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ABSTRACT

Occupational Differences in the Effects of Retirement on Hospitalizations for Mental Illness among Female Workers: Evidence from Administrative Data in China

Retirement, a major transition in the life course, may affect many aspects of retirees' well-being, including health and health care utilization. Leveraging differential statutory retirement age (SRA) by occupation for China's urban female workers, we provide some of the first evidence on the causal effect of retirement on hospitalizations attributable to mental illness and its heterogeneity. To address endogeneity in retirement decisions, we take advantage of exogeneity of the differing SRA cut-offs for blue-collar (age 50) and white-collar (age 55) female urban employees. We apply a Fuzzy Regression Discontinuity Design (RDD) around the SRA cut-offs using nationally representative hospital inpatient claims data that cover these workers. We show that blue-collar females incur more hospitalizations for mental illness after retirement, while no similar change is found for white-collar females. Conditional on blue-collar females being hospitalized, probabilities of overall and ER admissions due to mental illness increase by 2.3 and 1.2 percentage points upon retirement, respectively. The effects are primarily driven by patients within the categories of schizophrenia, schizotypal and delusional disorders; and neurotic, stress-related and somatoform disorders. Moreover, the 'Donut' RDD estimates suggest that pent-up demand at retirement unlikely dominates our findings for blue-collar females. Rather, our results lend support to their worsening mental health at retirement. These findings suggest that occupational differences in mental illness and related health care utilization at retirement should be considered when optimizing retirement policy schemes.

JEL Classification: I11, J26, J14, I18, H55

Keywords: mental illness, behavioral disorders, retirement, inpatient care, blue-collar females, white-collar females

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1 Introduction

Retirement represents a major transition in life that may affect health and well-being. Relative to the growing evidence of retirement on cognitive health, physical health and mortality (e.g., Coe and Lindeboom 2008; Coe et al. 2012; Celidoni et al. 2017; Lei and Liu 2018; Hagen 2018; Fitzpatrick and Moore 2018), its toll on mental health is less known (WHO 2017). It is well documented that in western countries, mental illness may lead to large lifetime medical costs, disability and death, and low quality of life (Kessler et al. 2008; National Research Council and Institute of Medicine 2009; Byers et al. 2012; MacEwan et al. 2016; Seabury et al. 2019).

This paper examines the impact of retirement policies on mental illness treatment in China. Retirement in China offers an interesting case because the country not only has the largest older population globally which is still growing but also a unique, statutory retirement age (hereafter SRA) policy. China's SRA policy differs for males and females and varies by occupation for females but not for males. Specifically, the SRA for all males is 60 but is 55 for white-collar females (WCF, composed of government employees or managers in private companies), and 50 for blue-collar females (BCF). We take advantage of medical claims data from the Urban Employee Basic Medical Insurance (UEBMI), which provides good coverage to formally employed people who enroll. UEBMI enrollees usually have higher insurance benefits in retirement than they did before retirement. These claims data enable us to track medical care use closely with retirement status.

Females are generally more prone to mental health problems than their male counterparts. Importantly, by studying within a female-only population, various factors are more comparable, e.g., underlying tendencies to suffer from mental health problems. Focusing on females with differing, exogenous retirement ages in the same system and using claims data allow us to identify the causal effect of retirement on inpatient care for mental illness within female populations.

Retirement may affect mental health in offsetting ways. On the positive side, retirement may eliminate work stress and grant more time for both medical and non-medical health investments (Midanik et al. 1995; Johnston and Lee 2009; Kolodziej and García-Gómez 2019; Eibich 2015; Westerlund et al. 2009). However, retirement may also harm mental health through lower income (Bonsang et al. 2012), stress of increased social isolation, greater caregiving burdens (Vo et al. 2015), and loss of purpose, work role identity, and life structures (Dave, Kelly, and Spasojevic 2007; Ashforth et al. 2008; Heller-Sahlgren 2017; Shiba et al. 2017).

Deterioration in retirees' mental health may increase the demand for mental health treatment. Retirement may also increase mental illness treatment through lower opportunity cost of time (Zhou et al., 2021), and lower price due to increased insurance reimbursement rates (Feng et al., 2020). However, lower income (Conde-Ruiz et al., 2013), and changes in other care-seeking constraints can also impact. The net effect of these multiple impacts is unclear a priori (Butterworth et al. 2006; Drentea 2002; Jokela et al. 2010; Mein et al. 2003). Some studies find no effect of retirement on mental health care (Blake and Garrouste 2019; Byles et al. 2016; Coe and Zamarro 2011; Lindeboom, Portrait, van den Berg 2002; Neuman 2008).

BCF typically work in jobs that are more physically demanding but less mentally demanding than those of WCF, and they tend to have a lower locus of control in these occupations (Frost and Clayson 1991). WCF likely have access to more resources throughout their lives and at retirement, and thus may cope with retirement better, but may experience a stronger psychological shock due to a greater diminishment in self-esteem. Studies suggest that those in physically straining jobs (e.g., blue-collar jobs) show improved physical health upon retirement, while retirement benefits mental health among those retiring from mentally straining jobs (likely white-collar jobs) (Eibich 2015) and those already in frail mental health (Kolodziej and García-Gómez 2019; Mazzonna and Peracchi 2017). Thus, it is important to separately assess the impacts of retirement on BCF versus WCF.

A common difficulty in estimating the impact of retirement on post-retirement health and related treatment is that worker mental or physical health may itself affect the decision to retire. For instance, workers in poor health may retire earlier than healthy workers (McGarry 2004). This endogeneity complicates the identification of the causal effect of retirement (Oksanen et al. 2011; Olesen et al. 2015). Existing causal studies often exploit variations in financial retirement incentives (Heller-Sahlgren 2017; Charles 2004) and in retirement policies (Hagen 2018). To estimate the causal impact of retirement, we implement a non-parametric fuzzy regression discontinuity design (RDD) leveraging the exogenously determined and varying SRAs for female workers by occupation. The large sample size of our claims data allows for small bandwidths and therefore close comparisons around the two SRAs for females, thus aiding in identification. Our unique data set also allow us to focus on more severe mental illness that leads to hospitalizations. These severe mental illnesses are generally more clinically complicated and persistent. The treatment and management of severe mental illnesses are usually associated with direct costs in health care spending and indirect socio-economic costs to the patient and the society (McEvoy, 2007).

The remaining paper is organized as follows. Section 2 introduces the dataset; Section 3 lays out our empirical approach; Section 4 presents the results; and Section 5 concludes and discusses policy implications of our findings.

2 Data

This study utilizes medical claims data for inpatient care in 2017-2019 obtained through the Data Center for High-Quality Hospital Management at Peking University Institute for Global Health and Development. The Center integrates data on healthcare services and management of representative hospitals in China for health policy and management research. The data cover hospital admission and discharge of all patients, providing accurate information on length of stay (LOS), disease categories (uniformly recorded in ICD-10 codes), health care utilization, age, insurance type, occupation, gender, and retirement status of the patients. Lin et al. (2022) introduces our data in greater detail.

The original data contains enrollees of New Rural Cooperative Medical Insurance (NRCMI) and UEBMI. We focus on urban female employees around retirement age as BCF and WCF are subject to the differential SRAs under UEBMI. We restrict the sample to two years around both the age 50 cut-off (for BCF) and the age 55 cut-off (for WCF) to obtain a 2-year narrow bandwidth with great comparability around each cut-off (Table 1). This yields a total of 986,817 females who were hospitalized, i.e., 423,709 around age 50 (column 1 and 2, Panel A) and 563,108 around age 55 (column 4 and 5, Panel A), among all female employees in the same age ranges. 15,339 females, i.e., 6,613 around age 50 (column 1 and 2, Panel B and C) and 8,726 around age 55 (column 4 and 5, Panel B and C), are hospitalized with mental illness and behavioral disorders (ICD-10 F00-F99) as their primary diagnoses. The sample selection procedure is shown in Figure S1.

Panel A Table 1 presents summary statistics on mental illness admissions, including those through ER, among all disease admissions, prior to and after the two SRAs for females. Panel B Table 1 shows the number of mental illness admissions by subcategory. The most common subcategories of mental illness around SRAs are: neurotic, stress-related, and somatoform disorders (F40-F48); followed by schizophrenia (F20-F29); and mood disorders (F30-F39). Seven less frequent sub-categories of mental illness grouped as the "other mental illness" category include organic (including symptomatic) mental disorders (F00-F09); mental and behavioral disorders due to psychoactive substance use (F10-F19); behavioral syndromes associated with physiological disturbance and physical factors (F50-F59); disorders of adult personality and behavior (F60-F69); mental retardation (F70-F79); disorders of psychological development (F80-F89); and behavioral and emotional disorders with onset usually occurring in childhood and adolescence (F90-F99). Panel C Table 1 presents summary statistics on length of stay for mental illness admissions.

3 Methods

This study employs a Regression Discontinuity Design (hereafter RDD) to estimate changes in hospital admissions due to mental illness around the two SRAs. In the RDD, retirement ('treatment status') is a function of reaching the SRA retirement age cut-offs for BCF and WCF separately (assignment variables). The treatment effect of retirement is identified by comparing values of outcome variables above and below the two SRA thresholds. The RDD strategy using the exogenous SRAs helps address the concern of endogenous retirement decisions, such as poor mental health affecting the decision to retire. This approach is widely used in policy evaluations (Lee and Lemieux 2010). A key assumption is that the outcome variables of interest would trend smoothly in the absence of the retirement.

The large sample size allows estimation using 2-year bandwidths around each SRA, which enhances comparability across the cut-offs by occupation. Although retirement is "statutory" at the age cutoffs, some may still retire prior to or after the SRAs. Thus, a Fuzzy RDD is estimated as not all females retire at the policy stipulated SRAs (e.g., non-compliers). We exclude the observations located exactly at the two SRAs.

The most straightforward way to estimate the treatment effect in a Fuzzy RD setting is to use the Wald estimate, i.e. dividing the outcome variable by the change in treatment status.

$$LATE_o = \frac{\lim_{\varepsilon \to 0^+} E\left(Y_{io} \mid Age_{io} = SRA_o + \varepsilon\right) - \lim_{\varepsilon \to 0^-} E\left(Y_{io} \mid Age_{io} = SRA_o + \varepsilon\right)}{\lim_{\varepsilon \to 0^+} E\left(R_{io} \mid Age_{io} = SRA_o + \varepsilon\right) - \lim_{\varepsilon \to 0^-} E\left(R_{io} \mid Age_{io} = SRA_o + \varepsilon\right)} \tag{1}$$

where o is a dichotomous variable indicating $\{White\,Collar, Blue\,Collar\}$. $LATE_o$ is the occupation-specific local average treatment effect of retirement. Y_{io} denotes a series of outcome variables of mental health service utilization for individual i in occupation o. R_{io} is a dummy variable equal to 1 if the individual i in occupation o is retired. In practice, we estimate local polynomial regressions of Y and R to measure the discontinuities of mental health service utilization and retirement status.

Since the inpatient database only observes those admitted to hospitals, we follow Card et al. (2008) and assume that the distribution of the underlying populations is smooth around the cut-off ages 50 and 55. Our empirical test in Figure S2 of Appendix 1 lends support to this assumption. Given this assumption, Appendix 1 further illustrates that the discontinuity of the observed number of admissions can be attributed to the discontinuity of probability of admission around SRAs and that it is estimable using a reduced form RDD, as we will show in Panel A of Table 2.

4 Results

4.1 Main Results

To validate the identification assumption, we first test discontinuity in the retirement rate at the SRAs. The results show sharp increases in the probability of retirement at both ages 50 and 55. Specifically, females' retirement rate significantly rises by 12.2 percentage points (hereafter pp) at age 50 and 6.37 pp at age 55 (Figure 1).

We next evaluate changes in the monthly volume of mental illness-related hospitalizations for females using reduced-form estimations (Table 2 Panel A). The results indicate changes in the total number of monthly hospitalizations and the emergency room (ER) admissions due to mental illness at the two SRAs. The volume of monthly admissions due to mental illness rises by 20.7% at age 50, i.e., the SRA for

BCF. However, at age 55, i.e., the SRA for WCF, the volume of monthly admissions due to mental illness only insignificantly rises by 2.5%. In addition, changes in mental illness admission from ER differ between groups. Specifically, BCF show a 16.6% increase in ER admissions, while there is no significant change for WCF. Thus, Panel A shows that BCF suffer more at their SRA of 50 from overall mental illness admissions, including more ER admissions.

Based on patient-level data, our fuzzy RDD estimates (Table 2 Panel B) show that the probability of mental illness hospitalization increases by 2.3 pp for BCF, while there is no significant change for WCF. For ER admission, results indicate that the proportion of mental illness admissions through ER increases by 1.2 pp for BCF only. Again, the visualized RDD estimates show that BCF at age 50 utilize more inpatient care for mental illness upon retirement (Figure 2), while WCF at age 55 do not exhibit significant changes (Figure 3).

We next use RDD to evaluate how retirement affects LOS per admission for mental illness, as displayed in Panel C of Table 2. LOS per admission tends to be longer after retirement, especially for BCF at age 50, though both estimates are statistically insignificant. As suggested by summary statistics in Panel C of Table 1, the slight increase in LOS could be driven by the rise in LOS for schizophrenia (F20-F29) but partially offset by the declined LOS for other mental illness (F00-F19; F50-F99).

4.2 Other Findings and Robustness

We further consider how retirement may differentially affect subcategories of mental illness. Table 3 shows the RDD estimates on the probability of hospitalization across mental illness categories. First, admissions due to schizophrenia, schizotypal and delusional disorders significantly increase at both SRAs. Other categories of mental illness are relatively shorter-term disorders, and retirement for BCF at age 50 has significant impacts on these hospitalizations. More specifically, the effect is mainly driven by neurotic, stress-related, and somatoform disorders category. The onset of various types of mental illness can be very different in the life course. Mental health disorders may be affected differently in part due to the fact that, while many people first develop mental disorders in young adulthood, many have a much later onset timing (Solmi et al. 2021).

We conduct a series of robustness checks. First, we test pseudo-SRA cutoffs to confirm that the significant discontinuities in retirement rate and mental illness admissions we identify for BCF are not coincidence. Reassuringly, results in Table S1 show no significant increase in the probability of retirement at the pseudo-SRA cutoffs 48 and 49. Changes in mental illness admissions at the pseudo cut-off ages for BCF are also negligible. Both suggest that our identified main effects in Table 2 are plausibly causal. Second, our main results still hold after adopting a rectangular kernel function to the RDD estimations that assigns equal weight to observations away from the cut-offs to minimize extreme values around the SRA cutoffs (see Table S2). Third, we control for the number of chronic conditions contained in the patient's secondary diagnoses though control variables are not necessary for RDD. The results remain the same as when there are no control variables (see Table S3). Fourth, we examine the continuity of the SRA non-applicable group at around 50 and 55 years of age as a placebo test. The reduced form RD results show almost no discontinuities in the monthly volume of mental illness-related hospitalizations and the probability of mental illness hospitalization (see Table S4).

4.3 Potential Mechanisms

The observed increase in mental healthcare utilization at retirement is the net effect of the changes in health conditions and health care seeking behavior. Changes in health conditions at retirement may be shaped by aging per se, changes in physical and social environment (both may be due to no longer being at the workplace), and changes in health behaviors. Health seeking behavior post-retirement may be due to declines in income and opportunity cost of time, and slightly more generous health insurance coverage after retirement.

Given that we use a narrow (i.e., 2-year) bandwidth in the main RD estimations, the estimated effects are likely driven by changes in diagnosis and treatment decisions as the change in health conditions, especially in mental health, would not be seen immediately post-retirement; they take longer to occur. Retirement could also change, either rapidly or slowly, health status through lifestyle choices and health behaviors. Our results of rising percentage of mental illness admissions through ER upon retirement may occur because the urgent need for treatment for some mental health conditions (even a pre-existing ones) and may be less subject to easing of time constraints or price constraints. Moreover, delayed diagnosis and treatment for an underlying mental health condition pre-retirement could worsen the mental health problem and result in more immediate use of diagnosis and treatment post-retirement.

One important potential mechanism to explain the immediate increase in health care utilization at retirement is pent-up demand, i.e., women may have needed or wanted care prior to retirement but found it difficult to obtain due to the higher opportunity cost of time and/or less generous health insurance coverage prior to retirement. This pent-up demand has been found after Medicare enrollment (Schimmel 2005). In China, the generosity of UEBMI medical care coverage increases modestly after retirement for both blue-collar and white-collar workers, thus people may delay treatment until retirement. The more binding budget constraint overall (including less generous health insurance coverage for BCF than for WCF before and after retirement) and earlier SRA may promote more pent-up demand from BCF than from WCF. In contrast, the larger opportunity cost of time while working may incentivize more pent-up demand from WCF. Overall, the relative impact of pent-up demand between BCF and WCF prior to retirement remains undetermined a priori, thus needs empirical analyses.

To estimate the extent of pent-up demand, we apply the "donut" RDD approach that excludes observations very close to the cutoff (Almond and Doyle 2011; Barreca et al. 2011). Specifically, we remove observations less than three months before or after retirement and re-estimate using the remaining sample; pent-up demand would most likely occur shortly after the relaxation of time and changes in insurance coverage due to retirement. If the new estimates are similar without observations "close" around the age cutoff, this suggests negligible pent-up demand.

The donut RDD results are shown in Table 4. Panel A in Table 4 shows that the increase in total volume of mental illness hospitalizations for BCF at age 50 remains significant with even a slightly larger effect size compared to baseline estimates in Table 2. This suggests that pent-up demand may not be the main reason behind the rising mental illness hospitalizations for BCF around age 50. The larger impact on admissions from ER for BCF adds to evidence that pent-up demand may not be the most prevailing cause, since ER admissions are presumably related to more severe conditions and are therefore less likely postponed. That said, postponed care before retirement, if any, may also lead to more severe mental health conditions and therefore

ER admissions. Panel B in Table 4 shows that the probability of mental illness admissions and its admissions through ER increase significantly for BCF but not for WCF, which presents the same pattern as the non-donut RDD in Table 2 and rules out the possibility of pent-up demand dominating the results. However, the donut RD results for different categories of mental illness show that the impacts of retirement on schizophrenia at age 50 are almost entirely due to the pent-up demand (Table S5).

Out-of-pocket (OOP) rates of medical spending differ by prefectural city, depending in large part on the local fiscal condition, and may affect the decision to be treated as well as the extent of pent-up demand. Table S6 shows re-estimation of the main results after classifying subsamples by the OOP rate of medical expenditures at the city level. For BCF, the average OOP rate two years around the SRA (age 50) was 18.3 percent, which was slightly higher than 17.5 percent for WCF two years around their SRA (age 55). RDD estimates showed a significant increase in the probability of being hospitalized due to mental illness in cities with below average OOP rate for BCF, while no such effect existed for cities with above average OOP rate. By contrast, the probabilities of mental illness hospitalizations through ER significantly increased for blue-collar patients, whatever their city-level OOP rates. This finding verifies that higher OOP rate may discourage inpatient care for mental illness in general but had limited influence on mental illness admission through ER.

5 Conclusions and Discussion

Conclusions

Using by far the largest set of Chinese inpatient medical records, this study offers novel evidence of the short-run effect of retirement on mental illness hospitalizations and explores some potential mechanisms underlying occupational differences. We find significant increase in mental illness admissions at the SRA (50) for BCF only. Reduced form estimates suggest that admissions through ER increase by 16.6%, shortly after age 50 for these BCF. The fuzzy RDD estimates suggest that the probability of mental illness admissions increases by 2.3 pp at age 50, and the probability of mental illness admissions through ER increases by 1.2 pp. Interestingly, only BCF experience slight rise in LOS per admission.

These findings are consistent with the idea that some BCF may experience worsening mental health problems with age. This combined with more generous coverage of treatment post-retirement may account for an increased use of treatment post retirement. Other possible mechanisms for the increase in hospitalizations after retirement include that: women have more time to focus on their mental health problems; family members may spend more time with the women and thus identify issues that merit treatment; or women may be informed about their mental illness when seeking general medical care after retirement and obtain information about mental health treatment opportunities.

Overall, we find no significant rise in mental illness admissions for WCF, except for the category of: schizophrenia, schizotypal and delusional disorders. There are several possible reasons: WC jobs may be more mentally stressful, so retirement may relieve stress and mental health problems for WCF; WCF are older at retirement and could have already addressed age-related mental problems; and they tend to have more resources which might protect them from symptoms of some mental disorders. Because BCF have less generous coverage than WCF, they may have obtained less treatment or of a lower quality treatment prior to retirement.

What we add

We complement and extend the retirement literature in three main aspects. First, China's differing SRA policies between WCF and BCF women offer an opportunity to examine retirement's impact by age and occupation. We advance the literature on retirement in China by examining the differential SRAs for BCF (age 50) and WCF (age 55). Other studies based on household social surveys or smaller-scale medical claims data have insufficient statistical power to implement a RDD at both SRAs, especially for the smaller group of WCF at age 55 (Zhang et al. 2018; Zhou et al. 2021). Our findings for the first time suggest large retirement impacts on mental illness hospitalizations for BCF, but not for WCF.

Second, many existing studies focus on high-income countries. To our knowledge, this is the first study to use causal inference methods to identify the causal effect of retirement on mental illness hospitalizations in China, a developing country. The large-scale administrative data with rich information on disease coding also offers a unique opportunity to examine various types of mental illness by occupation. In particular, we show that the effects on mental illness hospitalizations are primarily driven by BCF patients suffering from the categories of: schizophrenia, schizotypal or delusional disorders; and neurotic, stress-related, or somatoform disorders.

Third, our use of medical records suffers less from recall bias and other measurement errors relating to self-reports, as would be found in conventional survey data. However, social stigma or lack of knowledge may result in under-diagnosis of mental illness when using either type of data.

Limitations

While our medical records allow for rigorous analyses with strong data, there are limitations. First, our approach cannot fully distinguish the aging effect from the occupation effect as the two job categories (BCF vs. WCF) and two SRAs are inextricably linked. Second, we cannot separate suffering from mental health problems from seeking treatment for problems. Third, hospitalization records tend to include patients with more advanced mental illness (Bauhoff 2011), and our large medical claims data have the appropriate statistical power to identify them; patients suffering less severe conditions may be underrepresented. However, the relatively well-insured population of urban workers in our sample may mitigate the concern as they tend to have better access to hospital care and afford more medical costs; and the hospital is the first point of contact in China (not a primary care physician), thus hospitalizations should capture all patients who seek inpatient care for mental illness; Fourth, medical records lack patient-level data on factors such as socioeconomic status, health prior to retirement, and other patient characteristics, which limit our examination of additional mechanisms.

Policy implications

This study yields suggestions for improving retirement and other policies relating to mental illness and its treatment. Even prior to our analyses, one obvious point is that the SRAs seem too low to support the financial stability of the retirement plan in China's population, especially for BCF. The current SRAs in China were established in the 1950s, when life expectancy at birth was only around 43 years in China (Fang and Feng 2018). With the continued rise in life expectancy in China, and many other countries (WHO 2020), coupled with rapid population aging, there are concerns about the long-term solvency of public pension programs.

A second point relates to the findings of possible worsening of mental illness among BCF after retirement. BCF usually have lower earnings, earlier retirement, and subsequent lower income, and less generous health insurance coverage compared to WCF. Addressing their mental health problems prior to retirement would benefit BCF and may allow for a later SRA.

Reductions in workplace stress, more generous coverage of medical problems before retirement, and provision of information by the government to increase awareness of mental health problems could promote early detection and allow earlier treatment.

While raising SRAs of retirement would enhance the solvency of pension funds, especially for BCF whose current SRA can be too early, a recent study in Germany finds negative effects of increasing retirement age to 60 or older on mental health (Barschkett et al. 2022). As BCF in China retire at least ten years earlier than in Germany, more research is needed to evaluate optimal retirement age for Chinese workers that balances concerns over pension solvency, individuals' retirement preparation, and health loss.

A broader implication is that although mental health issues are important, they typically receive inadequate attention in low-and middle-income countries (LMICs). By 2050, more than 80 percent of the world's older individuals will be living in LMICs where awareness, prevention and treatment of mental illness remain low; fortunately to these is growing (Collins et al. 2011; Suzman et al. 2015). However, social stigma and lack of knowledge and low resources suppress the use of needed mental health services in LMICs (Hsieh and Qin 2018). As the population continues to age across many LMICs, mental health issues will be more prominent and will need to be addressed through retirement and other government policies and programs.

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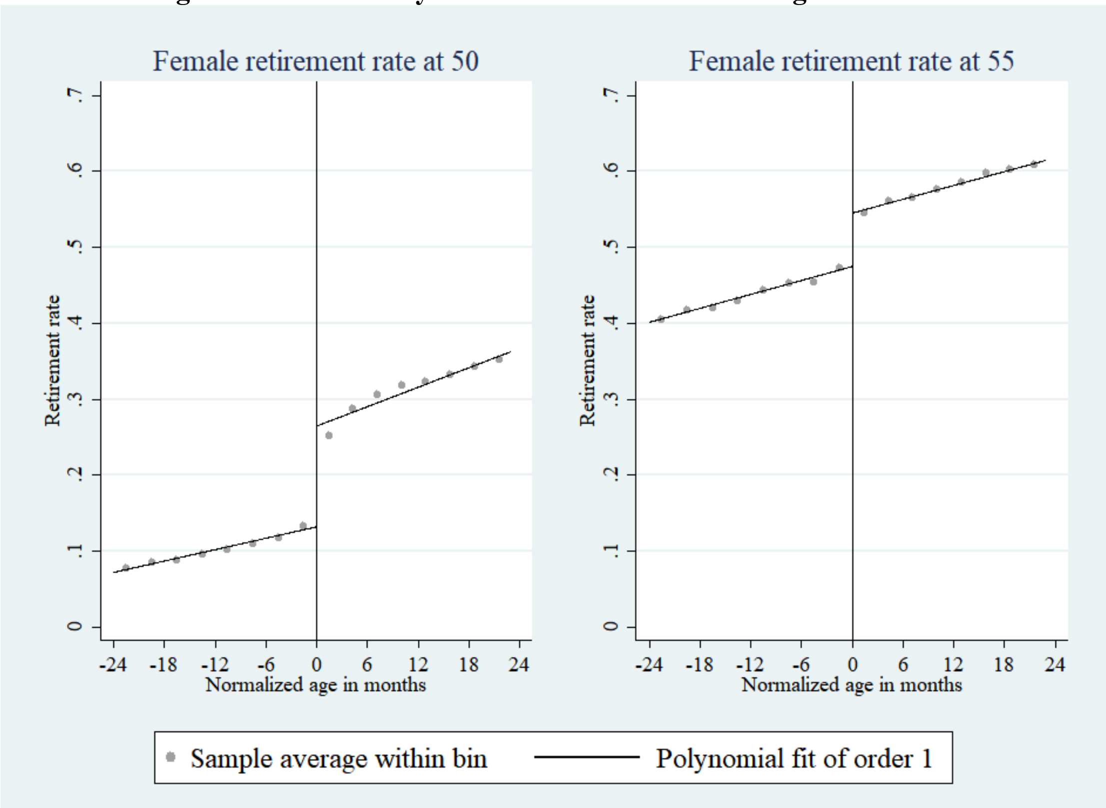
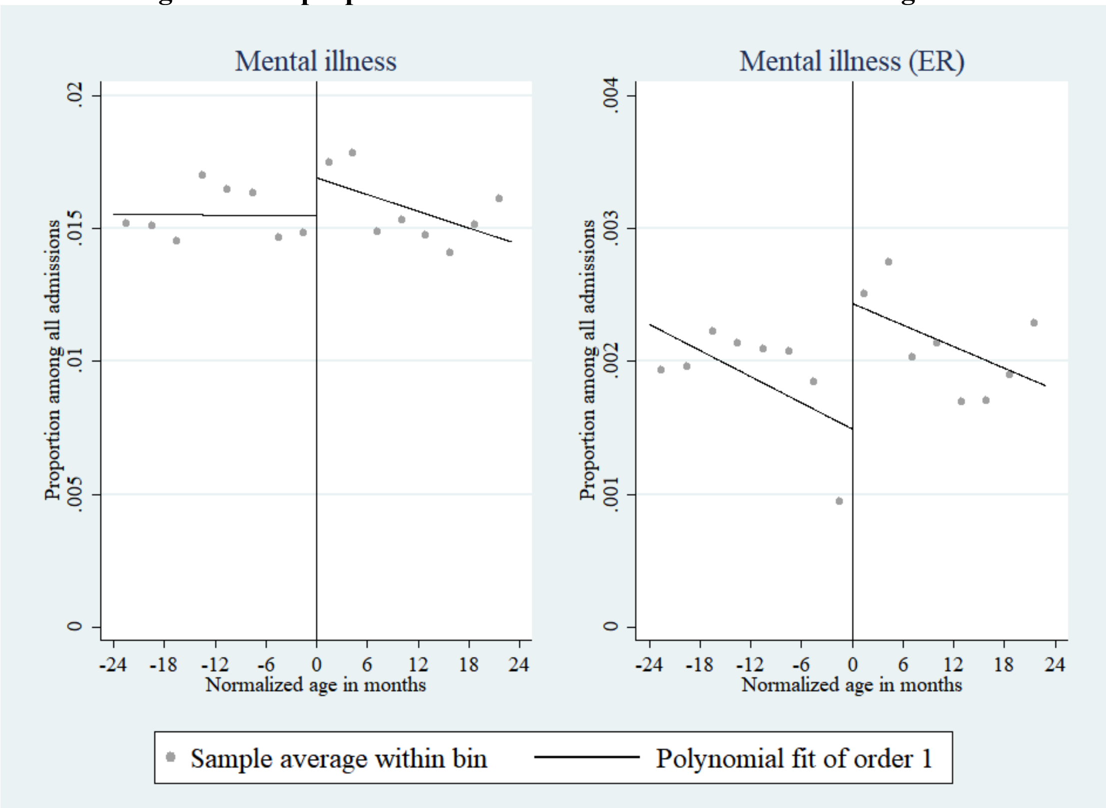
Figures and Tables

Figure 1 Discontinuity of retirement rates around ages 50 and 55



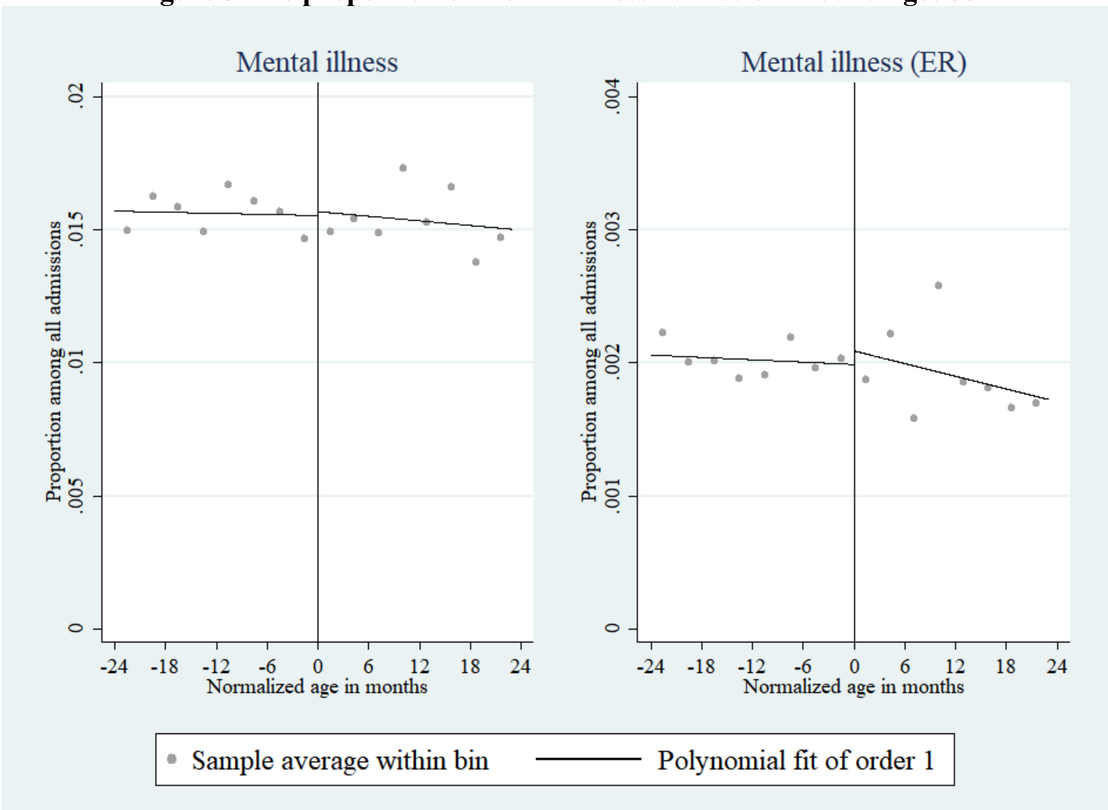
Notes: [1] The dots represent average retirement rate for each one-quarter-bin. [2] The left and right graphs are plotted using all women around the ages of 50 and 55, respectively. [3] The observations is 423,709 (left figure) and 563,108 (right figure).

Figure 2 The proportion of mental illness admission around ages 50



Notes: [1] The dots represent average proportion among all admissions within one-quarter-bin. [2] Left-side panel plots the proportion of all hospitalizations, including admission through ER and through outpatient department, that are primarily due to mental illness; the right-side panel plots the proportion of all hospitalizations that are primarily due to mental illness admitted through ER only.

Figure 3 The proportion of mental illness admission around ages 55



Notes: [1] The dots represent average proportion among all admissions within one-quarter-bin. [2] Left-side panel plots the proportion of all hospitalizations for mental illness, including hospitalization admitted through ER and through outpatient department, the right-side panel plots the proportion of hospitalizations for mental illness admitted through ER.

Table 1 Summary Statistics of Mental illness Types and Other Outcomes

Variables	Patient Characteristics Around Age 50 (SRA of blue-collar females)			Patient Characteristics Around Age 55 (SRA of white-collar females)		
	(1)	(2)	(3)	(4)	(5)	(6)
	[48,50)	[50,52)	Difference	[53,55)	[55,57)	Difference
Panel A. Proportion of Mental Illness and Behavioral Disorders *among All Admissions*[1]						
Mental illness (0/1) (%)	1.527	1.561	0.034	1.543	1.509	-0.034
	(12.263)	(12.397)	(0.038)	(12.326)	(12.191)	(0.033)
Mental illness through ER (0/1) (%)	0.194	0.218	0.024	0.207	0.196	-0.011
	(4.397)	(4.659)	(0.014)	(4.546)	(4.418)	(0.012)
# Mental illness through ER[2]	391	463	72	566	543	-23
Obs. = # All disease admissions	206,314	217,395	**11,081**	279,551	283,557	**4,006**
Panel B. Number of Mental Illness and Behavioral Disorders *by subcategory*[3]						
Schizophrenia, schizotypal and delusional disorders (F20-F29)	736	619	-117***	673	806	133**
	(0.361)	(0.289)	(-0.072)	(0.244)	(0.289)	(0.045)
Mood (affective) disorders (F30-F39)	455	507	52	564	627	63
	(0.211)	(0.231)	(0.021)	(0.196)	(0.220)	(0.024)
Neurotic, stress-related and somatoform disorders (F40-F48)	1,839	2,101	262**	2,864	2,663	-201***
	(0.874)	(0.954)	(0.080)	(1.008)	(0.906)	(-0.102)
Other mental illness (F00-F19; F50-F99)	167	189	22	264	265	1
	(0.081)	(0.086)	(0.005)	(0.094)	(0.093)	(-0.001)
Obs. = # Mental illness admissions[4]	3,197	3,416	**219**	4,365	4,361	**-4**
Panel C. *Length of Stay* by Mental Illness and Behavioral Disorders[5]						
Overall length of stay (LOS)	13.171	12.242	-0.932***	11.739	11.845	0.106
	(9.800)	(9.150)	(0.324)	(8.371)	(8.517)	(0.252)
Schizophrenia, schizotypal and delusional disorders (F20-F29)	23.506	24.056	0.550	22.411	22.728	0.317
	(9.411)	(9.056)	(0.567)	(8.520)	(9.131)	(0.519)
Mood (affective) disorders (F30-F39)	18.035	18.121	0.086	18.404	19.223	0.819
	(9.592)	(9.489)	(0.649)	(9.620)	(8.313)	(0.539)
Neurotic, stress-related and somatoform disorders (F40-F48)	9.266	9.370	0.104	9.142	9.448	0.306
	(6.629)	(6.826)	(0.216)	(6.378)	(6.391)	(0.173)
Other mental illness (F00-F19; F50-F99)	13.500	12.713	-0.787	13.580	14.300	0.720
	(9.227)	(7.782)	(0.928)	(7.770)	(9.375)	(0.777)
Obs. = # Mental illness admissions	3,197	3,416	**219**	4,365	4,361	**-4**

Notes: The classification of disease categories is according to ICD-10. *, **, and *** in the two columns of differences represent statistical differences below and above the age cut-offs at 10%, 5%, and 1% significance level, respectively.

[1] The mean and standard deviation for each outcome is presented.
[2] The total number of mental health ER admissions is 1,963.
[3] The number and proportion (%, in parentheses) of mental illness admissions by subcategory among all admissions are presented.
[4] The total number of mental health inpatient admissions is 15,339.
[5] The mean and standard deviation for length of stay by subcategory of mental illness are presented.

Table 2 Main Regression Results (RDD Estimates)

	BC Females (50)	**WC Females (55)**
Panel A: Log number of mental illness admissions at *the monthly level* (Reduced form)		
Log No. of monthly mental illness admissions	0.207***	0.025
	(0.056)	(0.056)
Log No. of monthly mental illness admissions through ER	0.166***	-0.040
	(0.058)	(0.180)
Obs. = # Months	48	48
Panel B: Proportion of mental illness *among all admissions*		
Probability of mental illness	0.023***	-0.000
	(0.007)	(0.011)
Probability of mental illness admissions through ER	0.012***	-0.001
	(0.002)	(0.004)
Obs. = # All disease admissions	**423,709**	**563,108**
Panel C: Length of stay *for mental illness*		
Length of Stay	2.648	0.314
	(5.789)	(3.870)
Obs. = # Mental illness admissions	6,613	8,726

Notes: [1] The RDD results are based on triangle kernel, and local linear regressions. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. [4] Panel A estimates RDD using monthly aggregated admissions, i.e., 2 years before / after each retirement cut-off age (in total 48 months). [5] Patients can be admitted to a hospital through ER or outpatient department, the former often means a worsened health condition.

Table 3 Additional Regression Analysis – Probability of Being in Each Subcategory of Mental Illness among All Disease Admissions (RDD Estimates)

Disease Category	BC Females (50)	WC Females 55
Schizophrenia, schizotypal and delusional disorders (F20-F29)	0.0072**	0.0108**
	(0.0033)	(0.0043)
Mental illness without long-term disorders	0.0160***	-0.0108
	(0.0061)	(0.0100)
Mood (affective) disorders (F30-F39)	0.0039	-0.0005
	(0.0025)	(0.0042)
Neurotic, stress-related and somatoform disorders (F40-F48)	0.0108**	-0.0065
	(0.0054)	(0.0088)
Other mental illness (F00-F19; F50-F99)	0.1361	-0.0040
	(0.2212)	(0.0027)
Obs. = # All disease admissions	**423,709**	**563,108**

Notes: [1] The outcome is the probability of hospitalization due to the specific disease category. [2] The statistics are based on a 2-year bandwidth. [2] The classification of disease categories is according to ICD-10. Seven sub-categories of mental illness, including organic mental disorders (F00-F09), mental and behavioral disorders due to psychoactive substance use (F10-F19), behavioral syndromes associated with physiological disturbance and physical factors (F50-F59), disorders of adult personality and behavior (F60-F69), mental retardation (F70-F79), disorders of psychological development (F80-F89), and behavioral and emotional disorders with onset (F90-F99), are grouped in the "other mental illness" owing to too few observations. [3] Mental illness without long-term disorders means mental illness other than Schizophrenia, schizotypal and delusional disorders. [4] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively.

Table 4 'Donut' RDD Estimates (excluding 3-month pre- and post- the SRAs)

	Female (50)	**Female (55)**
Panel A: Log number of mental illness admission at *the monthly level* (Reduced form)		
Log No. of monthly mental illness admissions	0.216**	0.030
	(0.086)	(0.062)
Log No. of monthly mental illness admissions through ER	0.496***	0.094
	(0.164)	(0.197)
Obs. = # Months	42	42
Panel B: Probability of mental illness *among all admission*		
Probability of mental illness	0.016**	-0.006
	(0.008)	(0.014)
Probability of mental illness admissions through ER	0.005*	0.002
	(0.003)	(0.005)
Obs. = # All disease admissions	369,809	487,623
Panel C: Length of stay *for mental illness*		
Length of Stay	3.149	4.532
	(8.775)	(2.928)
Obs. = # Mental illness admissions	5,735	7,613

Notes: [1] The results are based on triangle kernel, and local linear regressions. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. [4] Patients can be admitted to a hospital through ER or outpatient department, the former often means a worsened health condition. [5] The observations in each panel are less than that in Table 2 because the observations for the three months before and after the SRAs are removed for 'Donut' RDD estimations.

Appendix

Appendix 1

As inpatient medical records only observe those admitted to hospitals, we follow Card et al. (2008) to assume that the distribution of the underlying populations is smooth around the cut-off ages 50 and 55. This assumption is backed by our empirical test findings in Figure S2 below.

Specifically, the populations of age q in occupation o are denoted as N_{qo} and following the age trend function:

$$\log\left(N_{qo}\right)=h\left(q,o\right) \tag{2}$$

The logarithmic probability of hospitalization for individuals with age q and occupation o is

$$\log\left(P_{qo}\right)=g\left(q,o\right)+\pi D_{qo}+v_{qo} \tag{3}$$

where $g\left(q,o\right)$ is a smooth age profile that varies by occupation and D_{io} is an indicator variable equal to 1 if the individual i in occupation o is older than the occupation-specific retirement age MRA_{o}.

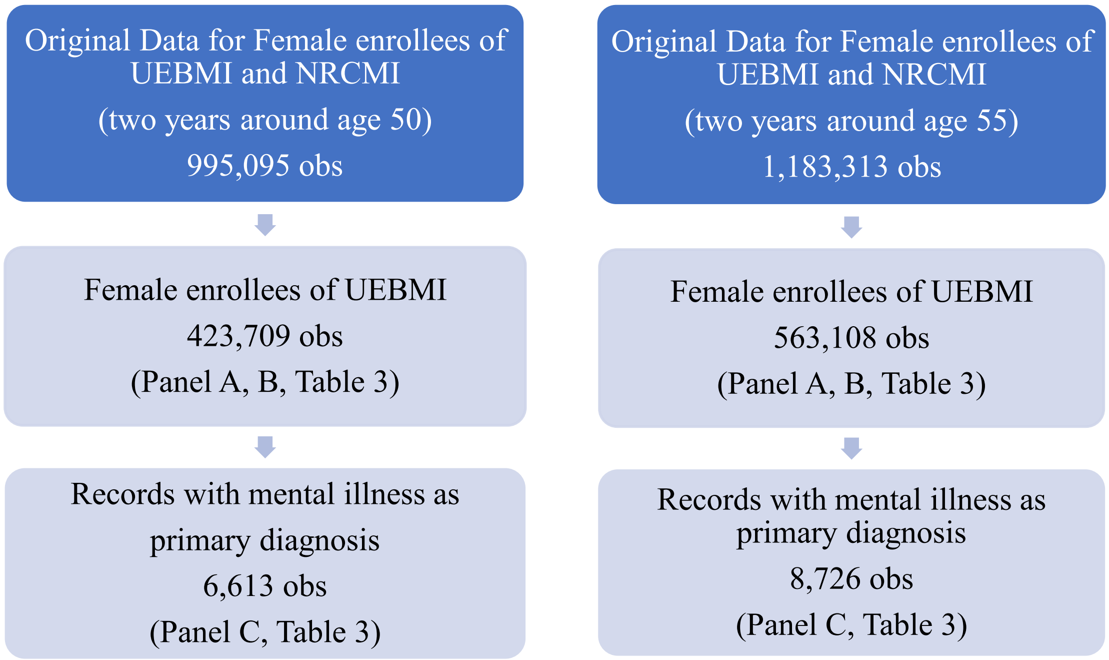
For age q and occupation o, the ratio of the observed number of admission A_{qo} and underlying population N_{qo} is a natural estimate of P_{qo}.

$$\log\left(P_{qo}\right)=\log\left(A_{qo}/N_{qo}\right)+\varepsilon_{qo} \tag{4}$$

Combining the equations above, the discontinuity of the observed number of admissions can be attributed to the discontinuity of log probability of admission around SRAs, which can be estimated via a reduced-form RDD, as we show in Panel A of Table 2.

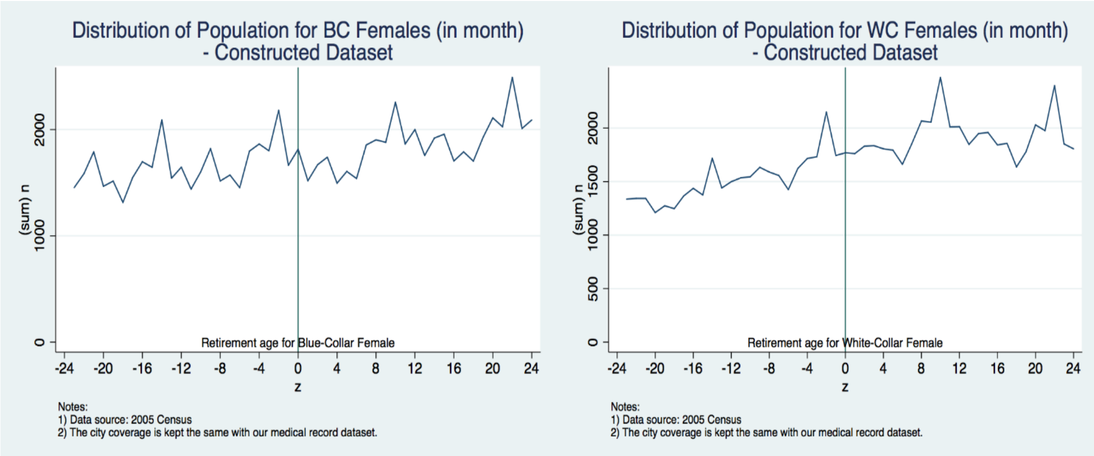
$$\log\left(A_{qo}\right)=h\left(q,o\right)+g\left(q,o\right)+\pi D_{qo}+v_{qo}-\varepsilon_{qo} \tag{5}$$

Figure S1 Flow Chart



Notes: [1] All samples are restricted to two years around the SRAs. [2] UEBMI = Urban Employee Basic Medical Insurance; NRCMI = New Rural Co-operative Medical Insurance.

Figure S2 Testing smoothness of the underlying female population around ages 50 and 55



Source: 2005 Chinese Mini-Census Data.
Notes:
[1] The dataset is processed in the following steps. First, we retain the birth cohorts that match our medical records. While the mini-Census was administered in 2005, the claims data cover 2017-2019. We next calculate their age in 2018 and center the age at each SRA. To simulate the three-year coverage (2017-2019) to make the underlying population conceptually similar to our claims data, we re-do the previous steps – calculate their age in 2017 and 2019, respectively, and center the age at each SRA. Finally, we combine the three datasets with respective age in 2017, 2018, 2019, centered the age at each SRA. This newly constructed dataset approximates our claims data in terms of city coverage, birth cohorts, and centered age.
[2] The vertical lines in this figure represent SRAs at which people in the 2005 mini-Census reach retirement age in 2017, 2018 or 2019.
[3] Within the 2-year time window before and after retirement age, the number of underlying population (measured in the birth month) is stable in general, although there appear to be some seasonal fluctuations. Although there is an increasing trend and some seasonal fluctuations in the graph, no discontinuity is found around age 50 or age 55. This test confirms that the discontinuities in retirement and mental health admissions that we observe are not due to changes in underlying populations. In other words, the discontinuities in observed number of admissions can be attributable to the abrupt changes in log probability of admission around SRAs, as explained in Appendix 1.

Table S1 Changes in retirement rate and mental illness admission around pseudo retirement age cut-offs

	Pseudo Retirement Age	
	2-year bandwidth	1-year bandwidth
	48	**49**
Retirement rate	0.0009	0.0040
	(0.0030)	(0.0049)
Log No. of monthly mental illness admission	0.053	0.123
	(0.070)	(0.097)
Probability of mental illness admissions	0.0007	0.0017
	(0.0008)	(0.0012)
Obs.	394,645	207,803

Notes: [1] The estimations are based on triangle kernel, and local linear regressions. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively.

Table S2 RDD estimates with alternative kernel function

	Female (50)	**Female (55)**
Panel A: Log number of mental illness admission at *the monthly level* (Reduced form)		
Log No. of monthly mental illness admissions	0.1442***	0.0569
	(0.0578)	(0.0580)
Log No. of monthly mental illness admissions through ER	0.5728***	0.0540
	(0.1666)	(0.1587)
Obs. = # Months	48	48
Panel B: Proportion of mental illness *among all admission*		
Probability of mental illness	0.0117**	0.0019
	(0.0058)	(0.0096)
Probability of mental illness admissions through ER	0.0073***	0.0011
	(0.0021)	(0.0035)
Obs. = # All disease admissions	**423,709**	**563,108**
Panel C: Length of stay *for mental illness*		
Length of Stay	-1.0013	3.7172
	(4.5033)	(3.0863)
Obs. = # Mental illness admissions	6,613	8,726

Notes: [1] The results are based on rectangular kernel, and local linear regressions. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. [4] Patients can be admitted to a hospital through ER or outpatient department, the former often means a worsened health condition.

Table S3 RDD Estimates controlling for the number of chronic conditions

	BC Females (50)	**WC Females (55)**
Panel A: Proportion of mental illness *among all admissions*		
Probability of mental illness	0.023***	-0.000
	(0.007)	(0.011)
Probability of mental illness admissions through ER	0.012***	-0.001
	(0.002)	(0.004)
Obs. = # All disease admissions	**423,709**	**563,108**
Panel B: Length of stay *for mental illness*		
Length of Stay	2.570	0.315
	(5.788)	(3.870)
Obs. = # Mental illness admissions	6,613	8,726

Notes: [1] The RDD results are based on triangle kernel, and local linear regressions. "Partial out" method is used to include control variable in the RDD estimates, i.e., regress the outcome variables in Panel A and Panel B on the number of chronic conditions and use the residual as a new dependent variable. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. [4] Panel A estimates RDD using monthly aggregated admissions, i.e., 2 years before / after each retirement cut-off age (in total 48 months). [5] Patients can be admitted to a hospital through ER or outpatient department, the former often means a worsened health condition.

Table S4 Reduced form RDD Estimates for SRA non-applicable groups

	Age 55	Age 50
Log No. of monthly mental illness admission	0.0832* (0.0479)	0.0705 (0.0597)
Log No. of monthly mental illness admission through ER	0.0427 (0.1354)	0.0700 (0.151)
Obs. = # Months	48	48
Probability of mental illness	0.0002 (0.0005)	0.0009 (0.0006)
Probability of mental illness admissions through ER	-0.0000 （0.0002）	0.0001 (0.0003)
Obs.=# All disease admissions	906,915	739,813

Notes: [1] The SRA non-applicable groups refer to white collar and rural residents (enrollees of NRCMI) at 50 and retirees and rural residents at 55. We define white collar as self-reported occupation as civil servants, professionals, staff, and business managers. [2] The results are based on a two-year bandwidth, rectangular kernel, and local linear regression. [3] The classification of disease categories is according to ICD-10. [4] *, **, and *** represent statistical significance at 10%, 5%, and 1% level respectively.

Table S5 Donut RDD Estimates for Probability of Being in Each Subcategory of Mental Illness among All Disease Admissions

	Donut RD Estimates	
	Female (50)	**Female (55)**
Schizophrenia, schizotypal and delusional disorders (F20-F29)	-0.0003	0.0125**
	(0.0034)	(0.0057)
Mood (affective) disorders (F30-F39)	0.0002	0.0022
	(0.0029)	(0.0053)
Neurotic, stress-related and somatoform disorders (F40-F48)	0.0126**	-0.0142
	(0.0059)	(0.0113)
Other mental illness (F00-F19; F50-F99)	0.0033*	-0.0068**
	(0.0017)	(0.0033)
Obs. = # All disease admissions	369,809	487,623

Notes: [1] The results are based on triangle kernel, and local linear regressions. [2] The classification of disease categories is according to ICD-10. [3] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively.

Table S6 Sub-sample Results by out-of-pocket (OOP) rate (RDD Estimates)

	BC Females (50)		WC Females (55)	
	Below average OOP rate	Above average OOP rate	Below average OOP rate	Above average OOP rate
Probability of mental illness among all admissions	0.033*** (0.010)	0.008 (0.009)	0.026* (0.015)	-0.039** (0.016)
Probability of mental illness (ER) among all admissions	0.014*** (0.003)	0.008** (0.004)	0.004 (0.005)	-0.010 (0.007)
observations	258,992	164,717	348,780	214,328
	423,709		**563,108**	

Notes: [1] The out-of-pocket rate is measured at the prefectural city-level using billing information in the data. The mean rates of out-of-pocket expenditure in [48,52] and [53,57] are 0.183 and 0.175, respectively. [2] The results are based on triangle kernel, and local linear regressions. [3] The classification of disease categories is according to ICD-10. [4] *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. [5] Patients can be admitted to a hospital through ER or outpatient department, the former often means a worsened health condition.