PANOECONOMICUS, 2026, Vol. 73, Issue 3, pp. 387-409
Received: 30 January 2023; Accepted: 29 August 2024.

UDC 331.526:159.938.363.6(470)"2010/2018"
https://doi.org/10.2298/PAN230130018K
Original scientific paper

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The Application of Quasi-Experimental Approaches to the Analysis of the Relationship between Employment and Health

Summary: This study is the first to use quasi-experimental approaches to analyze the employment-health relationship in Russia. We employ propensity score matching to assess the impact on self-reported health of being employed or unemployed during the period 2010-2018. Using a difference-in-differences estimator, we also explore the effect of re-employment on physical health. Controlling for selection bias, we find a negative impact of unemployment on physical health. We also confirm that being employed leads to better self-reported health than being unemployed. Part of the effect is related to improved individual mental health. Furthermore, the difference-in-differences estimator of the re-employment effect shows that finding a job after three years of not working increases self-reported health. The results have important policy implications. The government should actively promote employment and initiate information campaigns to promote free health checkups for the unemployed. In Russia, where the state bears the cost of healthcare, these policies will eventually allow the government to save money on medical treatment.

Keywords: Unemployment, Selection effect, Propensity score matching, Difference-in-differences estimator, Russia.

JEL: C21, I10, I12.

The research was funded by the Russian Science Foundation (project No. 24-28-00119).
The author declares no conflict of interest.

It is well established in the literature that unemployment is negatively associated with general physical health (Colin D. Mathers and Deborah J. Schofield 1998; Ioannis Theodossiou 1998; Annika Åhs and Ragnar Westerling 2006; Dorota Kaleta, Teresa Makowiec-Dabrowska, and Anna Jegier 2008; Maria Vaalavuo 2016; Johannes Stauder 2019). However, there is less of a consensus concerning the causal pathways from unemployment to health. Does unemployment cause a deterioration in health, or do individuals with poor health self-select into unemployment?

Researchers distinguish between two mechanisms that govern the relationship between unemployment and health (Maria Kaneva and Christopher J. Gerry 2021). The first is a direct or causal mechanism in which the experience of unemployment impairs health. The causal mechanism is linked to income reduction, since unemployed people are forced to adjust their living standards and spend their savings. The second is a selection or reverse causality mechanism: it is a pathway through which those experiencing ill health are more likely to become or remain unemployed. Health problems might reduce an employee's job performance and increase her days of absence and the probability of job loss. Once laid off, an employee with health problems takes more time to locate a new job or might be less successful in their job search because of their reduced effort and efficiency (Karsten I. Paul and Klaus Moser 2009).

Most studies estimate the overall negative associations between unemployment and health. Such estimations are performed in cross-sectional studies, and the design means that it is impossible to separate the selection and causation effects. The estimations are also not causal. Even in longitudinal studies, special methods (see the Methods section) must be applied to control for the selection effect and estimate the causal impact of joblessness on health.

The following section demonstrates that in the literature there are currently no studies on Russia that present the causal effect of the labor market on health while controlling for the selection effect. Taking this into consideration, in this study we aim to apply quasi-experimental approaches to disentangle the complex relationship between unemployment and health by controlling for the selection effect and estimating the causal impact of unemployment on health in the case of the Russian labor market.

Our research, employing the Russian Longitudinal Monitoring Survey for 2010-2018, shows that job loss adversely affects self-rated health after controlling for a possible selection effect via propensity score matching. Additionally, the difference-in-differences approach demonstrates that finding a job after a period of employment (three years in our case) improves physical health.

1. Literature Review and Formulation of Hypotheses

As shown in the Introduction, the relationship between unemployment and health includes both a direct causal mechanism through unemployment to changes in health and a selection effect from health to job loss.

The direct mechanism works as follows. Confronted with a loss of work and a reduction in income, people are obliged to follow the cheapest diet and to stop exercising, and they sometimes return to unhealthy habits like smoking and drinking. The worsening of health begins as unemployment starts. However, in many European countries where unemployment insurance exists, the longer the duration of unemployment, the stronger the direct effect on health is likely to become (Vaalavuo 2016; Stauder 2019; Kaneva and Gerry 2021).

If individuals leave the job market because of health problems, the selection mechanism is at play. People with poor health will avoid jobs that require increased effort and/or overtime working. As a result, such employees will have longer spells of unemployment than healthy workers. The selection effect postulates that poor health leads to unemployment and reduced earnings, rather than the other way around.

The impact of unemployment on health is frequently addressed in the literature. Studies can be of a cross-sectional or panel nature. The vast majority of cross-sectional studies demonstrate a negative relationship between physical health and unemployment (Theodossiou 1998; Ahs and Westerling 2006). However, cross-sectional studies do not account for the selection effect – that individuals with poorer health tend to self-select into unemployment. Self-selection leads to a negative association between unemployment and health; this effect influences the overall negative effect of unemployment on health.

Longitudinal data are needed for a proper evaluation of the association between unemployment and health. However, the conclusions from such studies vary between periods and countries. Some researchers find a negative effect of unemployment on health. For example, a panel study from Finland found that unemployment impairs the self-reported health (SRH) of Finnish people but has no effect on their biomarkers (level of glucose, hypertension, and level of c-reactive protein) (Edvard Johansson, Böckerman, and Annamari Lundqvist 2020). The years s were 2000 and 2011. The study accounted for selection bias by including past health in the covariates. Similarly, Drydakis (Nick Drydakis 2015) found a negative effect of unemployment on SRH and mental health (a scale from 0 to 60 on the CES-D depression scale) in Greece. Moreover, he pointed out that the negative effect was greater during a period of higher unemployment in the whole country (2010-2013) than during a period of low unemployment (2008-2009). However, this study did not explicitly address the selection bias problem.

Another strand of literature aims to minimize selection bias and produce unbiased estimates of the impact of unemployment on health. Böckerman and Ilmakunnas (Böckerman and Pekka Ilmakunnas 2009) used difference-in-differences and propensity score matching to demonstrate that the event of becoming unemployed does not affect SRH in Finland. In fact, the health status of those who become unemployed is worse than that of those who are continuously employed. Therefore, people self-select into unemployment. Jérôme Ronchetti and Anthony Terriau (2019) applied difference-in-differences propensity score matching to French longitudinal data to demonstrate that unemployment does not worsen self-perceived health. Gebel and Voßemer, using the same method for Germany, showed that the effect of unemployment is negative for psychological health but not for physical health (Michael Gebel and Jonas Voßemer 2014).

Another way to minimize selection bias is by using natural experiment data. Plant closures are natural experiments because they guarantee that people are laid off and do not self-select into unemployment because of poor health. Schmitz explored the effect of unemployment on health in Germany, differentiating unemployment caused by plant closure and unemployment for other reasons (Hendrik Schmitz 2011). He used health satisfaction (0-11) as a health indicator and found no negative effect of unemployment on health when endogeneity is considered.

Apart from the impact of unemployment on health, we are interested in the effect of re-employment. In Germany, the impact of re-employment was found to be positive for psychological health but not for physical health (Gebel and Voßemer 2014). Another study of an unemployed cohort in Rotterdam, which employed a Cox proportional hazards model, concluded that re-employment was associated with improvement in both general and mental health (Merel Schuring et al. 2011). In the case of Croatia, a longitudinal study showed that re-employment positively impacted psychological health, while physical health was not related to re-employment (Zvonimir Galić and Branimir Šverko 2008).

Only a few articles discuss the relationship between labor market status and SRH in Russia. Stepan Ermakov, Vitalii Kim, and Oksana Kuzmich (2011) analyzed bivariate associations in the RLMS-HSE[1] panel data between SRH and labor market status, confirming that the share of people with poor health is greater among the unemployed than among the employed. In a panel study of Russian pensioners in the RLMS, Merkurieva applied the Heckman sample selection model to control for selection bias. Her calculations demonstrated that the health of employed pensioners and those looking for a job was better than that of pensioners who were not economically active in the labor market (Irina Merkurieva 2004). Another panel study on job search using the RLMS dataset for 2000-2008 showed that infarction and stroke were associated with a lower probability of job search among males (but not females) (Kirill Furmanov and Irina Chernysheva 2012). However, the study did not find a significant association between SRH and the likelihood of finding a job or between SRH and unemployment duration.

Vladimir S. Gordeev et al. (2016) analyzed the resilience of the Russian population to economic shocks. Building a logistic regression model for 1994-2021, they found that employed respondents were 1.5 times more likely to report good health than unemployed or economically inactive individuals. Finally, Loretta Platts (2015) used Cox duration analysis for the RLMS for 2000-2007 to show that labor market status (unemployment) predicted individual-level declines in self-rated health. The level of the health decline had a similar magnitude to the decrease in health in the British Household Panel Survey (UK).

This literature review of studies on Russia concludes that none of the works can claim causality from unemployment to health (although the work of Merkurieva (2004) claims the reverse causality, from health to employment). However, if unemployment has a causal negative impact on health, such estimates are of the utmost importance for policymakers in Russia. These policymakers can then estimate the economic burden of diseases and develop policies that decrease this burden via improvements in the health of the unemployed.

Our article addresses the literature gap described above and provides causal estimates for the relationship between labor market status and health. We turn to two quasi-experimental approaches – propensity score matching and difference-in-differences estimators – to eliminate systematic differences, including the selection bias between the treatment (unemployed) and the control groups. To our knowledge, this is the first study to employ quasi-randomization designs to estimate the impact of unemployment/re-employment on health in the Russian setting[2]. To explore the effect of re-employment on health in a difference-in-differences setting, we choose a four-year period.

Four hypotheses are tested in this study:

[1] The Russian Longitudinal Monitoring Survey of the Higher School of Economics. More information on RLMS is presented in the Data section of this article.
[2] There is a paper (Ekaterina Aleksandrova, Venera Bagranova, and Christopher J. Gerry 2021) that applies difference-in-differences propensity score matching to study the opposite effect – the impact of health shocks on labor market outcomes.

H1. Unemployment leads to a decrease in self-reported health compared to employment, even when the selection effect is taken into account.

H2. Employment leads to an increase in self-reported health compared to unemployment.

H3. Unemployment after three years of working/labor market non-participation leads to a decrease in self-reported health.

H4. Re-employment after three years of not working increases self-reported health.

H1 and H2 are addressed in the propensity score matching framework, while for H3 and H4 we employ the difference-in-differences approach.

2. Methods

Below, we summarize the two quasi-experimental approaches that are employed in our research. Quasi-experimental approaches, by definition, lack random assignment. However, they identify a comparison group that is as similar as possible to the treatment group in terms of baseline (pre-intervention) characteristics. Quasi-experimental approaches account for and control the selection effect and estimate the causal treatment effect.

Propensity score matching

Propensity score matching (PSM) is an estimation technique used in observational studies when a randomized control trial/experiment is impossible. In observational studies, group selection into treatment is not random. PSM aims to find a control subject for each treated subject based on an index of observed characteristics termed the propensity score.

Propensity score matching is based on the conditional independence assumption (CIA) (or "selection on observables" assumption) . This is Assumption 1 in our analysis. The assumption states that, after controlling for the characteristics included in the propensity score, the treated and control units are equivalent in the remaining unobservable characteristics. This means that the unobservables do not affect participation in the treatment. If this assumption is valid, the difference in the outcome between the treated and the non-treated groups can only be attributed to the treatment. Under the CIA, PSM provides an unbiased estimate of the treatment effect (Paul R. Rosenbaum and Donald B. Rubin 1983). Matching does not make the linear functional-form assumption that is made for regression. If the CIA holds but linearity does not, then the matching is consistent (while the regression is not) (Glenn Weddell 2019). Therefore, even if the effects of unemployment on health are non-linear, the average treatment effect on the treated (ATT) computation in the PSM remains consistent.

Propensity scores are calculated as predicted values from logit or probit regressions, with treatment as the outcome variable and potential observed confounders as explanatory variables. The purpose of calculating the propensity score is to account for all the possible reasons why the treatment and control group differ, other than the treatment itself (Sarah J. Beal and Kevin A. Kupzyk 2013). The propensity score should be calculated using confounders related to treatment and outcome. Covariates affected by the treatment should be excluded from consideration (Melissa M. Garrido et al. 2014).

To match individuals in the treatment group to individuals in the control group, there should be an overlap in the range of propensity scores across the treatment and control groups. This overlap is termed "common support" and is Assumption 2 in our analysis. No inference can be made for a treated individual for whom there is no control individual with a similar propensity score (Garrido et al. 2014). The common support condition is validated by studying the propensity scores diagram for the two groups.

There are several matching algorithms. Two algorithms presented in this paper are nearest neighbor matching and kernel matching. Nearest neighbor matching is the most common method used for matching. For each treatment case it assigns the control case nearest to the treatment case in their respective propensity scores. The method involves running through the list of treated units and, for each one, selecting the closest eligible control unit to be paired with it (called 1-to-1 matching). Nearest neighbor matching does not aim to optimize any criterion – the aim is to pair units without referencing how they will be or have been paired.

We also employ kernel matching. Kernel matching matches units with the weighted average of all untreated units, with weights inversely proportional to the distance between treated and untreated unit propensity scores. Only observations outside the range of common support are discarded. Kernel matching maximizes precision (by retaining sample size) without worsening bias (by giving greater weight to better matches).

To assess the quality of matching and, thus, the validity of the causal inference, covariate balance should be studied.

To check for the balance in our model, we use the indicator called % of Absolute Standardized Bias (%ASB).

$$\%ASB = \left| \frac{\overline{X_t} - \overline{X_c}}{\sqrt{0.5(s_t^2 - s_c^2)}} \right|, \tag{1}$$

where t denotes treated, c denotes control, s denotes the standard deviation, and $\bar{X}$ indicates the mean. Ideally, differences that were in the sample before matching will be minimized. An indicator below the absolute value of five (Marco Caliendo and Sabine Kopeinig 2008) indicates a good balance between groups. A standardized difference of ≥10% for a given covariate indicates a significant imbalance.

Difference-in-differences

A difference-in-differences (DiD) model is a quasi-experimental approach that compares the changes in outcomes over time between the treatment and control groups.

In the simple base case of the difference-in-differences approach, there are two time periods, t and $t+1$. We distinguish between the treatment group D = 1, which experiences an unemployment transition at $t+1$, and the control group D = 0, which does not. For both groups, two potential outcomes – without and with treatment – at each time point are defined (Y^0, Y^1), but only one outcome is observed, whereas the second outcome remains an unobserved counterfactual. The following formula defines the effect of the unemployment transition:

$$E(Y_{t+1}^{1} - Y_t^{1} | D = 1) - E(Y_{t+1}^{0} - Y_t^{0} | D = 1), \quad (2)$$

where the second term is the counterfactual trend. The counterfactual trend in health is approximated by the actual change in health in the control group:

$$E(Y_{t+1}^{0} - Y_t^{0} | D = 1) = E(Y_{t+1}^{0} - Y_t^{0} | D = 0). \quad (3)$$

Thus, the average treatment effect on the treated (ATT) is calculated according to the following formula:

$$E(Y_{t+1}^{1} - Y_t^{1} | D = 1) - E(Y_{t+1}^{0} - Y_t^{0} | D = 0). \quad (4)$$

In the difference-in-differences estimate, by subtracting the before-outcome situation from the after-outcome situation we cancel out the effects of all characteristics unique to an individual that do not change over time (time-invariant). Therefore, DiD eliminates fixed effects not related to treatment.

DiD identifies the causal treatment effect if the treatment and control groups are on the same trajectories before the intervention. The parallel trend assumption implies that changes over time would have been identical if there had been no intervention. Only if the assumption holds are the results of the estimation unbiased. DiD allows unobservable, time-variant characteristics to be controlled for if the parallel trend assumption holds. The parallel trend assumption is tested graphically before the intervention.

For the two periods, a DiD OLS regression model can be estimated. We add control variables to the base model to quantify their impact. The formula for the regression is below:

$$SRH_{it} = \beta_0 + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 Post_t * Treated_i + \\ + \beta_4 Controls_{it} + \varepsilon_{it}, \quad (5)$$

where *Post* is a dummy variable that takes the value of 1 in the year 2018 and 0 otherwise, and *Treated* is a dummy variable that equals 1 if the individual is in the treatment group.

Our coefficient of interest is $\widehat{\beta_3}$. This is the difference-in-differences estimate of the treatment effect or the average treatment effect.

3. Data

We employ data from the Russian Longitudinal Monitoring Survey, years 2010-2018 (Waves 19-27) (the RLMS is conducted by the National Research University "Higher School of Economics" and ZAO "Demoscope", together with Carolina Population Center, University of North Carolina at Chapel Hill, and the Institute of Sociology RAS)[3]. The outcome variable in the analysis is self-reported health. SRH is an ordinary

[3] **National Research University - Higher School of Economics.** 2022. Russia Longitudinal Monitoring Survey of HSE.
www.cpc.unc.edu/projects/rlms-hse (accessed December 02, 2022).

variable ranging from 1 to 5, where 1 corresponds to very bad health and 5 to very good health. We consider only the working-age population in a reduced sample – females aged 16-54 and males aged 16-59. Fifty-five and sixty years old are the retirement ages for females and males, respectively.

We construct the variable of interest – being unemployed – from question J90 “primary occupation”. An individual is recorded as unemployed if he answers yes to the statement – “temporarily not employed for other reasons and looking for a job”. We also create the variables “working,” “retired,” and “outside the labor force (economically inactive)”[4]. The latter category includes carers, students, and those unemployed for health reasons. If an individual agrees to the statement “temporarily not employed for other reasons and not looking for a job”, he is also considered to be economically inactive. Following Ronchetti and Terriau (2019), persons who experience a spell outside the labor force during the period under consideration are removed from the sample. Early retirees are also removed from the sample.

We create two variables that reflect the employment history of an individual. The first one, “becoming unemployed at least once (BU)”, equals 1 for an individual for all time periods if he reported being unemployed in the analysis period. Similarly, the second variable, “becoming employed at least once (BE)”, equals 1 across all time periods for an individual if he reported having a job at any time between 2010 and 2018.

Table 1 Descriptive Statistics for the Variables Used in the Analysis

Variable	Obs	Mean	Std. dev.	Min	Max
Self-reported health	78,049	3.446	0.604	1	5
Becomes unemployed at least once during 2010-2018 (BU)	78,568	0.227	0.419	0	1
Becomes employed at least once during 2010-2018 (BE)	78,568	0.976	0.152	0	1
Gender	78,568	0.520	0.500	0	1
Age	78,568	38.045	10.450	16	60
Age squared	78,568	1556.610	816.438	256	3600
Basic education*	78,568	0.001	0.037	0	1
Incomplete secondary	78,568	0.111	0.314	0	1
Secondary	78,568	0.325	0.468	0	1
Vocational	78,568	0.255	0.436	0	1
Tertiary	78,568	0.308	0.462	0	1
Married*	78,568	0.728	0.445	0	1
Divorced	78,568	0.092	0.289	0	1
Single	78,568	0.156	0.363	0	1
Widowed	78,568	0.024	0.154	0	1
Town/city with over 300,000 inhabitants	78,568	0.702	0.457	0	1

Notes: * denotes reference category.

Source: Calculated from the RLMS dataset.

National Research University - Higher School of Economics. 2022. Russian Monitoring of the Economic Situation and Population Health at the National Research University Higher School of Economics. www.hse.ru/org/hse/rlms (accessed December 02, 2022).

[4] All categories of the economically inactive excluding pensioners.

We use the following explanatory variables in our analysis: gender, age, age squared, education, marital status, and a dummy for living in a city with a population of over 300,000. Education uses a series of dummy variables for basic, incomplete secondary, secondary, vocational, and tertiary education. Dummies for married, single, divorced, and widowed represent marital status. The dummy for being a resident of a town/city with a population over 300,000 is a confounder in the relationship between self-reported health and unemployment. It controls for job market size, on the assumption that finding a job in a bigger city might be easier. This variable is also related to the outcome, since bigger centers of population in Russia are usually characterized by higher-quality medical care.

Table 1 shows the descriptive statistics for the variables used in the analysis.

The sample is balanced across genders. The mean age is 38. The mean self-reported health is slightly better than the medium category. Thirty percent of the sample attained tertiary education. The majority (72%) are married and the majority reside in towns with a population of over 300,000 (70%).

4. Results

In this section, we discuss the four hypotheses formulated for this study. Each hypothesis corresponds to a case (four cases in total). Cases 1 and 2 employ propensity score matching, while Cases 3 and 4 utilize the difference-in-differences method.

Case 1. Propensity score matching: unemployment and self-reported health

We first explore the case of unemployment from 2010-2018. Our treatment group consists of individuals who have experienced unemployment at least once in the nine years. The treatment variable is denoted *BU*. Individuals who have been continuously employed from 2010 to 2018 form the control group.

We first validate the assumption of selection on observables. As stated above, we use gender, age, age squared, education, marital status, and a dummy for living in a city with a population over 300,000 as confounders in the propensity score matching. We posit that these variables have a major impact on becoming unemployed, while other unobserved variables have a minor impact. By doing this, we assume that the observable characteristics account for all the relative differences in outcome. When selecting the observable variables, we ensure that the chosen variables are not affected by the treatment.

To calculate the propensity score, we first run the probit regression with the selected confounders (Table 2, column 1).

The predicted values of the regression are the propensity scores (Table 3).

The area of common support is presented in Figure 1. We validate Assumption 2 as we have good common support (dashed = treatment). The common support extends across the whole distribution of the propensity score.

Table 2 Probit Regressions for Calculation of the Propensity Scores

Variables	(1) BU	(2) BE
sex	0.156***	0.080***
	(0.011)	(0.022)
age	-0.019***	0.089***
	(0.004)	(0.007)
agesq	0.000**	-0.001***
	(0.000)	(0.000)
incsec	-0.205*	0.243
	(0.125)	(0.178)
second	-0.311**	0.304*
	(0.124)	(0.177)
vocat	-0.565***	0.562***
	(0.125)	(0.178)
uni	-0.765***	0.800***
	(0.125)	(0.179)
div	0.281***	-0.230***
	(0.018)	(0.036)
sing	0.529***	-0.490***
	(0.015)	(0.027)
wid	0.082**	-0.087
	(0.036)	(0.069)
bigcity	-0.291***	0.288***
	(0.011)	(0.021)
Constant	0.263*	-0.195
	(0.144)	(0.220)
Observations	78,568	78,568
Pseudo R2	0.07	0.09

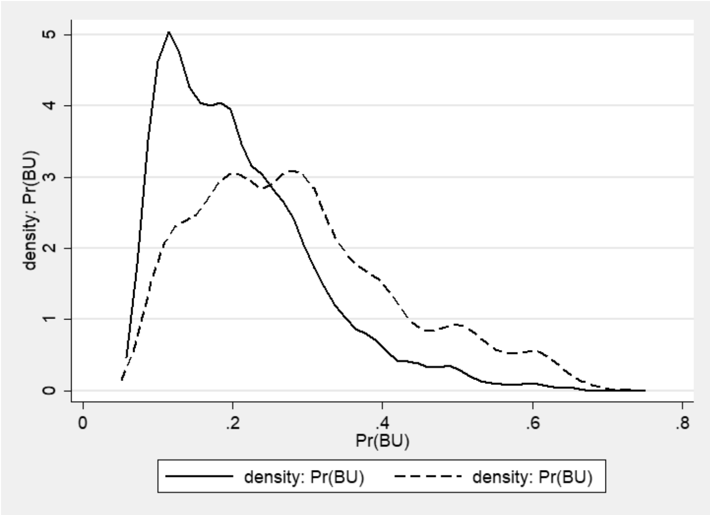
Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Calculated from the RLMS dataset.

Table 3 Summary of the Propensity Scores for the Likelihood of Becoming Unemployed

Variable	Obs	Mean	Std. dev.	Min	Max
pscore_BUcor	78,946	0.228	0.117	0.069	0.734

Source: Calculated from the RLMS dataset.



Source: Authors' calculations.

Figure 1 The Common Support Diagram for the Unemployed (Dashed = Treatment, Black = Control)

We employ nearest neighbor and kernel matching with the Epanechnikov kernel as the default (see Table 4 for the results).

Table 4 Estimation of the Average Treatment Effect on the Treated

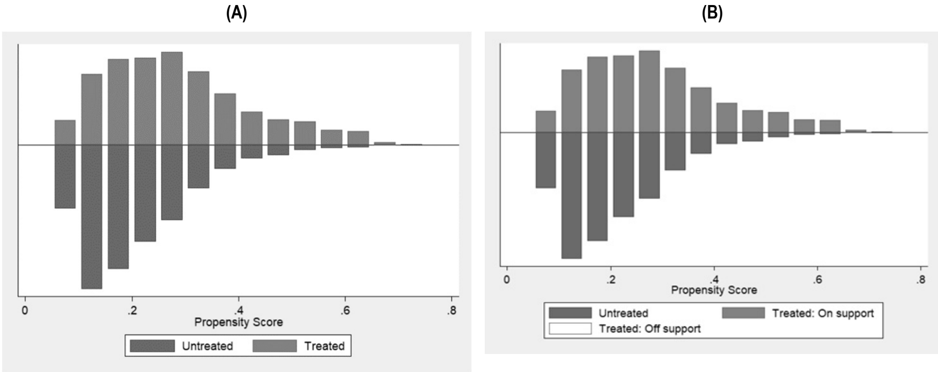
Variable	Sample	Treated	Controls	Difference	SE	T-stat
Nearest neighbor matching[5]						
Self-reported health (SRH)	Unmatched	3.461	3.442	0.019	0.005	3.64
	ATT	3.461	3.510	**-0.050**	0.023	-2.22
Kernel matching[6]						
Self-reported health (SRH)	Unmatched	3.461	3.442	0.019	0.005	3.64
	ATT	3.461	3.494	**-0.033**	0.006	-5.98

Source: Calculated from the RLMS dataset.

The estimated changes in self-reported health are small, but they are statistically significant and rule out the statement that there are no negative changes in the health of unemployed people after controlling for the selection effect.

Next, we plot the propensity score diagram. Again, our model shows no units that are off common support for the nearest neighbor method and one unit that is off common support for the kernel matching. This again validates our Assumption 2.

[5] On support untreated 60,347, treated 17,702, total 78,049.
[6] On support untreated 60,347, treated 17,701, off support treated 1, total 78,049.



Source: Calculated from the RLMS dataset.

Figure 2 The Propensity Score Diagram for the Nearest Neighbor (A) and Kernel (B) Matching Methods

After matching, the balance and bias calculations between the treated and the control group further confirm the high matching quality. Table 5 presents the balance for the nearest neighbor matching. As is evident from Table 5, all variables have a %ASB of less than 2.

Table 5 Means for Treatment and Control Groups and Bias between Groups for the Nearest Neighbor Matching

Variable	Mean treated	Mean control	%ASB
Gender	0.593	0.590	0.7
Age	35.8	35.73	0.6
Age squared	1396.3	1390.6	0.7
Incomplete secondary	0.167	0.167	0.1
Secondary	0.408	0.410	-0.3
Vocational	0.226	0.227	-0.1
Tertiary	0.195	0.194	0.2
Divorced	0.097	0.096	0.5
Single	0.275	0.276	-0.4
Widowed	0.019	0.017	1.2
Big city	0.602	0.603	-0.2

Source: Calculated from the RLMS dataset.

Overall, the matching algorithm confirms Hypothesis 1. The average treatment effects on the treated, in the case of nearest neighbor matching and kernel matching, are negative and statistically significant. Therefore, we conclude that the self-reported health of the unemployed is lower than that of the employed, even when we account for the selection effect.

Case 2. Propensity score matching: employment and self-reported health

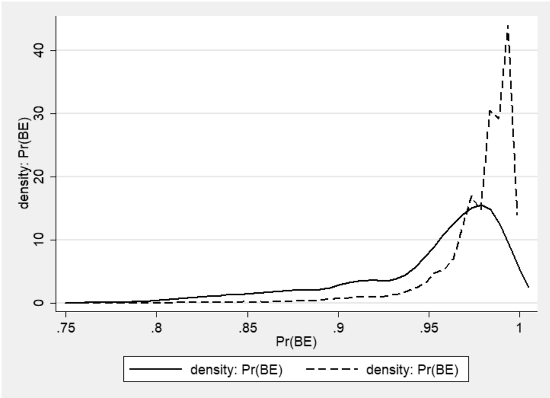
We now run a similar analysis for another treatment group – those who became employed at least once in 2010-2018. We validate Assumption 1 by arguing that the factors that have a major impact on the likelihood of unemployment are gender, age, age squared, marital status, and living in a city. The probit model for calculating the propensity scores is presented in Table 2 (column 2). The summary statistics for the p-scores are in Table 6.

Table 6 Propensity Scores for the Likelihood of Becoming Employed

Variable	Obs	Mean	Std. dev.	Min	Max
pscore_BEcor	78,946	0.976	0.026	0.753	0.997

Source: Calculated from the RLMS dataset.

The area of common support is presented in Figure 3. Again, we have a solid argument for the common support hypothesis.



Source: Calculated from the RLMS dataset.

Figure 3 The Common Support Diagram for the Employed (Dashed = Treatment, Black = Support)

Table 7 presents the ATT estimates.

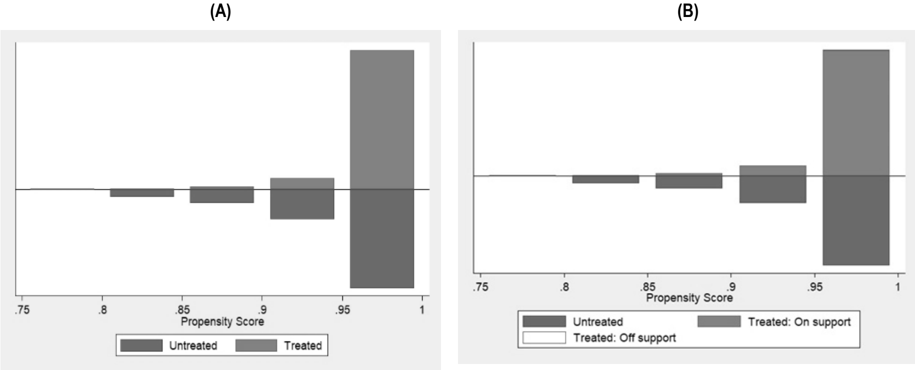
Table 7 Estimation of the Average Treatment Effects on the Treated for the Employed Group

Variable	Sample	Treated	Controls	Difference	SE	T-stat
Nearest neighbor matching[7]						
Self-reported health (SRH)	Unmatched	3.446	3.464	-0.018	0.014	-1.27
	ATT	3.446	3.318	**0.128**	0.035	3.61
Kernel matching[8]						
Self-reported health (SRH)	Unmatched	3.446	3.464	-0.018	0.014	-1.27
	ATT	3.446	3.364	**0.081**	0.018	4.59

Source: Calculated from the RLMS dataset.

[7] On support untreated 1,846, treated 76,203, total 78,049.
[8] On support untreated 1,846, treated 75,833, off support treated 370, total 78,049.

The results confirm Hypothesis 2. We observe better self-reported health for individuals who experienced employment. This effect is statistically significant at the 5% significance level for both matching algorithms. The propensity score diagrams are below (Figure 4).



Source: Calculated from the RLMS dataset.

Figure 4 Propensity Score Histogram for the Employed for the Nearest Neighbor (A) and Kernel (B) Matching Methods

Checking for balance, we estimate the mean standardized bias for the independent variables between the treatment and control groups. All %ASB values are below 10, indicating no significant imbalance between the groups (Table 8).

Table 8 Means for Treatment and Control Groups and Bias between Them for the Employed at Least Once Treatment Group

Variable	Mean treated	Mean control	%ASB
Gender	0.520	0.546	-5.2
Age	38.118	37.987	1.2
Age squared	1560.9	1554	0.8
Incomplete secondary	0.108	0.105	1.0
Secondary	0.321	0.355	-7.1
Vocational	0.256	0.253	0.7
Tertiary	0.313	0.285	7.0
Divorced	0.092	0.072	6.9
Single	0.150	0.147	0.8
Widowed	0.024	0.013	7.4
Big city	0.708	0.741	-6.8

Source: Calculated from the RLMS dataset.

The analysis for the "employed at least once" group identifies an improvement in self-reported health compared to the control group of the unemployed. This is robust across the matching methods. The improvement was 0.128 for the nearest neighbor method and 0.081 for the kernel matching. These changes are statistically significant.

We now turn to another quasi-experimental research design – the difference-in-differences estimation.

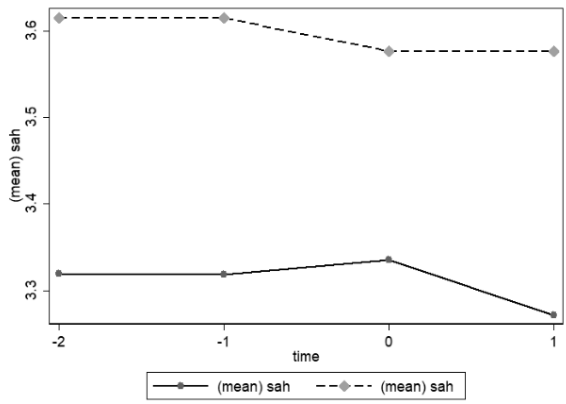
The difference-in-differences estimation for the effect of the labor market status on health

Moving on from the two-year base case in the Methods section, we now extend our discussion by presenting the results of the difference-in-differences model for the period 2015-2018. We present this four-period model because Joshua David Angrist and Jörn-Steffen Pischke (2015, p. 188) point out that the model works best with four or more data points.

Initially, the idea was to run a model without the sub-samples of economically inactive people and early retirees, but this resulted in too few cases for the variables of interest. For example, we only had ten individuals who were unemployed for three years and were employed in 2018. Therefore, the two groups were added back to the sample. So, for the difference-in-differences analysis, we built the models for unemployment after having a different labor market status and for re-employment after not working for three years. These models test Hypotheses 3 and 4, respectively.

Case 3. Difference-in-differences: unemployment after employment, retirement, or labor force non-participation in 2015-2017

Within this period, we define the treatment as becoming unemployed in 2018 after three years (2015-2017) of employment, retirement, or labor force non-participation. The control group consists of people who were employed, retired, or not in the labor market for four years. There are 104 individuals in the treatment group and 4,336 individuals in the control group. Figure 5 displays the means of self-reported health for the treatment and control groups for the four years, 2015-2018. As is evident from Figure 5, our sample fails the parallel trend assumption. Therefore, we are unable to apply the difference-in-differences estimation to our sample. Consequently, we stop here and consider our next case. We can neither confirm nor reject Hypothesis 3.



Notes: SAH = SRH.

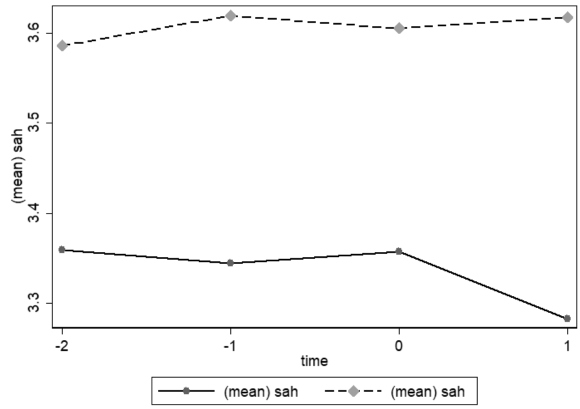
Source: Authors' calculations.

Figure 5 Parallel Trend Assumption for the Unemployed in 2018 Group (Black = Control, Dashed = Treatment)

Case 4. Difference-in-differences: re-employed after not working in 2015-2017

In the following case, we aim to estimate the effect of re-employment on self-reported health in 2018 after being out of work. The control group consists of individuals who did not have a job for four years. The treatment group has 253 individuals, and 1,228 individuals belong to the control group. Hypothesis 4 posits that re-employment positively affects health after controlling for time-variant and time-invariant unobservable characteristics (provided the parallel assumption holds).

Figure 6 depicts the trends in self-reported health for the two groups.



Source: Authors' calculations.

Figure 6 Parallel Trend Assumption for the Re-employed in 2018 Group (Black = Control, Dashed = Treatment)

The diagram shows that the treatment group has higher self-reported health at time zero. The groups are trending in a similar way (although the lines are not perfectly parallel) during the three years before the intervention, so we cautiously validate the parallel trend assumption. Difference-in-differences regressions – base case and full model with covariates (Equation 5) – are presented in Table 9.

Table 9 OLS Difference-in-Difference Models for the Effect of Re-employment on Self-Reported Health, 2015-2018

VARIABLES	(1) SRH	(2) SRH
Treated	0.250***	0.054**
	(0.025)	(0.024)
Post	-0.071***	-0.028
	(0.026)	(0.022)
Treated*Post	***0.085****	***0.076***
	(0.051)	***(0.047)***
sex		0.015
		(0.022)
agec		-0.043***
		(0.005)

agesq		0.000***
		(0.000)
div		-0.298***
		(0.044)
wid		-0.051
		(0.046)
sing		-0.076***
		(0.029)
incsec		0.457***
		(0.120)
second		0.610***
		(0.119)
vocat		0.588***
		(0.119)
uni		0.736***
		(0.120)
bigcity		-0.290***
		(0.018)
Constant	3.354***	4.194***
	(0.013)	(0.169)
Observations	5,876	5,872
R-squared	0.019	0.268

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Calculated from the RLMS dataset.

Table 9 confirms Hypothesis 4: re-employment has a positive effect on the health of an individual. It increases self-reported health by about 0.085 in the base case and 0.076 in the extended model which includes individual characteristics. The control group comprises unemployed individuals, labor market non-participants, and early retirees in 2015-2018. However, the DiD estimator allows us to claim causality from re-employment to health. Finding a job after three years has a positive effect on physical health. The first estimate is statistically significant at the 10% significance level, while the p-value for the second estimate is slightly over 0.100 (0.106).

5. Discussion

We have run two types of analysis – propensity score matching and the difference-in-differences estimator – and arrived at robust results for the two methods.

We analyze two aspects of labor market status. First, we look at the effect of having and not having a job during the period 2010-2018. This analysis disregards the duration of employment/unemployment. When using the quasi-experimental technique and eliminating the selection effect by constructing a control group, we find a causal negative effect of unemployment on health. This result is contrary to what has been found earlier for Finland and France (Böckerman and Ilmakunnas 2009; Ronchetti and Terriau 2019). However, in Russia, unlike these western countries, unemployment insurance is minimal[9] and is paid only to those registered as unemployed at the national labor exchange. This means that the hazards of unemployment affect individual health immediately after job loss. With no extra money, exercising in a gym or consuming healthy food is impossible. Psychological aspects also play a role – the individual is now deprived of his/her agenda and the societal role that employment brings. Thus, mental distress affects self-reported health, leading to lower health assessments. The negative change in health is not large (around -0.03 – -0.05) but is present. We rule out the statement that the negative change in the health of the unemployed is entirely due to the selection effect.

Next, we consider the impact of employment on self-reported health. The propensity score matching analysis shows that having a job is associated with improving SRH (in the range of 0.081-0.128) compared to the health of those without a job in 2010-2018. Employment brings a steady flow of income, part of which can be spent towards supporting a healthy lifestyle through better nutrition and regular exercise. Additionally, employment is a source of latent functions (Marie Jahoda 1982) that provide time structure and societal status, positively affecting self-reported health.

The improvement in SRH among the employed is linked to better mood, optimism, and mental health, resulting in higher physical health assessments. To further explore the link between mood, optimism, and employment, we estimated the impact of employment on mental (psychological) health. We used a dummy variable for the likelihood of depression and anxiety in the last 12 months as a proxy for psychological health. Applying the propensity score matching to the data, we found that being employed at least once in 2010-2018 is associated with a lower probability of reporting depression (by 4.2 percentage points), while experiencing at least one spell of unemployment leads to an increased likelihood of reporting depression (by 3.4 percentage points) (see the Appendix for details). These results indicate a direct link between better psychological health and employment that, in our opinion, is partially reflected in the higher assessment of physical health.

If the negative causal effect of unemployment increases with time, re-employment should bring about a health improvement. Our numerical findings show that this is indeed so. An alternative quasi-experimental approach, difference-in-differences, shows that SRH rises by around 0.085. This is an expected but significant result. Therefore, the government should understand that actively promoting employment can result in savings on healthcare expenditure. However, an important question that remains unanswered and should be addressed in future studies is how much of this improvement relates to improvement in psychological/mental vs. physical health. We believe that the former drives the increase in self-reported health. This is a topic of the author's future research.

Our analysis of re-employment using the difference-in-differences method includes a linear regression that provides information on how age, marital status, education, and living in a big city affect the self-reported health of those who found a job in year 4. Being older is associated with a lower health level for this treatment group. Married individuals have better health than those who are single, divorced, or

[9] The unemployment insurance in 2023 varied between USD 17 and USD 141 per month at the current exchange rate (Statista 2023).

widowed. We also observe an education gradient in health: attaining a higher level of education corresponds to having higher health levels. Finally, living in a big city worsens self-reported health. In the future, interaction variables between employment status and socioeconomic or demographic factors can be created for a more detailed analysis of how socioeconomic and demographic factors interact with employment status to affect health levels.

We checked the robustness of our estimates. First, we altered the upper age limit for males and females to reflect the upcoming reform that will increase the retirement age in Russia. The results were similar to the ones we reported in this paper. Second, for propensity score matching, we added back the early retirees and economically inactive people to arrive at similar estimates for the average treatment effect on the treated. We conclude that the results reported here are robust to different specifications.

Our research is done in a particular context at a specific time, so the generalizability of our findings is restricted to some extent. However, we show that negative health changes result from the fact that the unemployment benefits in Russia are small and bring about adverse changes in diet and physical activity, and a possible return to risky practices. In countries with welfare regimes and unemployment policies similar to Russia's, we would expect to see the same negative effect of unemployment on health.

Our research is not without limitations. First, our primary measure, self-reported health, is subject to a response bias. Respondents can conceal the correct answer or overestimate their self-rated health to look good in the eyes of the interviewer. Incorporating other health metrics, like mental health assessments, clinical health records, or stress-related biomarkers, could provide a more comprehensive understanding of health impacts. Second, the matching method is based on the theoretical conditional independence assumption. This assumption is not directly testable. In practice, we do not know the entire set of factors that should be controlled in the propensity score, and it might be the case that we did not consider some important characteristics that influence selection into treatment (Scott Cunningham 2021). This limitation is common to all propensity score matching analyses.

Further research can improve our understanding of the impact of unemployment and employment on individual health. Of particular interest are three directions. The first, mentioned above, is the extent of the effect of change in mental health on self-reported health following an alteration in labor market status. Second, collecting data for the former CIS countries, which run similar models, and making comparisons between the results for these countries and those for Russia can enrich the analysis. Third, getting data on the type of employment, such as voluntary, involuntary, part-time, and precarious (Guy Standing 2011), and differentiating between the employment types in the quasi-experimental approaches, could provide a deeper understanding of the links between health and employment.

6. Conclusion

Our study explored the effect of labor market status on self-reported health. First, using quasi-experimental approaches and controlling for the sample selection effect, we showed that employment and re-employment improve an individual's self-reported health.

We believe that this result has important policy implications. First, we demonstrated that additional morbidity risks related to unemployment manifest themselves through lower self-reported health. These are serious risks for working-age males who have extremely high mortality from cardiovascular diseases. In addition, unemployment can cause a return to unhealthy habits – smoking and drinking. We believe that introducing free health checkups for the unemployed (a measure currently being introduced in Finland) can improve the health of the presently jobless population. Those with elevated health risks can then be referred to district physicians for medical care. Vocational rehabilitation programs among the unemployed, especially those who have been unemployed for over a year, can increase the likelihood of finding employment and mitigate health risks. Such programs should include goal setting and job search planning, career counseling, job analysis, and placement services. Currently, the Russian government implements a unique program for employment promotion by teaching individuals how to access a digital platform, Work in Russia (trudvsem.ru), to perform a job search with specific characteristics. The government should advertise the digital platform better to increase the number of job applicants. Overall, the government should realize that actively promoting employment will ultimately reduce the burden of disease and save the government money on medical treatment.

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Appendix

Table A1 ATT Effects for Mental Health for Becoming Unemployed at Least Once

depress	Coeff.	Abadie-Imbens robust SE	z	P>|z|	Confidence interval	
ATT BU (1 vs 0)	0.034	0.003	11.24	0.000	0.028	0.040

Notes: Treatment model probit, N = 67,281.

Source: Author's calculations.

Table A2 ATT Effects for Mental Health for Becoming Employed at Least Once

depress	Coeff.	Abadie-Imbens robust SE	z	P>|z|	Confidence interval	
ATT BE (1 vs 0)	-0.042	0.014	-2.92	0.003	-0.070	-0.014

Notes: Treatment model probit, N = 67,281.

Source: Author's calculations.

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