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Impact of house price growth on mental health: Evidence from China



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ABSTRACT

JEL classification: 115 R21 R31 Keywords: House price increase Mental health China	<i>Background:</i> Housing boom has raised global attention in the past two decades. A number of studies attempted to analyse the effect of house price increase. However, little is known about the health consequence as a result of housing boom, likely due to the scarcity of the data. The objective of this paper is to investigate the relationship between housing affordability and mental health as a result of house price increase. <i>Methods:</i> Based on a panel dataset of 32 Chinese cities from January 2013 to December 2017, we used a fixed effect model adjusting for per capita disposable income to estimate the impact of house price growth rate on mental health, and applied the Instrumental Variable (IV) method to address the endogeneity problem. <i>Results:</i> From both Ordinary Least Squares (OLS) and IV estimations, the results suggested that a one standard deviation increase in house price increase rate in the past three months is associated with a 0.443 standard deviation increase in people consulting with doctors about their mental disorders in the city. This effect does not vary by gender, but was more pronounced in residents older than 40 years. <i>Conclusion:</i> These results revealed the potential negative consequences in people's mental health due to house price increase, necessitate appropriate policy responses.
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1. Introduction

The ongoing housing boom in China has attracted global attention for nearly two decades (Glaeser et al., 2017). The average national house price doubled between 2006 and 2014 (Fang et al., 2016; Glaeser et al., 2017; Guo et al., 2014; Wu et al., 2012), especially in the first-tier and second-tier cities, such as Beijing, Shanghai, and Shenzhen (Fang et al., 2016; Wu et al., 2016). By contrast, the per capita disposable income for urban residents increased from 11,759 to 20,167 Chinese Yuan (¥) (roughly equivalent to 1664 to 2854 US dollars) between 2006 and 2014. The rapid house price increases relative to the household income growth rate illustrated the housing affordability problem in China. Many studies have attempted to document the impact of rapid house price increase on labour supply (Fu et al., 2016) and corporate behaviour (Chen et al., 2016; Li & Wu, 2014; Rong et al., 2016). However, little literature has empirically demonstrated the health consequence of the housing boom in China due to data availability. This study filled this knowledge gap and provided valuable evidence.

Meanwhile, the increasing number of individuals diagnosed with mental disorders has raised global concerns. Major mental disorders

include depression and anxiety: 4.4% (i.e., 332 million patients) and 3.6% (i.e., 264 million patients) of the global population suffer from depression and anxiety, respectively. In China, 16.57% of adults suffered from mental disorders in 2019 (Huang et al., 2019). More importantly, the consultation rate of mental disorders, indicating the rate at which people consult their doctors about their mental disorders, has continuously increased in China. For instance, the number of clinical visits increased from 35 million in 2013 (China Public Health Statistical Yearbook, 2013) to 49 million in 2017 (China Public Health Statistical Yearbook, 2017) at the national level, given that the number of the total population is relatively stable. The increase in the consultation rate partially reflects the change in the incidence of mental disorders, especially in the short term. Besides, mental disorders have a negative impact on individuals, potentially impairs patients' physical and mental health (Ince & Gunusen, 2018) and have adverse effects on the patients' family (Iseselo et al., 2016). Moreover, mental disorders increase the societal and economic burden. The World Health Organization reported that the global economy loses US\$1 trillion per year due to anxiety and depression. Hence, a thorough evaluation is demanded on the causes and the impacts on mental health.

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The incidence of mental disorders has many influencing factors. In addition to genetic factors, economic and social factors also have an impact on it. Chung et al. (2020) find that housing affordability affects mental health, partially through deprivation (Chung et al., 2020). Bentley et al. (2012) find that average mental health is lower for individuals with longer exposure to housing affordability stress (Bentley et al., 2012). Bentley et al. (2011) find that entering unaffordable housing is detrimental to the mental health of individuals residing in low-to-moderate income households (Bentley et al., 2011). With the rapid development of the economy and society, the pace of life has accelerated markedly, psychological stress factors have increased, and common mental disorders such as anxiety and depression have increased year by year. This trend is more pronounced in large and medium-sized cities where the pace of social life is snowballing, such as Beijing (Huang, 2011), Zhejiang (Phillips et al., 2009) and Hunan (Wang et al., 2017). This phenomenon is consistent with the findings of international research (Cooper, 1971; Hinds et al., 2005; Susser & Martinez-Ales, 2018).

In this study, we explored the impact of house price increases on mental health based on a city-level panel dataset that covers 32 cities in mainland China from January 2013 to December 2017. House plays a vital role in the marriage market in China (Li & Chand, 2013; Wei & Zhang, 2011). Young couples are expected to purchase a house when they prepare to get married with the help of their parents. According to Chinese tradition, the parents of the fiancé are expected to provide the dwelling for the young couple to bless the newlyweds, and the parents of the fiancée will prepare other dowries such as cars, household appliances, etc. Meanwhile, under the influence of Chinese traditional family cultural values, parents will help to share the purchase funds when their children do not have enough financial means to buy a house on their own. In most cases, their parents would provide the downpayment, and the newly-married couple pays the mortgage because the newly-married couple does not have enough savings. As a result, the rapid house price increase worsens the social pressure of the housing affordability problem on adults in China. Published literature provides rich evidence that high social pressure would damage residents' mental health (Huang et al., 2019; Shields & Price, 2005; Smiley et al., 2007). The incidence rate of mental disorders varies across cities because of the variation in socioeconomic factors (Cooper, 1971; Huang et al., 2019; Susser & Martinez-Ales, 2018), homeownership (Susser & Martinez-Ales, 2018) and housing affordability (Bentley et al., 2011, 2012; Chung et al., 2018, 2020). More specifically, Therefore, it is reasonable to expect that rapid house price increase as well as the associated mortgage (Jenkins et al., 2008), would induce more mental disorders. Given the severe consequence of mental disorders for individuals (Ince & Gunusen, 2018) and society (Lam & Boey, 2005), it is of great importance to focus on the impact of the housing boom on mental health.

The objective of this paper is to investigate the relationship between housing affordability and mental health in China due to housing price increase.

2. Methods

2.1. Materials

In this study, we used a monthly city-level panel dataset of 32 Chinese cities from January 2013 to December 2017. Each observation contains information on mental health and the monthly house price growth rate of each city. The dataset is constructed based on two data sources.

The first source is a random and micro-level subsample of 32 cities from the China Health Insurance Research Association claims database, which was used to calculate the mental disorders outpatient service information. Patients in the sample who had been diagnosed with mental disorders were identified as individuals with the International Classification of Disease 10th revision (ICD-10) code F00– F99 (Mental

and behavioural disorders). Mental disorders-related medical records of sample patients were extracted based on patient ID. For each province, the provincial capital and another prefecture-level city were selected by the Ministry of Human Resources and Social Security of the People's Republic of China. The dataset covers all the diseases, which guarantees that the city list is not determined according to mental disorders. We obtain the data covering 32 cities because the house price indices only cover 32 cities among the sample cities. Although we cannot name the 32 cities as required by the data provider, we can provide some macrolevel statistics. On average, the per capita disposable income is ¥39,119 in 32 cities while it is ¥36,396 in overall mainland China; the per capita GDP is ¥88,343 in 32 cities while it is ¥59,660 in overall mainland China. The population of permanent residents is 8155 thousand in mainland China. In other words, the 32 cities are relatively large in mainland China, with a higher house price growth rate and likely worse mental health. Each record, which indicates an outpatient service, is a random sample of outpatients insured under Urban Resident Basic Medical Insurance (URBMI) and Urban Employee Basic Medical Insurance (UEBMI) from January 2013 to December 2017. As long as the insured patients are covered by URBMI/UEBMI, their medical records are recorded, regardless of whether these items are covered by URBMI/ UEBMI or not. URBMI is the public health insurance for urban nonworking residents that covers children, adolescents, college students, elderly individuals, and individuals with disabilities. UEBMI covers the working population (public and private sectors) in urban China. As required by the Decision of the State Council on Establishing the Urban Employee Basic Medical Insurance, all the urban employees should join the UEBMI accordingly (www.mohrss.gov.cn/yiliaobxs). Non-working residents voluntarily join URBMI. Residents cannot participate in both types of insurance at the same time. URBMI and UEBMI are the two largest public insurance providers for urban residents. In 2017, the total enrollees of URBMI and UEBMI reached 1.17 billion (www.mohrss.gov. cn/SYrlzyhshbzb), accounting for approximately 85% of the total population (1.39 billion) in China. The dataset contains information on the medical expenses (total cost and billings of each claim), patients demographics (gender, birth date), and diagnostic information (admission date, discharge date, diagnosis, medication). We also obtained the number of enrolees in each city by year from China City Statistical Yearbook.

The second source is the house price increase series extracted from Wu et al. (2014). The monthly quality-adjusted house price index was calculated based on the full sample of newly-built housing transactions using the hedonic model. Hence, the house price index could capture the pure price change over time controlling for house attributes. The house price index is reliable and widely used in the literature, such as Chen and Wen (2017) and Deng et al. (2018).

To mitigate the cofounding effect of income, we controlled for the per capita disposable income from the National Bureau of Statistics. Besides, we also investigated whether rent increase or stock price change causes mental disorders. As for the former, we adopted the monthly growth rate of the housing component in the Consumer Price Index from the National Bureau of Statistics as the indicator. As for the latter, we used the monthly Shanghai Composite Index growth rate and monthly Shenzhen Composite Index growth rate from Wind.

2.2. Measurements

House price increase as a primary predictor

To study the impact of house price increase on mental health, we computed the house price growth rate during the past 1, 3, 6, and 12 months for each city. While house price series can be calculated at monthly, quarterly or annual level, the monthly house price indices are widely used around the world, such as Case–Shiller Home Price Indices. In this study, we used the monthly data to reduce the impact of confounding factors and observed the short-term effect. Instead of listing all the results for each house price growth rate frequency, we demonstrated

1, 3, 6, and 12 months as examples.

The mental disorders outpatient consultation rate as an outcome

The consultation rate represents the rate at which people consult their doctors about their mental disorders, which is also widely used in pharmacoepidemiology. In the short term, the change in the consultation rate reflects the change in the incidence of mental disorders. The consultation rate was calculated according to the number of outpatients per month in the city. Hence, we aggregated the micro-level claim data to the city–monthly level, and the consultation rate was calculated as:

$$CR_{it} \cdot = \cdot VISIT_{it} \cdot / \cdot INSURED_{it} \cdot / \cdot PROPORTION_{i}$$
(1)

where: CR_{it} is the consultation rate of mental disorders in the city *i* at month *t*; *VISIT_{it}* is the number of outpatient services in the city *i* at month *t*; *INSURED_{it}* measures the total number of the population insured under Urban Resident Basic Medical Insurance and Urban Employee Basic Medical Insurance in the city *i* at year *t*; and *PROPORTION_i* is the sampling proportion, which equals to 5% in municipalities and provincial capitals, and 2% in prefecture-level cities.

2.3. Statistical analysis

We applied a fixed-effect model to estimate the impact of house price growth rate on mental health. The empirical model is

$$CR_{it} \cdot = \cdot \beta_1 \times HPG_{it} \cdot + \cdot \beta_2 \times INC_{it} \cdot + \cdot \theta_i \cdot + \cdot \gamma_t \cdot + \cdot \varepsilon_{it}$$
(2)

where: HPG_{it} measures the house price growth rate in month *t* in city *i*, and we adopt the house price increase rate during the past 1, 3, 6, and 12 months in different specifications; INC_{it} represents the per capita disposable income *i* in the city *i* at year *t*; θ_i and γ_t refer to city and year by monthly fixed effects, respectively; and ε_{it} is the error term. The city fixed effects capture the time-invariant characteristics within each city, while the year by month fixed effects capture the time trend across the country. The standard errors were clustered at the city level.

We also addressed the potential endogeneity problem by applying the Instrumental Variable (IV) method. Specifically, the omitted variables, such as macroeconomic factors, may affect both the house price growth rate and mental health, therefore bias the results in Ordinary Least Squares (OLS) estimation. Following Chaney et al. (2012) and Mian and Sufi (2011), we used the interaction of exogenous demand shock and local land supply elasticity as an IV. The assumption was that the house price growth rate would be higher in the cities with lower land supply elasticity and exogenous demand shock. The IV method uses the exact variation in house prices from the variation in the interaction of land supply and demand shock. In this study, we adopted the aggregated national house price growth rate $(NHPG_t)$ as the after controlling for the year by month demand shock, which was a common trend for the house price growth rate in each specific city. Following Saiz (2010), we used the amount of developable land per capital within the jurisdiction of each city (SE_i) as the land supply elasticity indicator. Therefore, the first stage specification is:

$$HPG_{it} \cdot = \cdot \beta_1 \times \cdot NHPG_t \cdot \times \cdot SE_i \cdot + \cdot \beta_2 \times INC_{it} \cdot + \cdot \theta_i \cdot + \cdot \gamma_t \cdot + \cdot \varepsilon_{it}$$
(3)

We adopted the growth rate of the housing component in the Consumer Price Index as the indicator to investigated whether rent increase change leads to mental disorders. We used the Shanghai Composite Index growth rate and Shenzhen Composite Index growth rate to investigated whether stock price changes lead to mental disorders. The specification was similar to Eq. (2), and we replaced the independent variable with the three indicators in turn.

We used areg in OLS and xtivreg2 in IV to estimate the fixed effects model. The data processing and analysis were performed in Stata® version 14 (Stata Corp LP, College Station, TX, USA). Tests were two-sided, with statistical significance at an α level of 0.10 (two-tailed).

3. Results

3.1. Descriptive statistics

Table 1 shows the summary statistics of house price increase on mental health. Our dataset includes 1116 observations in 32 cities from January 2013 to December 2017. The average consultation rate is 0.373% in the sample. Fig. 1 depicts an increase in the consultation rate of mental disorders from 0.459% to 0.875% with strong seasonality in a major city between January 2013 and December 2017. On average, the house price growth rate is 0.8%, 2.3%, 4.6%, and 9.2% during the past 1, 3, 6, and 12 months, suggesting that the house price rapidly increases in the sample cities during the sample periods.

Fig. 2 plots the house price growth rate against the consultation rate of mental disorders from January 2013 to December 2017. The house price growth rate was calculated during the past 1, 3, 6, and 12 months in different panels, respectively. Each dot represents a city–month observation. The figure demonstrated an illustration of the positive trend between the consultation rate of mental disorders and the house price growth rate.

3.2. Regression results

Table 2 reports the impact of house price growth rate on mental health using OLS and IV estimation, respectively. Panel A reports the OLS estimation results, while Panel B shows the IV estimation results. The outcome is the consultation rate, and the independent variables denoted in each column are house price growth rates during the past 1, 3, 6, and 12 months. The coefficients of the house price growth rates during the past 1 and 3 months are statistically and significant in the OLS and IV estimations. For each regression, we controlled for per capita disposable income, city fixed effects and the year by month fixed effects (FE in short). The Kleibergen-Paap rk LM statistic (KP LM Stat in short) and Kleibergen-Paap rk Wald F statistic (KP F Stat in short) in Panel B suggested that the IV could pass the underidentification test and weak identification test, respectively. The results in both panels suggested that the house price increase has a positive effect on the consultation rate of mental disorder. For instance, controlling for the per capita disposable income, city fixed effects and year by month fixed effects, a one standard deviation increases in house price increase rate in the past 3 months (Column 2 in Panel B) is associated with a 0.443 (0.042 \times 1.904/0.648 = 0.443) standard deviation increase in the consultation rate of mental disorders. However, the coefficient of the house price growth rate in the past 12 months is statistically insignificant, demonstrating an effect of house price change in the short term, instead of the long run.

We conducted a sensitivity analysis to assess the robustness of the current analysis, based on a dataset that excluded the cities observed only in a year during the sample period, given limited data availability. Table 3 showed the sensitivity analysis results based on this restricted sample covering 22 cities. As shown in the table, the coefficients of the house price growth rates in the past 1, 3, and 6 months are statistically significant in the OLS and IV regression, which is consistent with results in Table 2.

Besides, we study the heterogeneous effect on mental health by patients' characteristics, including age and gender. Table 4 reports the regression results from the IV method; the regression results from the OLS method are reported in Table A1. The impact is marginally statistically significant in residents aged between 30 and 34 years old. The effect is mainly observed in residents aged older than 40 years. Otherwise, the coefficients are not statistically and significant.

Then, we analysed the effect on male and female residents, respectively. Table 5 reports the regression results from the IV method; the regression results from the OLS method are reported in Table A2. In the table below, columns 1–4 showed the results for females, while columns 5–8 showed the results for males. The coefficients of the house price growth rate during the past 3 and 6 months for female and male

Table 1

Descriptive statistics.

Variable		Explanation	Obs.	Mean	Std. Dev.	Min	Max
CR		Consultation rate (%)	1116	0.373	0.648	0	3.700
HPG	1 month	House price growth rate	1116	0.008	0.027	-0.108	0.152
	3 months		1116	0.023	0.042	-0.128	0.202
	6 months		1116	0.046	0.064	-0.165	0.335
	1 year		1116	0.092	0.112	-0.230	0.703
CPG	1 month	Urban household consumer price growth rate (Residence)	876	0.0001	0.007	-0.038	0.040
	3 months		876	0.0002	0.011	-0.050	0.055
	6 months		876	0.0000	0.011	-0.061	0.063
	1 year		876	0.0001	0.010	-0.064	0.078
SCG (Shanghai)	1 month	Shanghai composite growth rate	1116	0.009	0.066	-0.226	0.206
	3 months		1116	0.029	0.131	-0.305	0.393
	6 months		1116	0.060	0.206	-0.253	0.835
	1 year		1116	0.100	0.314	-0.368	1.262
SCG (Shenzhen)	1 month	Shenzhen composite growth rate	1116	0.013	0.080	-0.268	0.232
	3 months		1116	0.045	0.159	-0.359	0.714
	6 months		1116	0.086	0.207	-0.211	0.967
	1 year		1116	0.172	0.333	-0.330	1.651



Fig. 1. Consultation rate of mental disorders in a major city from January 2013 to December 2017.

residents are both statistically significant, and the magnitudes are similar. The results demonstrated that the impact of house price growth rate does not vary across gender. Besides, we also studied the effect of age cohorts and gender. The results are shown in Table A3. The estimation results are consistent with Tables 4 and 5, suggesting that the effect is mainly observed in male and female residents older than 40.

Table 6 reports the regression results of the potential effect of other price changes. All the key coefficients are not statistically significant, suggesting that the rent increase rate or stock price change does not significantly induce more mental disorders in our sample cities.

4. Discussion

In sum, we observed that a one standard deviation increase in house price increase rate in the past three months is associated with a 0.443 standard deviation increase in people consulting with doctors about their mental disorders in the city, i.e., short-term rapid house price increase leads to more mental disorders. We also found that the effect is more pronounced in cohorts older than 40 years old, and similar across genders. The rent increase rate or stock price change was not statistically significantly associated with mental disorders.

4.1. House price growth and mental health

To our knowledge, this paper provides the first empirical study that

examines the relationship between house price growth and mental health using administrative data. Our study contributes to two strands of literature. First, existing studies have documented the impact of house price growth rate on corporate behaviour (Chen et al., 2016; Li & Wu, 2014; Rong et al., 2016) and labour supply (Fu et al., 2016), but lacking in evidence of the effects on mental health using administrative data. Second, current literature has documented the impact of social determinates of mental health, such as lifestyle (Gidugu & Jacobs, 2019), social habits (Cooper et al., 2007), unemployment, deprived areas, communication, and housing affordability (Bentley et al., 2011, 2012; Chung et al., 2018, 2020; Joshi, 2016; Kavanagh et al., 2016; Mason et al., 2013). Some studies analyse the impact of housing affordability on mental health. Bentley investigated whether people whose housing costs were more than 30% of their household income experienced a deterioration in their mental health, and found that entering unaffordable housing is harmful to the mental health of individuals residing in low-to-moderate income households (Bentley et al., 2011). Mason et al. (2013) investigated whether a relationship exists between unaffordable housing and mental health that differs for home purchasers and private renters among low-income households, and found that private renters appeared to be more vulnerable than home purchasers to mental health effects of unaffordable housing (Mason et al., 2013). Joshi (2016) found that lower local house prices have an adverse impact on the self-reported mental health of homeowners and renters (Joshi, 2016). Roger examined the association of housing affordability with general physical and mental health in Hong Kong with self-report data (Chung et al., 2020).

This study filled this knowledge gap and provided valuable evidence using the national health insurance claims database from China. Housing affordability decreases following the increase in housing prices and therefore, the expansion of social pressure will be important to mental health, a critical health consequence. Compared with the previous literature, we used medical service data, which is arguably more objective, to explore the relationship between house price increase and mental health across major cities in China. Besides, the previous studies failed to adjust confounding effects from macroeconomic factors (Joshi, 2016). The application of the IV method allowed us to capture the impact of house price growth on mental health, excluding the impact of economic barometers.

In this study, we employed the IV method to handle the confounding effect from macroeconomic factors. The IV method works because it only uses the exact variation in house prices from the variation in the interaction of land supply and demand shock. The difference in OLS and IV estimation results can attribute to three potential causes: weak instrument, violation of exclusion restriction, and local average treatment effect (LATE). The possibility of the weak instrument is less likely to happen for the reasons stated above (the Kleibergen-Paap rk Wald F



Fig. 2. House price growth rate and consultation rate.

Table 2

Impact of house price growth on mental health: Baseline.

	(1)	(2)	(3)	(4)				
	Dependent V	/ariable: Consulta	ation Rate					
Panel A: OLS	1 month	3 months	6 months	1 year				
HPG	0.681 ^a	1.007^{b}	0.397	-0.172				
	(0.325)	(0.519)	(0.437)	(0.371)				
Observations	1116	1116	1116	1116				
R-squared	0.647	0.649	0.647	0.646				
	Dependent Variable: Consultation Rate							
Panel B: IV	1 month	3 months	6 months	1 year				
HPG	12.599	6.836 ^b	4.950 ^b	2.652				
	(8.157)	(3.915)	(2.825)	(1.867)				
Observations	1116	1116	1116	1116				
R-squared	-0.510	-0.222	-0.270	-0.268				
KP LM Stat	14.19	15.77	13.35	13.90				
KP F Stat	17.71	13.74	11.93	9.615				
Ln(Lagged Income)	YES	YES	YES	YES				
City FE	YES	YES	YES	YES				
Year-month FE	YES	YES	YES	YES				

Robust standard errors clustered at the city level in parentheses.

***p < 0.01.

^a p < 0.05.

 b p < 0.1.

statistic of the first stage >10). We also think that the IV is less likely to violate the exclusion restriction. Because the local geography and population determined the land supply in 2010, and the aggregated national house price growth rate is a general trend, once we control for the time fixed effects and city fixed effects, both of them are exogenous. Their interaction is unrelated to any other factors except the local house price growth rate. Such that, the IV can only affect mental health through the housing market rather than other channels. Last, IV would capture the

Table 3Robustness check: Restricted sample.

	(1)	(2)	(3)	(4)	
	Dependent Va	riable: Consultati	ion Rate		
Panel A: OLS	1 month	3 months	6 months	1 year	
HPG	0.778 ^a	1.186 ^b	0.462	-0.182	
	(0.372)	(0.598)	(0.493)	(0.399)	
Observations	996	996	996	996	
R-squared	0.636	0.639	0.636	0.635	
	Dependent Variable: Consultation Rate				
Panel B: IV	1 month	3 months	6 months	1 year	
HPG	15.803 ^b	7.705 ^b	4.986 ^b	2.655	
	(9.502)	(4.223)	(2.781)	(1.854)	
Observations	996	996	996	996	
R-squared	-0.713	-0.252	-0.246	-0.260	
KP LM Stat	13.48	14.71	14.08	14.16	
KP F Stat	12.09	9.907	9.630	8.392	
Ln(Lagged Income)	YES	YES	YES	YES	
City FE	YES	YES	YES	YES	
Year-month FE	YES	YES	YES	YES	

Robust standard errors clustered at the city level in parentheses.

***p < 0.01.

^a p < 0.05.

^b p < 0.1.

local average treatment effect (LATE) among the subpopulation of compliers because of heterogeneous treatment effect, while OLS can capture the average treatment effect (ATE) over the entire population. Because the housing affordability varies across 32 cities and housing affordability is low in some big cities, the large impact using IV is likely a result of the LATE.

Although we cannot provide direct evidence on the impact mechanism because of the data availability, the results are consistent with

Table 4

Impact of house price growth on mental health: By age (IV).

Age Dependent Variable: Consultation Rate 25-29 years old 25-29 years old I month 3 months 6 months 1 year 1 month 3 months 6 months 1 year HPG 0.133 0.089 0.066 0.037 (0.728) (0.363) (0.265) (0.174) Observations 1116		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Dependent Va	ariable: Consultation	Rate					
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	Age	20-24 years of	old			25–29 years o	old		
HPG0.133 (0.191)0.089 (0.073)0.066 (0.072)0.075 (0.072)0.438 (0.728)0.438 (0.265)0.134 (0.267)0.134 (0.267)0.134 (0.267)0.134 (0.267)0.134 (0.267)0.134 (0.267)0.134 (0.267)0.135 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.267)0.260 (0.278)0.261 (0.278)1.374 (0.278)1.330 (0.278)1.410 (0.278)1.557 (0.271)1.330 (0.261)0.261 (0.271)0.261 (0.272)0.161 (0.161)1.160 (0.663)1.660 (0.271)0.3610 (0.271)0.2620 (0.271)0.261 (0.272)0.2610 (0.271)0.2610 (0.271)0.2610 (0.271)0.2610 (0.271)0.2311 (0.272)0.2620 (0.271)0.2311 (0.272)0.23		1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
(0.19) (0.093) (0.072) (0.047) (0.728) (0.363) (0.265) (0.174) Observations 1116 1116 1116 1116 1116 1116 1116 R-guared -0.090 -0.066 -0.100 -0.044 -0.422 -0.199 -0.260 -0.269 KP F Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 Age 30-34 years old - - 17.71 13.74 11.93 9.615 Age - - - - - 1.874 1.983 9.615 Age - - 0.636 0.476° 0.278 1.535 0.827 0.613 0.827 0.535 0.620 0.331 0.332 Observations 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116 1116	HPG	0.133	0.089	0.066	0.037	0.755	0.438	0.334	0.193
Observations 1116		(0.191)	(0.093)	(0.072)	(0.047)	(0.728)	(0.363)	(0.265)	(0.174)
R-squared -0.000 -0.066 -0.100 -0.040 -0.422 -0.199 -0.260 -0.260 KP IM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 13.90 Age 30-34 years old - - 35-39 years old - 1.93 9.615 Age 0.0240 0.636 ³⁰ 0.476 ¹⁶ 0.278 1.800h 300hths 6 months 1 year HPG 0.02770 0.3777 0.2720 0.1810 (1.060) 0.5310 0.3811 0.322 Observations 1116 1116 1116 1116 1116 1116 113.7 1.335 13.90 KP IM Stat 1.71 13.74 1.93 9.615 1.71 13.74 1.93 9.615 Common 1.947 1.93 0.529 0.570 0.264 0.325 0.352 1.577	Observations	1116	1116	1116	1116	1116	1116	1116	1116
KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age30-34 years old559.77113.7411.939.615HPG1000th0.636°0.476°0.2781.5350.8270.6140.353Observations11161116111611161116111611161116R-guared-0.404-0.246-0.325-0.355-0.570-0.260-0.331-0.328KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age-0.444 years old-1.982°0.5292.9751.5621.152°0.620Age1.077(0.799)(0.571)(0.374)(1.883)(0.891)(0.639)(0.415)Observations11161116111611161116111611161116Observations1161116111611161116111611161116Age-0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.236-0.236Observations1161116111611161116111611161116111611161116Age-0.554-0.23713.35 <td>R-squared</td> <td>-0.090</td> <td>-0.066</td> <td>-0.100</td> <td>-0.094</td> <td>-0.422</td> <td>-0.199</td> <td>-0.260</td> <td>-0.269</td>	R-squared	-0.090	-0.066	-0.100	-0.094	-0.422	-0.199	-0.260	-0.269
KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 11.93 9.615 Age 30-34 years olf 100th 3 months 6 months 1 year 1 month 3 months 6 months 1 year 1 month 3 months 6 months 1 year 1024 0.636* 0.476* 0.278 1.535 0.614 0.614 0.330 0bservations 1116 1116 1116 1116 1116 1116 1116 1116 1116 0.331 0.6341 0.331 <	KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
Age30–34 years old3months6 months1 year1 month3 months6 months1 yearHPG1.0240.636 ⁵ 0.476 ⁵ 0.2781.5350.8270.61810.03810.0249Observations1116111611161116111611161116111611161116R-squared0.4040-0.246-0.325-0.335-0.570-0.2600-0.331-0.332KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age40–44 years olf1.361 ⁵⁰ 0.982 ⁵⁰ 0.5292.9751.552 ¹² 1.132 ⁵⁰ 1.622C1.67770.7999(0.571)(0.374)(1.883)(0.891)(0.639)(0.415)Observations11161116111611161116111611161116C1.6777(0.799)(0.571)(0.374)(1.883)(0.891)(0.639)(0.459)Observations111611161116111611161116111611161116R-squared0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.250KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP Stat17.7113.741.930.61517.7113.741.939.615 <t< td=""><td>KP F Stat</td><td>17.71</td><td>13.74</td><td>11.93</td><td>9.615</td><td>17.71</td><td>13.74</td><td>11.93</td><td>9.615</td></t<>	KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
HPG1 month3 months6 months1 year1 month3 months6 months1 yearHPG0.6240.636 ¹ 0.476 ¹ 0.2781.5350.8270.6140.633Observations111611161116111611161116111611161116R-squared0.404-0.2460.325-0.335-0.5700.260-0.331-0.332KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age40-44 years off45-49 years off1.562 ¹ 1.132 ¹ 0.620Age40-44 years off1.9370.5211.562 ¹ 1.132 ¹ 0.620Age40-44 years off1.9370.3741.8830.89110.63910.620Age1.6770.79910.57110.3741.8830.89110.3350.3900.415Observations111611161116111611161116111611161116R-squared0.5540.5290.5290.5200.2400.2360.2500.240KP LM Stat14.193 months6 months1 year1 month3 months6 months1 yearP Stat11.6111.6111.6111.6111.6111.6111.6111.6111	Age	30–34 years o	old			35–39 years o	old		
HPG 1.024 0.636 ^h 0.476 ^h 0.278 1.535 0.827 0.614 0.331 0bservations 1116 1116 1116 1116 1116 1116 1116 R-squared 0.404 -0.246 -0.325 -0.335 -0.570 -0.260 -0.331 -0.325 KP IA Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 1.93 9.615 HPG 2.634 1.61 ^h 116 116 116 1.92 ^h 0.620 (1.677) 0.799 0.571 0.529 2.975 1.562 ^h 1.132 ^b 0.620 Observations 1116 1116 1116 1116 1116 116 R-squared -0.554 -0.237 0.294 -0.295 -0.505 -0.204 -0.236 -0.236 P F Stat 117.71 13.74		1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
0.677 (0.377) (0.272) (0.181) (1.060) (0.51) (0.381) (0.249) Observations111611161116111611161116111611161116R-squared 0.0404 0.246 0.325 0.335 0.570 0.260 0.331 0.332 KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age 0.444 years old $$	HPG	1.024	0.636 ^b	0.476 ^b	0.278	1.535	0.827	0.614	0.353
Observations111611080.0320.0330.04150.0330.04150.0330.04150.0340.0240.2360.2360.2360.2360.2360.2360.2360.2360.2360.2360.2360.236 <th< td=""><td></td><td>(0.767)</td><td>(0.377)</td><td>(0.272)</td><td>(0.181)</td><td>(1.060)</td><td>(0.531)</td><td>(0.381)</td><td>(0.249)</td></th<>		(0.767)	(0.377)	(0.272)	(0.181)	(1.060)	(0.531)	(0.381)	(0.249)
R-squared -0.404 -0.246 -0.325 -0.335 -0.570 -0.260 -0.331 -0.332 KP LM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 7.71 13.74 13.90 9.615 Age -0.44 years old - 1 month 3 months 0.982 ^b 0.529 2.975 1.562 ^b 1.132 ^b 0.620 1.677 0.799 0.5711 0.374 (1.883) 0.8911 0.6391 0.620 Observations 1116<	Observations	1116	1116	1116	1116	1116	1116	1116	1116
KP LM Stat KP F Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age 40 -44 years old1month3 months6 months1 year1 month3 months6 months1 yearHPG2.6341.361 ^h 0.982 ^h 0.5292.9751.562 ^h 1.132 ^h 0.620(1.677)(0.799)(0.571)(0.374)(1.883)(0.891)(0.639)(0.415)Observations11161116111611161116111611161116R-squared0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.256KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615KP G2.219 ^h 1.197 ^h 0.833 ^h 0.3941.323 ^h 0.724 ^h 0.513 ^h 0.247(1.295)(0.610)(0.438)(0.298)(0.726)(0.340)(0.247)(0.163)Observations11161116111611161116111611161116Required-0.305-0.135-0.163-0.296-0.107-0.113-0.095Observations11611161116111611161116111611161116Required-0	R-squared	-0.404	-0.246	-0.325	-0.335	-0.570	-0.260	-0.331	-0.332
KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age $40-44$ years old $45-49$ years oldHPG1 month3 months6 months1 year1 month3 months6 months1 year1.677(0.799)(0.571)(0.374)(1.883)(0.891)(0.639)(0.415)Observations11161116111611161116111611161116R-squared-0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.256KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.741.939.615HPG2.19°0.51°0.833°0.3941.323°0.724°0.513°0.247HPG2.19°1.197°0.833°0.3941.323°0.724°0.513°0.247HPG2.219°1.197°0.833°0.3941.323°0.724°0.513°0.247Observations1116111611161116111611161116HPG0.305-0.135-0.163-0.150-0.296-0.107-0.113-0.958KP LM Stat11.911.57713.35113.9014.1915.7713.3513.90HPG0.305-0.135-0.163-0.150-0.296-0.107-0.113-0.958 </td <td>KP LM Stat</td> <td>14.19</td> <td>15.77</td> <td>13.35</td> <td>13.90</td> <td>14.19</td> <td>15.77</td> <td>13.35</td> <td>13.90</td>	KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
Age40-44 years old45-49 years oldHPG1 month3 months6 months1 year1 month3 months6 months1 yearLPG2.6341.361 ^h 0.982 ^h 0.5292.9751.562 ^h 1.132 ^h 0.620(1.677)(0.799)(0.571)(0.374)(1.883)(0.891)(0.639)(0.415)Observations1116111611161116111611161116R-squared-0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.250KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615HPG2.219 ^h 1.197 ^m 0.833 ^h 0.3941.322 ^h 0.724 ^h 0.513 ^m 0.247HPG2.219 ^h 1.197 ^m 0.833 ^h 0.3941.322 ^h 0.724 ^h 0.513 ^m 0.247HPG0.3050.610(0.438)(0.298)(0.726)(0.340)(0.247)(0.163)Observations1116111611161116111611161116R-squared-0.305-0.135-0.163-0.150-0.296-0.107-0.113-0.095KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615 <td>KP F Stat</td> <td>17.71</td> <td>13.74</td> <td>11.93</td> <td>9.615</td> <td>17.71</td> <td>13.74</td> <td>11.93</td> <td>9.615</td>	KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Age	40-44 years of	old		45–49 years o	old			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	HPG	2.634	1.361 ^b	0.982^{b}	0.529	2.975	1.562 ^b	1.132^{b}	0.620
Observations1116 </td <td></td> <td>(1.677)</td> <td>(0.799)</td> <td>(0.571)</td> <td>(0.374)</td> <td>(1.883)</td> <td>(0.891)</td> <td>(0.639)</td> <td>(0.415)</td>		(1.677)	(0.799)	(0.571)	(0.374)	(1.883)	(0.891)	(0.639)	(0.415)
R-squared KP LM Stat-0.554-0.237-0.294-0.295-0.550-0.204-0.236-0.236KP LM Stat KP F Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age50-54 years oldFormula1 month3 months6 months1 year1 month3 months6 months1 yearHPG2.219 ^b 1.197 ^a 0.833 ^b 0.3941.323 ^b 0.724 ^a 0.513 ^a 0.247(1.295)(0.610)(0.438)(0.298)(0.726)(0.340)(0.247)(0.163)Observations1116111611161116111611161116R-squared-0.305-0.135-0.163-0.150-0.296-0.107-0.113-0.095KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Ln(Lagged Income)YESYESYESYESYESYESYESYESYESVear-month FEYESYESYESYESYESYESYESYESYES	Observations	1116	1116	1116	1116	1116	1116	1116	1116
KP F Stat14.19 17.7115.77 13.7413.35 11.9313.90 9.61514.19 17.7115.77 13.7413.35 13.90 9.615Age $50-54$ years old $55-59$ years old $55-59$ years old $5-5-59$ years oldAge $1 \mod M$ $3 \mod M$ $6 \mod M$ $1 year$ $1 \mod M$ $3 \mod M$ $6 \mod M$ HPG 2.219^b 1.197^a 0.833^b 0.394 1.323^b 0.724^a 0.513^a 0.247 Observations1116111611161116111611161116R-squared -0.305 -0.135 -0.163 -0.150 -0.296 -0.107 -0.113 -0.095 KP F Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.93 9.615 17.7113.7411.93 9.615 Ln(Lagged Income)YESYESYESYESYESYESYESYESYESYESYESYESVear-month FEYESYESYESYESYESYESYESYESYESYESYES	R-squared	-0.554	-0.237	-0.294	-0.295	-0.550	-0.204	-0.236	-0.250
KP F Stat17.7113.7411.939.61517.7113.7411.939.615Age $50-54$ years old $55-59$ years old $55-59$ years old $55-59$ years old $1000000000000000000000000000000000000$	KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
Age $50-54$ years old $55-59$ years old 1 1month3 months6 months1 year1 month3 months6 months1 yearHPG2.219 ^b 1.197 ^a 0.833 ^b 0.3941.323 ^b 0.724 ^a 0.513 ^a 0.247(1.295)(0.610)(0.438)(0.298)(0.726)(0.340)(0.247)(0.163)Observations1116111611161116111611161116R-squared-0.305-0.135-0.163-0.150-0.296-0.107-0.113-0.095KP LM Stat14.1915.7713.3513.9014.1915.7713.3513.90KP F Stat17.7113.7411.939.61517.7113.7411.939.615Ln(Lagged Income)YESYESYESYESYESYESYESYESYESVear-month FEYESYESYESYESYESYESYESYESYES	KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
I morth 3 months 6 months 1 year 1 morth 3 months 6 months 1 year HPG 2.219 ^b 1.197 ^a 0.833 ^b 0.394 1.323 ^b 0.724 ^a 0.513 ^a 0.247 (1.295) (0.610) (0.438) (0.298) (0.726) (0.340) (0.247) (0.163) Observations 1116 1116 1116 1116 1116 1116 1116 R-squared -0.305 -0.135 -0.163 -0.150 -0.296 -0.107 -0.113 -0.095 KP LM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 11.93 9.615 Ln(Lagged Income) YES YES </td <td>Age</td> <td>50–54 years o</td> <td>old</td> <td></td> <td></td> <td>55–59 years o</td> <td>old</td> <td></td> <td></td>	Age	50–54 years o	old			55–59 years o	old		
HPG 2.219 ^b 1.197 ^a 0.833 ^b 0.394 1.323 ^b 0.724 ^a 0.513 ^a 0.247 (1.295) (0.610) (0.438) (0.298) (0.726) (0.340) (0.247) (0.163) Observations 1116 1116 1116 1116 1116 1116 1116 R-squared -0.305 -0.135 -0.163 -0.150 -0.296 -0.107 -0.113 -0.095 KP LM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 11.93 9.615 Ln(Lagged Income) YES	U	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 vear
(1.295) (0.610) (0.438) (0.298) (0.726) (0.340) (0.247) (0.163) Observations 1116 1130 10.05	HPG	2.219^{b}	1.197^{a}	0.833 ^b	0.394	1.323^{b}	0.724 ^a	0.513 ^a	0.247
Observations 1116		(1.295)	(0.610)	(0.438)	(0.298)	(0.726)	(0.340)	(0.247)	(0.163)
R-squared -0.305 -0.135 -0.163 -0.296 -0.107 -0.113 -0.095 KP LM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 11.93 9.615 Ln(Lagged Income) YES	Observations	1116	1116	1116	1116	1116	1116	1116	1116
KP LM Stat 14.19 15.77 13.35 13.90 14.19 15.77 13.35 13.90 KP F Stat 17.71 13.74 11.93 9.615 17.71 13.74 11.93 9.615 Ln(Lagged Income) YES	R-squared	-0.305	-0.135	-0.163	-0.150	-0.296	-0.107	-0.113	-0.095
Ref Education Finite Finit F	KP LM Stat	14 19	15.77	13.35	13.90	14 19	15.77	13.35	13.90
Ln(Lagged Income) YES YES YES YES YES YES YES City FE YES YES YES YES YES YES YES Vear-month FE YES YES YES YES YES YES YES	KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
City FE YES YES YES YES YES YES YES YES YES YE	Ln(Lagged Income)	YES	YES	YES	YES	YES	YES	YES	YES
Vert-month FE VES VES VES VES VES VES VES	City FE	YES	YES	YES	YES	YES	YES	YES	YES
	Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at the city level in parentheses.

***p < 0.01.

 $p^{a} p < 0.05.$ $p^{b} p < 0.1.$

Table 5

Impact of house price growth on mental health: By gender (IV).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Dependent Va	riable: Consultation	Rate						
Gender	Female				Male				
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year	
HPG	6.113	3.337 ^a	2.450 ^a	1.340	6.486	3.499 ^a	2.500 ^a	1.312	
	(4.076)	(1.956)	(1.422)	(0.940)	(4.087)	(1.962)	(1.406)	(0.930)	
Observations	1116	1116	1116	1116	1116	1116	1116	1116	
R-squared	-0.549	-0.245	-0.302	-0.291	-0.457	-0.194	-0.234	-0.237	
KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90	
KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615	
Ln(Lagged Income)	YES	YES	YES	YES	YES	YES	YES	YES	
City FE	YES	YES	YES	YES	YES	YES	YES	YES	
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES	

Robust standard errors clustered at the city level in parentheses.

***p < 0.01.

 $p^{**}p < 0.05.$ a p < 0.1.

housing affordability instead of economic regard or wealth changes. First, we introduce the IV method to address the concern on macroeconomic factors such as economic barometer. Second, the effect on mental health concentrates in the short term instead of the long term, suggesting that the effect is not driven by wealth change because the households are unlikely to sell their house within six months. Third, in

Table 6

The potential effect of other price changes.

	(1)	(2)	(3)	(4)
	Dependent Va	riable: Consultati	ion Rate	
Panel A	1 month	3 months	6 months	1 year
CPG	0.539	0.405	-0.298	-1.241
	(0.942)	(0.735)	(0.815)	(1.179)
Observations	876	876	876	876
R-squared	0.629	0.629	0.629	0.629
Panel B	1 month	3 months	6 months	1 year
SCG (Shanghai)	-17.539	-5.752	-9.712	37.929
	(15.351)	(5.035)	(8.500)	(33.197)
Observations	1116	1116	1116	1116
R-squared	0.646	0.646	0.646	0.646
Panel C	1 month	3 months	6 months	1 year
SCG (Shenzhen)	-14.922	-6.220	-9.461	-7.313
	(13.061)	(5.444)	(8.281)	(6.401)
Observations	1116	1116	1116	1116
R-squared	0.646	0.646	0.646	0.646
Ln(Lagged Income)	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES

Robust standard errors clustered at the city level in parentheses.

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

the short term, the household income is stable while the house price might fluctuate. For example, the average national house price was doubled from 2006 to 2014 (Fang et al., 2016; Glaeser et al., 2017; Guo et al., 2014; Wu et al., 2012), while the per capita disposable income for urban residents increased from ¥11,759 to ¥20,167. The difference in the growth rate between house prices and household income demonstrated a severe housing affordability problem resulting in larger morbidity of mental disorder (Bentley et al., 2011, 2012; Chung et al., 2018, 2020; Joshi, 2016; Kavanagh et al., 2016; Mason et al., 2013). However, we acknowledge that the current empirical results cannot rule out other interpretations.

The impact of house price growth rate on mental health can be partially explained by marriage, which is in line with Wei and Zhang (2011). The newly-married couple is expected to purchase a house when they prepare to be married, while it is increasingly more acceptable that both the husband and the wife contribute to a home purchase. In most cases, due to the young couples do not have enough savings, their parents would provide the down-payment and pay the mortgage. Hence, the mental health of the elderly would suffer from the rapid house price increase. The results are consistent with our hypothesis. The impact was mainly observed in the residents older than 40 and is the strongest in the residents aged between 45 and 49, whose kids are faced with purchasing a house and getting married immediately. They need to finance for their kids to buy the wedding house, and thus suffer from the house price increase. We acknowledge that we cannot provide more direct evidence because of data limitations.

Last, we investigated whether rent increase or stock price change can also lead to mental disorders. The results suggested that the rent increase rate or stock price change does not significantly induce more mental disorders in our sample cities. This finding can be explained in two aspects: first, the homeownership rate (approximately 75% (2010 nationwide population census) is much higher than the proportion of shareholders (approximately 10% (sipf.com.cn) in China; second, house, instead of stock, acts as the primary asset for urban households, which accounts for 69.70% (gov.cn). The results further demonstrated the impact of the house price.

4.2. Limitations

We acknowledge that there are a few limitations in our study. First, we do not have access to detailed patients' characteristics, such as home ownership and income. Hence, we cannot analyse the impact of house price increase on mental health for those who suffer from housing affordability problems to study the potential mechanisms. Second, some residents with mental disorders, who were not aware of their mental health or unwilling to consult with their doctors owing to stigma, were excluded from our dataset. It would be helpful to combine the results with other analyses based on survey data with self-reported symptoms to understand the impact comprehensively. Third, the patients seeking help from private hospitals were not recorded in our study, which may have led to an underestimation in the consultation rate of mental disorder patients. Still, it is less likely to bias our estimate. Since public hospitals play a crucial role in mental health medical in China. China's mental health medical institutions include psychiatric hospitals, psychiatric departments in general hospitals, rehabilitation institutions and outpatient departments, among which psychiatric hospitals account for the largest proportion. According to China Health and Family Planning Statistical Yearbook (China Public Health Statistical Yearbook, 2016), there were 920 psychiatric hospitals in China by the end of 2015. Among them, there were 641 public hospitals and 279 non-public hospitals, with public hospitals accounting for 70%. Fourth, we cannot match the exact location where the patients live because of confidentiality, and when it comes to each address, the house price growth rate varies within the city. But the city-level house price is relatively stable, and it can objectively reflect the trend of a city's house price, so we use the city-level house price series. In the future, if within city-level data is available, we will update the current analysis. Last, we have only access to the data covering 32 cities, where the house affordability problem is more serious, and mental health is worse compared with other cities in China. Hence, if we extend the data to the whole country, the impact would exist, however, be smaller.

5. Conclusions

In this study, we explored the impact of house price growth rates on mental health. We observed that the rapid house price increase in the short term leads to more mental disorders. As a result, the rapid house price increase worsens the social pressure of the housing affordability problem on adults in China. Our findings have an important policy implication that curbing the soaring house price is urgent and demands policy responses.

Data availability

The datasets analysed in this document are available upon request in the repository of the China Health Insurance Research Association. House price increase series are available upon request in Wu et al. (2014).

Declaration of competing interest

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

Appendix

Table A1

Impact of House Price Growth on Mental Health: by Age (OLS).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Dependent Varia	able: Consultation F	Rate						
Panel A	20–24 years old	l			25-29 years old				
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year	
HPG	0.003 (0.011)	0.012 (0.016)	0.003 (0.015)	-0.001 (0.011)	0.030 (0.024)	0.066 (0.040)	0.037 (0.034)	0.004 (0.019)	
Observations	1116	1116	1116	1116	1116	1116	1116	1116	
R-squared	0.597	0.598	0.597	0.597	0.664	0.667	0.666	0.664	
Panel B	30–34 years old				35–39 years o	ld			
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year	
HPG	0.058	0.085	0.027	-0.012	0.088**	0.109	0.038	-0.014	
	(0.036)	(0.057)	(0.048)	(0.031)	(0.038)	(0.065)	(0.062)	(0.043)	
Observations	1116	1116	1116	1116	1116	1116	1116	1116	
R-squared	0.641	0.643	0.641	0.640	0.666	0.668	0.666	0.666	
Panel C	40-44 years old				45–49 years o	ld			
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year	
HPG	0.135*	0.171*	0.041	-0.065	0.152*	0.249*	0.122	-0.020	
	(0.066)	(0.085)	(0.083)	(0.084)	(0.084)	(0.129)	(0.090)	(0.064)	
Observations	1116	1116	1116	1116	1116	1116	1116	1116	
R-squared	0.613	0.614	0.612	0.613	0.635	0.638	0.636	0.635	
Panel D	50–54 years old				55–59 years old				
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year	
HPG	0.137**	0.179*	0.056	-0.066	0.079	0.135*	0.074	0.001	
	(0.064)	(0.096)	(0.088)	(0.102)	(0.052)	(0.076)	(0.059)	(0.036)	
Observations	1116	1116	1116	1116	1116	1116	1116	1116	
R-squared	0.599	0.601	0.599	0.600	0.662	0.665	0.663	0.662	
Ln(Lagged Income)	YES	YES	YES	YES	YES	YES	YES	YES	
City FE	YES	YES	YES	YES	YES	YES	YES	YES	
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES	

Robust standard errors clustered at the city level in parentheses.

 $\begin{array}{c} \text{***}p < 0.01. \\ \text{**} p < 0.05. \\ \text{*} p < 0.1. \end{array}$

Table A2

Impact of House Price Growth on Mental Health: by Gender (OLS).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Va	riable: Consultation	Rate					
Gender	female				male			
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	0.324*	0.464*	0.178	-0.061	0.357**	0.542**	0.219	-0.111
	(0.163)	(0.258)	(0.221)	(0.164)	(0.165)	(0.265)	(0.217)	(0.208)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	0.648	0.650	0.648	0.647	0.645	0.647	0.645	0.645
Ln(Lagged Income)	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-month FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered at the city level in parentheses.

 $\begin{array}{c} \text{reduct standad} \\ ^{**}p < 0.01. \\ ^{**}p < 0.05. \\ ^{*}p < 0.1. \end{array}$

Table A3

Impact of House Price Growth on Mental Health: by Age and Gender (IV).

Female	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Va	ariable: Consultation	Rate					
Age	20-24 years of	old			25–29 years o	ld		
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year

(continued on next page)

Table A3 (continued) _

Female	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Varia	ble: Consultation	Rate					
Age	20-24 years old				25–29 years ol	ld		
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	0.075	0.044	0.035	0.021	0.345	0.199	0.159	0.097
	(0.083)	(0.041)	(0.033)	(0.021)	(0.363)	(0.180)	(0.134)	(0.087)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.135	-0.054	-0.107	-0.105	-0.408	-0.199	-0.292	-0.304
KP EM Stat	14.19	13.74	13.35	9.615	14.19	13.74	13.35	9.615
Age	30–34 years old 1 month	3 months	6 months	1 vear	35–39 years ol 1 month	d 3 months	6 months	1 vear
HPG	0.509	0.328*	0.239*	0.139	0.778	0.410*	0.303*	0.172
	(0.384)	(0.185)	(0.133)	(0.088)	(0.478)	(0.241)	(0.171)	(0.113)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.368	-0.247	-0.299	-0.283	-0.648	-0.274	-0.334	-0.296
KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
Age	40-44 years old				45–49 years ol	ld		
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	1.070	0.559*	0.413*	0.223	1.547	0.826*	0.608*	0.357
	(0.671)	(0.321)	(0.233)	(0.154)	(1.015)	(0.481)	(0.350)	(0.229)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.445	-0.176	-0.236	-0.246	-0.723	-0.297	-0.342	-0.353
KP LM Stat KP F Stat	14.19 17.71	15.77	13.35	13.90 9.615	14.19	15.77	13.35	9.615
iti i bitit	17.71	10.71	11.90	9.010	17.71	10.7 1	11.90	5.010
Age	50-54 years old				55–59 years ol	ld		
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	1.148	0.622*	0.447*	0.222	0.641	0.351*	0.246*	0.109
o1	(0.758)	(0.358)	(0.259)	(0.175)	(0.395)	(0.184)	(0.135)	(0.091)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.337	-0.162	-0.209	-0.194	-0.231	-0.088	-0.086	-0.063
KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
34-1-	Described Verial		Dete					
Age	20_24 years old	Die: Consultation	Kale		25_20 years of	d		
nge	1 month	3 months	6 months	1 vear	1 month	3 months	6 months	1 vear
HPG	0.059	0.046	0.031	0.015	0.410	0.239	0.175	0.097
	(0.109)	(0.052)	(0.039)	(0.027)	(0.367)	(0.184)	(0.132)	(0.087)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.044	-0.050	-0.064	-0.054	-0.344	-0.157	-0.183	-0.189
KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
Age	30-34 years old				35–39 years ol	d		
U U	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	0.515	0.308	0.237*	0.140	0.757	0.418	0.311	0.181
	(0.391)	(0.197)	(0.144)	(0.096)	(0.592)	(0.296)	(0.214)	(0.139)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.370	-0.203	-0.295	-0.327	-0.411	-0.203	-0.268	-0.296
KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
KP F Stat	17.71	13.74	11.93	9.615	17.71	13.74	11.93	9.615
Age	40-44 years old				45-49 years ol	ld		
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	1.564	0.803*	0.569*	0.306	1.428	0.736*	0.523*	0.263
	(1.012)	(0.481)	(0.341)	(0.222)	(0.878)	(0.416)	(0.291)	(0.187)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
R-squared	-0.600	-0.269	-0.317	-0.311	-0.339	-0.111	-0.129	-0.140
KP LM Stat	14.19	15.77	13.35	13.90	14.19	15.77	13.35	13.90
AI I Judi	1/./1	13./7	11.75	7.013	1/./1	13.77	11.75	9.013
Age	50-54 years old				55–59 years ol	ld		
UDC.	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
HPG	1.071*	0.576**	0.386**	0.172	0.682**	0.373**	0.267**	0.139*
Observations	(0.560)	(0.262)	(0.185)	(0.126)	(0.347)	(0.166)	(0.121)	(0.078)
Observations	1116	1116	1116	1116	1116	1116	1116	1116
K Squared	-0.248	-0.099 15 77	-U.111 19 95	-0.100	-U.331 14 10	-U.114 15 77	-U.128	-0.123
KD E Stat	14.19	13.77	13.33	13.90 0.615	14.19	13.77	13.33	13.90
In(Lagged Income)	VFS	VFS	11.93 VFC	9.015 YFS	YFS	13.74 VFS	11.93 VFC	9.015 VEC
mithinggen medille)	110	0.110	1 10	1 1:0	1 110	011	1 1:0	11.0

(continued on next page)

Table A3 (continued)

Female	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Va	ariable: Consultation	Rate					
Age	20-24 years of	old			25–29 years old			
	1 month	3 months	6 months	1 year	1 month	3 months	6 months	1 year
City FE Year-month FE	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES

Robust standard errors clustered at the city level in parentheses.

***p < 0.01.

^{**} p < 0.05.

* p < 0.1.

Author statement

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Ethical statement

The ethical approval code obtained for this research is: IRB00001052-19007, approved by Office of Biomedical Ethics Committee of Peking University.

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