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ORIGINAL RESEARCH

Unemployment and Mental Health: An Instrumental Variable Analysis Using Municipal-level Data for Finland for 2002–2019

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Abstract
We explore the effect of unemployment on mental health, using data from Finnish municipalities for the period 2002–2019. We measure mental illness using a mental morbidity index, as well as mental health care utilization and the use of antidepressants. There are significant differences across municipalities in Finland in both prevalence of mental health issues and illnesses, along with unemployment. Establishing a causal link between these two variables is challenging because of their reverse causality and joint determination. Using instrumental variable estimation, we establish a causal effect from unemployment to mental health. We present a strong connection between unemployment and mental health, especially for males between 25 and 64 years of age. Similar connection is not found among younger or older males, nor among females. Our findings are robust, since the results hold for various mental health measures. Our results reflect the possibility of differing mental health effects across the sources of unemployment.

Keywords Mental health · Unemployment · Panel data · Instrumental (IV) estimation

1 Introduction

The association between unemployment and mental health is extensively examined in the literature (see, e.g., Milner et al., 2013, 2014; Paul & Moser, 2009). However, the question of causality between these two variables is still poorly understood. The factors that may weaken the mental health of unemployed people might be the same factors that select these individuals into unemployment. Schmitz (2011) reports three different pathways possibly leading to the observation that unemployed workers have worse mental health than employed ones (see also Farré et al., 2018). First, individuals who are mentally ill are more likely to lose their jobs and become unemployed. Second, many studies show that unemploy-

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ment leads to deterioration in mental health.[1] In a recent meta-analysis on the relationship between unemployment and health, Picchio and Ubaldi (2022) find that the psychological domains of health are those most sensitive to unemployment and that it is the occurrence of unemployment that matters, rather than its duration. Cygan-Rehm et al. (2017) also show that even short-term unemployment impairs mental health. Third, poor mental health increases the duration of unemployment which, by itself, is a risk factor for mental illness. In addition, there exist individual unobservable factors that affect both mental health and the probability of becoming unemployed. These joint determination effects might even be heritable or related to genetic factors (Middeldorp et al., 2006; Schmitz, 2011).

The reverse causality of and joint determination between unemployment and mental health can severely bias basic fixed effects (FE) regression estimates. The FE estimate of unemployment on mental health would be biased upwards if, for example, worsening mental health increases unemployment. On the contrary, estimates are biased downwards if, for example, during economic downturns or recessions, the unemployment rate tends to increase more in municipalities where it has less-adverse effects on mental health, perhaps due to already high levels of mental health problems or because of possible social norm effects of unemployment (see, e.g., Huikari & Korhonen, 2016). The bias of FE estimates can also be a result of a third factor, such as active labour market programmes that coincide with other social support programmes that tend to decrease both unemployment and mental health problems. To the extent that (mental) health problems cause unemployment, changes in labor market conditions can be endogenous to changes in local (mental) health indices. It is also possible that relatively more people become unemployed due to mental health problems, and if these problems continue and/or are severe, these people might end up receiving disability allowances or part-time or full-time disability pensions. This would lead to situations where worsening mental health would seemingly decrease these people's unemployment status because they would no longer be considered officially unemployed but mentally disabled and, therefore, unable to work.

To deal with these above-mentioned potential reverse causalities and simultaneous biases, we employ an instrumental variable (IV) strategy in this study. Commonly used variables for explaining exogenous variation in unemployment, when identifying the causal effect of job loss on health, are plant closures and mass layoffs (Browning & Heinesen, 2012; Eliason & Storrie, 2009; Schaller & Stevens, 2015; Sullivan & von Watchter, 2009). These instrumental variables are used to isolate the part of job loss that is exogenous to an individual worker's health (Browning & Heinesen, 2012; Schaller & Stevens, 2015; Sullivan & von Watchter, 2009). However, plant closures and mass layoffs are relatively rare events, and they may be limited to specific populations (often blue-collar workers) in specific geographic areas, therefore restricting the generalizability of the study (Brand, 2015).

In this study, we follow Bartik (1991), Gould et al. (2002), Öster and Agell (2007), and Farré et al. (2018) and combine the local industry composition with national changes in employment across industries to isolate local labor demand shocks. The idea behind our identification strategy is to use the industrial composition at the municipal level, at the beginning of the period of our study, to predict any exogenous changes in municipal employment levels over time. Our instrument therefore also implicitly includes plant closures or mass

[1] Important opposite results have also been presented, for example, Böckerman and Ilmakunnas (2009), using the European Community Household Panel for Finland over the period 1996–2001, did not find negative effects of unemployment on health indicators that also covered mental aspects of health.

layoffs in Finnish municipalities. In addition, it takes into account possible larger sectoral shifts in the demand for labor that could affect unemployment.

Exploring the relationship between unemployment and mental health is particularly interesting in Finnish context, due to at least two aspects. First, Finland has the highest estimated prevalence of mental health disorders in EU (with rate of 18.8% of the population with at least one disorder in 2016). The most common mental disorder is depressive disorder, which affected 6% of Finnish population in 2016-well above the EU28 average (OECD, 2018, 2020).[2] In addition, drug and alcohol use disorders affect 4% of Finns, compared with the EU28 average of 2.4% (OECD, 2018, 2020). According to Finnish Centre for Pensions (https://www.etk.fi/en/topical-issues/mental-disorders-the-most-common-reason-for-retirement-on-a-disability-pension/), mental disorders are currently the most common reason for retirement on a disability pension.

Second, the unemployment rate in Finland has been at a relatively high level in the aftermath of the financial crisis and subsequent recession. Especially the variation in unemployment is high between municipalities. In 2016, for example, the unemployment rate varied from 4.1 to 21.1% between municipalities in our study sample, with the national unemployment rate of 13.2% (Ministry of Economic Affairs and Employment, https://tem.fi/en/regional-annual-averages).

We utilize municipal-level data from 258 Finnish municipalities (the smallest administrative units across all regions of the country) for the period 2002–2019. An important novelty of our paper is that we are able to use several different mental health measures. The first measure, a mental health index, measures mental distress at the level of the municipality. It refers to the prevalence of mental health problems, for different age groups, at the municipal level. The second measure for the prevalence of mental health is the proportion of anti-depressant users, data for which is derived from the prescription registry of the Social Insurance Institution of Finland. The proportion of antidepressant users provides a relevant proxy for the number of people with depression (Hiilamo, 2014). The third measure is psychiatric hospital care, measured as the number of periods of care days, during the year, for different age groups.

In addition, our data cover a relatively long time period that includes large variations in unemployment rates. In Finland, aggregate unemployment rates for the sample period range from a low of 2.2% to a high of 28.4%. The relatively large variation in the unemployment rate provides us with a deeper understanding of the association between unemployment and mental health. Our data also cover the financial crisis of 2008–2009 and the European Exchange Rate Mechanism crisis of 2011. This allows us to say something about the effects of economic crises on mental health.

We find that, in general, mental health worsened in Finland during the sample period. At the municipal level, mental health worsened in 130 (50.4%) of the 258 municipalities in our study. However, unemployment increased only in 8.5% of these municipalities, when comparing the economic situation between years 2002 and 2019.[3] The correlation coeffi-

[2] The World Health Organization (WHO) place Finland in the 8th highest place position among the countries with the highest depression rates (WHO, 2017).

[3] The national unemployment rate declined rapidly from 2015 to 2018, by 2.1% points. That was a result of the Finnish economy finally returning to a strong growth path in 2016, after an almost decade-long stagnation (Kyyrä & Pesola, 2020).

cient between unemployment and mental health at the municipal level was 0.49 ($p<0.001$) across the sample period.

Our main finding is that mental health deteriorates when unemployment increases. Our IV estimates suggest a significant negative effect of unemployment on overall mental health at the municipal level. Further, the unemployment rate is particularly related to poorer mental health among middle-aged men. Our IV estimates show that, controlling for the year effects, municipality fixed effects, and municipality-specific time trends, a one-percentage-point increase in the municipal unemployment rate is associated with a 0.28% increase in the share of antidepressant users and an 8.7% increase in the number of care periods in psychiatric hospitals among males in the 25–64 age group.

This paper proceeds as follows. The next section explains the research design. Section 3 presents the data used in our analysis, while Section 4 reports the empirical results. Section 5 discusses our findings and Section 6 concludes.

2 Research Design

The starting point for our investigation is the following standard fixed effects specification:

$$health_{mt} = \alpha_m + \theta ue_{mt} + \lambda_t + \delta_m t + \epsilon_{mt}, \tag{1}$$

where *m* and *t* indicate the municipality and time; $health_{mt}$ is dependent variable; α_m represents municipality fixed effects; λ_t is the year fixed effects; $\delta_m t$ denotes municipal-level time trends; and ue_{mt} is the unemployment rate.

To tackle the potential problems in Eq. (1), since the unemployment rate is likely to be endogenous because of the potential for both omitted variable bias and reverse causality, we estimate an IV fixed effects model in which ue_{mt} is instrumented by the growth in the total labor demand in municipality *m*. The instrumental variable estimation technique is commonly used to explore the relationship between unemployment and health. The identification strategy is to find a variable that predicts exogenous changes in unemployment over time but that does not directly affect mental health. The estimation is conducted in two steps. First, the instrumental variable is used to predict the unemployment rate in a first-stage equation. Secondly, the predicted unemployment is used in the original equation to estimate the causal effect.

By following the approach developed by Bartik (1991) and utilized by Blanchard and Katz (1992) and Autor and Duggan (2003), we construct our IV by interacting the initial sectoral composition of employment in each municipality with the national trends in the composition of employment. We exploit cross-municipality differences in the industrial composition and national-level changes in employment to predict employment growth at the level of the individual municipality. Provided that national industry growth rates are uncorrelated with municipal-level labor supply shocks, this approach will identify the exogenous variation in employment at the state level. The data for employment at both the municipal and national levels are obtained from Statistics Finland (2022a, 2022b) for the period 2002–2016. Industry *i*'s employment growth nationally between times *t-1* and *t* is

$$growth_i = \left(f_{i|t}/f_{i|t-1}\right) - 1,$$

where i denotes the industry and $f_{i|t}$ is industry i's share of employment at time t at the national level.

A change in total labor demand in municipality m is represented by

$$growthtotal_m = \sum_i f_{i|m,t-1} growth_i,$$

where $f_{i|m,t-1}$is industry i's share of employment at time t-1; that is, the share of employment in municipality m is lagged by one period. This is our first instrument for unemployment in municipality i. The second instrument is constructed in a similar manner to the first one, except that the industrial composition of employment in municipality m is lagged by two periods (Öster & Agell, 2007). We use these two variables as instrumental variables in order to identify the exogenous variation in the unemployment rate.

Similar to a study by Farré et al. (2018), the idea behind this IV approach is that aggregate changes in employment are not driven by municipal-specific characteristics. Instead, the effects identified through the IV approach are driven by changes that take place at the municipal level (that is, by changes within each of the almost 300 Finnish municipalities), such as a plant closure, causing a mass layoff. This implies that aggregate changes in employment cannot be explained by changes in the local economic climate or in the type of public sector spending, at the municipal level, that may directly affect the health and mental health of resident workers (see, Farré et al., 2018).

3 Data and Descriptive Statistics

This paper uses an unbalanced panel data set for Finnish municipalities, for the period 2002–2019, to explore the relationship between unemployment and mental health. Municipalities are the smallest administrative units across all regions of the country. Finland has 309 municipalities (2022). The average population of a municipality is around 17,000 inhabitants, ranging from several hundred in small communities to about 650,000 in the capital, Helsinki (Johansson et al., 2020). In Finland, local authorities may organize municipal administration relatively freely. They have strong self-government based on local democracy and decision-making and the right to levy taxes. Local authorities have also broad responsibility for the provision of basic public services to their residents (https://www.localfinland.fi/finnish-municipalities-and-regions).

Based on data availability, our panel data set includes between 254 and 258 of Finland's 309 municipalities.[4] The data underlying the results presented in the study are publicly available. We use municipal-level data, since both the economic situation and prevalence of mental health disorders vary significantly between regions, causing the heterogeneity among municipalities within a country. Furthermore, with municipality-level panel data,

[4] Due to the large effects of random variation on the mental health index, Finland's National Institute for Health and Welfare (THL) does not present that for the smallest municipalities, i.e. the population of a municipality less than 2,000 inhabitants. Of those smallest municipalities, the majority include in the autonomous region of Åland Islands. The population of Åland is only about 0.5% of that of mainland Finland, and the population of all the municipalities that are not in our study sample is about 1.4% of total population in Finland.

Table 1 Descriptive statistics

Variable	Mean	SD	Min	Max	Correlation	N
Mental health index	114.1	35.1	38.6	268.2	0.485***	4644
Unemployment rate (unemployed as a % of labor force)						
Total	10.8	3.8	2.2	28.4		4644
Male	11.3	4.5	1.7	31.8		4644
Female	10.1	3.4	2.5	24.0		4644
Unemployed young people, aged 18–24	14.1	5.7	1.2	36.7		4612
Reimbursements for depression medicines as a % of total population of the same age						
Total recipients aged 18–24	8.4	1.6	3.6	16.0	0.050***	4644
Total recipients aged 25–64	4.5	1.6	0.6	11.9	<0.001	4472
Total recipients aged 65 and over	10.6	1.9	3.2	19.2	-0.175***	4644
Male recipients aged 18–24	6.5	1.4	2.3	14.7	0.083***	4644
Male recipients aged 25–64	3.5	1.3	0.7	11.2	0.126***	3549
Male recipients aged 65 and over	7.9	1.8	1.6	18.4	-0.123***	4644
Female recipients aged 18–24	10.3	2.0	4.3	18.9	0.032**	4644
Female recipients aged 25–64	6.5	2.4	1.2	20.0	-0.069***	4056
Female recipients aged 65 and over	12.8	2.3	4.1	22.6	-0.187***	4644
Psychiatric inpatient care, periods of care per 1000 persons of the same age						
Total aged 18–24	11.5	8.1	0.8	177.1	0.098***	3830
Total aged 25–64	9.4	5.2	0.5	38.2	0.122***	4382
Total aged 65 and over	5.4	3.8	0.3	37.1	-0.098***	4388
Males aged 18–24	11.9	8.7	0.8	73.7	0.033*	3440
Males aged 25–64	9.9	6.2	0.4	44.7	0.098***	4608
Males aged 65 and over	5.8	5.0	0.4	78.6	-0.047***	3833
Females aged 18–24	16.3	14.7	1.0	311.1	0.051***	3400
Females aged 25–64	8.8	5.5	0.4	42.1	0.137***	4565
Females aged 65 and over	6.1	4.7	0.4	60.0	0.088***	4056

Number of municipalities ranges between 254 and 258, according to data availability. The source of data is the Finnish institute for health and welfare (THL) which can be accessed at https://sotkanet.fi/sotkanet/en/index. Correlations are pairwise correlations between mental health measures and unemployment rate. ***$p<0.01$, **$p<0.05$, *$p<0.1$

time-invariant region-specific effects as well as time effects, which are common in all regions but vary over time, can also be controlled.

Data on unemployment and mental health variables are obtained from the Sotkanet Indicator Bank (https://sotkanet.fi/sotkanet/en/index), which provides data obtained from Finland's National Institute for Health and Welfare (THL) and from various other official sources. These data offer key population welfare and health statistics from 1990 onwards for all Finnish municipalities. The THL is also responsible for the maintenance and development of statistical and registry resources. Table 1 shows the summary statistics of all of the variables used in our empirical analyses. A detailed description of the variables used and their sources are presented in the Online Resource: Variable descriptions and data sources.

The main dependent variable is the *Mental Health Index (MHI)*, which comprises three core mental health indicators of equal weight: suicides and suicide attempts, entitlement to special refunds for psychosis-related medications, and disability pensions due to mental health issues. The *MHI* is updated annually and provides information about the prevalence of mental health problems in various municipalities in Finland. This index is calculated according to a base index value of 100 for the whole country. The lower the figure, the healthier the population in a municipality, and vice versa. We use an age-standardized version of the mental health index, since it describes those regional differences that do not depend on differences in age structure.

The data on the components of the mental health index are not publicly available at municipal level, nor is the data on sex-specific or age-group specific mental health index. However, we are able to use other variables as measures for the prevalence of mental health problems, namely *reimbursements for depression medications* and *psychiatric inpatient care*. *Reimbursements for depression medications* show the number of people aged between 18 and 65 years and over, who are receiving reimbursements for antidepressants, per 1,000 persons of the same age during the year. The data are available across three age groups (18–24, 25–64, and 65 and over). *Psychiatric inpatient care (periods of care)* shows the number of periods of care for those in the same age groups who are in psychiatric hospital care, per 1,000 persons of the same age during the year.

Our main explanatory variable, *the unemployment rate (as % of labor force)*, shows the rate of unemployment as a percentage of the total labor force. An unemployed person is one who is not in an employment relationship or who is not full-time self-employed or a full-time student in the manner referred to in the Unemployment Security Act. The unemployment rate is measured for the total population, as well as separately for males and females. *Unemployed young people (as a percentage of the labour force)* shows the percentage of unemployed people aged 15 to 24 in the labor force. Unemployed young people are jobless people aged between 15 and 24 years. An unemployed jobseeker is an individual without employment who is available for full-time employment or who is waiting for an employment relationship to begin. Those laid off are also counted as unemployed. Persons who receive unemployment pensions (before year 2012 the unemployment pension was a significant route to early retirement in Finland) are not included.

Table 1 shows substantial variation in both mental health measures and unemployment between municipalities. This suggests that using the municipal-level data in exploring the relationship between unemployment and mental health is important, since both the economic situation and prevalence of mental health disorders vary significantly within a country. Table 1 shows also the pairwise correlations of mental health measures and unemployment. The correlation coefficient between unemployment rate and mental health index is reasonably strong, 0.485 ($p<0.01$). The correlation between unemployment and the shares of antidepressant users is 0.126 ($p<0.01$) and −0.069 ($p<0.01$) for males and females aged 25–64, respectively. The correlation between unemployment and the periods of care in psychiatric hospitals is 0.098 ($p<0.01$) and 0.137 ($p<0.01$) for males and females aged 25–64, respectively. The correlation coefficients between unemployment rate and mental health measures for males and females aged 65 and over are all negative.

4 Empirical Results

We begin our analysis by exploring the levels of mental health measures between high and low unemployment municipalities. We define a municipality as high unemployment municipality if its unemployment rate exceeds the national unemployment rate for a given year, and as low unemployment municipality if municipality's unemployment rate is below or equal to the national unemployment rate. Table 2 presents the results of t-tests testing the difference in means of mental health measures between high and low unemployment municipalities. The results show that mental health is in general worse in high unemployment municipalities. Among both males and females between 18 and 64 years of age, share of antidepressant users, and care periods in psychiatric hospitals are higher in high unemployment municipalities. Among both males and females of 65 years of age and older the results seem to be opposite.

Next, we explore the effects of unemployment on mental health indicators using FE and IV-FE regression methods. Table 3 presents the FE and IV estimates of the unemployment effects on overall mental health. The FE estimate suggests that unemployment has a positive, but statistically insignificant ($p > 0.10$) association with mental health. In addition, the parameter estimate is also relatively low in magnitude; for example, a one-percentage-point increase in the unemployment rate is associated with a 0.69 unit increase in the mental health index. Given that, in our study sample, the values of the mental health index range between 38.6 and 268.2, the effect is not large.

Table 3 also presents the IV estimation results for the unemployment effect on mental health. At the bottom of the table, we report the validity tests for the instruments used in the first-stage regressions. We use the Sanderson-Windmeijer (SW) Chi-Squared statistic for the under-identification test that shows that both IVs are identified and, thus, are correlated with the endogenous explanatory variable ($p < 0.05$). The weak identification test, using the SW F-statistic, suggests that the instruments are not weakly correlated with the endogenous variable ($p < 0.05$). Finally, the Hansen J-test of the over-identifying restrictions suggests that the IVs used are uncorrelated with the error term ($p > 0.10$). Overall, these diagnostic tests from the first-stage regressions suggest that the validity and strength requirements for the IVs used are satisfied.

The IV estimation results show that when the endogeneity between unemployment and mental health is accounted for, a one-percentage-point increase in the unemployment rate increases the mental health index by 1.56 units; that is, mental health deteriorates. The effect is statistically significant ($p < 0.05$). The size of the estimated effect exceeds the corresponding value of the FE estimate. We should also mention that it is not necessarily rare to see large changes in the magnitude of the coefficients or even for the signs to be reversed when switching between the OLS and the IV approach in the same analysis (see, e.g., Caroli & Godard, 2016; Coe & Zamarro, 2011; Reichert & Tauchmann, 2011; Vandoros et al., 2020). In addition, the FE model shows associations between dependent variable and explanatory variables, while the IV-FE model investigates the effects of the explanatory variable on the dependent variable, subject to the assumptions regarding the instruments used (Vandoros et al., 2020). The changes in the coefficients are also in line with our earlier reasoning of the ignored reverse causality, the joint determination, and the omitted variables most likely biasing the FE estimates in ambiguous directions, ex ante.

Table 2 T-test results of difference in means of mental health measures between high and low unemployment municipalities

	High unemployment municipalities (n)	Low unemployment municipalities (n)	Mean in high unemployment municipalities	Mean in low unemployment municipalities	Difference in means	t-value	p-value
Mental health index	2218	2426	126.05	97.19	28.86	32.25	$<0.001^{***}$
Reimbursements for depression medicines as a % of total population of the same age							
Total recipients aged 18–24	2526	2118	8.48	8.22	0.26	5.80	$<0.001^{***}$
Male recipients aged 18–24	2526	2118	6.67	6.33	0.34	8.15	$<0.001^{***}$
Female recipients aged 18–24	2526	2118	10.45	10.21	0.24	4.10	$<0.001^{***}$
Total recipients aged 25–64	2114	2358	4.61	4.43	0.18	3.85	$<0.001^{***}$
Male recipients aged 25–64	1507	2042	3.67	3.37	0.30	7.10	$<0.001^{***}$
Female recipients aged 25–64	2040	2016	6.63	6.43	0.20	2.70	0.007^{***}
Total recipients aged 65 and over	2218	2426	10.38	10.86	-0.48	-8.70	$<0.001^{***}$
Male recipients aged 65 and over	2017	2627	7.79	8.00	-0.21	-3.95	$<0.001^{***}$
Female recipients aged 65 and over	2425	2219	12.35	13.20	-0.85	-12.75	$<0.001^{***}$
Psychiatric inpatient care, periods of care per 1000 persons of the same age							
Total aged 18–24	2127	1703	12.14	10.60	1.54	5.90	$<0.001^{***}$
Males aged 18–24	1971	1469	12.17	11.46	0.71	2.40	0.017^{**}
Females aged 18–24	1900	1500	17.07	15.40	1.67	3.30	0.001^{***}
Total aged 25–64	2116	2266	10.23	8.71	1.52	9.85	$<0.001^{***}$
Males aged 25–64	2001	2607	11.00	9.14	1.86	10.3	$<0.001^{***}$
Females aged 25–64	2385	2180	9.41	8.16	1.25	7.70	$<0.001^{***}$
Total aged 65 and over	2088	2300	5.19	5.62	-0.43	-3.75	$<0.001^{***}$
Males aged 65 and over	1640	2193	5.60	6.00	-0.40	-2.40	0.017^{**}
Females aged 65 and over	2078	1978	5.90	6.36	-0.46	-3.10	0.002^{***}

A municipality is defined as high unemployment municipality if its unemployment rate exceeds the national unemployment rate for a given year, and as low unemployment municipality if municipality's unemployment rate is below or equal to the national unemployment rate. ***$p<0.01$, **$p<0.05$, *$p<0.1$

The results in Tables 4 and 5 show the FE and IV-FE estimation results for the effects of unemployment on the shares of antidepressant users in three different age groups for the total population and also separately for males and females. In all of the regressions for the 18 to 24 age group, total unemployment is the explanatory variable because data on sex-specific unemployment for younger members of the labor force are not available at the municipal level. Among those in the 25 to 64 age group, we use sex-specific unemployment rates for males and females, respectively. For those aged 65 years and older, we use the total unemployment rate in all of our regressions because the unemployment rate for that age group is not available. Furthermore, unemployment per se is likely not that important an issue for the oldest age group, but the general unemployment rate can still be used as a proxy for the macroeconomic conditions, in the analysis. Total, sex- and age-specific unemployment rates are used in the same manner in the estimations of the effects of unemployment on the number of periods of care in psychiatric hospitals. Those results are reported in Tables 6 and 7.

The FE estimation results in Table 4 show a negative relationship between unemployment and the share of antidepressant users among the 18 to 24 and 25 to 64 age groups, and positive relationship among males and females of 65 years of age and older. However, the effects are statistically insignificant ($p > 0.10$) except among females in the 25 to 64 age group.

Table 5 presents the IV results for the relationship between unemployment and the share of antidepressant users. Both the under-identification tests and the weak-identification tests show that a change in the total labor demand at the municipal level is not a strong predictor for the unemployment rate of 18 to 24 year old, in general, or for females aged between 25 and 64. However, for males aged 25 to 64, the test results show that both IVs are identified and that the instruments are not weakly correlated with the unemployment rate, indicating that, for this group, it is very unlikely that the estimate is being biased by the weak instrument. Thus, once the endogeneity between unemployment and the usage of antidepressants is accounted for, a one-percentage-point increase in the unemployment rate increases the share of antidepressant users by 0.28% points for males aged 25 to 64. Another statistically significant relation between unemployment and the usage of antidepressants seems to exist among females aged 65 or older, with one-percentage-point increase in the unemployment rate increasing the share of antidepressant users by 0.15% points. This result needs to be cautiously interpreted, since unemployment per se shouldn't be an issue among aged 65 or older, but rather it might imply the effect of the general macroeconomic conditions.

Tables 6 and 7 present the FE and IV-FE estimates of the impact of unemployment on the number of periods of care in psychiatric hospitals. The FE results show negative and significant associations between unemployment and periods of psychiatric care for males aged between 18 and 24 and for females aged 65 years and older. Table 7 presents the IV results for the relationship between unemployment and the number of care periods in psychiatric hospitals. Once accounting for the endogeneity between unemployment and mental health care periods, we can see that for males aged between 25 and 64, a 1%-point increase in the unemployment rate increases the number of care periods in psychiatric hospitals by 8.7%.

Table 3 Fixed effects and instrumental variable estimates for the impact of unemployment on mental health

	FE Mental health	IV-FE Mental health
Unemployment	0.069 (0.46)	1.56** (0.77)
Obs	4644	4644
R^2	0.47	
1st -stage coeff. instrument$_1$		-12.82*** (2.44)
1st -stage coeff. instrument$_2$		-19.02** (7.87)
SW chi-squared (p-value)		32.46 (<0.001)
SW F-statistic (p-value)		14.42 (<0.001)
Hansen J-statistic (p-value)		1.94 (0.16)

FE refers to fixed effects estimates and IV-FE refers to instrumental variable fixed effects estimates. The dependent variable is the mental health index. All regressions include municipal-specific effects, year-specific effects, and municipal-level trends. Regressions are weighted by the square root of the population living in municipalities. Standard errors (in parentheses) are robust to heteroskedasticity and consistent with respect to serial correlation within municipalities. The unemployment variable used in the IV-FE model is the observed unemployment rate in a municipality instrumented by two predicted employment change measures: the national trend in industrial growth rates interacted with the municipal-level composition of industrial employment, lagged one period and two periods, respectively. The Sanderson-Windmeijer (SW) chi-squared and F-statistic test the null hypotheses of under-identification and the weak instruments, respectively, for the endogenous regressor (here, the unemployment rate). The Hansen J-statistic tests the over-identifying restrictions. The associated p-values are given in parentheses under the test statistics. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 4 Fixed effects estimates of unemployment on shares of antidepressant users

	18–24	18–24 males	18–24 females	25–64	25–64 males	25–64 females	65+	65+males	65+females
Unemployment	-0.009* (0.005)	-0.009 (0.006)	-0.009 (0.005)	-0.060*** (0.011)	-0.007 (0.005)	-0.078*** (0.024)	0.015 (0.019)	0.014 (0.017)	0.018 (0.022)
Obs	4612	4612	4612	4472	3549	4056	4644	4644	4644
R^2	0.90	0.84	0.88	0.64	0.48	0.62	0.69	0.60	0.66

All regressions include municipal-specific effects, year-specific effects, and municipal-level trends. Regressions are weighted by the square root of the municipal population. Standard errors (in parentheses) are robust to heteroskedasticity and are consistent with respect to serial correlation within municipalities. ***$p<0.01$, **$p<0.05$, *$p<0.1$

5 Discussion

We analyze the effects of unemployment on mental health, using Finnish municipal-level data for the period 2002–2019. Establishing a causal link between these two variables is challenging because of their reverse causality and joint determination. The simultaneity

Table 5 Instrumental variable estimates of unemployment on shares of antidepressant users

	18–24	18–24 males	18–24 females	25–64	25–64 males	25–64 females	65+	65+males	65+females
Unemployment	0.22 (0.15)	0.24 (0.15)	0.15 (0.13)	0.15 (0.10)	0.28*** (0.04)	0.44 (0.27)	0.23** (0.10)	0.37* (0.20)	0.15*** (0.06)
Obs	4612	4612	4612	4472	3569	4054	4644	4644	4644
1st -stage coeff. instrument_1	-20.12 (12.32)	-20.02 (12.35)	-20.26 (12.28)	-12.55*** (2.80)	-23.23*** (4.08)	-5.61** (2.77)	-12.61*** (2.31)	-12.76*** (2.27)	-12.49*** (2.34)
1st -stage coeff. instrument_2	-22.63 (16.42)	-22.28 (16.49)	-23.08 (16.34)	-19.41** (8.00)	-29.68** (11.72)	-10.88** (5.11)	-19.31** (7.95)	-19.51** (7.95)	-19.16** (7.94)
SW chi-squared	3.29 (0.19)	3.23 (0.20)	3.38 (0.18)	25.18 (<0.001)	38.29 (<0.001)	9.78 (0.01)	35.76 (<0.001)	37.93 (<0.001)	34.30 (<0.001)
SW F-statistics	1.46 (0.26)	1.43 (0.27)	1.50 (0.25)	11.16 (<0.001)	16.69 (<0.001)	4.31 (0.03)	15.89 (<0.001)	16.85 (<0.001)	15.24 (<0.001)
Hansen J-statistic	0.03 (0.87)	0.03 (0.87)	<0.01 (0.98)	2.88 (0.09)	1.50 (0.22)	1.76 (0.18)	1.48 (0.22)	1.30 (0.25)	1.31 (0.25)

All regressions include municipal-specific effects, year-specific effects, and municipal-level trends. Regressions are weighted by the square root of the population living in municipalities. Standard errors (in parentheses) are robust to heteroskedasticity and are consistent with respect to serial correlation within municipalities. The unemployment variable used in the IV-FE model is the observed unemployment rate in a municipality, instrumented using two predicted employment change measures: the national trend in industrial growth rates interacted with the municipal-level composition of industrial employment, lagged one period and two periods, respectively. The SW chi-squared and F-statistics test the null hypotheses of under-identification and weak instruments, respectively, for the endogenous regressor (here, the unemployment rate). The Hansen J-statistic tests the over-identifying restrictions. The associated p-values (in parentheses) are given in parentheses under the test statistics. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 6 Fixed effects estimates of unemployment on periods of care in psychiatric hospitals

	18–24	18–24 males	18–24 females	25–64	25–64 males	25–64 females	65+	65+males	65+females
Unemployment	-0.003 (0.003)	-0.011** (0.005)	0.078 (0.045)	-0.001 (0.004)	0.004 (0.004)	-0.007 (0.007)	-0.006 (0.006)	0.004 (0.005)	-0.026*** (0.006)
N	4029	3430	3390	4637	4608	4565	4388	3833	4056
R^2	0.20	0.19	0.27	0.48	0.41	0.36	0.29	0.24	0.25

In all of the regressions, the dependent variable is the log of the number of periods of care in psychiatric hospitals. All of these regressions include municipal-specific effects, year-specific effects, and municipal-level trends. Regressions are weighted by the square root of the municipal population. Standard errors (in parentheses) are robust to heteroskedasticity and are consistent with respect to serial correlation within municipalities. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

in the health–unemployment relationship can bias fixed effects estimates of how unemployment is associated with health and especially mental health (e.g., Milner et al., 2014; Schmitz, 2011). We propose an identification strategy based on an instrumental variable approach to estimating the causal effects of unemployment on mental health. We instrument unemployment rates at the municipal level by the change in total labor demand in municipalities to predict exogenous changes in unemployment over time. We provide evidence that the mental health of males aged 25 to 64 years markedly deteriorates when this group experiences increased unemployment. This is in line with the earlier literature that stressful life-events, like unemployment have a more negative effect especially for mid-age males

Table 7 Instrumental variable estimates of unemployment on care periods in psychiatric hospitals

	18–24	18–24 males	18–24 females	25–64	25–64 males	25–64 females	65+	65+males	65+females
Une	0.049 (0.051)	0.229 (0.197)	-0.926 (0.134)	0.036 (0.021)	0.087*** (0.026)	-0.267* (0.141)	0.024 (0.071)	0.160* (0.089)	-0.039 (0.077)
N	4029	3429	3390	4637	4608	4565	4388	3832	4056
1st -stage coeff. instrument$_1$	-22.23 (13.49)	-21.46 (14.05)	-23.51 (16.47)	-12.82*** (2.50)	-19.94*** (4.02)	-4.76** (2.02)	-11.23*** (2.17)	-10.32*** (2.27)	-10.81*** (1.87)
1st -stage coeff. instrument$_2$	-25.17 (16.32)	-19.03 (15.72)	-31.32 (17.82)	-19.05** (7.88)	-26.78** (11.12)	-9.86* (5.41)	-18.56** (7.96)	-18.51** (8.66)	-17.70** (7.85)
SW chi-squared	3.41 (0.18)	2.83 (0.24)	3.60 (0.17)	31.06 (<0.001)	28.65 (<0.001)	9.61 (0.01)	34.18 (<0.001)	28.47 (<0.001)	47.57 (<0.001)
SW F-statistics	1.50 (0.25)	1.23 (0.32)	1.56 (0.24)	13.80 (<0.001)	12.72 (0.001)	4.26 (0.03)	15.13 (<0.001)	12.48 (0.001)	20.94 (<0.001)
Hansen J-statistic	2.19 (0.14)	2.45 (0.12)	1.33 (0.25)	0.17 (0.68)	0.51 (0.47)	0.53 (0.47)	1.06 (0.30)	1.54 (0.21)	1.71 (0.19)

In all of the regressions, the dependent variable is the log of the number of periods of care in psychiatric hospitals. All regressions include municipal-specific effects, year-specific effects, and municipal-level trends. Regressions are weighted by the square root of the population living in municipalities. Standard errors (in parentheses) are robust to heteroskedasticity and are consistent with respect to serial correlation within municipalities. The unemployment variable used in the IV-FE model is the observed unemployment rate in a municipality, instrumented using two predicted employment change measures: the national trend in industrial growth rates interacted with the municipal-level composition of industrial employment, lagged one period and two periods, respectively. The SW chi-squared and F-statistics test the null hypotheses of under-identification and weak instruments, respectively, for the endogenous regressor (here, the unemployment rate). The Hansen J-statistic tests the over-identifying restrictions. The associated p-values (in parentheses) are given in parentheses under the test statistics. ***$p<0.01$, **$p<0.05$, *$p<0.1$

(Kendler & Gardner, 2014). Similar results are not found for males aged 18 to 24, males aged 65 years and older, or among females of any age group. An important novelty of our study is that we are able to use three different mental health measures in our analysis. Our findings are robust, since the results hold for various mental health measures. The data that are used in analyses constitute of approximately 98% of the total population in Finland, so our results can be regarded nationally representative.

While our results, per se, might not be directly generalized to other countries, the study setting however, should be generalizable. Our findings are in line with some previous studies (e.g., Artazcoz et al., 2004; Farré et al., 2018), and in addition, we offer important methodological insights regarding the association between unemployment and mental health. Whereas it would be optimal to use individual-level data in examining the relationship between mental health and unemployment, we argue that there are some advantages to using aggregate-level data. First, we are interested in studying group-level effects; that is, municipal-level effects of unemployment on the population's mental health; therefore, aggregate-level data is useful for our purposes. Second, using aggregate-level data stems from our identification strategy. When using instrumental variable estimation techniques, it is challenging to find plausible instruments for potentially endogenous variables. If we consider individual-level data, then finding a strong predictor for individuals' employment status—one that would not directly affect their mental health—is probably even more challenging than trying to find a strong predictor for area-specific unemployment that would not be a direct cause of mental health problems in the area. In several studies that use individual data, plant closures or mass layoffs are used to isolate the part of a job-loss that is exogenous to individual workers' health (e.g., Browning & Heinesen, 2012, Schaller & Stevens, 2015, Sullivan & von Watchter, 2009). However, plant closures are relatively rare events and they may be limited to specific populations (often blue-collar workers) in specific geographic areas, therefore, restricting a study's generalizability (Brand, 2015). As we use the industrial composition at the municipal level, for the initial part of the period, to predict exogenous changes in municipal-level employment over time, our instrument variables not only implicitly include plant closures or mass layoffs in municipalities but also take into account possible larger sectoral shifts in the demand for labor.

We also acknowledge some possible limitations of our study. Municipal-level data do not allow us to exploit the effects of unemployment at the individual level. Individual-level data are needed to establish the specific explanations behind the relation between unemployment and mental health. Bonamore et al. (2015) and Laliotis and Stavropoulou (2018) argue that the association between unemployment and mortality might be non-linear. Similarly, there is a possible non-linear or asymmetry relationship between unemployment and mental health. The effect of an increase in unemployment on mental health might be positive, negative or insignificant depending on the level of unemployment itself or the level of unemployment in reference region (see, e.g., Huikari & Korhonen, 2016). In addition, the time-series dimension of our data is relatively short, and we are unable to look at possible long-run mental health trends over several decades. To address potential reverse causality and endogeneity concerns, we employ a widely used Bartik-style shift-share instrument for municipality unemployment in two-stage least squares fixed effects estimates. Recent papers by, for example, Borusyak et al. (2022), Goldsmith-Pinkham et al. (2020), and Jaeger et al. (2018) point out, that the usage of Bartik instruments are not without potential challenges. These challenges are, for example, related to the need for substantial variability, to assumptions around linearity and to the absence of interactions (Osman & Kemeny, 2022). While the Bartik-style IV may have drawbacks, it provides also major advantages in studies like the current one, which requires time-varying instrument (Osman & Kemeny, 2022).

It should also be noted that the instrumental variable results must be interpreted in terms of local average treatment effects (Imbens & Angrist, 1994). Thus, instrumental variable estimates only reflect the effects among the sample that is actually affected by the instrument used. This means that our IV-FE estimate provides the average effect of unemployment on those municipalities for which local labor demand shocks pose a key determinant of unemployment. This reflects the possibility of differing mental health effects across the sources of unemployment.

6 Concluding Remarks

Our study contributes to a relatively large literature that examines the effects of unemployment on health (e.g., Ruhm, 2000, 2005, 2015; Tapia Granados, 2005; Tapia Granados & Diez Roux, 2009). These studies show that recessions might improve health and decrease overall mortality, arguing that during economic downturns, health improves as individuals improve their health behaviors because increases in leisure time increase the possibilities of partaking in more health enhancing activities. However, related to mental health, these studies also show evidence of the positive association between unemployment and suicide.

In this study, we show clear evidence that economic downturns increase mental health problems in society.

Our findings provide important insights. Regarding the negative effects of unemployment on mental health, especially vulnerable group seems to be working-aged males. Similar connection is not found among younger or older males, nor among females, suggesting that some other factors besides labor market conditions play more important role in influencing mental health among those groups. Further research is thus needed to shed more light on the differences of factors related to mental health between sex- ang age-groups. In addition, since there are significant differences across municipalities in Finland in both prevalence of mental health issues and illnesses, along with unemployment, it is essential to consider the possible tailored support actions in regional policy-making in case of rising unemployment due to, for example, structural changes.

In general, we suggest that it is important to use disaggregated data across regions in analyzing the effects of unemployment on mental health. It is also crucial to take the possible reverse causality into account, since the persons who have poor mental health may be selected into the pool of the unemployed. Our policy recommendation is that regarding the mental health effects of unemployment, the focus should be on as disaggregated level as possible, since economic conditions may have such diverse effects on different regions, and different groups of people.

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