Abstract

Aims: This is the first longitudinal study to examine the relationship between depression and the labour market in Russia. Using data from 2011-2017 we identify the impact that not being in employment has on mental distress and we explore the mechanism underlying the observed association.

Methods: Using data from the Russia Longitudinal Monitoring Survey – Higher School of Economics, we employ random effects regression models to estimate the impact of employment conditions on the likelihood of reporting mental distress in Russia. This method allows us to distinguish between the selection effect associated with mental distress and direct causation.

Results: Controlling for a range of socioeconomic and demographic characteristics we find that unemployment and labour market inactivity are strong predictors of the likelihood of reporting depression and serious nervous breakdown. However, we find that, rather than negative labour market events giving rise to mental distress, the selection effect actually dominates, and the direction of causality therefore operates in reverse.

Conclusions: Knowledge of the underlying mechanism that links unfavourable labour market outcomes with mental distress is crucial for designing policies that can address this link. We argue that our findings provide grounds for the initiation of anti-stigma campaigns among employers, policy makers, health practitioners and politicians as well as the general population. Eradication of the perception that mental disorders are somehow different to 'real' illnesses will not only prevent Russians from self-selection into unemployment but may also transform outdated approaches to mental health care in Russia.

Keywords: mental distress, depression, unemployment, Russia, causation, selection

Word count: 3,888

Introduction

The socio-economic and political reforms that began in Russia during the 1990s and that continue today are known to have had a major impact on the physical and mental health of the population. However, in 2014, the WHO [1] noted that research into the socio-economic drivers of general mental disorders in the post-communist countries was limited. Bobak et al. [2], looking at Russia, Poland and the Czech Republic, reported that depressive symptoms were associated with material deprivation, being unmarried, and binge drinking but not with unemployment. Averina et al. [3], in a descriptive, cross-sectional study, in Arkhangelsk, found that lower income respondents (and pensioners) were significantly more likely to suffer from depression, anxiety and sleeping disorders compared with those in high income groups. Roberts et al. [4] associated decreases in psychological distress, in 8 Former Soviet countries between 2001 and 2010, with better socioeconomic conditions. Jaehn et al. [5] investigated the relationship between gender role attitudes and depression between 2015-17, finding that those experiencing less favourable labour market circumstances were more likely to report symptoms of depression. This nascent thread of research begins to point towards a socioeconomic gradient in mental health, but the nature of the association with the labour market remains unclear.

It is well-established that unemployment is negatively associated with general measures of ill-health [6-9] and increasing attention has been paid to identifying a strong negative association between insecure employment and mental health [10-13]. It has been argued that the unemployed are more likely to exhibit depressive symptoms [14], stress and distress [15], and lower self-reported well-being [16-17]. That unemployed workers (and those outside of the labour force) have worse mental health conditions than employed workers comes as no surprise. Employment provides a source of income and a route to financial security but also provides for the fulfilment of socially defined needs through providing social status, identity and a sense of achievement. It follows that less secure, more precarious employment and short- or long-term unemployment are associated with physical and mental health scars that stem from diminished material possibilities and the effects of social exclusion. However, establishing the nature of the relationship is not straightforward, even once the empirical association is established.

There are three distinct mechanisms which may govern the relationship [18]. First, is what we call the *direct* mechanism, in which the experience of unemployment leads to a deterioration in mental health. There is a wealth of epidemiological evidence [19] that unemployment causes long-term health problems, including psychological problems. Second is the *selection or reverse causality* mechanism, through which those experiencing mental ill-health are themselves more likely to become and/or remain unemployed and/or inactive [13; 20-22]. Third is the *confounding* mechanism, which describes how a third factor (observed or unobserved) may give rise to a spurious relationship between dependent and independent variables, in the way, for example, that risky health behaviours are associated with both lower socioeconomic status and psychiatric morbidity [23].

In this paper, we focus on the relationship between mental distress (measured as self-reported depression and/or nervous breakdown) and the labour market in Russia, during an extended period of economic stagnation following the 2008-9 financial crisis. Coincident with economic stagnation, Russia has seen a major growth in mental illness during recent years, the population exhibits high levels of unhealthy behaviour (e.g. smoking and drinking), the health system is centralised and inflexible, mental health is heavily stigmatised and care remains institutionalised. Meanwhile, on the labour market side, only rudimentary supportive welfare measures are in place.

Against this background we address the following research questions using Russian survey data: (i) Is there a statistically significant relationship between different measures of labour market status and depression? (ii) Is there evidence to support the hypothesis that there is a direct causal link between labour market status and depression? (iii) Is the relationship between depression and other socioeconomic and demographic variables consistent with that reported in related literature? To our knowledge, this study represents the first longitudinal study of the relationship between mental distress and labour market status in Russia and the first attempt to distinguish among the three mechanisms introduced above to provide quantitative estimates and interpretation of the relationship between labour market status and depressive symptoms.

Methods

Data

We use Phase II (1994-2019) data from the 'Russia Longitudinal Monitoring Survey – Higher School of Economics' population survey (hereafter RLMS), which collects data pertaining to a wide range of socioeconomic, demographic and health characteristics and began routinely asking about mental health in 2011. Following Stauder [18], the sub-sample used in this research comprises of the adult working population, recorded as being employed in the first year of observation, and either remaining in employment, retiring, leaving the labour force or becoming unemployed in subsequent years. This yields an unbalanced panel of 22,954 males and 25,580 females. Full descriptive statistics are provided in Appendix 1.

The survey asks all adults whether, during the past 12 months, they have had depression or have suffered a serious nervous breakdown. An obvious advantage of this question is that it is straightforward and does not require special medical knowledge to answer it. However, the wording of the question does not allow for easily distinguishing between blue mood and clinical depression. Nevertheless, it is reasonable to assume – particularly given the stigma associated with mental illness in Russia – that those answering yes to this question had experienced some sort of notable mental distress. Using the responses to this question we create a binary variable (*depress*) where "yes" responses are coded 1 and other responses are coded 0.

As employment variables we use self-reported current economic activity to classify individuals as employed (including self-employed), retired, unemployed or out of the labour force (e.g. caregivers, students and those with a declared disability). Additionally, we proxy the duration of unemployment (and labour force inactivity) through creating dummy variables that indicate an individual is unemployed (out of labour force) for one year, two years, three years and more than three years. Explanatory variables, which we treat as exogenous, include age categories, marital status, presence of children, educational level achieved, income quintile, religious denomination, settlement type and year [24-26]. In addition, we incorporate a variable to control for co-morbidities, in the form of seven self-reported chronic illness indicators.

Statistical approach

In order to identify the impact of employment conditions on the likelihood of reporting depression or/and serious nervous breakdown we need to distinguish the direct causal mechanism from the selection and confounding mechanisms. An inherent advantage of longitudinal data is that it allows us to control for time invariant unobserved heterogeneity. Specifically, fixed effects regression utilises within-panel variation over time and the estimates 'partial out' the effects of unobserved time-invariant variables with time-invariant effects. They also, however, partial out the effects of time-invariant observed variables, inflate the standard errors for variables with little within individual variation (e.g. education) and discard observations for which the dependent variable exhibits no within person variation (e.g. anyone never reporting mental illness). We therefore preference a set of more efficient random effects models. The random-effects estimator is a matrix-weighted average of the fixed effect results and the between estimator results which takes into account the cross-sectional differences between the subjects. Random effects models allow us to control for unobserved heterogeneity which is constant over time and uncorrelated with the independent variables and to maximise our use of the available data. As robustness checks, we compare the results with the less efficient, but consistent, fixed effects approach.

In longitudinal regressions the problem of simultaneity occurs, presenting a threat to model validity [27]. That is, estimates of the effect of an independent variable (X) on the dependent variable (Y) comprise of two different effects: a direct (causal) effect of X on Y and a reverse effect of Y on X. The latter effect is referred to as a 'selection effect', in the econometric and related literature, and is distinct from the form of selection effect stemming from possible sampling (selection) bias e.g. when the treatment (or exposure) group in a study has a higher chance of including people with the pre-existing health condition under investigation (see [19] for a mental health illustration).

A key contribution of this paper is to separate the direct causal effects (from labour market to mental health) from the selection mechanism or reverse causality mechanism (from mental health to labour market). The methodology is based on the one proposed by Stauder [18] and focuses on the duration of unemployment. The direct effect that unemployment has on mental health, leads to material deprivation, loss of social status, and diminished social capital. Hence, the longer the duration of unemployment, the stronger the direct (rather than the selection) effect on mental health is likely to become. This approach is supported by a strand of epidemiological literature that allows for the concomitant establishment of forwards and backwards processes [19, 24-25]. In contrast, the selection effect reflects a more stable relationship, because it can reasonably be assumed that the feedback from depression to the labour market is relatively time-constant. Therefore, in our analysis the duration of unemployment variables play a decisive role.

We estimate three models, separately for males and females, with the binary variable, *depress*, as the dependent variable. First, we estimate a baseline multivariate logistic model (*Model 1*), controlling for individual demographic and socio-economic conditions. This model attenuates the confounding effect through random effects but does not attempt to separate the selection and causation mechanisms. Second, *Model 2* augments the baseline model with the duration variables for unemployment (2A) and being out of the labour force (2B). If the duration variables are significant it is interpreted as evidence of a causal effect (of X on Y). If the duration variables are not significant, we conclude that the selection effect dominates. Finally, *Model 3* incorporates chronic conditions which provide important time-varying information about an individual's physical well-being while still evaluating causation and selection effects. This approach not only allows us to distinguish selection from cause, but also allows for a deeper exploration of the socioeconomic gradient in mental health confirmed in prior studies [28-29].

Results

According to the RLMS-HSE data, around 11% of the employment oriented sample report suffering some form of depression in the panel. This estimate is lower than the 35% given in [5], when cross-sectional depression was measured using PHQ-9 (>5); and is lower than an older cross-sectional estimate, of 23%, for 2000 [2]. This difference is not unexpected given that we focus on an employed entry sample that overall has a better health than those without jobs, but also because we report descriptive statistics based on a longitudinal dataset with repeated observations across the same individual. In the sample, 89% of males and 83% of females report being in work. Of the remainder, for males, 5%, 1% and 5% respectively are pensioners, out of the labour force and unemployed while, the corresponding figures for females are 7%, 7% and 3%. Briefly, the two largest age groups in our sample are those age 18-34 and 35-49. Eighty four percent of males and 66% of females are married, while 78% of males and 85% of females have children. One-quarter of males and 36% of females have a university degree. Finally, given the focus on the most severe chronic illnesses, a relatively large number of individuals report having such conditions: over 6% (9%) of males (females) report having a heart condition, approximately 14% (18%) report having a chronic gastrointestinal or spinal condition and around 4% (7%) report liver, lung or kidney conditions.

The results of estimating Models 1-3, with odds ratios and confidence intervals, are presented in Tables 1-3 below. Model 1 clearly demonstrates that employment status is a strong predictor of mental distress among Russian men and women: both unemployed and labour force non-participants are more likely to experience depression or a nervous breakdown among males; while, among females, there is no effect of labour force participation as the proportion in this category is relatively small. For men the effect of labour force non-participation is more detrimental to mental health than unemployment (OR =3.89 vs. OR=1.833) while, for women, the odds ratio for the unemployment effect is 1.829. Elsewhere, the results are consistent with the previous literature for Russia [30] and for other countries [31], finding strong evidence that the probability of reporting depression or nervous breakdown is associated with being divorced or widowed. For education, consistent with the literature [2; 5; 32], the results are inconclusive, Only for women do we see a significant effect for those with tertiary education, with the most educated being the least likely to report suffering from depression. The income quintiles give a clear steer for both males and females: those in the upper quintiles are the least likely to report mental health problems. We also observe that Russia’s Muslim population appears less likely to report mental distress and those in oblast centres (the bigger regional towns) are marginally more likely to report being depressed than those in other areas, though there is no difference in comparison with rural areas.

(TABLE 1 HERE)

Tables 2A and 2B examine the underlying mechanism linking unemployment and mental health. For males, we observe again that current employment status is a strong predictor of the absence of depression or nervous breakdown, but we find no evidence that the duration variables are significant. That is, we find no evidence that the direct mechanism is driving the results. Instead, for males, it would appear that it is mental well-being that influences labour market outcomes (selection effect) rather than the other way around. For women, we observe no contemporaneous relationship between labour market status and mental distress but, as for males, we do find the selection effect is present in the case of unemployment. For both men and women, the other results remain as reported in Table 1.

(TABLES 2A AND 2B HERE)

While these effects estimates allow us to mitigate the confounding effects of unobserved time-invariant variables, it is plausible that there are unobserved time-varying changes in individual health during the period of analysis. We therefore re-estimate Model 2B, incorporating a variable that captures physical health status, in the form of a series of chronic illness dummy variables. We do indeed find that physical morbidities are strong predictors of mental distress. For example, men (women) with a chronic spinal condition are 2.07 (1.75) times more likely to report depression and/or nervous breakdown in the past year. We find that for both men and women, the main results concerning the direct effect and selection effect mechanisms remain qualitatively intact though there is a suggestion that we observe an age effect (for females) once we control for health conditions.

(TABLE 3 HERE)

Finally, before turning to a discussion of these results, we report three sets of robustness tests (available on request). First, we re-estimate the models, lagging all independent variables by 1 period and, in so doing, remove the possibility of a selection effect from the estimate. For both males and females, the lagged effects of unemployment and labour force non-participation are not significant, suggesting that, once the selection mechanism is removed, there is no relationship between unemployment/labour market inactivity and mental distress. Second, we further note that the results also remain qualitatively the same when estimated with the, more consistent, fixed effects logit model. Third we estimate the models using only the balanced panel of individuals present in all of years 2011-2017.

Discussion

The relationship between unemployment and mental health has been extensively explored and pervasive evidence of a negative association has accumulated in relation to many OECD and advanced economy settings. There is more limited evidence on the link between exiting the labour market and mental health but, what there is, it suggests a similar association. There is less consensus regarding the nature of this negative association: does unemployment result in worsening mental health or (and) are people with mental health problems more likely to become unemployed? There is little empirical evidence on either of these questions for Russia. Yet with its peculiar set of labour market institutions, that embed wage flexibility and precarity while supressing unemployment, and with the attitudinal legacies of a Soviet regime hostile to the idea of mental illness, Russia represents an intriguing case.

In this paper, we address each of these questions by exploring the relationship between the labour market and depression or nervous breakdown in the Russian context. Identifying a large sample of employed adults in 2011 and following their labour market experiences in annual surveys through to 2017, we are able to demonstrate the association and say something of the mechanism which underlines it. We claim three main contributions. First, we find that individuals exiting employment, whether into unemployment, retirement or otherwise out of the labour force, are significantly more likely to report depression and/or nervous breakdown, regardless of gender. Second, the evidence in these data are more supportive of the proposition that this relationship reflects a selection effect rather than suggesting an underlying direct causal link from unemployment to mental distress. That is, we find that it is those reporting mental illness that are themselves more likely to relinquish employment. Third, we document evidence of a clear socioeconomic gradient in mental well-being and a strong association with other chronic conditions. Those with higher incomes and women with better educational records are less likely to report suffering mental illness, while those with chronic illnesses are more likely to do so.

To be clear, we are not arguing that exiting from employment does not have a deleterious impact on mental health. Far from it, becoming unemployed, leaving the labour market, being forced to take early retirement, can all result in profound psychological distress which extends well beyond the financial and material burdens that may befall the individual and their family. Instead, we are making the case that, because there is only very limited evidence (for males in long term unemployment) of a link between the duration of unemployment/labour market inactivity and mental distress, it would appear that processes of mental disintegration which are likely to be triggered by ongoing labour market frustrations and perceived failures do not capture the underlying mechanism in Russia's case.

Instead, the evidence suggests that, in Russia, it is the selection effect that dominates. That is, it is mental distress itself that triggers job loss, attrition from the labour market and perhaps also early retirement. How precisely this mechanism operates is beyond the scope of this research. It may be that individuals with mental illness find themselves with reduced hours, or lower wages, or in less fulfilling jobs that result in disengagement and perhaps dismissal, or early exit from the labour market. This may reflect, as suggested by Westerlund et al. [25], that these individuals are more likely to become fatigued or less productive and therefore are more likely to exit the labour market. Alternatively, or as well, intolerance, unfair treatment, inflexible work patterns, being tasked with unmanageable workloads, and facing unsympathetic employers are all factors that can result in either 'voluntary' or forced attrition from the formal labour market.

Policy implications

Knowledge of the mechanism that underscores the negative association between unemployment and mental health is crucial because it dictates the appropriate policy response. The selection effect, which we document in this research, may stem from pervasive stigma and persistent misunderstandings and misconceptions, between employers, employees and co-workers concerning what mental illness is and is not. The associated behaviours and actions can force employees to self-select into less favourable positions, to leave employment or to be dismissed. The policies to address this are quite distinct from those required to address mental illness when it is a *consequence* of unemployment or inactivity rather than a contributing *cause*.

To address the selection effect, occupation-based policies involving the re-design of work patterns and places, healthcare interventions, or both, may be required to facilitate enhanced labour market participation of the growing numbers of individuals facing mental ill-health. Additionally, policy makers should initiate widespread anti-stigma campaigns in places of work, among the lay population and also among policy makers, politicians, academics and practitioners within the healthcare system. The widespread conception in Russia that mental disorders are somehow different to 'real' illnesses should be addressed and Russia's labour code must protect those with mental (or physical) health problems from being discriminated against. Third, mental health care in Russia itself needs destigmatising and deinstitutionalising so that those suffering from mental illness can be supported through modern treatment regimens that facilitate their continued and successful labour market activity. These policies differ from those which would address the direct effect of unemployment on mental health problems. The latter (also important) call for a focus on supporting people back into the labour market rapidly before mental ill-health can take a grip, rather than seeking to sustain workers with mental illness in the labour market in the first place.

Limitations

This study is, of course, not without limitations and our results should therefore be viewed with appropriate caution. First, our dependent variable, proxying mental health, is self-reported and so could include a lot of different psychic reactions. Second, by construction the study does not capture the adverse effects of part-time employment or reduced wages though we argue that these outcomes themselves may be products of mental ill-health among labour market participants and therefore part of the selection process. Third, though our empirical specification reflects the richness of the data, not everything is captured. For example, Lazarus stated that the "anticipation of harm can have effects as potent as experiencing the harm itself" [33], while Stauder notes that the relationships may themselves be time specific [18]. Fourth, while mental distress can be a short-term phenomenon, for many people it is persistent and enduring in ways that demand a more dynamic empirical setting that is beyond the scope of the current paper. Fifth, as with all empirical work of this kind, there are potential endogeneities within our modelling framework that we do not address. Finally, the recent COVID-19 pandemic has demonstrated that there are complex bidirectional links between physical and mental health including an increased risk of the prevalence of psychiatric disorders among those infected with physical diseases [34]. Since our study does not cover the period of the pandemic, we do not account for the possible adverse effect of COVID-19 in the mechanisms we discuss. However, future studies may need to account for a range of additional negative consequences for the mental health linked to self-isolation, compulsory furlough, dislocation from the work environment, the burden of home schooling, intensified online interaction and even the fear of pandemic. All of these limitations provide for a rich future research agenda related to mental well-being in Russia and beyond.

Conclusion

Depression, with more than 250 million recorded sufferers globally, is a leading cause of disability worldwide and is a major contributor to the overall global burden of disease. This paper has identified one important source of that disease burden, in the form of a labour market which is unable to adequately accommodate those with mental illness and instead forces them into unemployment, out of the labour market and into early retirement. Reducing mental health stigma in the Russian workplace, providing psychological and psychiatric support to those with mental health problems and redesigning occupational intervention strategies will improve the functioning of the Russian labour market, reduce the burden of disease and make for a fairer and more just society.

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Table 1: Baseline panel logit model with random effects, 2011-2017 (Model 1)

	Males		*Females*	
	OR	*CI*	*OR*	*CI*
Age 2	1.181	0.944-1.480	1.045	0.870-1.256
Age 3	1.154	0.882-1.510	0.965	0.777-1.120
Age 4	1.210	0.725-2.020	0.966	0.661-1.413
Single	0.999	0.695-1.435	1.146	0.888-1.480
Divorced	2.295***	1.580-3.336	1.898***	1.571-2.294
Widowed	7.854***	4.066-15.170	2.072***	1.631-2.632
Kids	1.007	0.766-1.324	0.931	0.742-1.167
Secondary	0.885	0.687-1.139	0.916	0.712-1.179
Technical & Medical	0.916	0.679-1.236	0.793*	0.608-1.035
University	0.856	0.627-1.170	0.540***	0.411-0.708
Pensioner	1.720**	1.215-2.435	1.600***	1.264-2.025
Out of labour force	3.890***	2.208-6.853	1.120	0.880-1.426
Unemployed	1.833***	1.366-2.462	1.829***	1.369-2.443
Income quintile 2	0.963	0.724-1.279	0.965	0.806-1.156
Income quintile 3	0.753*	0.562-1.010	0.757**	0.620-0.925
Income quintile 4	0.657**	0.492-0.878	0.721**	0.585-0.889
Income quintile 5	0.548***	0.406-0.739	0.699**	0.555-0.881
Orthodox denomination	1.203	0.949-1.525	1.067	0.819-1.391
Islamic denomination	0.682	0.414-1.122	0.547**	0.339-0.883
Other religion	0.335	0.031-3.596	1.623	0.572-4.601
PGT	0.361***	0.220-0.591	0.413***	0.284-0.602
Rural	0.953	0.731-1.244	1.038	0.841-1.282
Town	0.819	0.638-1.051	0.837*	0.689-1.017
2012	1.244*	0.969-1.598	1.110	0.927-1.330
2013	1.460**	1.138-1.873	1.186*	0.987-1.424
2014	1.331**	1.026-1.728	1.041	0.860-1.262
2015	1.225	0.938-1.600	1.043	0.858-1.268
2016	1.115	0.851-1.461	1.178*	0.969-1.432
2017	1.321**	1.006-1.735	0.723**	0.586-0.891
LR chi-square (31) *Prob>chi-square*	205.80 [0.0000]		245.80 [0.0000]	
Number of groups	*5,014*		*5,194*	
Total observations	*22,954*		*25,580*	

Notes: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 2A: Panel logit model with random effects, 2011-2017, plus unemployment duration (Model 2A)

	Males		*Females*	
	OR	*CI*	*OR*	*CI*
Unemployed for 2 years	0.862	0.479-1.551	0.949	0.490-1.837
Unemployed for 3 years	1.082	0.451-2.594	0.503	0.142-1.781
Unemployed for more than 3 years	2.172	0.773-6.102	0.502	0.039-6.511
LR chi-square (36) *Prob>chi-square*	208.61 [0,0000]		248.99 [0,0000]	
Number of groups	*5,014*		*5,194*	
Number of observations	*22,954*		*25,580*	

Notes: OR adjusted for age, marital status, children in household, education, religious affiliation, type of settlement; the full table is available from the authors upon request; ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 2B: Panel logit model with random effects, 2011-2017, plus unemployment duration and out of the labour force duration (Model 2B)

	Males		*Females*	
	OR	*CI*	*OR*	*CI*
Unemployed for 2 years	0.861	0.478-1.550	0.949	0.490-1.838
Unemployed for 3 years	1.082	0.451-2.593	0.503	0.142-1.782
Unemployed for more than 3 years	2.169	0.772-6.094	0.501	0.039-6.496
Out of labour force for 2 years	0.814	0.243-2.728	0.861	0.569-1.304
Out of labour force for 3 years	0.431	0.032-5.844	0.660	0.330-1.321
Out of labour force for more than 3 years	-	-	2.054	0.824-5.120
LR chi-square (41) *Prob>chi-square*	210.73 [0,0000]		252.35 [0,0000]	
Number of groups	*5,014*		*5,194*	
Number of observations	*22,949*		*25,580*	

Notes: OR adjusted for age, marital status, children in household, education, religious affiliation, type of settlement; the full table is available from the authors upon request; ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 3: Panel logit model with random effects, 2011-2017, including chronic conditions (Model 3)

	Males		***Females***	
	OR	*CI*	*OR*	*CI*
Age 2	1.061	0.844-1.332	0.932	0.776-1.120
Age 3	0.842	0.640-1.109	0.716**	0.574-0.893
Age 4	0.928	0.554-1.553	0.564**	0.381-0.835
Single	1.028	0.715-1.479	1.156	0.897-1.492
Divorced	2.371***	1.621-3.469	1.761***	1.456-2.128
Widowed	6.591***	3.366-12.905	1.887***	1.483-2.401
Kids	0.967	0.733-1.276	0.967	0.772-1.213
Secondary	0.901	0.696-1.167	0.934	0.724-1.203
Technical & Medical	1.014	0.749-1.372	0.803	0.616-1.047
University	0.888	0.648-1.216	0.548***	0.417-0.718
Pensioner	1.486**	1.035-2.131	1.473**	1.158-1.874
Out of labour force	3.594***	1.919-6.733	1.168	0.879-1.552
Unemployed	1.770***	1.262-2.483	1.856***	1.356-2.542
Income quintile 2	0.977	0.729-1.310	0.960	0.798-1.154
Income quintile 3	0.770*	0.570-1.041	0.747**	0.610-0.916
Income quintile 4	0.649**	0.482-0.875	0.715**	0.578-0.884
Income quintile 5	0.549***	0.403-0.747	0.673***	0.532-0.851
Orthodox denomination	1.178	0.925-1.500	1.112	0.850-1.455
Islamic denomination	0.603**	0.363-1.002	0.563**	0.349-0.910
Other religion	0.312	0.030-3.276	1.761	0.608-5.100
PGT	0.398***	0.244-0.648	0.435***	0.301-0.627
Rural	0.997	0.764-1.301	1.062	0.864-1.307
Town	0.865	0.675-1.110	0.915	0.756-1.107
Unemployed for 2 years	0.875	0.467-1.638	0.857	0.432-1.700
Unemployed for 3 years	0.837	0.320-2.185	0.603	0.168-2.161
Unemployed for 3+ years	2.802*	0.924-8.504	0.496	0.039-6.322
Out of labour force for 2 years	0.927	0.271-3.172	0.902	0.592-1.374
Out of labour force for 3 years	0.371	0.026-5.240	0.678	0.338-1.359
Out of labour force 3+ years	-	-	2.072	0.830-5.170
Heart	2.074***	1.573-2.735	1.750***	1.441-2.127
Lungs	1.622**	1.180-2.232	1.227	0.952-1.582
Liver	2.107***	1.523-2.914	1.503***	1.214-1.860
Kidney	1.259	0.869-1.826	1.483***	1.203-1.829
Gastro	1.382**	1.110-1.721	1.453***	1.247-1.694
Spine	2.293***	1.879-2.803	1.630***	1.394-1.905
Other	1.673**	1.012-2.764	1.848***	1.378-2.477
LR chi-square (48) *Prob>chi-square*	366.08 [0.0000]		444.73 [0.0000]	
Number of groups	*4,999*		*5,179*	
Total observations	*22,251*		*24,790*	

Note: adjusted for time dummies; ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

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Electronic Supplementary Material

Table ES1. Descriptive statistics for core samples

Variable Name	*Definition*	*Males*		*Females*	
		Mean	**SD**	**Mean**	**SD**
	Model 1	**N=22,954**		**N=25,580**	
Depress	1= serious nervous breakdowns, depression, past 12 months; 0=otherwise	0.069	0.253	0.118	0.323
*Age 1**	Age group 0. 1 = individuals below 34; 0=otherwise	0.361	0.480	0.283	0.451
Age 2	Age group 2. 1 = individuals aged 35-49; 0=otherwise	0.357	0.479	0.378	0.485
Age 3	Age group 3. 1 = individuals aged 50-64; 0=otherwise	0.246	0.431	0.292	0.455
Age 4	Age group 4. 1= individuals aged 65+; 0=otherwise	0.035	0.183	0.046	0.210
Sing	1=single; 0=otherwise	0.109	0.311	0.098	0.297
Div	1=divorced or married but not living together; 0=otherwise	0.040	0.196	0.148	0.356
Wid	1= widowed; 0=otherwise	0.010	0.099	0.099	0.298
*Mard**	1=married; 0=otherwise	0.841	0.365	0.655	0.475
Kids	1=has children; 0=otherwise	0.777	0.416	0.850	0.357
*Less than secondary**	1=basic or incomplete secondary education; 0=otherwise	0.146	0.352	0.076	0.263
Second	1=secondary education; 0=otherwise	0.380	0.485	0.255	0.436
Vocational	1=vocational education; 0=otherwise	0.226	0.418	0.306	0.461
Uni	1=higher education or graduate degree; 0=otherwise	0.247	0.432	0.363	0.481
*Work**	1=employed; 0=otherwise	0.893	0.309	0.829	0.376
Pens	1=retired; 0=otherwise	0.045	0.207	0.074	0.262
Out_lf	1=out of labour force; 0=otherwise	0.008	0.090	0.067	0.251
Unemp	1=unemployed; 0=otherwise	0.054	0.226	0.029	0.169
Orthod	1=religion is Orthodoxy; 0=otherwise	0.814	0.389	0.902	0.297
Isl	1=religion is Islam; 0=otherwise	0.062	0.240	0.044	0.206
Reloth	1=another religion (not Islam or Orthodoxy); 0=otherwise	0.003	0.051	0.003	0.053
*Athe**	1=atheism 0=otherwise	0.115	0.319	0.043	0.203
*Ob_centr**	1=regional (oblast) centre; 0=otherwise	0.385	0.489	0.405	0.491
Pgt	1=urban-type settlement; 0=otherwise	0.068	0.252	0.068	0.252
Rural	1= rural settlement; 0=otherwise	0.252	0.434	0.233	0.423
Town	1= town; 0=otherwise	0.294	0.456	0.294	0.456
	Model 2 (duration)				
Unemp_2y	1=unemployed for 2 consecutive years; 0=otherwise	0.018	0.135	0.007	0.086
Unemp_3y	1=unemployed for 3 consecutive years; 0=otherwise	0.008	0.092	0.003	0.053
Unemp_+3	1=unemployed for 3 or more consecutive years; 0=otherwise	0.004	0.062	0.001	0.031
Out_2y	1=out of labour force for 2 consecutive years; 0=otherwise	0.002	0.047	0.032	0.175
Out_3y	1=out of labour force for 3 consecutive years; 0=otherwise	0.001	0.028	0.013	0.112
Out_+3	1=out of labour force for 3 or more consecutive years; 0=otherwise	0.000	0.015	0.004	0.065
	Chronic illness variables (Model 3)	**N=22,251**		**N=24,970**	
Heart	1=has heart disease 0=otherwise	0.066	0.249	0.095	0.294
Lungs	1=has lungs disease 0=otherwise	0.052	0.221	0.055	0.228

Liver	1= has liver disease 0=otherwise	0.043	0.204	0.074	0.262
Kidney	1= has kidney disease 0=otherwise	0.038	0.192	0.077	0.266
Gastro	1=has gastrointestinal problems 0=otherwise	0.136	0.343	0.178	0.383
Spine	1=has spine disease 0=otherwise	0.143	0.350	0.164	0.370
Other	1=has other chronic condition 0=otherwise	0.015	0.123	0.027	0.161