table 6 Here]

Second, our baseline hurdle models (including 2PM and 4PM) are based on the assumption that the error terms in the participation and intensity equations are not correlated, and thus the two equations can be estimated separately. However, the sample selection problem can also be caused by some unobserved common factors, justifying the use of the Heckman selection model. For sensitivity check purpose, we hereby adopt the Heckman model and re-estimate the participation and intensity equations through a joint maximum likelihood approach. The results are provided in Column (3)-(4) of Table 6. As shown, the estimated impacts of depression and depressive symptoms in both the participation and intensity equations are similar to those given by 2PM, suggesting the main results in Section 5.1 and 5.2 are robust. Furthermore, the estimated covariance between the random errors of the two equations are not significantly different from zero, indicating that the sample selection correction is not needed, which in turn supports the use of our baseline hurdle models.

Third, we use the instrumental variable (IV) method to address the potential endogeneity problem of the depression indicators in our main regressions. The mental health status of an individual can be endogenous due to the following two reasons: (1) unobserved factors such as lifestyles can lead to depression and increased medical expenditure simultaneously; (2) depression can be caused by higher medical spending due to financial concerns, thus the two variables are subject to "reverse causality". Such endogeneity can bias the coefficient estimates, either upward or downward, in the 2PM and 4PM regressions. As a solution, we use the prevalence rates of depression and depressive symptoms in the respondent's residential community as well as the interaction term of these two variables as IVs to address the potential endogeneity of the two mental health indicators. The percentage prevalence rates are defined as the number of people with depression / depressive symptoms (using our original CES-D cutoffs of 20 and 28) by the total number of respondents (excluding the individual him-/her-self) within the community, where a community refers to an urban neighborhood or a rural village as defined by the CFPS site identifiers[11].

The reasons why we choose these IVs are as follows. First, medical literature provides strong evidence on the geographic clustering of mental health problems such as depression due to the contextual effect[12] (Aneshensel and Sucoff, 1996; Chaix, B, et al. 2006). This in turn is contributed by structural factors (such as unemployment and income inequality) and experiential factors (such as vandalism, criminality and the lack of social cohesion) in a common socioeconomic environment that may lead to the prevalence of mental and emotional impairment among local residents (Fox, 1990; Liem and Liem,1978; Mechanic,1972). This phenomenon can be further explained by the following two epidemiological pathways: psychopathological outcomes may result from the daily stress of living in a place where social order is less apparent and social incivilities occur (Ross, 2000; Silver, Mulvey and Swanson, 2002; Ross, Reynolds and Geis, 2000; Wandersman and Nation, 1998; Ewart and Suchday, 2002); the difficulties of sustaining supportive social contacts in an unequal or disorganized social environment may present additional psychological stress on the local residents (Sampson, Raudenbush and Earls,1997; Geis and Ross, 1998; Lindström, Merlo and Ostergren, 2003; Elliott, 2000). The strong correlation between the community-level prevalence and the individual-level mental health status is also evidenced in our data: the F-statistics associated with the Stock and Yogo test are 147.39 and 293.68 in the first-stage regressions (reported in Table A1), and the

[11] Observations whose residential community contains only one sample individual are dropped, thus the sample size associated with the IV-2PM regressions is reduced to 30,452.

[12] In medical literature, a contextual effect is an aspect of cognitive psychology that describes the influence of environmental factors on one's perception of a stimulus. Morgan (2005) provides strong evidence of the contextual effect among people in the same residential communities.

Cragg-Donald Wald F-statistic for the weak identification test is 51.371, both showing that the IVs are not likely to be weak (Stock et al., 2002). Second, the area-based prevalence rates should (arguably) not directly correlate with the individual medical expenditure without affecting the individual's mental health status. This is because the medical expenditure and insurance reimbursement are not shared or cross-subsidized on the community level in China, and individuals within the same neighborhood are only responsible for paying their own medical bills. This exclusion restriction condition is statistically verified by Hansen's J test in our over-identified IV model: the p-value for the exclusion restriction hypothesis is 0.2391, suggesting that the IVs are not directly correlated with the unexplained portion of the individual medical expenditure. Third, our IV approach is supported by many prior studies that also use area-based measures to instrument individual-level behaviors (Currie and Cole, 1993; Goldman et al., 2001; Bhattacharya and Bundorf, 2009; Grabowski and Hirth, 2003; Lo Sasso and Buchmueller, 2004; Morris, 2007; Lei and Lin, 2009; Pan et al., 2013; Qin and Pan, 2016).

The results of the IV-2PM regressions are reported in Column (5)-(6) of Table 6. After controlling for the endogeneity of mental health status, our basic results remain the same in the sense that both depression and depressive symptoms are associated with higher probability and higher conditional values of medical spending. However, some of the estimated coefficients (especially in the intensity equation) are not statistically significant, which may be due to the small number of the compliers[13] who incur non-zero medical spending in our sample. With regard to other explanatory variables, the estimated coefficients reported in the IV-2PM model are generally consistent with the baseline regression reported in Table 2. Overall, these additional results indicate that the basic findings in our study on the positive association between depression and medical spending is valid and consistent.

[13] In our context, the compliers are the individuals who change their medical spending due to the changes in IVs.

VI. Discussions and Conclusions

During the past decades, China's rapid economic growth has been accompanied by rapid changes in lifestyle and an increasing prevalence of NCDs such as mental disorders. Previous studies show that the prevalence rate of depression, estimated with CES-D, is high and unevenly distributed across regions and subpopulations (Qin et al., 2016). However, few studies have paid attention to the impact of depression on healthcare costs. This paper provides the first nationally representative estimate on the medical costs induced by depression and depressive symptoms in China, the largest developing country in the world; in addition, it contributes to the health economic literature by expanding the use of hurdle models (such as 2PM and 4PM) to the burden of disease estimation in the mental health area.

Our population-based estimation methodology is justified by the stylized fact that psychological, social and institutional barriers often prevent or delay the mental health patients from seeking appropriate care, leading to severe under-diagnosis and under-treatment of mental health conditions. Furthermore, due to the co-existence of mental conditions and other chronic physical conditions (such as hypertension and diabetes), the cost impact of depression is also driven by the cost-shifting effect from mental healthcare to general healthcare and the co-morbidity effect between mental conditions and other NCDs. The existence of these two effects highlights the advantage of using survey data to quantify the impact of depression and depressive symptoms on healthcare costs, which in turn highlights two important findings. First, our regression results indicate that the mental health conditions significantly increase both the probability and the amount of medical spending by the Chinese adults, and the impact is significant for both the outpatient and inpatient spending, and robust under different model specifications. The counter-factual analysis (based on 2PM) suggests that depressive symptoms and depression are associated with 7.8% and 6.9% higher *expected* medical costs. Second, the induced costs are not evenly distributed across regions and subpopulations, with women, the rural residents, the elderly people and the low-educated groups paying a higher share of medical spending due to depression and depressive symptoms. This suggests that these disadvantaged groups may have more difficulty in overcoming the social and institutional barriers in accessing mental healthcare in China.

The above conclusions shed light on the urgent need for reforming the current mental health system in China, and further government involvement is required to improve the treatment and prevention of the mental health conditions. An important priority of the reform is to move away from a *hospital-centered* health system towards a *patient-centered* system, in which patients with mental illnesses and other NCDs are incentivized to be treated at the community level[14]. Given that our estimated medical costs of depression and depressive symptoms are almost three times as large as the cost impact of obesity and overweight (Qin and Pan, 2016), which is another public health concern and increasingly catches the public attention, China will have to battle against the escalating disease burden induced by these NCDs in the coming years, and a hospital-centered health system would be ill-suited for this task. As a result, the legal, regulatory and policy changes are needed to strengthen the primary mental healthcare system. For example, training more qualified mental health physicians and establishing more primary mental healthcare facilities are both in urgent need to close the fundamental gap between the supply and demand of mental healthcare in China. Favorable financing and payment schemes can also be designed to reduce the monetary hurdle that prevents the mental illness patients from accessing primary mental health services. In addition, legislation efforts can also be made to reduce the social stigma on people with mental conditions, which can be a formidable non-monetary barrier in seeking mental healthcare. Given the uneven distribution of depression-induced medical costs, our results also suggest that more policy attention should be devoted to the underserved areas and the disadvantaged groups such as

[14] As China has made significant progress in achieving universal coverage in recent years, the challenge of healthcare reform shifts from the financing system to the delivery system. A significant impact of expanding insurance coverage is that increasing percentage of population choose hospitals instead of primary care institutions for seeking healthcare, as local clinics are often seen as of poor quality.

women, rural residents and the low-educated people, which in turn may be an effective way to improve the overall mental health status for the country that hosts the world's one fifth population.

[Insert Table A1 Here]

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Table 1: Sample Summary Statistics for Key Variables

Variable	Definition	Full sample (1)	Mhs=0 (2)	Mhs=1 (3)	Mhs=2 (4)
cesd	CES-D score	12.92	9.97	22.68*	33.36*
		(7.96)	(4.88)	(2.17)	(5.31)
expenditure	Annual medical expenditure	1843.75	1560.89	2628.27*	4199.53*
		(6984)	(6258)	(8450)	(1144)
female	Gender (1=female)	0.51	0.49	0.61*	0.65*
		(0.50)	(0.50)	(0.49)	(0.48)
age	Age in years	45.22	44.35	47.53*	52.76*
		(16.60)	(16.56)	(16.3)	(15.3)
Marriage status					
married	Married (1=yes)	0.80	0.81	0.79	0.76
		(0.40)	(0.40)	(0.41)	(0.43)
single	Never married (1=yes)	0.13	0.14	0.11	0.07*
		(0.34)	(0.35)	(0.31)	(0.26)
divorced/widowed	Divorced or widowed(1=yes)	0.07	0.06	0.10*	0.17*
		(0.25)	(0.23)	(0.3)	(0.38)
familysize	Number of family members	4.34	4.34	4.39	4.28
		(1.87)	(1.86)	(1.93)	(1.91)
urban	Urban residents (1=yes)	0.31	0.33	0.23*	0.20*
		(0.46)	(0.47)	(0.42)	(0.4)
Education					
primary	Primary school or below (1=yes)	0.50	0.46	0.63*	0.76*
		(0.50)	(0.5)	(0.48)	(0.43)
middle	Middle school (1=yes)	0.28	0.30	0.23*	0.15*
		(0.45)	(0.46)	(0.42)	(0.36)
high	High school (1=yes)	0.14	0.15	0.10*	0.07
		(0.35)	(0.36)	(0.3)	(0.25)
college	College or above (1=yes)	0.08	0.09	0.04*	0.02*
		(0.27)	(0.28)	(0.21)	(0.13)
income	Per capita annual household net income (*yuan*)	13,323	14009	10778*	9260*
		(22803)	(24031)	(17776)	(10775)
Employment status					
nowork	Not working (1=yes)	0.25	0.25	0.27*	0.33*
		(0.44)	(0.43)	(0.44)	(0.47)
farm	Household farming (1=yes)	0.24	0.22	0.28*	0.34*
		(0.42)	(0.42)	(0.45)	(0.48)
government	Government employee (1=yes)	0.08	0.08	0.05*	0.03*
		(0.26)	(0.28)	(0.21)	(0.18)
collective	Collective firm employee (1=yes)	0.02	0.02	0.01*	0.01*
		(0.13)	(0.13)	(0.11)	(0.11)
private	Private firm employee (1=yes)	0.28	0.30	0.25*	0.15*
		(0.45)	(0.46)	(0.43)	(0.36)

other	Other employment type (1=yes)	0.13 (0.34)	0.13 (0.34)	0.14* (0.35)	0.13 (0.34)
Observation	Sample Size	30,568	24833	4128	1607

Note: Data Resource: China Family Panel Studies (2012). The reported statistics are the sample mean with standard deviation in parentheses. Columns (2) to (4) correspond to the mentally healthy group (Mhs=0), depressive symptom group (Mhs=1) and depression group (Mhs=2), which are categorized using the CES-D score (depressive symptoms = CES-D between 20 and 27; depression = CES-D of 28 or higher). Asterisks (*) in column (3) and (4) denote statistically significant differences between the depressive symptom group / depression group and the mentally healthy group (at 5% confidence level).

Table 2: Regression Results for the Two-Part Model

Variable	Participation (1)	Intensity (2)
Mhs=1	0.088***	1,029.778***
	(0.0101)	(124.2407)
Mhs=2	0.110***	1,836.518***
	(0.0171)	(195.9880)
female	0.053***	-263.787***
	(0.0051)	(100.6466)
age	0.004***	35.998***
	(0.0003)	(4.1991)
single	0.004	-1,057.578***
	(0.0091)	(140.0699)
divorced/ widowed	-0.011	-731.291***
	(0.0109)	(115.2224)
familysize	-0.004*	-40.335
	(0.0022)	(28.0694)
urban	-0.011	173.464
	(0.0137)	(146.8622)
middle	0.001	-46.192
	(0.0087)	(121.3465)
high	-0.006	188.364
	(0.0107)	(181.1377)
college	0.017	-302.750
	(0.0114)	(192.4721)
log(income)	0.012***	152.486***
	(0.0034)	(46.6227)
farm	0.003	-1,469.186***
	(0.0118)	(157.8444)
government	-0.016	-1,208.706***
	(0.0127)	(230.6926)
collective	-0.024	-1,020.709*
	(0.0204)	(525.6120)
private	-0.004	-1,191.097***
	(0.0097)	(170.6624)
other	-0.042***	-845.372***
	(0.0142)	(188.1412)
Province dummy	Yes	Yes
Sample Size	30,568	23,767

Note: The reported statistics are the marginal effects of the explanatory variables with the county-level clustered standard errors shown in parentheses. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively.

Table 3: Regression Results for the Four-Part Model

Variable	Participation_1 (1)	Participation_2 (2)	Intensity_1 (3)	Intensity_2 (4)
Mhs=1	0.088***	0.040***	457.181***	1,768.317**
	(0.0101)	(0.0051)	(60.5261)	(768.1409)
Mhs=2	0.110***	0.069***	882.560***	3,773.924***
	(0.0171)	(0.0085)	(91.7069)	(1,215.5623)
female	0.053***	0.007	95.085**	-3,953.329***
	(0.0051)	(0.0044)	(43.2199)	(805.0371)
age	0.004***	0.001***	18.218***	22.735
	(0.0003)	(0.0002)	(2.2165)	(25.3398)
single	0.004	-0.064***	-241.929**	-3,033.633**
	(0.0091)	(0.0072)	(105.2402)	(1,405.1736)
divorced/widowed	-0.011	-0.018***	-141.357**	-3,915.030***
	(0.0109)	(0.0061)	(60.3838)	(664.2030)
familysize	-0.004*	-0.001	-7.644	-322.126*
	(0.0022)	(0.0013)	(12.8620)	(181.7481)
urban	-0.011	0.005	89.617	722.885
	(0.0137)	(0.0071)	(61.4090)	(1,002.6685)
middle	0.001	0.000	-61.728	1,088.871
	(0.0087)	(0.0062)	(46.5010)	(876.3226)
high	-0.006	0.006	96.897	586.524
	(0.0107)	(0.0075)	(93.7847)	(1,232.6610)
college	0.017	0.009	-77.149	-1,906.685
	(0.0114)	(0.0117)	(84.5203)	(1,367.5486)
log(income)	0.012***	0.002	60.405***	812.648***
	(0.0034)	(0.0020)	(23.4463)	(282.0944)
farm	0.003	-0.065***	-487.127***	-4,197.002***
	(0.0118)	(0.0078)	(71.1060)	(874.8755)
government	-0.016	-0.061***	-424.623***	-3,428.957**
	(0.0127)	(0.0099)	(86.3087)	(1,729.5091)
collective	-0.024	-0.073***	-271.940	-1,737.986
	(0.0204)	(0.0165)	(197.8315)	(4,560.7086)
private	-0.004	-0.069***	-323.904***	-3,542.696***
	(0.0097)	(0.0075)	(86.3577)	(987.8870)
other	-0.042***	-0.051***	-186.488**	-2,298.614*
	(0.0142)	(0.0088)	(84.8986)	(1,284.2939)
Province dummy	Yes	Yes	Yes	Yes
Sample Size	30,568	23,767	21,054	2,713

Note: The reported statistics are the marginal effects of the explanatory variables with the county-level clustered standard errors shown in parentheses. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively.

Table 4: Estimated Personal Medical Costs Attributable to Depressive Symptoms and Depression Based on 2PM

(A) depressive symptoms

Sample	category	Sample size	Expected expenditure	Count-factual expenditure	Expected cost of depressive symptoms	% cost of depressive symptoms	t-statistics	p-value
All sample	baseline	30,568	1836.95	1694.53	142.42	7.75%	58.53	0.000
region	rural	21,204	1631.04	1488.42	142.62	8.74%	53.43	0.000
	urban	9,364	2303.23	2161.27	141.97	6.16%	27.54	0.000
gender	male	14,964	1786.69	1667.28	119.41	6.68%	35.72	0.000
	female	15,604	1885.16	1720.67	164.49	8.73%	46.74	0.000
age	young	11,447	1001.06	927.30	73.76	7.37%	34.86	0.000
	middle aged	12,560	1856.24	1708.60	147.64	7.95%	41.51	0.000
	elderly	6,561	3258.41	3006.19	252.22	7.74%	31.18	0.000
education	primary	15,329	2087.58	1902.00	185.58	8.89%	47.87	0.000
	middle	8,666	1542.17	1437.79	104.38	6.77%	26.82	0.000
	high	4,231	1807.17	1697.67	109.50	6.06%	17.81	0.000
	college	2,342	1341.10	1280.92	60.18	4.49%	12.58	0.000

(B) depression

Sample	category	Sample size	Expected expenditure	Count-factual expenditure	Expected cost of depression	% cost of depression	t-statistics	p-value
All sample	baseline	30,568	1836.95	1710.57	126.38	6.88%	35.58	0.000
region	rural	21,204	1631.04	1498.50	132.53	8.13%	32.91	0.000
	urban	9,364	2303.23	2190.79	112.45	4.88%	15.70	0.000
gender	male	14,964	1786.69	1693.00	93.68	5.24%	20.77	0.000
	female	15,604	1885.16	1727.42	157.73	8.37%	29.00	0.000
age	young	11,447	1001.06	966.48	34.58	3.45%	15.69	0.000
	middle aged	12,560	1856.24	1722.98	133.26	7.18%	25.99	0.000
	elderly	6,561	3258.41	2985.03	273.38	8.39%	21.80	0.000
education	primary	15,329	2087.58	1893.01	194.57	9.32%	31.65	0.000
	middle	8,666	1542.17	1480.17	62.01	4.02%	13.27	0.000
	high	4,231	1807.17	1740.75	66.42	3.68%	9.14	0.000
	college	2,342	1341.10	1314.51	26.58	1.98%	4.66	0.000

Note: 1) All subsample results are based on the two-part model. 2) Counter-factual expenditure in Panel (A) is the expected medical expenditure when the people suffering from depressive symptoms are set to be mentally healthy, holding other personal characteristics at the actual levels. Similarly, the counter-factual expenditure in Panel (B) is the expected medical expenditure when people with depression are set to be mentally healthy. 3) The t-statistics and p-values are associated with the t test on the significance of the cost estimates (the difference between the predicted expenditure and counter-factual expenditure). 4) Age groups are based on the following age categorization: Young = between 16 and 40; Middle-aged = between 40 and 60 (include 40); Elderly = aged above 60 (include 60).

Table 5: Estimated Personal Medical Costs Attributable to Depressive Symptoms and Depression Based on 4PM

(A) depressive symptoms

Sample	category	Sample size	Expected expenditure	Count-factual expenditure	Expected cost of depressive symptoms	% cost of depressive symptoms	t-statistics	p-value
All sample	baseline	30,568	1834.82	1697.63	137.19	7.48%	59.12	0.000
region	rural	21,204	1610.01	1473.89	136.12	8.45%	54.12	0.000
	urban	9,364	2343.88	2204.27	139.62	5.96%	27.95	0.000
gender	male	14,964	1785.26	1668.08	117.18	6.56%	35.90	0.000
	female	15,604	1882.34	1725.96	156.37	8.31%	47.54	0.000
age	young	11,447	1030.70	955.15	75.55	7.33%	34.64	0.000
	middle aged	12,560	1861.49	1716.77	144.72	7.77%	41.27	0.000
	elderly	6,561	3186.71	2956.38	230.32	7.23%	31.06	0.000
education	primary	15,329	2034.89	1861.55	173.34	8.52%	48.40	0.000
	middle	8,666	1607.57	1499.56	108.01	6.72%	26.92	0.000
	high	4,231	1816.86	1709.39	107.47	5.92%	18.11	0.000
	college	2,342	1398.61	1336.35	62.26	4.45%	12.60	0.000

(B) depression

Sample	category	Sample size	Expected expenditure	Count-factual expenditure	Expected cost of depression	% cost of depression	t-statistics	p-value
All sample	baseline	30,568	1834.82	1709.39	125.42	6.84%	36.19	0.000
region	rural	21,204	1610.01	1479.01	131.00	8.14%	33.51	0.000
	urban	9,364	2343.88	2231.08	112.81	4.81%	16.02	0.000
gender	male	14,964	1785.26	1688.75	96.51	5.41%	20.94	0.000
	female	15,604	1882.34	1729.19	153.15	8.14%	29.77	0.000
age	young	11,447	1030.70	993.16	37.54	3.64%	15.67	0.000
	middle aged	12,560	1861.49	1724.34	137.15	7.37%	11.23	0.000
	elderly	6,561	3186.71	2930.39	256.31	8.04%	21.84	0.000
education	primary	15,329	2034.89	1846.13	188.76	9.28%	32.28	0.000
	middle	8,666	1607.57	1540.44	67.12	4.18%	13.52	0.000
	high	4,231	1816.86	1747.72	69.13	3.80%	9.16	0.000

college	2,342	1398.61	1370.33	28.28	2.02%	4.80	0.000

Note: 1) All subsample results are based on the four-part model. 2) Counter-factual expenditure in Panel (A) is the expected medical expenditure when the people suffering from depressive symptoms are set to be mentally healthy, holding other personal characteristics at the actual levels. Similarly, the counter-factual expenditure in Panel (B) is the expected medical expenditure when people with depression are set to be mentally healthy. 3) The t-statistics and p-values are associated with the t test on the significance of the cost estimates (the difference between the predicted expenditure and counter-factual expenditure). 4) Age groups are based on the following age categorization: Young = between 16 and 40; Middle-aged = between 40 and 60 (include 40); Elderly = aged above 60 (include 60).

Table 6: Regression Results for Robustness Check

Variable	Alternative Threshold participation (1)	Alternative Threshold intensity (2)	Heckman Model participation (3)	Heckman Model intensity (4)	IV Regression participation (5)	IV Regression intensity (6)
Mhs=1	0.077***	1,087.669***	0.085***	1,144.711***	0.185**	2,003
	(0.0091)	(123.3422)	(0.0075)	(145.8760)	(0.0735)	(1,465)
Mhs=2	0.109***	2,600.123***	0.105***	2,626.256***	0.294***	-112.5
	(0.0133)	(332.9048)	(0.0125)	(218.3777)	(0.0928)	(1,577)
female	0.051***	-235.332**	0.053***	-386.944***	0.042***	-350.9***
	(0.0051)	(97.2799)	(0.0048)	(106.3357)	(0.0055)	(119.0)
age	0.004***	36.626***	0.004***	31.880***	0.003***	34.62***
	(0.0003)	(4.3740)	(0.0002)	(4.5534)	(0.0002)	(4.617)
single	0.003	-1,033.960***	0.003	-988.934***	-0.002	-970.4***
	(0.0092)	(144.7266)	(0.0084)	(197.7162)	(0.0085)	(200.9)
divorced/ widowed	-0.013	-730.200***	-0.013	-1,027.534***	-0.026**	-893.9***
	(0.0108)	(117.2782)	(0.0109)	(205.0186)	(0.0123)	(217.4)
familysize	-0.004*	-32.012	-0.004***	-55.898*	-0.003**	-61.31**
	(0.0022)	(27.7526)	(0.0014)	(29.3085)	(0.0014)	(29.67)
urban	-0.010	178.624	-0.012*	262.419*	-0.007	234.6*
	(0.0137)	(141.1751)	(0.0062)	(135.3414)	(0.0062)	(137.8)
middle	0.002	-2.894	0.001	193.525	0.008	147.5
	(0.0087)	(120.6344)	(0.0059)	(129.7684)	(0.0062)	(136.3)
high	-0.004	164.938	-0.006	228.124	0.003	184.4
	(0.0106)	(173.0485)	(0.0077)	(170.7450)	(0.0080)	(177.7)
college	0.019*	-253.250	0.017*	-121.796	0.026**	-164.7
	(0.0112)	(196.7381)	(0.0100)	(234.3299)	(0.0100)	(241.2)
log(income)	0.013***	159.926***	0.012***	174.378***	0.015***	173.9***
	(0.0035)	(44.8232)	(0.0021)	(46.4503)	(0.0022)	(49.04)
farm	0.001	-1,481.633***	0.004	-2,028.600***	0.001	-2,017***
	(0.0118)	(149.1812)	(0.0075)	(156.4790)	(0.0076)	(157.9)
government	-0.017	-1,197.322***	-0.015	-1,883.977***	-0.017	-1,897***
	(0.0127)	(234.6496)	(0.0106)	(236.0008)	(0.0107)	(238.0)
collective	-0.027	-979.105*	-0.024	-1,892.504***	-0.030	-1,888***
	(0.0204)	(541.0354)	(0.0182)	(411.1295)	(0.0186)	(415.9)
private	-0.005	-1,163.862***	-0.003	-1,864.707***	-0.005	-1,905***
	(0.0096)	(169.5387)	(0.0071)	(157.9692)	(0.0073)	(163.2)
other	-0.043***	-817.415***	-0.041***	-1,428.392***	-0.045***	-1,450***
	(0.0146)	(183.4866)	(0.0085)	(181.5054)	(0.0085)	(184.5)
Province dummy	Yes	Yes	Yes	Yes	Yes	Yes
Sample Size	30,568	23,767	30,568	30,568	30,452	23,678

Note: 1) The reported statistics are the marginal effects of the explanatory variables with the robust standard errors shown in parentheses. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively. 2)

Column (1) and (2) report the 2PM regression results based on alternative CES-D standard (depressive symptoms = CES-D between 16 and 27; depression = CES-D of 28 or higher). 3) Column (3) and (4) report the regression results of the Heckman selection model. The p-value for the LR test on H0: rho=0 is 0.607, which implies that the correlation between the random errors of the participation and intensity equations is weak. 4) Column (5) and (6) report the regression results based on the IV-treated two-part model (IV-2PM), in which the instrumental variables are the community-level prevalence rates of depressive symptom and depression as well as their interaction term, where a community refers to an urban neighborhood or a rural village in which the respondent lives in. The p-value for the Hansen's J test on the exclusion restrictions of the IV model is 0.2391.

Table A1: First Stage Regression Results for IV-2PM

Variable	mhs=1 (1)	mhs=2 (2)
IV: mhs1_rate	0.0495**	0.526***
	(0.0208)	(0.0327)
IV: mhs2_rate	0.355***	0.483***
	(0.0725)	(0.0865)
IV: mhs1_rate * mhs2_rate	1.402***	-1.141***
	(0.368)	(0.433)
female	0.0528***	0.0257***
	(0.00398)	(0.00257)
age	0.00103***	0.00102***
	(0.000168)	(0.000111)
single	0.00998**	0.0121*
	(0.00434)	(0.00724)
divorced/ widowed	0.0539***	0.0284***
	(0.00764)	(0.00935)
familysize	-0.00389***	-0.00240***
	(0.00116)	(0.000757)
urban	-0.00227	0.000834
	(0.00494)	(0.00307)
middle	-0.0216***	-0.0259***
	(0.00290)	(0.00484)
high	-0.0211***	-0.0319***
	(0.00354)	(0.00603)
college	-0.0218***	-0.0311***
	(0.00395)	(0.00758)
log(income)	-0.00999***	-0.00425***
	(0.00185)	(0.00125)
farm	0.00299	-0.00407
	(0.00460)	(0.00648)
government	-0.00468	-0.00114
	(0.00474)	(0.00780)
collective	0.00588	0.00923
	(0.00835)	(0.0136)
private	-0.00725*	0.0133**
	(0.00374)	(0.00598)
other	0.00194	0.0140**
	(0.00465)	(0.00698)
Province dummy	Yes	Yes
Stock and Yogo F statistics	147.39	293.68
Sample Size	30,452	30,452

Notes: 1) The reported statistics are the marginal effects of the explanatory variables with robust standard errors shown in the parentheses. *, **, *** denote statistical significance at 10%, 5%, 1% levels, respectively. 2)