NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Ekaterina A. Aleksandrova, Venera I. Bagranova,
Christopher J. Gerry

THE EFFECT OF HEALTH SHOCKS ON LABOUR MARKET OUTCOMES IN RUSSIA

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: ECONOMICS
WP BRP 237/EC/2020

Ekaterina A. Aleksandrova[1], *Venera I. Bagranova*[2],
Christopher J. Gerry[3]

THE EFFECT OF HEALTH SHOCKS ON LABOUR MARKET OUTCOMES IN RUSSIA[4]

This paper provides evidence for the effects of health shocks measured by any negative change in self-assessed health (SAH) status on employment, personal income, and wages in the Russian population. We employ the average treatment effect on the treated (ATET) estimator combined with propensity score and nearest neighbour matching and data from Russian Longitudinal Monitoring Survey-HSE (RLMS-HSE) for 2000–2018. We find that adverse health shocks are associated with a reduction in the probability of remaining employed by 2%, and losses of income and wages of 17% and 11%, respectively. For men the consequences of health shocks are more drastic. Severe health shocks that are measured as a drop in SAH by two or more levels are associated with greater losses: respondents aged 30–45 years old lose approximately 60% of their monthly income for severe shocks, and those aged 46–72 lose 35–45% of their wages and 9–10% in the probability of remaining employed.

JEL Classification: C23, I12, J60.

Keywords: health shock, labour market outcomes, matching, difference-in-difference, Russia.

[1] International Centre for Health Economics, Management and Policy, National Research University Higher School of Economics, St. Petersburg, Russian Federation. Email: ea.aleksandrova@hse.ru

[2] Center for Market Studies and Spatial Economics, National Research University Higher School of Economics, St. Petersburg, Russian Federation.
Corresponding author, Email: vbagranova@hse.ru

[3] Oxford School of Global and Area Studies, University of Oxford, Oxford, UK. Email: christopher.gerry@sant.ox.ac.uk

[4] This work is supported by the Russian Science Foundation under grant (project № 20-18-00307, The Health of Nation: the Multidimensional Analysis of Health, Health Inequality and Health-Related Quality of Life).

Introduction

Health plays an important role in explaining labour market outcomes and decisions. Deterioration of one's health condition can lead to devastating consequences for the household or individuals in terms of employment, household and personal income, wage, working hours, and medical out-of-pocket money. The vast part of the literature in the fields of labour and health economics provides evidence in support of a consistent effect of health and health changes on labour market outcomes across a variety of countries: (García-Gómez & López-Nicolás, 2006; Lundborg et al., 2015; Zucchelli et al., 2010; García-Gómez et al., 2010; Disney et al., 2006; García-Gómez et al. 2013).

The majority of countries are experiencing an increase in life expectancy and an inexorable decline in the number of the working-age population. The burden on the pension funds is constantly extending. Understanding the labour market decisions driven by a health deterioration is fundamental for policymakers to reduce the gap between those who have experienced a health shock and those who have not. Awareness of potential losses in terms of employment, wages, and income faced by individuals becomes an important issue for maintaining this part of the population and compensating for their losses.

Previous studies argue that the estimated effect is strongly connected with the institutional environment of a particular country (García-Gómez, 2011; Gupta et al., 2015). The Russian demographic situation falls behind of most European countries'. Life expectancy is among the lowest both for males and females, and the gender gap is among the largest in the world. Russia is one of the world leaders in alcohol and tobacco consumption. The Russian labour market is, however, characterized by a very small response of employment to shocks but highly volatile wages.

There has been no evidence on the causal link between health deterioration and labour market outcomes either in Russia or in other countries with similar demographic and labour market environments. The primary aim of the study is to fill this gap and identify the effect of health shocks, measured as any negative change in self-assessed health (SAH), on labour market outcomes in Russia. Another research question is whether gender asymmetry in life expectancy and the health of males and females implies some heterogeneity in the estimated effect.

We used Russian Longitudinal Monitoring Survey, RLMS (waves 9–27, 2000–2018), which provides a battery of labour market characteristics, including employment, wages, personal and household income, working hours, and a comprehensive set of health variables—SAH measures, chronic conditions, acute events, such as a heart attack, stroke, or ambulance calls. Using the extended data set and the econometric strategy proposed by García-Gómez and López-Nicolás (2006) and developed by Lenhart (2019) which measure a health shock as a transition from good

SAH status to bad, we found that adverse health changes have negative consequences on the probability of remaining employed, wages, and personal income. The panel structure of the data set allows us to mitigate concerns about unobserved heterogeneity, as we compare the self-reported variables of an individual only with her previous ones. The econometric approach lets us identify the causal effect of health shock on labour market outcomes. In particular, we found that the probability of remaining at work after health deterioration reduced by 2% a year after a health shock occurred. Additionally, adverse health shocks lead to 17% and 6–12% reduction in personal income and wages, respectively. The estimates reveal gender asymmetry in the effects: men lose up to 3% in the probability of remaining employed and 28% in income, while women do not bear any burden in these categories. However, potential losses in wages are very similar. Severe health shocks are associated with much more prominent losses: up to 10%, 40% and 16% in the probability of remaining employed, income and wages, respectively. All matching estimates are robust to the matching technique chosen - propensity score, kernel or nearest-neighbour.

In this paper, we found quite small potential losses in employment and more substantial losses in income and wages, especially for severe health shocks. Our findings are perfectly related to the Russian labour market flexibility in wages and inflexibility in employment. Russians facing a health deterioration suffer losses mainly in intensive margin rather in the extensive. Therefore, the often proposed policy to encourage employers to implement flexible working hours or distant work may not be the most appropriate way to reduce the gap between the treated and control groups as it cannot alleviate the losses in remuneration.

Section 2 reviews the literature; Section 3 describes the empirical strategy; Section 4 presents the Russian context and the data used; Section 5 describes the results and Section 6 provides some sensitivity analysis; Section 7 discusses the results; Section 8 concludes.

Background

The literature

The paramount role of health for labour market outcomes is well established in health and labour economics (Currie & Madrian, 1999; Bound & Burkhauser, 1999). Empirical evidence documents the detrimental effect of bad and worsening health on employment, household and personal income, wages, and working hours for a variety of countries: Spain (García-Gómez & López-Nicolás, 2006), China (Lindelow & Wagstaff, 2005), Sweden (Lundborg et al., 2015), Australia (Zucchelli et al., 2010), the UK (García-Gómez et al., 2010; Disney et al., 2006), the Netherlands (García-Gómez et al., 2013). It is important to note that health shocks are not only negative changes in health but also positive ones. Therefore, Lindelow and Wagstaff (2005) estimated the effect of positive and negative health shocks on labour market outcomes and found a significant effect of adverse shocks, but no effect of positive ones.

Estimating the effect of health status and changes in health requires dealing with several challenges: the joint determination of health and labour supply, unobserved preferences, and justification bias in self-assessed variables. Previous studies have addressed these issues of bias via a wide range of approaches. Strategies exploit the onset of health conditions (García-Gómez, 2011) and acute admissions episodes (Mitra et al., 2016). For instance, García-Gómez et al. (2013) found that health shocks decrease the probability of remaining in work by 8% and decrease the annual personal income two years after the shock by 5%, defining a health shock as an unplanned hospitalization for at least three inpatient nights. Another way to mitigate endogeneity concerns is by using accidents and injuries (Dano, 2005; Lindeboom et al., 2016; Halla & Zweimüller, 2013; Zucchelli et al., 2010) as an exogenous health shock. Several papers utilize the incidence of cancer, a stroke, or a heart attack (Gupta et al., 2015; Trevisan & Zantomio, 2016). Coile (2004) found that males and females are 35% and 23% more likely to exit the labour market after experiencing cancer, a stroke, or a heart attack.

Moreover, the system of social benefits, the institutional setting, and the specifics of a labour market could significantly affect the labour market effects of adverse health changes in different countries (García-Gómez, 2011; Gupta et al., 2015).

The majority of previous studies have investigated labour market decisions and outcomes made by the elderly population (Disney et al., 2006; Zucchelli et al., 2010; Au et al., 2005; Coile, 2004) with less emphasis on young and middle-aged workers. However, younger individuals have started to become a topic of particular interest: they have a greater number of remaining working years but do not have many options in the face of adverse health events.

The studies above provide evidence for the effects of health and health shocks on labour market outcomes. However, up-to-date evidence on the causal effect of adverse health changes on labour market outcomes is still sparse. The estimated effect is far from unambiguous. The magnitude of potential losses in employment, wages, and income strongly depends, first, on the definition of a health shock, secondly, on the institutional environment and the particular labour market, and thirdly, the effect is heterogeneous by gender, age, income and the severity of the health shock. In this paper, we address this gap in the literature, proving evidence for the case of Russia, a country with a quite unfavorable demographic situation, gender asymmetry and a distinct labour market. We used the universal econometric strategy introduced by García-Gómez and López-Nicolás (2006) and further developed by Lenhart (2019), which utilized a transition from good to bad SAH status as a health shock combined with different matching techniques.

The Russian labour market and demographics

The specifics of the labour market and the demographic situation stand out Russia from other more developed and countries in transition. Russia has experienced several macroeconomic shocks, including economic downturns in 2009 and 2014. An illustration of the Russian labour market is presented in Figure 1. It displays the key economic and labour indicators: GDP per capita, labour force participation rate, employment and unemployment rates, and real wages. During the economic recession, GDP per capita dropped by 7.8% in 2009. However, employment remained relatively stable and weakly sensitive to this shock, falling by a modest 1.9%. Alternatively, real wages adjusted in a more responsive way, decreasing by 3.5%. As Gimpelson and Kapeliushnikov (2013) point out, the low responsiveness of employment to macroeconomics shocks and volatility in output are key characteristics of the Russian labour market. This relative stability in employment and the low unemployment rate comes at the price of flexible and highly volatile wages and working hours. Compared to European countries, where the GDP elasticity of employment during the downturn was around 0.47 (ECB Economic Bulletin 2016), Russia exhibits quite low employment elasticity caused GDP reduction, amounting to 0.24. Further in our estimations we have divided the sample into three subsamples, trying to capture the macroeconomic environment in the effect. In Figure 1, the thresholds of 2007 and 2010[6] are indicated by vertical dotted lines.

The issue of a significant decline in the size of the total and working-age population has raised some demographic questions. The total population in Russia has decreased from 146.6 million in 2000 to 144.5 in 2018 and the working-age population contracted from 72.1% in 2010 to 67.6% in 2018, sharply contrasting with the average OECD dynamics (OECD, Working age population (indicator), 2020). Additionally, Russia ranks very low for life expectancy at birth compared not only with OECD countries but also with BRICS countries. The life expectancy at birth of a newborn boy and girl in 2017 was 67.5 and 77.6 years, respectively; in Brazil the figures were 72.1 and 79.3 years; and in China 74.9 and 78 years (OECD, Life expectancy at birth (indicator), 2020). Thus, the gender gap in life expectancy in Russia greatly exceeds that of most OECD and BRICS countries, even the leading ones by 7-8 years.

There have been legislative initiatives aimed to discourage alcohol and tobacco consumption in Russia, which lead to a decline in alcohol consumption from 19.8 liters per capita in 2002 to 11 liters in 2017. Notwithstanding, in 2017 Russia was among the world leaders in tobacco and alcohol consumption (OECD, Alcohol consumption (indicator), Daily smokers (indicator), 2020).

[6] We have additionally estimated the effect on employment, personal income and wage in 2013-2015, however, there is no statistically significant effect

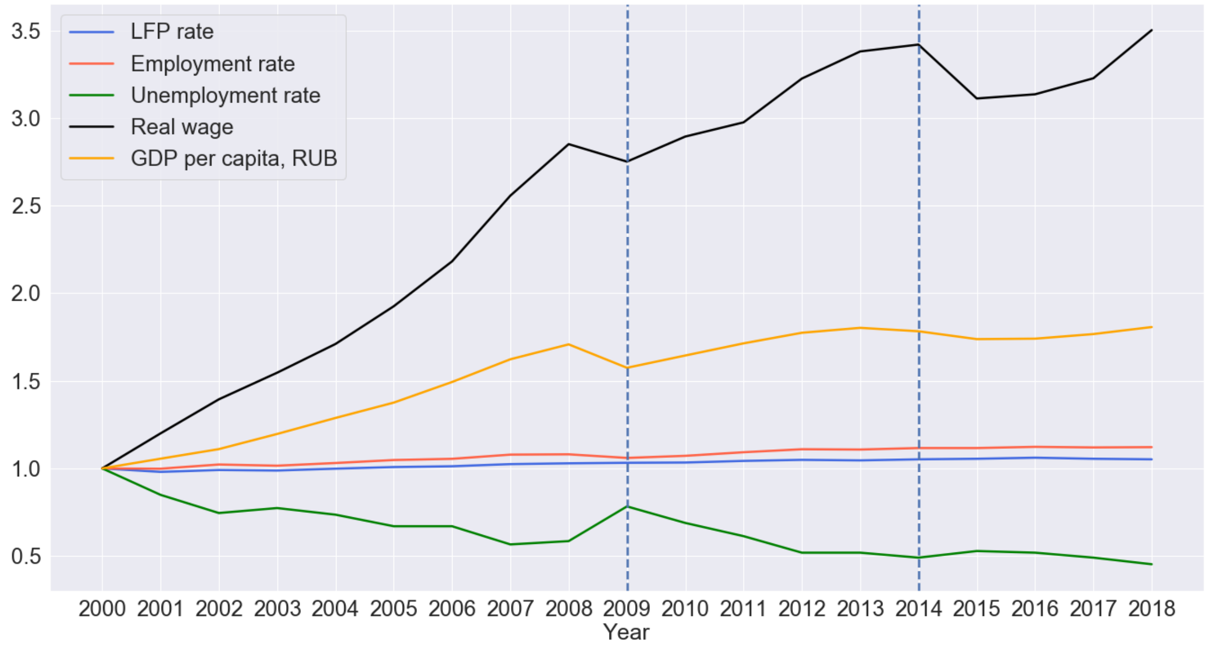

Fig. 1. GDP per capita, Labour Force Participation Rate, Employment Rate, Unemployment Rate and Real Wage in the Russian Economy, 2000-2018, percent (2000 = 100%=1). Source: https://www.gks.ru/.

Denisova and Shapiro (2013) point out that Russia missed the cardiovascular revolution, when infectious diseases lost their importance and give away to chronic and man-made diseases. Chronic diseases are the reason of 86% of all deaths in Russia and there is a 30% probability to die from the four major chronic conditions (cancer, diabetes, cardiovascular disease and chronic respiratory diseases) between the age of 30 to 70 (World Health Organization, 2018, Kaneva et al., 2018). What is worse, the probability of dying from the most specific causes of death in Russia is strongly biased towards younger ages in comparison with more advanced economies (Denisova & Shapiro, 2013).

Methodology

Empirical strategy

The measure of a health shock relies on five possible responses to the RLMS–HSE question "*How do you assess your health?": very good, good, fair (neither good, nor bad), bad, or very bad*. It is assumed that an individual experiences a deterioration of health or, equivalently, a negative health shock if in any period he or she reports fair, bad, or very bad health, while the health of the previous period was reported as good or very good. It is important to note that a health shock may occur at any time between these time points: immediately after the "before" survey or shortly before the "after" survey. To evaluate how the health shock affects employment status, we construct treatment and control groups as follows:

1. Consider a three-year sequence for each individual. This generates 17 possible three-year sequences over the time span covered by the data. Let $t = -1$, $t = 0$, and $t = 1$ denote these three years;
2. Each individual in the sample is in good or very good health at $t = -1$ and employed[7] at $t = -1$ and $t = 0$;
3. The treatment group are individuals who report bad health status (fair, bad or very bad SAH) in $t = 0$ and $t = 1$, that is, those individuals who experience a health shock after $t = -1$ and for whom this health shock continues at least over $t = 1$. Therefore, the sequence for these respondents is Good, Bad, Bad (GBB);
4. The control group are individuals who still report good health (very good or good) at $t = 0$ and $t = 1$. Thus, the sequence for these respondents is Good, Good, Good (GGG).

Individuals in the treatment and control groups are matched on the basis of propensity score matching. Propensity scores for individuals are obtained by including conditioning variables: gender, age, type of settlement, education level, marital status, number of children in a household, type of occupation and the logarithm of personal income for the last 30 days.

In this setting, we restrict our sample to respondents who are initially employed, accounting for potential simultaneous determination of health condition and employment (García-Gómez & López-Nicolás, 2006). The treatment occurs before potential changes in the variable of interest which provides some guarantee that the observed effects are not the result of reverse causality. By assumption, we are ruling out the possibility of anticipation effects consisting of respondents who expect a health deterioration and decide to transit into unemployment one period in advance to justify their unemployed status. Figures A1 and A2 in the Appendix provide a visual test for the parallel trend assumption for the continuous variables of interest—personal income and wages. Both for income and wages, no statistically significant differences are observed during the two years before a health shock or in terms of 3-year sequences at $t = -2$ and $t = -1$. These figures provide suggestive evidence that the parallel trend assumption is satisfied.

Econometric approach

The procedure conducted in the study is similar to the approach of (García-Gómez & López-Nicolás, 2006; García-Gómez, 2008) and (Lenhart, 2019) and employs a difference-in-difference (DID) framework with propensity-score and nearest-neighbour matching to test whether there is an effect of health shocks on labour market outcomes.

The empirical strategy is based on a comparison of the labour market status of individuals who have undergone a health shock with those who have not. In this way, we evaluate propensity-

[7] We consider those individuals who reported that he or she is currently on paid or unpaid leave as unemployed

score and nearest-neighbour matching models combined with the difference-in-difference econometric approach to estimate Average Treatment Effect on the Treated (ATET), which measures how the outcome of interest changes, on average, for those who have experienced a health deterioration with those who have not. As it was pointed out by (García-Gómez & López-Nicolás, 2006) matching methods are often criticized for assuming away potential biases that might be caused by unobserved heterogeneity. They state that one way to mitigate concerns about such biases is to use longitudinal data which includes data from before and after a health shock. In our study, we use the data from the Russian Longitudinal Monitoring Survey-HSE (RLMS-HSE) which allows us to first difference the outcomes of interest of the treatment and control groups to eliminate any unobservable fixed effects that might influence assignment to the treatment group and the outcomes.

In the empirical analysis, we use three alternative matching techniques: (1) kernel matching on the propensity score; (2) nearest-neighbour matching on the propensity score (four nearest neighbours); (3) nearest-neighbour matching on the set of covariates based on the Mahalanobis distance (four nearest neighbours). In the latter we additionally use exact matching on the year of the shock, trying to capture unobserved heterogeneity across time.

Introduced by Rosenbaum and Rubin (1983), the conditional independence assumption with the use of a function of *X*, called the propensity scores *P*(*X*), rather than a dimensional vector of covariates is stated in the following form:

$$E\left(Y_{1,0}\middle|T=1,P(X)\right)=E\left(Y_{1,0}\middle|T=0,P(X)\right) \quad (1)$$

where $Y_{1,0}$ indicates outcomes of interest under treatment and no treatment respectively, and $T = 1\ ,\ 0$ denotes treatment. The study uses propensity scores P(X), measured as the probability of being treated given a vector of conditioning variables, to match individuals from the treatment group with similar individuals from the control group. The propensity scores are based on pre-treatment covariates and estimated using a probit model. To obtain the propensity scores we include observable characteristics: gender, age, type of settlement, education level, marital status, number of children in the household, type of occupation and the logarithm of personal income for the last 30 days.

Therefore, the matching and DID estimator for the ATET can be estimated as:

$$\widehat{ATET_{MDID}}=\frac{1}{N}\sum_{i\in\{T=1\}}((Y_{i1}^{t+1}-Y_{i1}^{t})-\sum_{j\in C(i)}h(i,j)(Y_{j0}^{t+1}-Y_{j0}^{t})) \quad (2)$$

where *N* is the number of treated individuals, $Y_{i,j}$ is the outcome of interest for the treated and control respondents. $T = 1, 0$ indicate treatment, *t* and *t+1* denote the time periods before and after treatment occurs. *h(i, j)* is the matching weights assigned to control individual *j* when compared with treated individual *i*.

Data

This study uses data from waves 9 to 27 (2000 to 2018) of RLMS-HSE, which is a nationally representative panel survey constructed to monitor the effects of Russian reforms on the economic welfare and health of households and individuals in the Russian Federation. The use of RLMS-HSE provides several advantages for the study. RLMS-HSE is one of the few databases that provides a wide range of characteristics of the labour market (including employment, wages, personal and household income, working hours, and informal employment). It also contains a comprehensive set of health variables (SAH measures, chronic conditions, acute events, such as heart attack, stroke, or ambulance calls). Due to the panel structure, this dataset allows us to account for individual unobserved time-invariant heterogeneity. The potential reference bias, which arises because different individuals apply different thresholds when reporting their health status, is reduced since the health of each individual is only compared with his own previous health status.

Table 1 illustrates the main patterns of health status by age groups and gender. Bad or very bad health are more common for respondents older than 46 while younger individuals are more likely to report good or very good health status. Another issue is the incidence of negative and positive health shocks both of which occur among the young and middle-aged respondents with a higher probability. However, that does not necessarily imply that they experience health changes more often compared with the older part of the sample. The second part of Table 1 indicates the incidence of eight 3-year patterns of health status. For example, GBB shows the proportion of GoodBadBad patterns out of all possible patterns. In this way, the most of treated respondents, or respondents reporting GBB sequence, are concentrated among the 30–59 y.o. respondents, while the control response GGG—among respondents less than 46 years old. Despite the fact that respondents from groups 18–29 and 30–45 are more likely to experience a decline in health status, the year after deterioration, respondents 18–29 report good health with a higher probability, in contrast with those who are over 30, who report bad health they next year with a higher probability. Respondents aged 18–29 and 30–45 more often report health improvements, and the following year most of them are still in good health (BGG). While individuals aged 30–59 are more likely to again report bad health the following year (BGB). Nevertheless, the size of the treated and control groups is almost equal, accounting for 12% of the whole sample.

Concerning gender differences, males are more likely to report good or very good health, compared to females who report bad or very bad health more often. Men are more likely to experience any changes in health status in 2-3-year sequences. In other words, the SAH of men changes from year to year more frequently. However, females are more likely to be in bad health three years in a row.

Despite the fact that SAH status can be a reliable proxy for mortality and morbidity (Kaplan & Camacho, 1983; Idler & Benyamini, 1997), it is subject to reference bias and measurement error. Table A1 shows how our constructed health shock is correlated with more objective health shocks, including the incidence of heart attacks, strokes, and ambulance calls during the last year, the fact of missing a certain number of days at work or study during the last month and the last year. The probability of experiencing a health shock or reporting bad health is strongly correlated with the probability of experiencing a heart attack, stroke, ambulance call, missing a certain number of days due to health problems, and reporting lower values of the EQ-5D index, which is a standardized instrument for measuring generic health status. The second part of Table A1 shows the correlation of health shocks and SAH with the incidence of several chronic conditions. A health shock is strongly correlated only with kidney problems but not with the others. However, there is evidence that individuals adjust and adapt to chronic illnesses, even to severe ones (Kaneva et al., 2018; Gerry & Kaneva, 2020), and do not reflect them in their health status assessment.

Tab. 1. Health-related descriptive statistics across age groups and gender

	18-29	**30-45**	**46-59**	**60-72**	**Females**	**Males**	**Total**
SAH=1	0.002	0.003	0.011	0.036	0.012	0.009	0.010
SAH=2	0.022	0.044	0.119	0.260	0.110	0.076	0.095
SAH=3	0.385	0.528	0.673	0.625	0.582	0.501	0.548
SAH=4	0.553	0.409	0.191	0.076	0.285	0.391	0.330
SAH=5	0.039	0.016	0.005	0.003	0.012	0.023	0.017
Negative health change	0.100	0.112	0.079	0.043	0.081	0.099	0.089
Severe	0.006	0.006	0.005	0.004	0.004	0.006	0.005
Mild	0.096	0.107	0.075	0.039	0.078	0.094	0.084
Positive[8] health change	0.100	0.104	0.072	0.038	0.078	0.090	0.083
Severe	0.005	0.004	0.003	0.003	0.003	0.005	0.004
Mild	0.096	0.101	0.069	0.035	0.075	0.087	0.080
N	47897	66043	50929	34328	113893	85304	199197
GBB	0.106	0.122	0.116	0.082	0.106	0.118	0.111
GBB mild	0.101	0.116	0.109	0.074	0.101	0.111	0.105
GBB severe	0.005	0.006	0.008	0.008	0.006	0.007	0.006
GGG	0.241	0.140	0.052	0.019	0.112	0.159	0.133
GBG	0.088	0.076	0.044	0.022	0.060	0.073	0.065
GGB	0.112	0.106	0.066	0.035	0.081	0.100	0.090
BGG	0.114	0.098	0.058	0.033	0.081	0.091	0.086

[8] Positive health changes and corresponding patterns BGG, BGB, BBG, BBB are defined in a way similar to negative health changes and shocks as transition from fair, bad or very bad health status to good or very good.

BGG mild	0.005	0.004	0.002	0.002	0.003	0.004	0.003
BGG severe	0.110	0.095	0.057	0.031	0.079	0.087	0.082
BGB	0.079	0.093	0.088	0.063	0.083	0.086	0.084
BBG	0.103	0.109	0.096	0.068	0.101	0.098	0.099
BBB	0.158	0.255	0.480	0.678	0.376	0.275	0.332
N	20660	27097	17865	8735	41876	32481	74357

Balancing test

A key assumption in estimating propensity score matching DID estimates is the overlap assumption, which is satisfied when there is a possibility of having observations in the control and treated groups at each combination of covariates. Figure 2 provides a plot of the estimated probability densities of the propensity scores both for the treated and control groups. The graph presents clear evidence that the overlap assumption is satisfied.

Table 2 provides descriptive statistics for the pre-treatment conditioning variables. Column 1 shows the means for the treatment group, column 2 and 3 shows the means for control and matched control groups. Estimates also indicate that initially unskilled workers over 46 years old, who live in a city, who completed only high school, have one child in the household, and have lower wages and income are more likely to experience a health shock. Overall, the balancing test results indicate that the matching succeeds in balancing covariates, mitigating a considerable part of the unbalancedness.

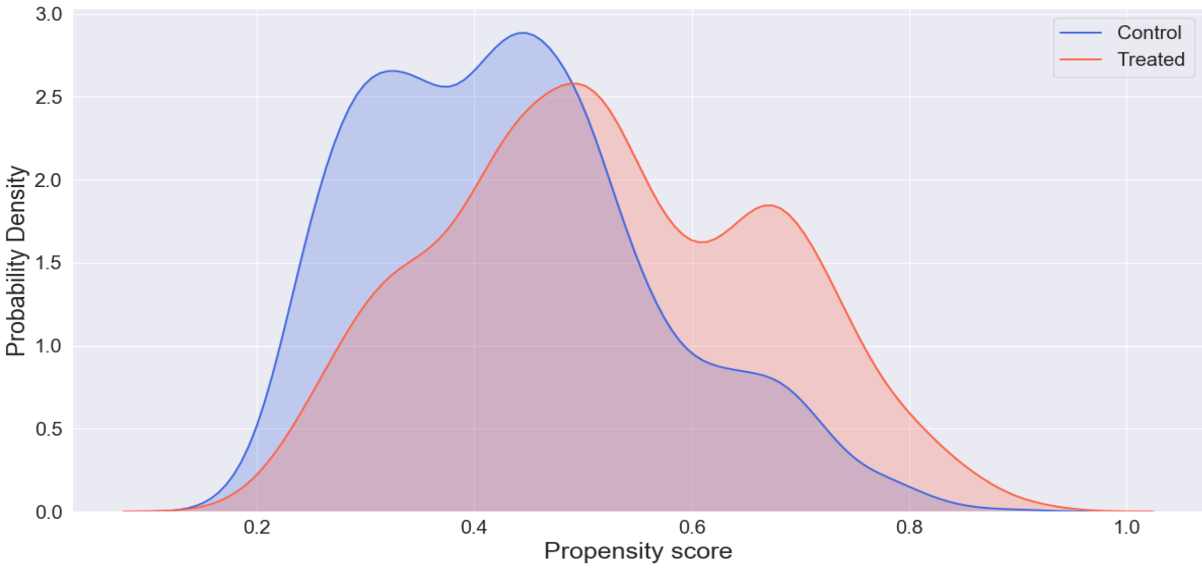

Fig. 2. Density of propensity score for treated and control groups

Tab. 2. Balancing test before and after propensity score matching

	Mean (treated)	**Mean (control)**	**Mean (matched control)**
Male	0.522	0.608***	0.513
Age: 18-29	0.232	0.429***	0.230
Age: 30-45	0.473	0.465	0.458

Age: 46-59	0.267	0.117***	0.282*
Age: 60-72	0.034	0.006***	0.030
Regional Capital	0.405	0.392	0.423*
City	0.301	0.273***	0.302
Rural	0.294	0.335***	0.275**
Incomplete high school	0.106	0.103	0.095*
High school	0.365	0.350*	0.351
Incomplete higher education	0.261	0.259	0.267
Higher education	0.267	0.288**	0.286**
Single	0.118	0.200***	0.116
Married	0.758	0.717***	0.759
Divorced	0.091	0.070***	0.093
Widow	0.033	0.013***	0.032
No children	0.474	0.493**	0.479
1 child	0.340	0.318**	0.340
2 children	0.155	0.149	0.152
≥3 children	0.031	0.039**	0.028
Top level workers	0.385	0.404**	0.397
Middle level workers	0.219	0.218	0.215
Skilled worker	0.323	0.325	0.321
Unskilled worker	0.073	0.054***	0.067
Log(personal income)	9.506	9.689***	9.927***
Log(wage)	9.790	9.907***	9.852***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Personal income and wages are in constant 2018 prices, deflated by Consumer Price Index.

Results

Employment

General sample

Table 3 presents[9] propensity score and nearest neighbour DID effects of sudden declines in SAH status on the probability of remaining employed across age and time groups. The estimates in the last column provide evidence that a negative health shock has a substantial negative effect on the probability of remaining employed. The nearest-neighbour matching estimate indicates a potential loss of 2%. The effects on employment obtained via kernel and propensity-score matching are smaller in magnitude,1.4% and 1.3%, respectively.

The effect is heterogeneous by age groups, respondents aged 30–45 facing a health deterioration experience a 1–1.3% loss in the probability of remaining employed, while those aged 40–56 and 46–72 experience 2–3.5% and 3–4.5% losses. The youngest group of respondents aged 18–29 does not experience any employment losses associated with a sudden health deterioration.

[9] Number of observations across all subgroups used for the estimation is presented in Table B.2

Regarding the dynamics of the estimated effect, before the economic downturn in 2009 only individuals aged 30–45 were sensitive to a health shock (3.5%) which is reflected in 1.8% reduction for the whole pre-crisis subsample. After the economic crisis, the estimates find significant losses only for older respondents aged 45–59 and 46–72, 3.9% and 4.6%, respectively, and 1.4% for the whole post-crisis subsample. During the crisis from 2008 to 2010, there is no statistically significant reduction in the probability of remaining in work.

Tab. 3. ATET effects of a health shock on employment (general sample)

		18-29	**30-45**	**46-59**	**46-72**	**18-72**
Kernel	2000-2007	-0.002	-0.035***	0.027	0.008	-0.018*
		(0.020)	(0.009)	(0.037)	(0.027)	(0.011)
	2008-2010	0.005	-0.006	-0.017	-0.009	-0.005
		(0.023)	(0.017)	(0.039)	(0.047)	(0.018)
	2011-2018	-0.002	-0.000	-0.039**	-0.046**	-0.014*
		(0.017)	(0.007)	(0.019)	(0.020)	(0.007)
	2000-2018	-0.001	-0.013**	-0.020*	-0.030**	-0.014***
		(0.012)	(0.006)	(0.012)	(0.014)	(0.005)
PS	2000-2018	0.003	-0.010*	-0.015	-0.031**	-0.013**
		(0.011)	(0.006)	(0.015)	(0.015)	(0.006)
NN	2000-2018	-0.008	-0.009	-0.035***	-0.045***	-0.020***
		(0.011)	(0.006)	(0.013)	(0.014)	(0.005)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Males vs females

Tables 4 and 5 show the matching estimations for subsamples of males and females separately. The main patterns for males are very similar to those revealed for the general sample. nearest-neighbour matching finds that men after experiencing a health shock face a 2.6% loss in the probability of remaining employed. The figures obtained via kernel and propensity score are slightly smaller, 2.1% and 2.3%, respectively.

The effect for middle-aged males is smaller in magnitude, 1.4-1.8%, while the effect for older males is 3.6–4.6% for the age group 46-59 and up to 5.3% for the age group 46–72. Like the general sample, only males aged 30–45 experience employment losses of 3.6% before the economic crisis and males aged 46–59 after the downturn (6.3%), while in the period of crisis matching estimates find no effects.

Table 5 shows no statistically significant robust results for females, neither across age nor time subsamples.

Tab. 4. ATET effects of a health shock on employment (male sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.013	-0.036***	-0.002	-0.012	-0.023**
		(0.023)	(0.014)	(0.040)	(0.039)	(0.012)
	2008-2010	0.000	-0.010	-0.039	-0.041	-0.019
		(0.021)	(0.026)	(0.031)	(0.044)	(0.016)
	2011-2018	-0.017	0.000	-0.063***	-0.045	-0.019
		(0.015)	(0.008)	(0.024)	(0.031)	(0.012)
	2000-2018	-0.013	-0.014**	-0.036**	-0.043**	-0.021***
		(0.008)	(0.006)	(0.016)	(0.018)	(0.007)
PS	2000-2018	-0.018*	-0.013	-0.045***	-0.052***	-0.023***
		(0.010)	(0.008)	(0.014)	(0.017)	(0.007)
NN	2000-2018	-0.012	-0.015**	-0.046***	-0.053***	-0.026***
		(0.011)	(0.008)	(0.017)	(0.017)	(0.006)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Tab. 5. ATET effects of a health shock on employment (female sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	0.007	-0.034**	0.067	0.042	-0.008
		(0.040)	(0.016)	(0.067)	(0.062)	(0.012)
	2008-2010	0.018	0.010	-0.005	-0.027	0.006
		(0.057)	(0.027)	(0.089)	(0.074)	(0.026)
	2011-2018	0.011	-0.001	0.003	-0.001	-0.006
		(0.033)	(0.014)	(0.032)	(0.032)	(0.012)
	2000-2018	0.012	-0.011	0.005	-0.009	-0.005
		(0.020)	(0.008)	(0.025)	(0.029)	(0.010)
PS	2000-2018	0.019	-0.014*	0.005	-0.005	-0.007
		(0.021)	(0.009)	(0.021)	(0.021)	(0.010)
NN	2000-2018	0.021	-0.003	-0.028	-0.043**	-0.005
		(0.022)	(0.010)	(0.021)	(0.021)	(0.009)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Personal income

General sample

The consequences of health deterioration on personal income are much more prominent. Table 6 shows matching estimates of a sudden reduction of health status on personal income for the last 30 days. The last column indicates that a health shock decreases personal income by 17% in nearest-neighbour matching and by 16% and 17% in kernel and propensity-score matching. Regarding the difference across age groups, losses in income are concentrated among younger respondents. Youngest individuals aged 18-29 lose up to one-third of their monthly income. The figures for respondents aged 30-45 are more modest, but still notable, 16-22%. Alternatively, matching estimates find no statistically significant losses in income for respondents over 46 years.

When it comes to the differences across time subsamples, it can be seen that before and after the downturn effects are mostly among young and middle-aged respondents: 29% for the age group 18–29 before the crisis and 24% for the age group 30–45 after the crisis. During the economic downturn kernel matching estimates shows much more prominent figures for respondents over 30 years old: 32%, 49% and 40% for the age groups 30–45, 46–59 and 45–72, respectively.

Tab. 6. ATET effects of a health shock on the logarithm of personal income (general sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.285*	-0.043	-0.123	-0.085	-0.146
		(0.159)	(0.142)	(0.233)	(0.289)	(0.107)
	2008-2010	-0.035	-0.320**	-0.493***	-0.392**	-0.316***
		(0.254)	(0.126)	(0.188)	(0.185)	(0.091)
	2011-2018	-0.228	-0.237***	0.055	0.053	-0.181***
		(0.139)	(0.072)	(0.114)	(0.112)	(0.052)
	2000-2018	-0.224**	-0.180***	-0.049	-0.071	-0.164***
		(0.093)	(0.063)	(0.100)	(0.099)	(0.050)
PS	2000-2018	-0.216**	-0.164**	-0.017	-0.085	-0.169***
		(0.102)	(0.066)	(0.120)	(0.092)	(0.048)
NN	2000-2018	-0.293***	-0.224***	-0.247**	-0.199*	-0.173***
		(0.099)	(0.063)	(0.109)	(0.107)	(0.047)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Males vs females

Tables 7 and 8 show estimates of a health shock's effects on the logarithm of personal income for males and females separately. The last column of Table 7 provides evidence that health reduction is associated with a 28% loss in personal income for males. This effect is mostly concentrated among individuals below 46 years old: men aged 18–29 and 30–45 face up to 40% and 31% income reduction due to a negative health shock. Additionally, nearest-neighbour matching estimates show that males aged 46–59 lose almost 38% of their monthly income. Before 2008 and after 2011 only the youngest male age group seem to have statistically significant losses in income, around 41% in both cases. During the crisis, on the contrary, the effect of health deterioration is observed only for males aged 46–59.

The estimates for females in Table 8 show that for the whole sample of women there is no effect of health shocks, while nearest-neighbour matching estimates provide evidence that women aged 30–45, 46–59 and 46–72 experience substantial income reduction, 17%, 24%, and 22%, respectively. During and after the economic downturn females aged 30–45 and 46–72 lose almost one-third of their income, while in the period before the crisis kernel matching estimates find no statistical evidence.

Tab. 7. ATET effects of a health shock on the logarithm of personal income (male sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.406*	-0.285	-0.287	-0.104	-0.262*
		(0.214)	(0.206)	(0.378)	(0.391)	(0.142)
	2008-2010	-0.330	-0.332	-0.687**	-0.533	-0.417**
		(0.296)	(0.294)	(0.337)	(0.365)	(0.181)
	2011-2018	-0.407**	-0.167	0.057	0.058	-0.188***
		(0.187)	(0.103)	(0.185)	(0.173)	(0.062)
	2000-2018	-0.373***	-0.254***	-0.046	-0.054	-0.224***
		(0.131)	(0.095)	(0.177)	(0.140)	(0.059)
PS	2000-2018	-0.395***	-0.296***	-0.069	-0.030	-0.202***
		(0.126)	(0.089)	(0.196)	(0.187)	(0.075)
NN	2000-2018	-0.397***	-0.311***	-0.377**	-0.266	-0.279***
		(0.135)	(0.091)	(0.176)	(0.167)	(0.066)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Tab. 8. ATET effects of a health shock on the logarithm of personal income (female sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.133	0.202	-0.413	-0.385	-0.005
		(0.282)	(0.208)	(0.271)	(0.278)	(0.155)
	2008-2010	0.186	-0.274*	-0.293	-0.298*	-0.186
		(0.359)	(0.158)	(0.179)	(0.165)	(0.126)
	2011-2018	-0.060	-0.295***	0.165	0.076	-0.162**
		(0.228)	(0.100)	(0.200)	(0.181)	(0.074)
	2000-2018	-0.052	-0.103	-0.137	-0.128	-0.078
		(0.126)	(0.085)	(0.102)	(0.093)	(0.059)
PS	2000-2018	0.018	-0.092	-0.090	-0.150	-0.012
		(0.151)	(0.089)	(0.155)	(0.097)	(0.076)
NN	2000-2018	-0.104	-0.168*	-0.244**	-0.223**	-0.071
		(0.160)	(0.091)	(0.095)	(0.092)	(0.064)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Wage

General sample

Table 9 provides evidence of the statistical effects of acute drops in health status on the logarithm of the real wage. The last column of Table 9 shows that in general respondents lose 6–12% of their monthly wage. This effect is substantial across all age groups and all matching estimators. The youngest part of the sample—respondents below 45 years old—lose 4–11% of the wage, while their older counterparts, 7–22%.

Kernel matching estimates provide evidence that elderly respondents were the most sensitive to a health shock before the downturn, suffering a 17% wage loss. During the crisis, these figures reached 34%, and 25% including individuals over 60. In contrast, after the downturn, the most sensitive part of the sample was respondents up to 45 years old. Potential losses in wages are 9% and 3% for the first two age groups, respectively.

Tab. 9. ATET effects of a health shock on the logarithm of monthly wage (general sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.054	-0.066	-0.138	-0.166**	-0.091**
		(0.047)	(0.058)	(0.085)	(0.080)	(0.037)
	2008-2010	0.055	-0.058	-0.337***	-0.245***	-0.080**
		(0.064)	(0.054)	(0.097)	(0.081)	(0.038)
	2011-2018	-0.085**	-0.030*	-0.049	-0.053	-0.048***
		(0.037)	(0.018)	(0.038)	(0.035)	(0.018)
	2000-2018	-0.044**	-0.045**	-0.106***	-0.085***	-0.062***
		(0.019)	(0.018)	(0.030)	(0.031)	(0.015)
PS	2000-2018	-0.033	-0.022	-0.085**	-0.069**	-0.068***
		(0.027)	(0.021)	(0.036)	(0.035)	(0.016)
NN	2000-2018	-0.077***	-0.108***	-0.211***	-0.222***	-0.117***
		(0.027)	(0.021)	(0.040)	(0.038)	(0.014)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Males vs females

Table 10 shows estimates of the effects of health shocks on males' monthly wages. The matching estimates find a 7–11% loss for the whole male sample. Similar to patterns revealed for the general sample, estimated effects in Table 10 provide evidence of 6–8% wage reduction for the youngest age group, 7–11%, and 8–15% for middle-aged and elderly respondents. When it comes to dynamics of the effect, different age groups are sensitive across certain periods, namely after the crisis individuals below 45lose up to 11% of their wage, and during the crisis respondents aged 46–59 lose more than one-third of their monthly wage.

Table 11 additionally provides matching estimates for the female sample. Similar to males' estimates, we observed statistically significant effects for all age groups of respondents. Women over 46 lose 13–25% of their wages due to adverse health shocks, which reflected in 4–11% losses for the whole female sample. Effects for age groups 18–29 and 30–45 are less noticeable: only nearest-neighbour matching estimates finds significant figures of 8–9%

The patterns across time periods contrast sharply with the males' results. Only females over 45 seem to have significant wage reductions before and during the downturn, specifically 24–36% but none after the crisis.

Tab. 10. ATET effects of a health shock on the logarithm of monthly wage (male sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.093	-0.073	-0.092	-0.067	-0.087*
		(0.059)	(0.060)	(0.117)	(0.119)	(0.047)
	2008-2010	0.030	-0.045	-0.362***	-0.189	-0.099**
		(0.096)	(0.088)	(0.125)	(0.151)	(0.047)
	2011-2018	-0.105**	-0.054*	-0.043	-0.036	-0.065***
		(0.046)	(0.029)	(0.074)	(0.054)	(0.023)
	2000-2018	-0.057**	-0.074***	-0.074	-0.067	-0.076***
		(0.028)	(0.025)	(0.046)	(0.045)	(0.018)
PS	2000-2018	-0.036	-0.074**	-0.082*	-0.077*	-0.074***
		(0.035)	(0.029)	(0.043)	(0.045)	(0.021)
NN	2000-2018	-0.075**	-0.108***	-0.151**	-0.151***	-0.112***
		(0.035)	(0.028)	(0.060)	(0.057)	(0.020)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Tab. 11. ATET effects of a health shock on the logarithm of monthly wage (female sample)

		18-29	30-45	46-59	46-72	18-72
Kernel	2000-2007	-0.014	-0.048	-0.235*	-0.217	-0.080
		(0.075)	(0.071)	(0.130)	(0.143)	(0.052)
	2008-2010	0.129	-0.049	-0.358**	-0.127	-0.070
		(0.104)	(0.065)	(0.159)	(0.172)	(0.051)
	2011-2018	-0.060	-0.007	-0.084	-0.069	-0.026
		(0.060)	(0.036)	(0.080)	(0.063)	(0.029)
	2000-2018	-0.017	-0.003	-0.145***	-0.128***	-0.041**
		(0.039)	(0.027)	(0.043)	(0.046)	(0.019)
PS	2000-2018	-0.027	0.005	-0.143***	-0.140***	-0.042*
		(0.042)	(0.029)	(0.052)	(0.045)	(0.023)
NN	2000-2018	-0.080*	-0.090***	-0.244***	-0.255***	-0.105***
		(0.043)	(0.032)	(0.055)	(0.052)	(0.021)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Heterogeneity

Table 12 provides evidence of the heterogeneity of the estimated effect of adverse health shocks on the probability of remaining employed and the logarithms of monthly personal income and wage. The first part of the table illustrates the differences across types of occupation. In general, middle level and skilled workers are the most exposed to negative labour consequences: they lose 2–3% of the probability of remaining in work, 21–26% in income, and 10–15% in wages. Additionally, top-level workers lose approximately 11% of their wages. Unskilled workers seem to have no losses at all.

The second part of Table 12 illustrates education asymmetry. Respondents with two lowest levels of education experience huge losses in employment (3–8%), in income (31–43%), and in wages (15%), and high school graduates lose less than non-graduates. Moreover, even university graduates lose around 9% of their wages, but experience no losses in terms of employment or income.

Tab. 12. ATET effects of a health shock on labour market outcomes across occupation type, education level and level of personal income

	Employment	**Log(personal income)**	**Log(wage)**
Top level workers	0.002	-0.042	-0.109***
	(0.008)	(0.064)	(0.021)
Middle level workers	-0.023*	-0.212**	-0.148***
	(0.013)	(0.098)	(0.030)
Skilled worker	-0.034***	-0.263***	-0.100***
	(0.009)	(0.090)	(0.025)
Unskilled worker	-0.033	-0.153	-0.078
	(0.029)	(0.251)	(0.073)
Incomplete high school	-0.078***	-0.431***	-0.147***
	(0.017)	(0.166)	(0.047)
High school	-0.031***	-0.312***	-0.151***
	(0.009)	(0.086)	(0.026)
Incomplete higher	-0.021**	-0.042	-0.122***
education	(0.009)	(0.085)	(0.027)
Higher education	0.004	-0.023	-0.093***
	(0.009)	(0.067)	(0.024)
Below the median	-0.025**	-0.379***	-0.103***
of personal income	(0.011)	(0.091)	(0.025)
Above the median	-0.015***	-0.067	-0.108***
of personal income	(0.006)	(0.045)	(0.014)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

The last part of the table shows estimates across the level of personal income. Respondents with personal income below the sample median have to face more severe consequences: 2.5% loss in employment and 38% in income, compared with those with higher income. However, losses in wages are almost equal for the two groups, around 10–11%.

Sensitivity

Employment

We redefined a health shock, dividing all cases of shocks into two types—mild and severe.

Mild health shocks are defined as at most one level decline in SAH status, while severe ones indicate a drop in health status at least by two levels. Table 13 presents the matching effects on the probability of remaining in work for two the levels of health shocks - severe and mild, the first five columns show results for the joined sample of males and females, while the last two columns show females and males separately. As expected, the adverse effects on employment are substantially larger for those who experienced severe health shocks than for respondents whose health declined by at most one level.

Overall, the reduction of health status by at most one level is associated with 1.1–1.7% loss in the probability of remaining employed, while figures for those who experienced severe shocks are 6.5–9.6%. nearest-neighbour matching estimates find that respondents aged 46–59 face losses in the likelihood of being employed only in the case of mild health deterioration. However, the inclusion in this group of individuals over 60 is statistically significant: the probability of remaining employed decreases for individuals 46–72 by 2.7–3.8% and 8.5–10.3% for mild and severe health reductions, respectively. Middle-aged members of the sample also experience losses in employment, but numbers are smaller, 1.1–1.2% for mild shocks and 5.7–5.8% for severe ones.

Estimates show a difference in employment consequences for males and females. Both mild and severe health shocks substantially affect men's employment—adverse health changes decrease the probability by around 2% or 7% depending on the severity. In sharp contrast, women face losses only in the case of severe health shock (7–13%).

Tab. 13. ATET effects of a health shock on employment (severe and mild)

		18-29	**30-45**	**46-59**	**46-72**	**18-72**	**Females**	**Males**
Kernel	Severe	-0.087	-0.058*	-0.055	-0.086**	-0.075***	-0.071*	-0.060**
		(0.056)	(0.034)	(0.051)	(0.034)	(0.021)	(0.041)	(0.029)
	Mild	0.002	-0.011**	-0.017	-0.027**	-0.012*	-0.002	-0.020***
		(0.010)	(0.005)	(0.019)	(0.013)	(0.006)	(0.010)	(0.006)
PS	Severe	-0.110***	-0.036***	-0.047	-0.085*	-0.065***	-0.067*	-0.073**
		(0.043)	(0.003)	(0.045)	(0.044)	(0.025)	(0.036)	(0.030)
	Mild	0.006	-0.012**	-0.016	-0.031**	-0.011**	-0.002	-0.021***
		(0.011)	(0.006)	(0.014)	(0.014)	(0.006)	(0.011)	(0.006)
NN	Severe	-0.047	-0.057*	-0.068	-0.103**	-0.096***	-0.126***	-0.084**
		(0.057)	(0.032)	(0.043)	(0.044)	(0.025)	(0.042)	(0.033)
	Mild	0.001	-0.005	-0.034***	-0.038***	-0.017***	-0.002	-0.023***
		(0.011)	(0.007)	(0.012)	(0.014)	(0.005)	(0.009)	(0.006)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Personal income

Table 14 presents the results for the logarithm of personal income. Again, as expected, income reductions are much more prominent for those who experienced severe negative shocks. Moreover, potential losses in income are more substantial. Overall, individuals experienced mild shocks face 15–17% income reductions, while those experienced drops in health status by more than two levels lose up to half of their monthly income.

In comparison with the results for employment, effects are concentrated among the younger parts of the sample. The most sensitive groups are respondents aged 30–45, they lose 58–67% of their income. The figures are more modest for mild shocks, 16–21%. Additionally, all of the matching estimates find a significant effect for respondents aged 18–29, after decreasing health status by one level they lose 26–30%, in other words, even relatively small health declines can reduce income by one-third. Males lose up to half of their income, however, the results indicate that any drop in health status does not affect females' income.

Tab. 14. ATET effects of a health shock on the logarithm of personal income (severe and mild)

		18-29	30-45	46-59	46-72	18-72	Females	Males
Kernel	Severe	-0.139	-0.662**	-0.331	-0.217	-0.393**	-0.352	-0.404*
		(0.411)	(0.285)	(0.297)	(0.337)	(0.174)	(0.263)	(0.227)
	Mild	-0.229***	-0.168***	-0.040	-0.068	-0.156***	-0.067	-0.218***
		(0.081)	(0.059)	(0.126)	(0.089)	(0.049)	(0.057)	(0.057)
PS	Severe	-0.128	-0.581*	-0.178	-0.119	-0.412**	-0.101	-0.296
		(0.320)	(0.302)	(0.226)	(0.270)	(0.181)	(0.200)	(0.266)
	Mild	-0.261***	-0.163**	-0.150	-0.065	-0.146***	-0.022	-0.202***
		(0.099)	(0.064)	(0.110)	(0.108)	(0.051)	(0.075)	(0.072)
NN	Severe	0.353	-0.671*	-0.092	-0.180	-0.409**	-0.181	-0.554*
		(0.415)	(0.348)	(0.320)	(0.281)	(0.187)	(0.341)	(0.298)
	Mild	-0.295***	-0.209***	-0.167	-0.120	-0.168***	-0.069	-0.275***
		(0.100)	(0.064)	(0.124)	(0.118)	(0.047)	(0.065)	(0.066)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Wage

Table 15 includes the matching estimates for the logarithm of the monthly wages for severe and mild shocks. Wage reductions are more modest compare with reductions of income but exceed losses in the probability of remaining in work. In general, those who experienced a one-level drop in health status lose 6–12% of the wage, those who experienced severe changes up to 16%. Mild health shocks decrease the wages for all age groups, starting from 5–7% for respondents aged 18–29 up to 19% for respondents aged 46–72. Middle-aged and elderly individuals additionally face huge wage reduction for a severe health deterioration: 15–41% of their monthly wage. Concerning the gender differences, only mild health shocks seem to have negative effect on monthly wages both for males and females.

Tab. 15. ATET effects of a health shock on the logarithm of monthly wage (severe and mild)

		18-29	30-45	46-59	46-72	18-72	Females	Males
Kernel	Severe	0.120	-0.001	-0.335***	-0.333***	-0.100*	-0.073	-0.123
		(0.082)	(0.089)	(0.093)	(0.084)	(0.057)	(0.076)	(0.081)
	Mild	-0.050**	-0.048***	-0.094***	-0.074**	-0.062***	-0.041*	-0.075***
		(0.024)	(0.017)	(0.033)	(0.032)	(0.013)	(0.022)	(0.022)
PS	Severe	0.030	0.154**	-0.392***	-0.287***	-0.068	0.011	-0.136*
		(0.068)	(0.067)	(0.081)	(0.093)	(0.057)	(0.089)	(0.074)
	Mild	-0.048*	-0.036*	-0.067*	-0.068**	-0.060***	-0.026	-0.062***
		(0.028)	(0.021)	(0.038)	(0.034)	(0.016)	(0.024)	(0.021)
NN	Severe	0.104	0.055	-0.385***	-0.412***	-0.160**	-0.156	-0.118
		(0.095)	(0.078)	(0.114)	(0.105)	(0.063)	(0.111)	(0.102)
	Mild	-0.073***	-0.104***	-0.200***	-0.193***	-0.116***	-0.110***	-0.110***
		(0.027)	(0.020)	(0.031)	(0.031)	(0.014)	(0.021)	(0.020)

Robust standard errors based on Abadie & Imbens (2006), are shown in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1

Discussion

In this paper, we have provided evidence for the Russian population suggesting that adverse health shocks have a substantial negative effect on the probability of remaining in work, monthly personal income, which is a sum of labour and non-labour earnings, and monthly wage. In particular, we have found relatively small but significant effects on employment of around 2%, which is comparable with the results obtained by Lenhart (2019), who found that negative health shocks decrease the likelihood of being employed by 2%. However, the figures obtained are slightly smaller than those presented by García-Gómez and López-Nicolás (2006) and García-Gómez (2011) (5–6%) based on the Spanish population. Additionally, estimates show that transition from good to bad health is associated with large income reductions, namely 17% of income for the last thirty days. However, losses in labour earnings (wage) are relatively smaller, but still remarkable and robust, approximately 6–12%. The figures let us suppose that individuals experienced health shocks lose a significant part of their non-labour income, such as pensions, social benefits, bonuses, and other profits. Compared to the results obtained by García-Gómez et al. (2013), the losses that are faced by Russian citizens are much larger than those by Spanish citizens; they appear to lose only 5% of their personal income.

The literature on the Russian labour market represented by Gimpelson and Kapeliushnikov (2013) and Gimpelson (2019) supposes that the specifics of the labour market in Russia is stable with an anchored level of employment and unemployment on the one side, and flexible and volatile wages, which can adjust to economic shocks, on the other hand. Figure 1 illustrates this institutional model: labour force participation rate and employment rate are stable, however exhibit moderate upward trend. As Gimpelson (2019) points out, the Russian labour market has maintained a high employment rate and low unemployment rate despite several macroeconomic shocks but at the cost of extremely volatile wages. The large difference between the extensive and intensive margins of labour consequences of adverse health shocks can be reasonably explained with the help of this model.

Gimpelson and Kapeliushnikov (2013) indicate that there are two ways to maintain the stability of employment. The first one is through flexible working hours which allow firms to avoid massive layoffs during downturns and rebound employment through overtime work during the recovery. The second instrument is flexible wages. Employers could adjust to the current economic situation by altering the premium part of the wage, which in fact is not fixed in labour contracts or by introducing "envelop payments".

In this paper, we have found that negative health shock is associated with considerable wage and personal income reduction but more modest employment loss. Individuals experienced a drop in SAH status have to face detrimental consequences giving up 17% of their personal income and 12% of the wages be it by mutual agreement with the employer or involuntarily, however, their chances of remaining in work are still high. In other words, the process of adjustment to health shocks in Russia occurs mainly through changes in income and wages rather than through dismissal.

All matching estimates provide evidence of gender asymmetry across the effects. In particular, we found that females do not lose any part of their personal income, even in case of severe health shocks. As estimates indicate, women tend to lose up to 11% of their wages if their health deteriorates by one level and lose up to 13% in the probability of remaining in work if their health worsens by more than one level. The potential losses of males are more serious. Men's sudden declines of health lead to a 28% loss in personal income in general and up to 55% in case of severe health shocks. Men experience losses in all the labour outcomes we considered: severe health shocks decrease the likelihood of remaining employed by up to 8% and wages by 14%. Males suffer from adverse labour consequences even in case of mild health deterioration. Specifically, they lose approximately 2% in the probability of remaining in work and up to 28% in income if their health status drops only by one level, females in the same position do not bear any burden.

We found that males are more likely to experience negative and positive health shocks and that they generally change self-reported health status from year to year more often compared to females (Table 1). Nevertheless, men's shocks can be regarded as more objective health shocks. In Table 16, we present the correlation between self-reported health measures with more objective ones: ambulance calls, the fact that respondents missed a certain number of days due to health reasons and EQ-5D index. It can be seen that SAH shocks of females are not correlated with the first three indicators, while shocks of males are strongly correlated. This lets us suppose that when men reported that their health status decreases with higher probability, they indeed face some health problems which lead to missing days and ambulance calls. Kaneva et al. (2018) and Gerry and Kaneva (2020) using the same data from RLMS-HSE found that females report chronic illnesses more often compared to men but the adverse effect on SAH is larger for males. They suppose that even minor conditions in women's health are reflected in their bad health assessments, while men report bad health only if they experience conditions that bring more severe discomfort and cannot be ignored.

Self-assessed health status is strongly correlated with objective measures for males as for females but the coefficients are larger for males than for females. That is one possible explanation for the difference in men's and women's labour consequences of health deterioration. When men report about even mild health shocks, there is a high probability that these shocks are connected with serious health events which lead to missing days from work or study.

These gender differences in SAH variables can be regarded as a possible limitation of the study. As women consider even minor ailments when reporting a health shock, the major deterioration in health we are interested in is measured with an error which potentially leads to biased estimations. However, since for women we did not capture any effects on labour market outcomes even in the presence of severe health shocks which can be more likely attributed to major health deterioration, we could partly eliminate concerns related to measurement error bias in female estimations.

Another explanation of the gender asymmetry is a males' careless attitude towards health. There is empirical evidence that women are more willing to report their health problems and associated symptoms than men (Green & Pope, 1999; Ladwig et al., 2000). The rate of preventive care and the number of visits to a primary care provider is higher among women than men (Green & Pope, 1999; Vaidya et al., 2012; Thompson et al., 2016). The behaviour of men that is reflected in being quite irresponsible to their health delays help-seeking when experiencing illness is called "traditional masculine behaviour" in the literature. In this way, men's health deterioration is sharper than female's and the negative effects of such deterioration towards employment, income and wages are more pronounced.

We have provided evidence of the age asymmetry of the estimated effects. In particular, we found that respondents over 46 are more likely to lose their jobs due to health shocks, compared with the younger respondents. At the same time, there is limited evidence that older respondents lose a part of their income, while individuals under 45 years old lose up to one-third of their personal income. In other words, young and middle-aged respondents can stay at work after a health shock occurred but at the cost of lost income and wage, alternatively, older respondents not only lose wages and income but also employment with a higher probability.

Finally, we have shown the matching estimates across the types of occupation, level of education and the level of personal income and found the estimated effects on employment and income are strongly heterogeneous: middle level and skilled workers and those with the lowest levels of education and personal income experience more prominent losses in the probability of remaining in work and in income. However, all groups lose a significant part of their monthly wages.

Tab. 16. Correlation of self-assessed health measures and objective health measures for females and males

	Self-assessed health shock	**SAH (1 = very bad, …, 5 = excellent)**
Females		
Ambulance call in last 12 months	0.061	-0.287***
	(0.073)	(0.013)
15 missed days at work or study out of last 1 month	0.225	-0.318***
	(0.151)	(0.026)
30 missed days at work or study out of last 12 months	0.090	-0.345***
	(0.104)	(0.020)
EQ-5D index	-0.008***	0.018***
	(0.003)	(0.001)
Males		
Ambulance call in last 12 months	0.252***	-0.367***
	(0.095)	(0.020)
15 missed days at work or study out of last 1 month	0.549***	-0.423***
	(0.141)	(0.031)
30 missed days at work or study out of last 12 months	0.313***	-0.394***
	(0.114)	(0.025)
EQ-5D index	-0.014***	0.021***
	(0.003)	(0.001)

Robust standard errors are shown in parentheses. All estimates are controlled for age, type of settlement, education level, marital status, number of children in a household, type of occupation and the logarithm of personal income. ***p < 0.01, **p < 0.05, *p < 0.1

Conclusion

We found that a health shock measured as a decline from good or very good SAH to bad or very bad significantly decreases the probability of remaining employed, personal income, and wage. For Russians, the probability of remaining at work after a health deterioration reduces by 2% in the year after a health shock occurred. Additionally, adverse health shocks are associated with 17% and 6–12% reduction in personal income and wages, respectively.

The matching estimates reveal gender asymmetry in the effects. In particular males generally suffer from more severe labour consequences after a health shock. Men lose 2.6% in the probability of remaining employed and 28% in personal income, while females do not bear any burden in terms of income or employment. However, losses in wages for males and females are similar, 7–12% and 4–12%, respectively.

Further, we redefined a health shock, dividing all cases of shocks into two types—mild and severe. Mild health shocks are defined as at most one level decline in SAH status, while severe ones indicate a drop in health status by at least two levels. In the latter case, potential losses are much more prominent, in particular, respondents aged 30–45 lose approximately 60% of their monthly income in case of severe shocks, respondents aged 46–72 lose around 29–41% of their wages and 9–10% in the probability of remaining employed.

In this paper, we have provided evidence for the Russian population suggesting that adverse health shocks have a statistically significant causal effect on the probability of remaining employed, personal income and wages. Our aim was to estimate the adverse labour consequences in the presence of a shock due to health problems.

Concerning the policy implications, there are various federal programs for disease prevention and medical examinations. The goal of such programs is to maintain the level of public health so that the population stays longer in the labour force. The flexible methodology we employ potentially allows us to measure the effectiveness of such programs and the change of the fraction of population exiting from the labour market because of health problems before and after the implementation of certain programs or policies. SAH is a rough proxy for health status, but our results nonetheless confirm that the effect of health shocks on the labour market is significant. The measurement of SAH is cost-efficient, which is why the implementation of this methodology makes the estimation of program's effectiveness faster and less complicated. Additionally, the methodology allows defining age-sex groups which are exposed to losses caused by a health shock to a greater extent.

References

Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, *74*(1), 235-267.

Au, D. W. H., Crossley, T. F., & Schellhorn, M. (2005). The effect of health changes and long-term health on the work activity of older Canadians. *Health economics*, *14*(10), 999-1018.

Bound, J., & Burkhauser, R. V. (1999). Economic analysis of transfer programs targeted on people with disabilities. *Handbook of labour economics*, *3*, 3417-3528.

Coile, C. C. (2004). *Health shocks and couples' labour supply decisions* (No. w10810). National Bureau of Economic Research.

Currie, J., & Madrian, B. C. (1999). Health, health insurance and the labour market. *Handbook of labour economics, 3*, 3309-3416.

Dano, A. M. (2005). Road injuries and long-run effects on income and employment. *Health economics*, *14*(9), 955-970.

Denisova, I., & Shapiro, J. (2013). *Recent Demographic Developments in the Russian Federation. Oxford Handbooks Online.* doi:10.1093/oxfordhb/9780199759927.013.001

Disney, R., Emmerson, C., & Wakefield, M. (2006). Ill health and retirement in Britain: A panel data-based analysis. *Journal of health economics*, *25*(4), 621-649.

ECB Economic Bulletin (2016). URL: https://www.ecb.europa.eu/pub/economic-bulletin/html/eb201606.en.html

García-Gómez, P. (2011). Institutions, health shocks and labour market outcomes across Europe. *Journal of health economics*, *30*(1), 200-213.

García-Gómez, P., Jones, A. M., & Rice, N. (2010). Health effects on labour market exits and entries. *Labour Economics, 17*(1), 62-76.

García-Gómez, P., & López-Nicolás, Á. (2006). Health shocks, employment and income in the Spanish labour market. *Health economics*, *15*(9), 997-1009.

García-Gómez, P., Van Kippersluis, H., O’Donnell, O., & Van Doorslaer, E. (2013). Long-term and spillover effects of health shocks on employment and income. *Journal of Human Resources*, *48*(4), 873-909.

Gerry, C. J., & Kaneva, M. (2020). Adapting to the Challenges of Chronic Non-communicable Diseases: Evidence from Russia. *Applied Research in Quality of Life*, 1-17.

Gimpelson, V. (2019). The labour market in Russia, 2000-2017. *IZA World of Labour*, (466).

Gimpelson, V., & Kapeliushnikov, R. (2013). *Labour Market Adjustment: is Russia Different? Oxford Handbooks Online.* doi:10.1093/oxfordhb/9780199759927.013.001

Green, C. A., & Pope, C. R. (1999). Gender, psychosocial factors and the use of medical services: a longitudinal analysis. *Social science & medicine*, *48*(10), 1363-1372.

Gupta, N. D., Kleinjans, K. J., & Larsen, M. (2015). The effect of a severe health shock on work behavior: evidence from different health care regimes. *Social Science & Medicine*, *136*, 44-51.

Halla, M., & Zweimüller, M. (2013). The effect of health on earnings: Quasi-experimental evidence from commuting accidents. *Labour Economics*, *24*, 23-38.

Idler, E. L., & Benyamini, Y. (1997). Self-rated health and mortality: a review of twenty-seven community studies. *Journal of health and social behavior*, 21-37.

Kaneva, M., Gerry, C. J., & Baidin, V. (2018). The effect of chronic conditions and multi-morbidity on self-assessed health in Russia. *Scandinavian Journal of Public Health*, *46*(8), 886-896.

Kaplan, G. A., & Camacho, T. (1983). Perceived health and mortality: a nine-year follow-up of the human population labouratory cohort. *American journal of epidemiology*, *117*(3), 292-304.

Ladwig, K. H., Marten-Mittag, B., Formanek, B., & Dammann, G. (2000). Gender differences of symptom reporting and medical health care utilization in the German population. *European journal of epidemiology*, *16*(6), 511-518.

Lenhart, O. (2019). The effects of health shocks on labour market outcomes: evidence from UK panel data. *The European Journal of Health Economics*, *20*(1), 83-98.

Lindeboom, M., Llena-Nozal, A., & van der Klaauw, B. (2016). Health shocks, disability and work. *Labour Economics*, *43*, 186-200.

Lindelow, M., & Wagstaff, A. (2005). *Health shocks in China: are the poor and uninsured less protected?*. The World Bank.

Lundborg, P., Nilsson, M., & Vikström, J. (2015). Heterogeneity in the impact of health shocks on labour outcomes: evidence from Swedish workers. *Oxford Economic Papers*, *67*(3), 715-739.

Mitra, S., Palmer, M., Mont, D., & Groce, N. (2016). Can households cope with health shocks in Vietnam?. *Health economics*, *25*(7), 888-907.

OECD (2020), Alcohol consumption (indicator). doi: 10.1787/e6895909-en (Accessed on 08 August 2020)

OECD (2020), Daily smokers (indicator). doi: 10.1787/1ff488c2-en (Accessed on 08 August 2020)

OECD (2020), Life expectancy at birth (indicator). doi: 10.1787/27e0fc9d-en (Accessed on 08 August 2020)

OECD (2020), Working age population (indicator). doi: 10.1787/d339918b-en (Accessed on 08 August 2020)

Thompson, A. E., Anisimowicz, Y., Miedema, B., Hogg, W., Wodchis, W. P., & Aubrey-Bassler, K. (2016). The influence of gender and other patient characteristics on health care-seeking behaviour: a QUALICOPC study. *BMC family practice*, *17*(1), 38.

Trevisan, E., & Zantomio, F. (2016). The impact of acute health shocks on the labour supply of older workers: Evidence from sixteen European countries. *Labour Economics*, *43*, 171-185.

Vaidya, V., Partha, G., & Karmakar, M. (2012). Gender differences in utilization of preventive care services in the United States. *Journal of women's health*, *21*(2), 140-145.

World Health Organization (2018), 'Noncommunicable diseases country profiles –Russia'. URL: https://www.who.int/nmh/countries/2018/rus_en.pdf?ua=1

Zucchelli, E., Jones, A. M., Rice, N., & Harris, A. (2010). The effects of health shocks on labour market exits: Evidence from the HILDA survey. *Australian Journal of Labour Economics*, *13*(2), 191.

Appendix

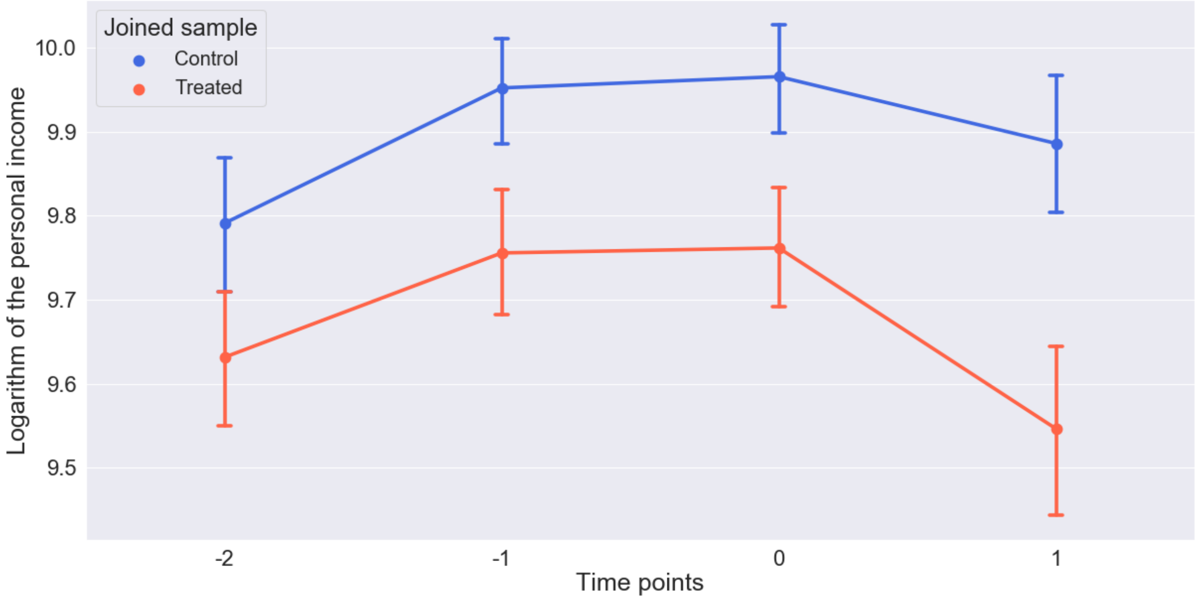

Fig. A1. Pre-treatment trends of the logarithm of personal income for the last 30 days. In constant 2018 prices, deflated by Consumer Price Index

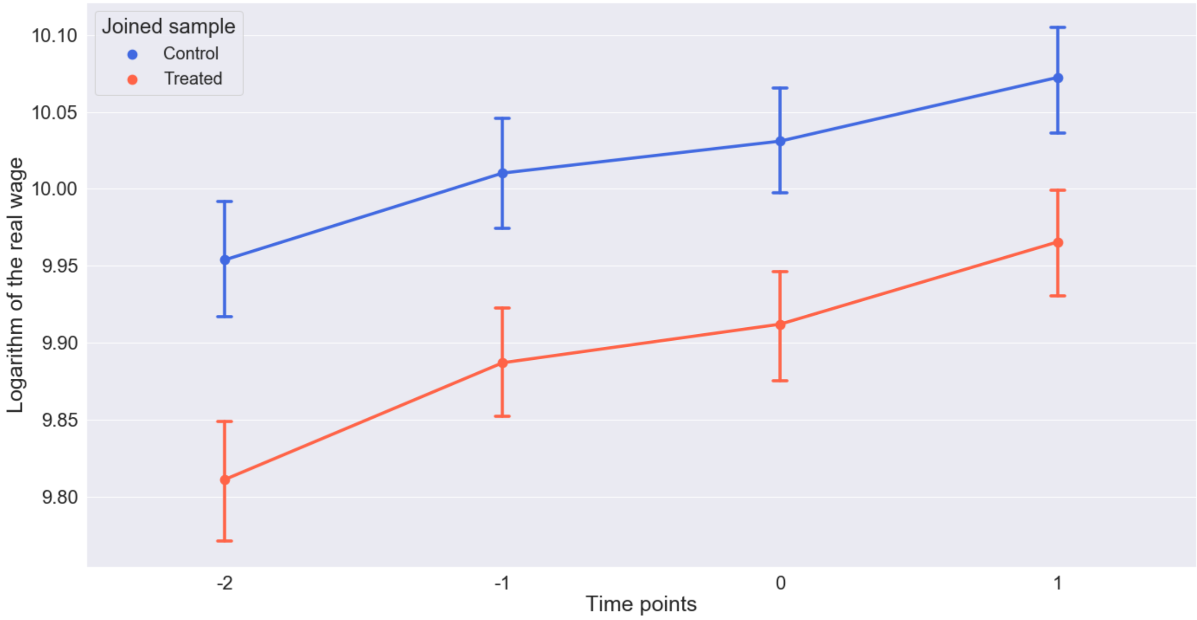

Fig. A2. Pre-treatment trends of the logarithm of wage for the last 30 days. In constant 2018 prices, deflated by Consumer Price Index

Tab. A1. Correlation of self-assessed health measures and objective health measures

	Self-assessed health shock	**SAH (1 = very bad, …, 5 = very good)**
Heart attack[10]		-0.496***
		(0.099)
Stroke		-0.626***
		(0.102)
Ambulance call	0.132**	-0.313***

[10] We do not have enough variation in heart attack and stroke variables vs self-assessed health shock, in this way, there is no opportunity to estimate reliable correlation coefficients.

	(0.058)	(0.011)
15 missed days at work or study out of last 1 month	0.389***	-0.364***
	(0.102)	(0.020)
30 missed days at work or study out of last 12 months	0.186**	-0.365***
	(0.077)	(0.016)
EQ-5D index	-0.011***	0.019***
	(0.002)	(0.000)
Chronic conditions		
Heart	0.541	-0.385***
	(0.363)	(0.073)
Lungs	0.061	-0.671***
	(0.750)	(0.115)
Liver	0.099	-0.344***
	(0.428)	(0.068)
Kidney	0.859***	-0.280***
	(0.279)	(0.059)
Dugestive system	-0.103	-0.362***
	(0.293)	(0.045)
Spine	0.746	-0.215*
	(0.717)	(0.129)

Robust standard errors are shown in parentheses. All estimates are controlled for gender, age, type of settlement, education level, marital status, number of children in a household, type of occupation and the logarithm of personal income. ***p < 0.01, **p < 0.05, *p < 0.1

Tab. A2. Number of observations

		18-29	30-45	46-72	18-72
2000-2007	Control	774	629	155	1558
	Treated	459	816	452	1727
2008-2010	Control	357	338	89	784
	Treated	217	429	283	929
2011-2018	Control	1061	1508	383	2952
	Treated	426	1129	745	2300
2000-2018	Control	2446	2799	718	5963
	Treated	1200	2562	1625	5387
Severe shocks	Control	2390	2799	701	5963
	Treated	43	83	85	211
Mild shocks	Control	2446	2799	718	5963
	Treated	1157	2479	1540	5176

Contact details and disclaimer:

Venera I. Bagranova
Center for Market Studies and Spatial Economics, National Research University Higher School of Economics, St. Petersburg, Russian Federation. Email: vbagranova@hse.ru.

Any opinions or claims contained in this Working Paper do not necessarily reflect the views of HSE.