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Self-Assessed Health Status of Individuals with Chronic Diseases During and After the COVID-19 Pandemic

Songul Cinaroglu

Hacettepe University, Faculty of Economics and Administrative Sciences (FEAS), Department of Health Care Management, Ankara, Türkiye

ABSTRACT

Objective: This study aims to explore how the self-assessed health (SAH) status of individuals with chronic diseases has changed during and after the COVID-19 pandemic, compared to their status before the pandemic.

Materials and Methods: This research utilized panel data, tracing the socio-demographic and health status indicators of individuals and applying a difference-in-difference model to determine whether individuals with chronic diseases reported a greater decrease in SAH status during the pandemic. Data were derived from the Turkish Statistical Institute's Survey of Income and Living Conditions panel data spanning four waves from 2017 to 2020. The dependent variable of this study is SAH, while socio-demographic and health status indicators of individuals serve as independent variables.

Results: Statistically significant differences were observed between individuals with and without chronic diseases in terms of SAH status ($p<0.001$). Due to the negative and significant interaction parameter obtained from caliper matching (-0.09582; $p<0.001$), the decrease in SAH status among individuals with chronic diseases was pronounced during and following the pandemic.

Conclusion: The findings of this study indicate that the COVID-19 pandemic has led to a reduction in the SAH status of individuals with chronic diseases. These results provide insights for managers of chronic diseases to enhance the management of chronic conditions during pandemic times.

Keywords: Self-assessed health status, chronic diseases, COVID-19 pandemic, panel data.

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Address for correspondence:
Songul Cinaroglu.
Hacettepe University, Faculty of Economics and Administrative Sciences (FEAS), Department of Health Care Management, Ankara, Türkiye
Phone: +90 312 297 63 56 /57/58-114
E-mail:
songulcinaroglu@gmail.com

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INTRODUCTION

Self-assessed health (SAH), also known as self-rated health, is a measure that indicates risk factors and poor health outcomes in the general population.[1,2] In public health, SAH serves as a widely utilized subjective assessment of an individual's health status.[3,4] A poor perceived health status is associated with an increased risk of poor health outcomes. Specifically, the pandemic has exacerbated self-rated health issues and widened health disparities, especially among the elderly, the isolated, and the deprived.[5] Studies have found that COVID-19 infection and chronic disease are significantly associated with a poor self-rated health status.[6] However, the impact

of the COVID-19 pandemic on the SAH status of individuals with chronic diseases remains uncertain. Self-reported health status has been strongly linked to chronic diseases. The relationship between self-rated health and long-term health conditions, such as diabetes, is not well understood, with only a few studies assessing the self-rated health of individuals with diabetes in population samples.[7] The burden of chronic diseases is particularly high in developing countries, including Türkiye. Since 2003, under the Health Transformation Program, Türkiye has enacted health reforms based on primary healthcare services and an efficient, graduated referral system to establish a comprehensive and easily accessible healthcare system.[8,9] Noncommunicable Diseases (NCDs), such as cancer, cardiovascular diseases, diabetes, and chronic respiratory diseases, pose a major challenge for public health and development in Türkiye. In 2015, the country's death rate due to NCDs was 87.5%, and a person living in Türkiye faced an increased risk of premature death (16.8%) from one of the four major NCDs.[10]

Self-rated health has become one of the most commonly used health measures in social science research, thanks to the increasing use of nationwide population surveys that collect socioeconomic, demographic, and health data.[11] However, there is limited knowledge about the impact of chronic diseases on SAH status. It is noted that the prevalence of chronic diseases is lower among young adults. Chronic diseases can significantly impact the health-related quality of life and self-rated health status of adults and middle-aged individuals.[12] However, it is less clear how chronic diseases affect these aspects of health across different age groups. The literature indicates that multimorbidity is consistently associated with a decrease in health-related quality of life and self-rated health across all age groups.[13]

There is an awareness that individuals with chronic diseases have a low perception of SAH during the pandemic, yet this issue has not been extensively explored. This study aims to address this gap by examining the SAH of individuals with chronic diseases during the COVID-19 pandemic. Chronic diseases are closely linked to changes in health behaviors, and understanding SAH is crucial for uncovering the developmental origins of health and disease and combating chronic conditions. The objective of this study is to assess the impact of chronic disease on SAH status by comparing the average change in SAH status during the COVID-19 pandemic for individuals with chronic diseases against those without chronic diseases. The findings of this study will offer valuable insights for health policymakers to better understand the extent to which individuals with chronic diseases experience a greater decline in SAH during pandemic times.

MATERIALS AND METHODS

Subjects and Study Data

This study utilized the Survey of Income and Living Conditions (SILC) as one of its primary data sources. We employed micro-data provided by TurkStat, named SILC datasets, which cover the period between 2017 and 2020.[14] Each year, a nationally representative panel dataset and a cross-sectional dataset are generated from this survey. The SILC dataset encompasses a total of 122,947 households, providing detailed information on the income sources of individuals and households. The SILC question "What is the status of your health?" serves as the subjective measure. These responses are based on a Likert scale, where 1=very bad, 2=bad, 3=fair, 4=good, and 5=very good. SAH is a popular assessment method in health surveys and is widely used in this area. It is an excellent instrument with remarkable properties for better understanding the general well-being of the population. The SILC question asks, "Is there a limitation in the individual's daily activities due to any physical or mental health problem that has persisted for at least 6 months?" with options for Yes/No answers.

The Type of the Study

Data on Turkish household income and living conditions were systematically collected using a panel dataset by the Turkish Statistical Institute (TurkStat) over a given time period. This data provides information about income, poverty and social inclusion of individuals.

Ethical Statements and Data Availability

The panel dataset used in this study was generated by following the official procedures emphasized by TurkStat, adhering to established protocols and ethical principles. Given that our research involved a secondary analysis of an existing survey panel dataset, ethical approval was not required. The data is available upon request and with the permission of TurkStat.

Study Question and Hypothesis

In light of the study's objective, the research question of this study is: "Does the COVID-19 pandemic reduce the SAH status of individuals with chronic diseases?"

Hypothesis: Individuals with chronic diseases will report a decrease in SAH status during the COVID-19 pandemic.

In this study, we test the hypothesis that the COVID-19 pandemic has reduced individuals' SAH status using a difference-in-difference model.

Statistical Analysis

In this study, Propensity Score Matching (PSM) was employed due to significant socio-demographic and health status indicators observed between the unmatched treatment

and control groups. Furthermore, the efficacy of PSM largely depended on the characteristics of the dataset. It was anticipated that matching using PSM might be influenced by factors such as small sample size and imbalance in the propensity score distributions.[15] To match the socio-demographic status of individuals effectively, a nationwide panel dataset proved to be useful.[16] Additionally, this study utilized difference-in-difference regression analysis to explore the effect of COVID-19 on the self-rated health status of individuals.

Propensity Score Matching

In this study, regression-based models with propensity score matching were used to estimate the robustness of the basic results. Propensity score matching allows for the evaluation of the impact of treatment on treated individuals.[15] The choice of the optimal matching strategy is contingent upon the unique characteristics of the dataset and the objectives of the analysis. Provided that the treatment outcome has not been estimated prior to the selection of a strategy, other approaches can be explored.[17,18] Nearest-neighbor 1-to-1 matching without replacement is one of the widely used matching methods. This method identifies the closest propensity score match between each treated unit and a non-treated unit.[18] Caliper matching serves as an alternative approach, envisioned creating a boundary around each unit that limits which other units can be paired with it. The propensity score or other factors are used as the basis for setting these calipers.[19] When determining the typical treatment effect on the treated, the propensity scores are integrated with both nearest neighbor matching (1-to-1 matching with replacement) and caliper matching approaches.[17] Literature suggests that researchers should use a caliper width of 0.20 of the logit of the propensity score for matching.[20] Consequently, in our study, we set 0.20 as the width parameter for Caliper matching. To assess the independence of continuous and categorical covariates between the treatment and control groups, independent sample t-tests and chi-square tests were utilized in this investigation,[21,22] respectively.

Difference-in-Difference Regression

When randomized control trials are not feasible, the difference-in-difference design offers a quasi-experimental approach that can be used to investigate causal relationships in public health research.[23] To determine the average treatment effect on the treated group in this study, we utilize propensity scores alongside nearest neighbor matching (1-to-1 and caliper matching procedures) without replacement. In this case, we analyze an ordinal dependent variable using a difference-in-differences (DiD) approach. Specifically, we compare the SAH status of individuals with chronic diseases, referred to as the treatment group, against those without chronic diseases, referred to as the control group. Consistent with existing literature,[16] this study assumes that SAH status is a cardinal outcome metric, and the Average Treatment effect on the Treated (ATT) is calculated using equation (1). We aim to estimate three coefficients through DiD regression based on the logit model as follows:

Table 1. Descriptive statistics for the years 2017–2020

	n	%
Socio-demographic indicators		
Continuous variables		
Age, Mean, SD	38.17	13.78
Categorical variables		
Gender		
Male	60,25	49
Female	62,69	51
Marital status		
Married	83,45	67.9
Not-married	39,49	32.1
Education		
Illiterate	8,33	6.8
Literate or graduated	114,61	93.2
Labor		
Working full-time	58,53	47.6
Not working full-time	64,40	52.4
Health status		
Categorical variables		
General health status		
Very good	9,94	8.1
Good	79,24	64.5
Fair	24,99	20.3
Bad	7,84	6.4
Very bad	0,93	0.8
Suffering from any chronic illness or condition		
Yes	36,57	29.8
No	86,36	70.2
Limitation in daily activities at least 6 months		
Yes	25,57	20.8
No	97,37	79.2
Total	122,94	100

SD: Standard deviation.

Table 2. Effect of COVID-19 on SAH status of individuals (individuals with and without chronic diseases): PSM-DiD results

PSM-DiD performance indicators	Beta coefficients	1:1 NN matching without replacement	Caliper matching (δ=0.20)	Caliper matching (δ=0.40)
Treated	β_1	-0.81544*** (0.01588)	0.18715*** (0.02736)	0.18649*** (0.02732)
Time	β_2	0.01546* (0.00651)	0.11420*** (0.01121)	0.12276*** (2.2e-16)
Treated * Time	β_3	-0.03906*** (0.00915)	-0.09582*** (0.01614)	-0.09342*** (6.14e-09)
Multiple R-squared		0.3645	0.00601	0.006927
Adjusted R-squared		0.3645	0.00587	0.006791
F-statistic		1.3980	42.54	50.97
P-value		2.2e-16***	2.2e-16***	2.2e-16***

*: P<0.05; **: P<0.01; ***: P<0.001. The values in parentheses indicate the standard errors.

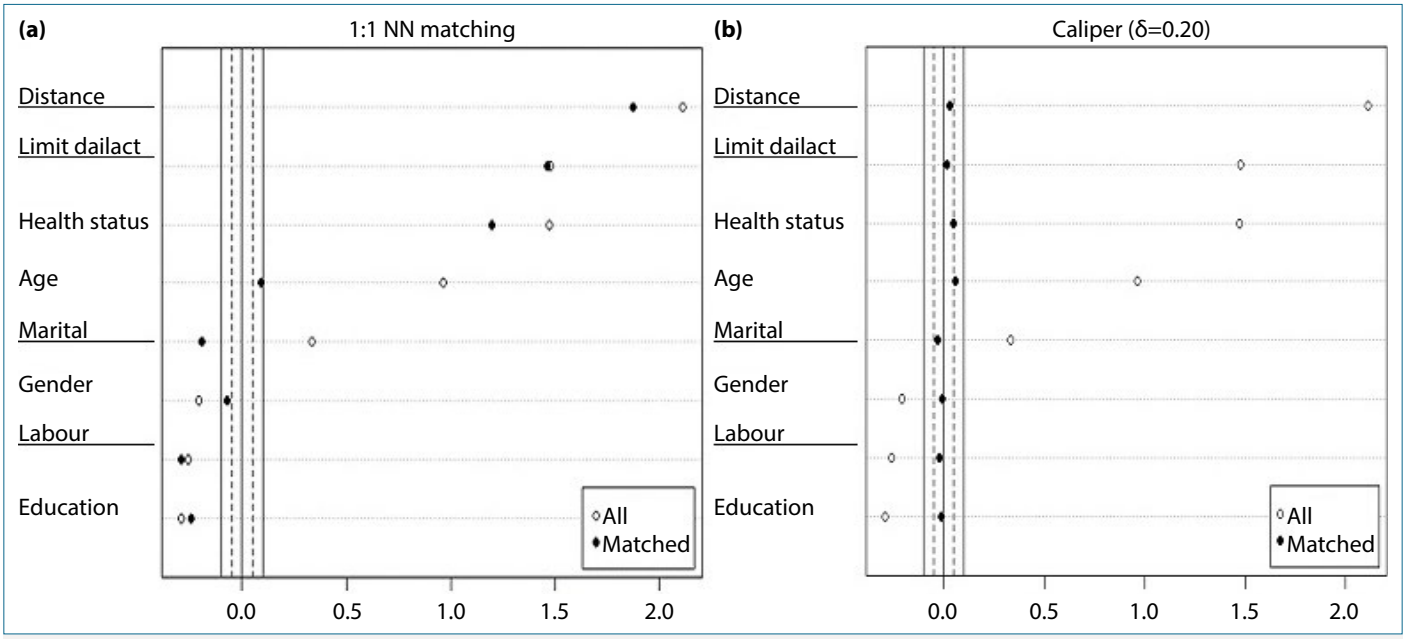

Figure 1. Standardized mean differences.

$$Y=\beta_0+\beta_1 * Treatment+\beta_2 * Post+\beta_3 * Treatment * Post+\varepsilon \quad (1)$$

In equation (1), Y represents the outcome variable, which is the SAH status. The Treatment variable is a dummy indicating the treatment group, i.e., individuals with a chronic disease or illness (=1), and the control group, i.e., individuals without a chronic disease or illness (=0). Post is a dummy variable indicating pre-COVID-19 times (2017 and 2018) (=0) and post-COVID-19 times (=1). Treatment * Post is a dummy variable indicating whether the outcome (SAH status) was observed in the treatment group (individuals with chronic diseases) after the intervention (=1), or in any other case (=0).

RESULTS

Basic Statistics

Table 1 presents the descriptive statistics derived from the Turkish Statistical Institute's SILC panel dataset for the years 2017, 2018, 2019, and 2020, focusing on the population aged between 15–64 years.[24] The analysis reveals that 67.9% of individuals within this age group are married, and 93.2% are literate or have attained primary education or higher. Additionally, 52.4% are not employed full-time. The average age is 38.17 (±13.78) years. Regarding health assessments, 64.5% of individuals rate their health as "good," 70.2% report no suffering from chronic illnesses or conditions such as

diabetes, hypertension, asthma, kidney failure, or rheumatic diseases. Moreover, 79.2% have not experienced limitations in daily activities for at least 6 months due to physical or physiological health problems.

Covariate Balancing: Differences Before and After Matching

The balance before and after matching is detailed in Appendix 1. Matching diagnostic tests indicate that socio-demographic and health status markers significantly discriminate between the unmatched treatment and control groups. In this study, 1-to-1 nearest neighbor matching and Caliper matching were applied, using caliper widths of 0.20 and 0.40, respectively. The current research emphasizes the importance of employing a caliper width of 0.20 when matching on the propensity score logit.[20] Balance diagnostics employed the Chi-square test (χ^2) for categorical variables and the independent sample t-test for continuous variables related to age. The results in Appendix 1 demonstrate that Caliper matching, with a width parameter of 0.20, more effectively balances the treatment and control groups across socio-demographic indicators such as gender (χ^2=0.172; p>0.05), marital status (χ^2=5.719; p>0.05), education (χ^2=1.406; p>0.05), and labor (χ^2=1.713; p>0.05).

Standardized Mean Differences

Standardized mean differences obtained from three matching methods are presented in Figure 1a, b. The standardized difference in means, calculated as the difference between the means of the covariates divided by the (unweighted) standard deviation, is a popular method for demonstrating group similarity.[25] According to widely accepted theory in the literature on propensity scores, a standardized difference in means greater than 0.10 or 0.20 indicates a significant difference across groups, making standard regression adjustment for that covariate potentially incorrect.[25] In our case, standardized mean differences obtained from 1-to-1 nearest neighbor (NN) matching and Caliper matching (δ=0.20) included covariates and indicate improvements toward 0.0 (no difference) after Caliper matching (δ=0.20) (Fig. 1 b).

Difference-in-Difference Results

Table 2 shows the effects of the COVID-19 pandemic on the SAH status of individuals by incorporating PSM and DiD results. The coefficient β_3 (difference-in-difference) is significant and different from zero. This key parameter, β_3, is of primary interest in our estimation. It shows how much the average SAH status of individuals with a chronic disease has changed in the period after the COVID-19 pandemic, in contrast to the outcome for the same group without the COVID-19 pandemic period. In other words, β_3 represents the difference between the counterfactual scenario and the average SAH status of individuals with a chronic disease in the period following the COVID-19 pandemic. We presented DiD results obtained from Caliper matching (δ=0.20) due to good covariate balancing results. Owing to the strong and unfavorable interaction discovered during Caliper matching (δ=0.20) (β_3= -0.09582; p<0.001), the decrease in SAH status is high in individuals with chronic diseases. Therefore, it is evident that the COVID-19 pandemic times have reduced individuals' SAH status, and the study hypothesis is accepted.

DISCUSSION

The main findings of our study highlight that individuals with chronic diseases reported a greater decrease in SAH during the COVID-19 pandemic. These insights enable public health policymakers to develop strategies for chronic disease management that consider individuals' physiological well-being alongside SAH. This research provides policymakers with valuable insights for navigating the challenges posed by COVID-19 and can inspire ongoing analysis of chronic disease trends and subjective health assessments.

Our findings, when interpreted in the context of existing knowledge, reveal a strong association between SAH and chronic diseases. Moreover, the COVID-19 pandemic has significantly impacted various aspects of life. Literature indicates that the burden of chronic diseases, such as increased rates of cardiovascular disease, is negatively correlated with SAH.[2,3] Our study's conclusions align with the existing body of knowledge on self-rated health and the chronic morbidity of individuals in Türkiye. Self-perceived health was examined in developed European nations and Türkiye, focusing on the impact of socioeconomic factors on individuals' SAH status. The findings provide insights for policymakers to develop strategies for chronic disease management that consider people's physiological well-being and SAH. The supportive findings of this study indicate that between 70–75% of the population aged 16 years or older reported very good or good self-rated health, while the prevalence of chronic diseases averaged around 30–35%. Additionally, socioeconomic factors in the EU-28 and Türkiye have a significant impact on self-rated health status. Many factors contribute to poor health status reporting, including income, education, gender, employment status, marital status, and age groups.[26]

The study found that individuals with good self-rated health before the pandemic reported no change in their self-rated health during the pandemic, while those with previously poor self-rated health reported improvements.[27] Furthermore, the findings underscore the negative relationship between chronic diseases and SAH during the pandemic. Covariates affecting health and chronic diseases, such as age, employment, and income, are associated with SAH status.[3] SAH is strongly linked to special types of chronic diseases, such as cardiovascular illnesses.[28]

In the EU-28 and Türkiye, one in three people reported having one or more chronic conditions.[26] Hypertension and cardiovascular risk factors are closely related and are important predictors of severity and mortality in COVID-19.[29] A decline in SAH during the COVID-19 pandemic was observed among individuals with chronic conditions, including diabetes, hypertension, asthma, and kidney failure. The COVID-19 pandemic has influenced the health behaviors of adults, with a high proportion of individuals with diabetes perceiving a higher risk of COVID-19 infection and subsequently increasing their smoking and drinking habits during these times.[29] Therefore, it is essential to bolster population-based efforts aimed at enhancing prevention, early diagnosis, and treatment of chronic diseases.

Emerging evidence indicates that the COVID-19 pandemic has posed threats not only to the physical health of individuals but also to the mental well-being of communities.[27] It has become apparent that perceived vulnerability to COVID-19 among adults plays a mediating role. Women, older adults, and those with lower subjective health evaluations are more likely to experience emotional reactions to the epidemic.[29] Therefore, it is crucial to consider the complex interactions between mental health issues, such as depressive symptoms, and chronic diseases, and how these affect seniors' perceptions of their health status and their use of healthcare services.[27, 29] Particular attention should be paid to how SAH influences depressive symptoms in the years following retirement, as well as the relationship between depressive symptoms and SAH in older individuals. Further studies are necessary to understand the burden of chronic diseases and related covariates on SAH by comparing observations before and after the implementation of health policies or interventions.

In this study, a combination of matching analysis and difference-in-difference is utilized to determine whether individuals with chronic diseases report a decrease in SAH status during the COVID-19 pandemic. The matching process creates balanced groups with and without chronic diseases in terms of socio-demographic and health status variables. After conducting matching diagnostics on covariates, we used the matched samples to generate difference-in-difference models. Existing knowledge underscores the trends in SAH and chronic illnesses among adults in Türkiye.[26] To our knowledge, this study is the first to employ a multi-stage analysis and to use SAH as a primary outcome indicator in a difference-in-difference model to explore the time-differing effects of the COVID-19 pandemic on individuals with chronic diseases. Considering changes in population dynamics, such as the increase in the elderly population, is essential for exploring the complex interrelationships between SAH and chronic conditions. One limitation of this study is that the parallel trends assumption was not tested during the DiD procedure. In our case, we applied matching for covariates before conducting the DiD analysis, which, as an alternative to statistically controlling for non-parallel trends, makes the estimated treatment effect more credible.[30] Further studies are planned to examine the parallel trends assumption.

The findings of this study provide valuable insights for behavioral health practitioners to understand how the self-rated health status of individuals with chronic diseases changes during pandemics. Health services researchers need further insight into preparedness for health crises. This study can inspire continuing examination of trends in chronic diseases and subjective health assessments. Community-based self-care programs are essential for managing chronic diseases, improving behavioral health, and preventing complications.

CONCLUSION

In summary, the findings of this study reveal a decline in the SAH status of individuals with chronic diseases in the period following the COVID-19 pandemic. Clinical health policymakers are urged to consider the subjective well-being of individuals and to develop community-based self-care programs to combat chronic diseases and their complications. These findings can serve as a catalyst for the ongoing monitoring of emerging chronic disease trends and the subjective health status of individuals, which merit further investigation in the context of pandemic times.

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Appendix 1. Sample size and sensitivity analysis for different matching models

	Variables	1:1 NN matching without replacement						Caliper matching (δ=0.20)						Caliper matching (δ=0.40)					
Socio-demographic & health status indicators	Gender: Male	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p
		Before matching	C	44,960	74.6	1078	<0.001	Before matching	C	44,960	74.6	1078	<0.001	Before matching	C	44,960	74.6	1078	<0.001
			T	15,294	25.4				T	15,294	25.4			Matching	T	15,294	25.4		
		After matching	C	16,605	52.1	95.53	<0.001	After matching	C	4,867	50.2	0.172	0.679	After matching	C	5,113	51.3	12.530	<0.001
			T	15,294	47.9				T	4,837	49.8				T	4,852	48.7		
	Marital status: Being married	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p
		Before matching	C	55,066	66	2264	<0.001	Before matching	C	55,066	66	2264	<0.001	Before matching	C	55,066	66	2264	<0.001
			T	28,391	34				T	28,391	34				T	28,391	34		
		After matching	C	31,346	52.5	796.89	<0.001	After matching	C	8,418	50.4	5.719	0.056	After matching	C	8,708	50.4	4.410	0.036
			T	28,391	47.5				T	8,277	49.6				T	8,581	49.6		
	Low education: Illiterate	Matching status	C	n	%	χ^2	p	Matching status	C/T	T	%	χ^2	p	Matching status	C/T	n	%	χ^2	p
		Before matching	C	3,288	39.5	4049	<0.001	Before matching	C	3,288	39.5	4049	<0.001	Before matching	C	3,288	39.5	4049	<0.001
			T	5,042	60.5				T	5,042	60.5				T	5,042	60.5		
		After matching	C	1,944	27.8	1518.87	<0.001	After matching	C	683	48.5	1.406	0.236	After matching	C	10,231	50.1	0.827	0.363
			T	5,042	72.2				T	726	51.5				T	10,197	49.9		
	Full time working	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	T	%	χ^2	p	Matching status	C/T	n	%	χ^2	p
		Before matching	C	44,372	24.2	1646	<0.001	Before matching	C	44,372	24.2	1646	<0.001	Before matching	C	44,372	24.2	1646	<0.001
			T	14,167	75.8				T	14,167	75.8				T	14,167	75.8		
		After matching	C	19,353	57.7	1480	<0.001	After matching	C	5,169	50.5	1.713	0.191	After matching	C	5,399	50.7	3.629	0.057
			T	14,167	42.3				T	5,074	49.5				T	5,258	49.		
	Age	Matching status	C/T	n	Mean	t	p	Matching status	C/T	n	Mean	t	p	Matching status	C/T	n	Mean	t	p
		Before matching	C	86,369	34.62	-151.40	<0.001	Before matching	C	86,369	34.62	-151.40	<0.001	Before matching	C	86,369	34.62	-151.40	<0.001
			T	36,578	46.57				T	36,578	46.57				T	36,578	46.57		
		After matching	C	36,578	45.42	-14.064	<0.001	After matching	C	10,543	44.77	-4.095	<0.001	After matching	C	10,964	43.59	-8.91	<0.001
			T	36,578	46.57				T	10,543	44.07				T	10,964	45.11		
	Self-assessed health: bad&very bad	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p	Matching status	C/T	n	%	χ^2	p
		Before matching	C	68	0.8	21806	<0.001	Before matching	C	68	0.8	21806	<0.001	Before matching	C	68	0.8	21806	<0.001
			T	8,701	99.2				T	8,701	99.2				T	8,701	99.2		

C: Control group; T: Treatment group; χ^2: Pearson's Chi-square test. See Table 1 for descriptive statistics of socio-demographic indicators and health status of individuals for the years between 2017 and 2020.