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DISCUSSION PAPER SERIES

IZA DP No. 15913

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ABSTRACT

Work Loss and Mental Health during the COVID-19 Pandemic*

We study the impact of work loss on mental health during the COVID-19 pandemic. Combining data on work loss and health care consultations from comprehensive individual-level register data, we define groups of employees delineated by industry, region, age, and gender. With these groups, we use a difference-in-differences framework to document significantly increased rates of consultations for psychological conditions among workers with higher exposure to work loss. The increases, and their persistence, were markedly higher for consultations in specialist (vs. primary) care, indicating that the deterioration of mental health was more than a widespread increase in lighter symptoms. Overall, our findings suggest that the economic disruptions of the COVID-19 pandemic adversely affected the mental health of workers most exposed to loss of work.

JEL Classification: I12, I14, I18, J65

Keywords: COVID-19, layoffs, work loss, job loss, mental health

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1 Introduction

While there is a well-established correlation between unemployment and mental health, identifying the causal impacts of job loss is challenging. On the one hand, the stress and uncertainty of job loss could adversely affect mental health. On the other hand, poor mental health could make it more difficult to find and keep a job. More generally, correlated unobservables imply that correlations between unemployment and health status could reflect selection bias, in addition to causal effects of job loss.

In this paper, we study health effects from pandemic work loss by comparing health care consultations across groups of workers who were differentially exposed to work loss. We link individual-level Norwegian register data on health care utilization from January 2017 to December 2021 with data on pandemic work loss by industry, county, gender, and age. To estimate effects, we compare the trends in consultation numbers before and during the pandemic for workers with different exposures to work loss using a difference-in-differences strategy. Rather than individual worker exposure, we compare groups or employees with jobs in industries and regions differentially affected by the labor market implications of the pandemic.

Throughout the pandemic, younger workers living in the capital region experienced the highest rates of job loss. These compositional differences could have an independent effect on changes in consultation rates due to the pandemic. To illustrate, the capital region had more restrictive social distancing mandates throughout the pandemic relative to the rest of the country; these policies could affect mental health directly, independent of work loss. To account for such confounding factors, we estimate a set of event study regressions that control for the differential impacts of observed confounders over time.

We present three key findings. First, pandemic work losses led to higher consultation numbers for mental health. In the years leading up to the pandemic, workers with high and low exposure to pandemic work loss had similar trends in consultation rates. Following the onset of the pandemic, workers with a high exposure to work loss had disproportionate increases in the number of mental health consultations. These increases can only to a limited extent be explained by differential impacts of the pandemic across geographical areas, age groups, or genders. The results are robust to a range of alternative model specifications and variable definitions. Overall, our results indicate that pandemic-related job losses may have had significant adverse impacts on workers' mental health.

Second, we find no evidence of economically meaningful spillovers to the children of affected workers. In other words, while children and adolescents did experience significant increases in mental health consultation volumes during the pandemic, the effect does not appear to be driven by parental work losses. Meanwhile, we find suggestive evidence that parental work loss significantly reduced children's somatic consultation rates in the early phase of the pandemic, consistent with increased parental supervision during the period of initial school closures.

Third, we document significant heterogeneity in the estimated effects of pandemic work loss on mental health across demographic subsamples. These heterogeneous impacts are correlated with the estimated effects of work losses on income. While our data does not allow us to assess the underlying mechanisms directly, these findings suggest that income loss and financial stress could be a contributing factor in spite of the generous unemployment insurance during the pandemic.

While a large literature examines impacts of pandemic lockdowns and other containment measures on economic and labor market outcomes (Alexander & Karger 2021, Cronin & Evans 2020, Courtemanche et al. 2020, Goolsbee & Syverson 2021, Allcott et al. 2020, Sears et al. 2020), less is known about the indirect health impacts of the COVID-19 slowdown in economic activity. The empirical evidence from early studies examining associations between work loss and mental health during the pandemic remains inconclusive (Velthorst & Witteveen 2020, Achdut & Refaeli 2020, Posel et al. 2021, Guerin et al. 2021). These early studies are primarily descriptive and based on small samples of survey respondents. To our knowledge, our study is the first to analyze the effects of pandemic-induced work loss on healthcare utilization using full-population register data.

Our study also contributes to the large literature on the association between work loss and mental health. Unemployment is associated with lower levels of mental health (see, e.g. Paul & Moser 2009, for a meta-analysis). Studies exploiting exogenous causes for job loss, such as plant closures, provide evidence for a negative causal effect of job loss on mental health (Browning & Heinesen (2012), Farré et al. (2018), Kuhn et al. (2009), Marcus (2013), Schaller & Stevens (2015); but see Mörk et al. (2020), Salm (2009), Schmitz (2011)). Expected income losses (Avdic et al. 2021) as well as changes in social roles affecting identity and social relations might be other mechanisms linking job loss to reductions in mental health (Brand 2015).

Finally, our results for children contribute to the smaller literature on within-household spillovers of work loss. Studies of spillover effects of parental job loss to children find mixed results. A majority of existing studies rely primarily on survey data with self-reported measures of mental health or well being.[1] Since work loss is a low probability event, the limited sample sizes in longitudinal survey studies typically lead to limited statistical power to detect effects, and thereby a false-negative bias in results. Bubonya et al. (2017) find negative effects of parents', in particular mothers', job loss concentrated among adolescent girls. Using Swedish data, Mörk et al. (2020) find no effects of parental job loss on children's hospitalization for mental health causes. Schaller & Stevens (2015) find indications of improved mental health due to maternal job loss, but deteriorating mental health due to paternal job loss, both concentrated among children with low SES.

2 Institutions and data

2.1 Institutions

Policy response to the pandemic. National measures to contain the pandemic were introduced in Norway on March 12, 2020. The initial national policy response included closure of childcare facilities and schools/universities, strict travel restrictions, and closure of bars and restaurants. To compensate for the expected economic consequences for employees and firms, several economic compensation schemes were introduced, including a more generous scheme for temporary layoffs and a cash subsidy to firms to cover parts of their fixed costs. While national restrictions were eased gradually during the spring and early summer of 2020, local restrictions were introduced, eased, and re-introduced at different time points during the pandemic.

The spread of the pandemic in Norway was geographically uneven: while the capital region saw repeated surges in confirmed caseloads and hospitalizations, other regions were less affected. The policy response reflected this, with more frequent business closures generally in Oslo and other larger cities.

[1] Notable exception is Mörk et al. (2020).

Income compensation for work loss. With very few exceptions, unemployment insurance (UI) eligibility is universal, contingent on having had sufficient earnings in the previous 12 calendar months. Pre-pandemic unemployment insurance covered 62.4% of wages up to about 600,000 NOK; during the pandemic, benefits were expanded to cover 80% of previous wages up to 300,000 NOK (35,000 USD).

Healthcare in Norway. Healthcare in Norway is largely financed by general taxation. For primary care and outpatient specialist care, co-payments are generally low and capped at an annual total of 2,921 NOK (around 330 USD). Inpatient hospital care is free and access to specialist healthcare generally requires the referral of a primary care doctor/GP. In addition to the publicly funded healthcare sector, there is a small, but growing number of privately funded/self-pay providers. While some employers offer private health insurance, these policies remain comparatively rare: in 2020, 12% of the population (650,000 individuals) were covered by such insurance policies (Finansnorge.no n.d.).

2.2 Sample and data

Data on individual employee health care utilization and work loss are collected from different administrative sources. Since both registers contain an employer identifier, we can calculate health outcomes and work loss exposure for groups of workers delineated by workplace and individual characteristics. To link the two data sources, we collapse individual data into cells defined by age (10-year age groups), gender, county, and 4-digit industry (NACE-codes). In the analyses, individuals are allocated to a cell based on their primary job on March 1st 2020, immediately before the onset of the pandemic. Our main analysis sample includes all resident wage earners aged between 20 and 69 on January 1st 2020. We retain individuals who were employed according the employer-employee data ("A-meldingen") - part-time or full-time - on March 1st 2020; self-employed and freelance workers are not included in the sample. Pandemic-induced work losses occurred almost exclusively in private sector firms. The pandemic may have differentially impacted public sector employees, such as healthcare workers or teachers.[2] Our baseline model therefore excludes workers in in public administration, teaching,

[2]See for example De Kock et al. (2021), Magnavita et al. (2021), Rose et al. (2021), Nabe-Nielsen et al. (2022) and Schug et al. (2022).

healthcare and social services.[3]

To measure health care utilization, we include all records from publicly financed healthcare institutions. We use the the national patient register (NPR) containing all specialist healthcare providers and hospitals, and the Norwegian Control and Distribution of Health Reimbursement database (KUHR) containing data from primary care. Consultations are typically with doctors, but services from other health personnel such as physiotherapists are also included. Data from the health registries are used to construct quarterly consultation numbers for each individual from the first quarter of 2017 to the fourth quarter of 2021. We focus primarily on consultations for mental health, though we also analyze effects on somatic conditions.[4] Privately funded healthcare (self-pay and/or private health insurance) is not included in the data.

To capture work loss, we combine individual records from the employer-employee register with weekly reports on hours worked among workers who were temporary or permanently laid off during the first ten months of the pandemic. Individual reports to the Norwegian Labour and Welfare Administration (NAV) form the basis for unemployment benefit payments and contain hours worked for each week of the claimant's unemployment insurance (UI) spell. To focus on COVID-19 induced loss of work, we follow the approach of Alstadsæter et al. (2020) and combine UI records for the 44 weeks between March 1, 2020, and the end of the year. For each week, we first compute the UI claimant's loss of work hours compared to their March 1st job record, yielding a number between 0 and 100%. For completed UI spells and for individuals not filing for UI insurance, we set the loss of work hours to zero. Next, for each employee, we compute the COVID-19 induced loss of work as the mean loss of work over the 44 week period. Finally, to form the loss of work index for each labor market cell, we compute the average loss of work across the workers in the cell. Unemployment benefit entitlement is based on the sum of labor earnings over the previous twelve months and the threshold was reduced when the pandemic hit. Because only a small minority of employees were not entitled to UI benefits, the measurement error in work loss by using UI claimants only is unlikely to affect our estimates. While our primary measure of work loss is continuous, we discretize treatment using the quartiles of the work loss distribution.

[3] NACE codes 84-88. Results are qualitatively robust to this exclusion, see section 4.

[4] Mental health conditions are coded from ICD chapter F for specialist healthcare; ICPC-2 chapter P for primary care.

2.3 Descriptives

Table 1 presents summary statistics of the estimation sample, pooled and by quartile of the work loss distribution.[5] Workers in the first quartile of the work loss distribution experienced negligible loss of work during the pandemic, on average 0.6% of pre-pandemic working hours. Meanwhile, workers in the quartile with the highest risk of work loss (fourth quartile) experienced a 17% reduction in working hours on average.

Compared to the full sample of private sector workers, employees in the fourth quartile tend to be younger, they are more likely to be female, and they and are more likely to live in Oslo. High exposure workers have higher consultation rates both before and after the pandemic. For fourth quartile workers, average mental health consultation rates increased from 18 consultations per 100 workers pre-pandemic to 21 consultations per 100 workers after 2020, corresponding to a 19% increase. For comparison, consultation rates for first quartile workers increased from 13 to 14 per 100 workers, a relative increase of 11%.

Figure 1 illustrates trends in consultation rates by quartile of the work loss distribution. The upper panel plots average quarterly consultations per 1,000 workers. Both before and after the onset of the pandemic, there are considerable level differences in consultation volumes across groups. Pre-pandemic consultation rates are monotonically increasing in the quantiles of the work loss distribution: workers with the highest exposure to pandemic job losses had the highest rates of mental health consultations in the three years leading up to the pandemic. This pattern could reflect compositional differences. For example, female workers, younger workers and workers living in Oslo tend to have higher average rates of healthcare utilization. In spite of these level differences, pre-pandemic trends are largely parallel across quantiles up to the end of 2019.

At the start of the pandemic, there is a significant jump in average consultation rates. However, the size of the jump varies across quantiles of the work loss distribution. As a consequence, the gaps between the lines in Figure 1 widen after the start of the pandemic. This divergence can be seen more clearly in panel (b), which plots trends in consultation rates indexed to the first quarter of our sample period. Up to and including 2019, the indexed trends largely overlap. At the start of 2020, there is an

[5] Note that the number of cells differ between quartiles, reflecting unequal number of workers in each cell.

Table 1: Summary statistics

	(1) All	(2) Q1	(3) Q2	(4) Q3	(5) Q4
Work loss	0.0638	0.00613	0.0259	0.0525	0.171
	(0.0782)	(0.00566)	(0.00533)	(0.0124)	(0.0890)
Age	42.03	46.23	42.30	40.30	39.29
	(12.90)	(12.77)	(12.34)	(12.94)	(12.45)
Oslo	0.148	0.138	0.0973	0.149	0.206
	(0.355)	(0.345)	(0.296)	(0.356)	(0.404)
Female	0.341	0.364	0.231	0.262	0.507
	(0.474)	(0.481)	(0.422)	(0.440)	(0.500)
All consultations	0.152	0.130	0.138	0.151	0.189
	(0.181)	(0.211)	(0.134)	(0.162)	(0.202)
All, 2017-2019	0.142	0.125	0.130	0.140	0.175
	(0.173)	(0.202)	(0.128)	(0.154)	(0.195)
All, 2020-2021	0.167	0.139	0.152	0.167	0.209
	(0.191)	(0.223)	(0.141)	(0.171)	(0.212)
Primary care consultations	0.0766	0.0702	0.0715	0.0749	0.0899
	(0.0814)	(0.0979)	(0.0597)	(0.0706)	(0.0899)
Primary care, 2017-2019	0.0677	0.0629	0.0630	0.0655	0.0794
	(0.0721)	(0.0870)	(0.0522)	(0.0619)	(0.0806)
Primary care, 2020-2021	0.0900	0.0812	0.0842	0.0891	0.106
	(0.0919)	(0.111)	(0.0675)	(0.0800)	(0.100)
Specialist consultations	0.0754	0.0601	0.0668	0.0756	0.0991
	(0.139)	(0.162)	(0.0991)	(0.123)	(0.157)
Specialist, 2017-2019	0.0746	0.0616	0.0665	0.0743	0.0959
	(0.138)	(0.161)	(0.0992)	(0.122)	(0.157)
Specialist, 2020-2021	0.0767	0.0577	0.0673	0.0777	0.104
	(0.140)	(0.164)	(0.0990)	(0.125)	(0.158)
Workers	1,578,488	394,672	394,822	394,408	394,586
Observations	737,240	312,540	87,700	127,500	209,500

Note: Population-weighted averages. Column (1) presents summary statistics for the full sample; columns (2)-(5) show the corresponding figures by quartile of the job loss distribution. Rows 1-3 show average quarterly consultations per capita. Q1-Q4: quartiles of the work loss distribution. Cells are given by combinations of age (10-year brackets), gender, municipality, and industry of employment.

immediate and persistent divergence between quartiles. The gap is largest between workers in the first and fourth quartiles, with second and third quartile workers in the middle.

Figure 2 plots the average change in consultation rates before and after the pandemic against the ventiles of the work loss distribution. Panel (a) shows unadjusted changes, while panel (b) shows the residualized values from a regression with calendar time by age, county and gender. Both panels indicate a positive correlation between changes in consultation rates and pandemic work loss.

3 Empirical models

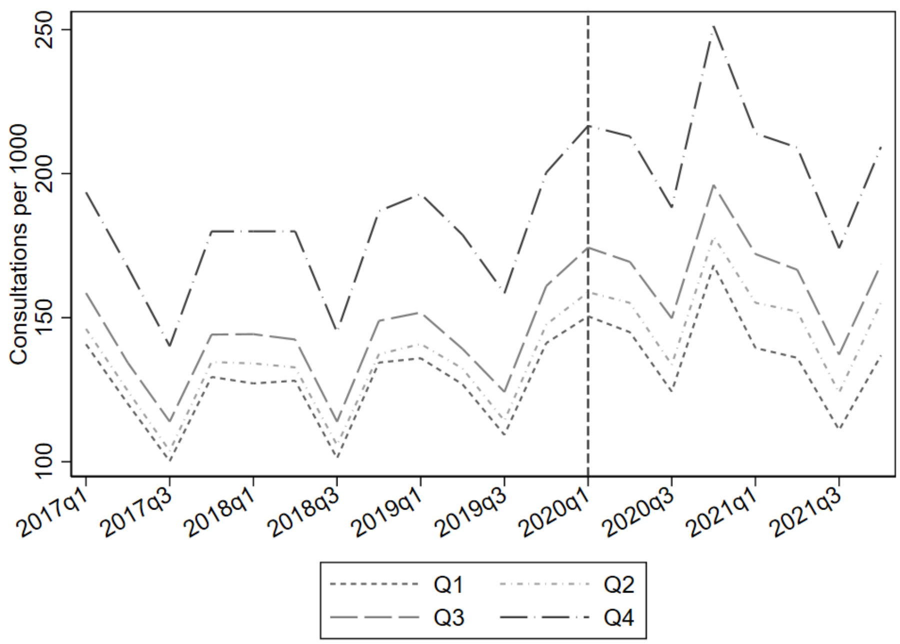
Letting y_{gt} denote outcomes of cell g in quarter t, our baseline regression specification can be written as follows

$$y_{gt} = \theta_g + \theta_{tx(g)} + \sum_{\tau=2}^{4} \sum_{t,t \neq 2019Q4} \left(\theta_t \times Q_{\tau g}\right) \rho^{t\tau} + \varepsilon_{gt} \tag{1}$$

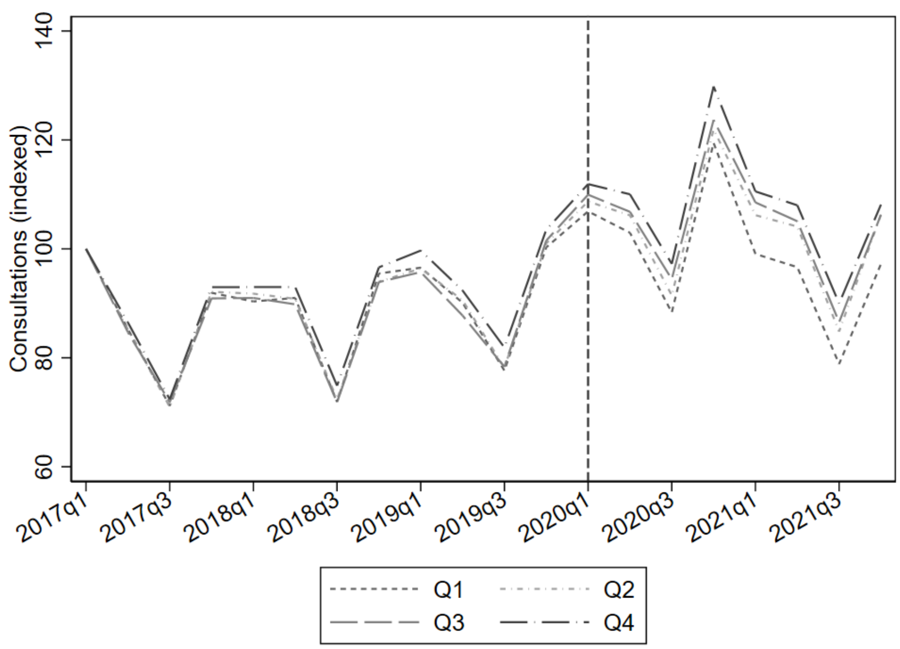
Here, θ_g are cell fixed effects, and $\theta_{tx(g)}$ are fixed effects for quarterly calendar time, interacted with age, gender, and geography. ε_{gt} standard errors clustered at the cell level. $Q_{\tau g}$ is a dummy variable equal to 1 if cell g is in quartile τ of the work loss distribution. The primary parameters of interest are the coefficients $\rho^{t\tau}$ ($t > 2019q4$); these capture the differential changes in consultations for workers in the τth quartile of the work loss distribution around the time of the pandemic.

The difference-in-differences identification strategy is based on the fact that the pandemic hit some industries and regions more than others. Our strategy builds on key identifying assumptions. First, we require non-anticipation, i.e. individuals should not change their behaviors in the pre-period in expectation of treatment. In our setting, we argue this assumption is likely to hold since by February 2020, workers had little reason to expect the pandemic to turn out the way it did. Second, we require parallel trends for workers with different exposure to work loss. That is, we assume that in the counterfactual scenario of no work losses during the pandemic, the number of consultations of high exposure workers would have trended in parallel with the the number of consultations of workers with low exposure to work loss. Since the work loss is driven by the nature of the pandemic and the policies to limit its consequences, it is likely independent of any differential trend in health conditions. Parallel pre-trends

Figure 1: Quarterly psychological consultations by quartile of work loss distribution



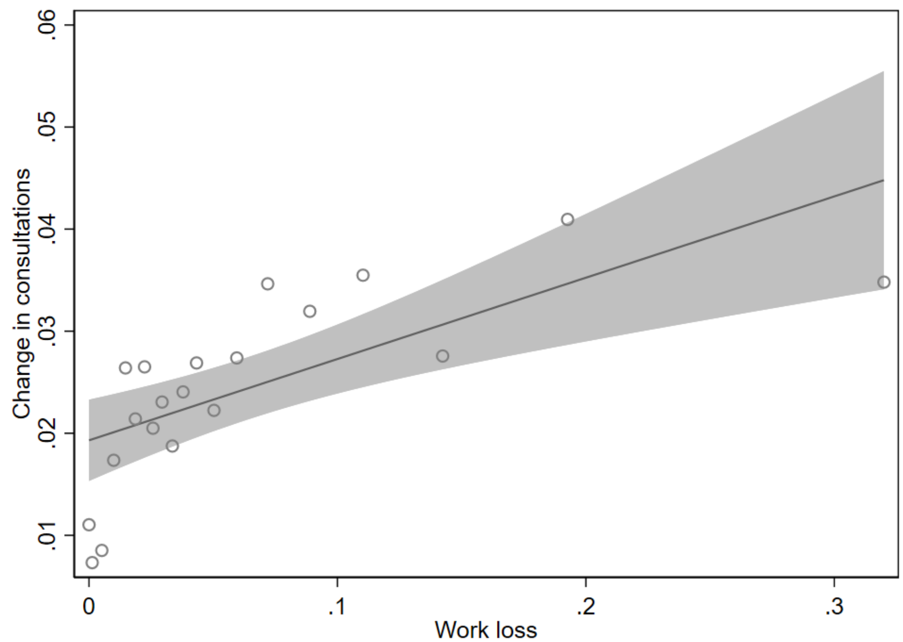
(a) Consultations per 1,000 workers



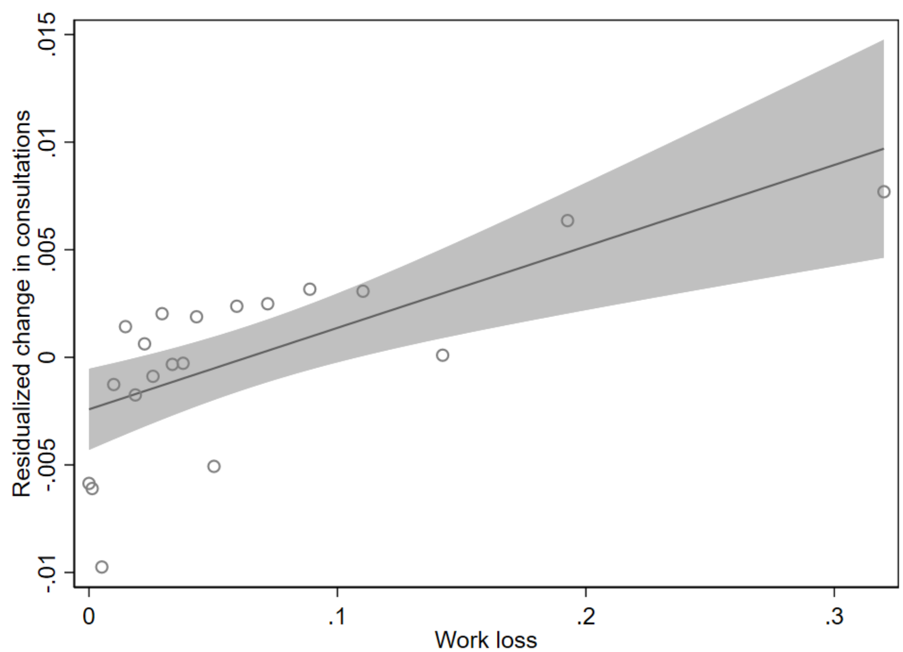
(b) Consultations (indexed)

Note: Figure shows average quarterly psychological consultations per 1,000 workers by quartile of the work loss distribution.

Figure 2: Change in psychological consultation volumes by work loss



(a) Raw changes



(b) Residualized changes

Note: Figure plots changes in average quarterly consultation rates from pre-pandemic baseline 2017-2019 to 2020-2021 against the ventiles of the work loss distribution. Panel (a) plots raw changes, panel (b) plots residualized changes controlling for age, gender and county.

mean that the coefficients $\rho^{t\tau}$ are close to 0 and insignificantly different from each other before the pandemic ($t < 2019q4$). Visual inspection of the event-study models provides support for parallel pre-trends. For $t > 2019q4$, the estimated $\rho^{t\tau}$ capture any differential effects of the pandemic on the number of consultations of workers with greater exposure to work loss.

The predicted dynamics of the $\rho^{t\tau}$-coefficients in the post period are theoretically ambiguous in our setting. In general, we would not necessarily expect a discontinuous jump at $t = 2020q1$. Income losses are increasing with the duration of unemployment. At the onset of the pandemic, business closures may not have been expected to be as long lasting as they turned out to be. Mental health could deteriorate gradually in response to continued non-employment, rather than suddenly.

To summarize the results in a single point estimate, we estimate a second regression specification where the eight quarters after the onset of the pandemic are grouped together. In this model, the reference period includes all pre-pandemic quarters. Letting $post_t$ denote an indicator variable equal to one for the last eight quarters (2020q1 - 2021q4), this specification can be written as:

$$y_{gt} = \theta_g + \theta_{tx(g)} + \sum_{\tau=2}^{4} (post_t \times Q_{\tau g})\, \beta^{POST,\tau} + \varepsilon_{gt} \tag{2}$$

Since we study the effects of work loss to workers delineated by industry of employment, county of residence, age, and gender, the shocks also hit fellow workers. The impact on health will therefore extend beyond individual exposure and will capture peer-effects, for example, concern for your colleagues as well as the insecurity arising from holding a job where colleagues frequently are out of work. We find this total effect relevant, even in contexts other than the Covid pandemic: Over the business cycle, workers are often exposed to unemployment shocks together with fellow workers, not as single individuals randomly drawn from the population. Hence, the impact will typically extend beyond individual exposure.

The cell design implies that we avoid bias from selective individual exposure to work loss within observably similar groups of employees. To illustrate, if we studied the impact of work loss during the pandemic using *individual exposure* and industry fixed effects, the effect would include the unobserved difference between colleagues (temporary) laid off and those who remained at work.

4 Results

4.1 Main results

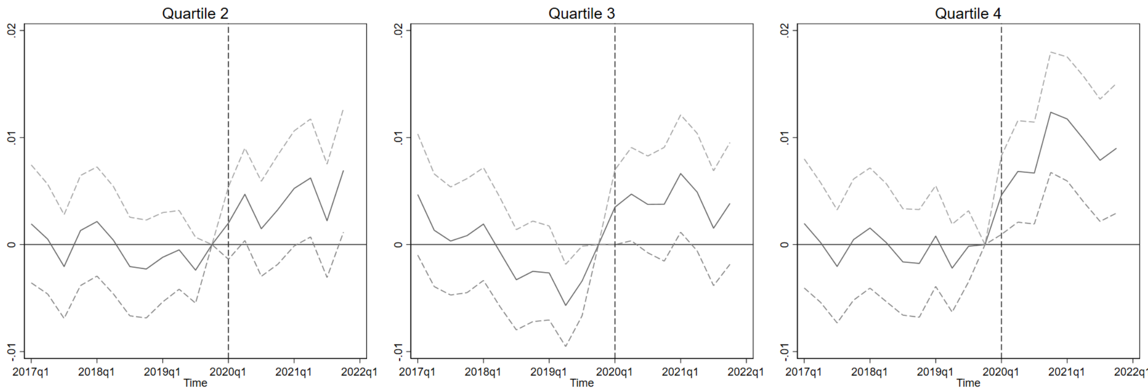
Figure 3 presents results from the estimation of the event study model (equation 1). Overall, we find little evidence of systematic pre-trends, that is, we find no evidence of systematic differential changes in the number of consultations for higher exposure workers in the period from 2017-2019. After the onset of the pandemic, the overall number of mental health consultations appears to increase more for workers who are more exposed to job loss. For all three quartiles, there is an immediate jump after the onset of the pandemic; effects persist over time.

While the jump is more pronounced for fourth quartile workers, people in the second and third quartiles also have statistically significant increases in the number of consultations. While these increases are smaller than the estimated effects for fourth quartile workers, they are larger than what we might expect given the low rates of work loss these workers face. This could indicate a non-linear association, with a relatively large difference between the first and second quartile of work loss exposure, and only relatively small additional effects of further increases in work loss.

Quantitatively, our estimates point to economically meaningful effects. Table 2, column (1), summarizes the estimated effects during the post period. Our results indicate that pandemic-induced work-loss induced an additional 8.8 quarterly mental health consultations per 1000 fourth quartile workers. Relative to the pre-pandemic mean (142 per 1000 workers), this corresponds to a 6.2% increase in mental health consultations.

We have estimated models of two additional metrics of healthcare utilization: (i) the share of workers that have at least one consultation for a psychological condition in a given quarter, and (ii) the average number of quarterly consultations for patients who have one or more consultations. Results from this exercise suggest that our findings primarily reflect an extensive margin response. We find no significant effects for the average quarterly consultation rates per patient, conditional on being seen at least once. Meanwhile, the share of workers with one or more quarterly consultations exhibits significant differential increases for high-exposure workers in the post-period (see Appendix Figure A1 for the estimated event study plots).

Figure 3: Event study estimates



Note: Figure shows the estimates of $\rho^{t\tau}$ in Equation (1), with 95% confidence intervals. Cell-population-weighted estimates. Standard errors are clustered at the group level.

Table 2: Difference-in-difference estimates

	(1) All cons	(2) Cons (any)	(3) Cons per patient	(4) Primary	(5) Specialist
Post × Q2	0.00435**	0.00106***	0.00390	0.00231***	0.00205
	(0.00172)	(0.000321)	(0.0260)	(0.000741)	(0.00138)
Post × Q3	0.00484***	0.00125***	0.0123	0.00283***	0.00201
	(0.00176)	(0.000328)	(0.0255)	(0.000749)	(0.00143)
Post × Q4	0.00884***	0.00163***	0.0336	0.00112	0.00772***
	(0.00192)	(0.000362)	(0.0252)	(0.000791)	(0.00159)
N	737240	737240	357023	737240	737240
Pre mean	0.142	0.0495	2.756	0.0677	0.0746
Rel effect Q2	0.0306	0.0214	0.00142	0.0341	0.0274
Rel effect Q3	0.0340	0.0252	0.00448	0.0418	0.0270
Rel effect Q4	0.0621	0.0329	0.0122	0.0165	0.104

Note: Table presents estimates from equation (2). Dependent variable in columns (1) is the average number of quarterly consultations per worker, in column (2) the fraction of workers with at least one consultation during the quarter, in column (3) the average number of quarterly consultations conditional on being seen at least once, and in columns (4) and (5) the average number of primary care and specialist care consultations per worker, respectively. Models include calendar time and cell fixed effects, and covariates (age, gender, county) interacted with calendar time. Observations weighted with the population in each cell. Standard errors in parentheses, clustered at the group level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Finally, we have estimated the models separately for primary and specialist consultations. While patients with milder symptoms often receive treatment from their GPs, patients with moderate to severe symptoms are typically referred to specialist care. Results from these models indicate that the estimated increases in the number of psychological consultations are driven primarily by consultations with specialist providers. While our estimated event study models find sharp, persistent increases in specialist consultations, the corresponding models of primary care consultations find no significant changes; see Appendix Figure A1. Relative to the sample mean, point estimates indicate a 10.4% increase in specialist consultations for psychological conditions (Table 2, column 5).

4.2 Robustness and extensions

Sample selection and variable definitions

We implement a number of robustness tests to assess the validity of our findings. Results from these exercises are summarized in Table 3; the corresponding event study estimates are presented in Appendix Figure A2 and A3.

Table 3: Difference-in-difference estimates - robustness

	(1) Any WL	(2) 10%+ WL	(3) 20%+ WL	(4) Occup	(5) With public sector
Post × Q2	0.00584***	0.00468***	0.00429**	0.00328**	0.0112***
	(0.00174)	(0.00173)	(0.00173)	(0.00157)	(0.00181)
Post × Q3	0.00837***	0.00651***	0.00553***	0.00662***	0.0113***
	(0.00171)	(0.00173)	(0.00176)	(0.00182)	(0.00169)
Post × Q4	0.00812***	0.00815***	0.00814***	0.0106***	0.0137***
	(0.00197)	(0.00195)	(0.00193)	(0.00199)	(0.00168)
N	737240	737240	737240	560000	804060

Note: Table presents estimates from equation (2). All models include calendar time and cell fixed effects. Models (1)-(5) include covariates (age, gender, county) interacted with calendar time. Columns (1) - (3) assigns cells to quartiles using share of workers with (1) any registered work loss, (2) share lost 10% or more of pre-pandemic hours, (3) share of workers lost 20% or more of pre-pandemic hours. Column (4): sample where cells defined by 4-digit occupation instead of 4-digit industry classifiers. Column (5) shows models estimated on expanded sample including public sector employees. Observations weighted with the population in each cell. Standard errors in parentheses, clustered at the group level. * $p < .10$, ** $p < .05$, *** $p < .01$.

In our baseline specification, work loss is defined using average working hours lost relative to pre-pandemic hours. To assess the robustness of our findings to these choices, we estimate a set of event study models where workers are grouped based on three alternative definitions of work loss: (i) the share of workers with any work loss, (ii) the share of workers reporting work loss of at least 10% of pre-pandemic working hours, and (iii) the share of workers reporting work loss of at least 20% of pre-pandemic working hours. Results from this exercise are very similar to our baseline findings. In a related exercise, we estimate the event study models on a sample where cells are instead based on four-digit occupation classifiers instead of industry (4-digit NACE codes). Results from this model are consistent with our preferred specification.

Our baseline model excludes public sector workers. When public sector workers are included in the sample, the event study plots suggest non-parallel pre-trends. That said, our main results are qualitatively unchanged.

Somatic conditions

While the main focus of our paper is effects of work loss on mental health, our data also includes consultations for somatic conditions. Appendix B presents descriptive analysis and estimated event study models, together with a set of robustness checks. The event study plots are less conclusive; post-pandemic, estimates are more volatile, and estimated pre-trends suggest that fourth quartile workers' somatic consultation rates were growing faster relative to those of the first quartile comparison group in the years leading up to the pandemic. As a consequence, our difference-in differences estimates may be biased upwards. With that caveat, estimates from equation (2) point to an average increase in quarterly consultation rates for fourth quartile workers of 44 consultations per 1000 workers, corresponding to a 5.1% increase relative to the sample mean.

Heterogeneous effects

Workers with high exposure to work loss saw significantly larger increases in healthcare utilization relative to less affected workers. To examine whether these effects vary across demographic groups, we have estimated the model separately by gender, geography (capital Oslo vs the rest of the country) and age (younger/older than 40). Results from this exercise are presented in Table 4.

Our estimated models indicate that for fourth quartile workers living outside Oslo, the pandemic induced an additional 4.9 consultations per 1,000 workers; fourth quartile workers living in Oslo experience an additional 23 consultations per 1,000 workers. Estimating effects by gender, we find no statistically significant impacts for men, coupled with a statistically significant and economically meaningful differential effect for women. Similarly, allowing for heterogeneous impacts by age, the main effect for fourth quartile workers aged 40 or older is not statistically different from zero. For younger workers, age 20-39, the estimated differential increase is both statistically significant and economically meaningful.

Overall, our findings suggest that the effect is qualitatively different across demographic groups. The estimated models indicate that the effect of work loss exposure on psychological consultations is driven primarily by workers living in Oslo, women, and younger workers. These differences could reflect differences in the impacts of the pandemic, e.g., if higher incidence rates and stricter social distancing mandates in the capital region amplified the psychological impacts of work losses. The heterogeneous patterns could also reflect differences in average work losses (conditional on being in the fourth quartile of work losses) or realized income losses. We return to this question in our discussion of potential mechanisms in section 5.

4.3 Spillovers to children

During the pandemic, Norwegian children's number of consultations for mental health have increased substantially, with a near 50% increase for adolescents' primary care consultations (Evensen et al. 2021). Parental work loss could have contributed to this increase, both directly through income loss, and indirectly through the worsening of parental mental health. To test whether the impacts of pandemic-induced work losses on mental health and well-being could extend beyond the affected workers, we have estimated our event study model on minor children. [6] Our sample consists of all children aged 6 to 16 who have at least one parent employed in a private sector firm. For these children, we link data on consultations in primary care (somatic and mental health) and specialist care

[6] Our data allows us to link parents to their biological children - see Appendix C for results by parental status.

Table 4: Heterogeneous effects

	(1) By Oslo	(2) By gender	(3) By age
Post × Q2	0.00379**	0.000475	0.00330*
	(0.00173)	(0.00171)	(0.00185)
Post × Q3	0.00262	0.00155	0.00293
	(0.00177)	(0.00178)	(0.00189)
Post × Q4	0.00485**	0.00260	0.00344
	(0.00192)	(0.00208)	(0.00214)
Post × Oslo × Q2	0.00102		
	(0.00656)		
Post × Oslo × Q3	0.0156**		
	(0.00644)		
Post × Oslo × Q4	0.0227***		
	(0.00654)		
Post × female × Q2		0.0117**	
		(0.00458)	
Post × female × Q3		0.00915**	
		(0.00453)	
Post × female × Q4		0.0148***	
		(0.00409)	
Post × age2039 × Q2			0.00384
			(0.00373)
Post × age2039 × Q3			0.00571
			(0.00373)
Post × age2039 × Q4			0.0118***
			(0.00403)
N	737240	737240	737240

Note: Table presents estimates from equation (2). Models include calendar time and cell fixed effects, and covariates (age, gender, county) interacted with calendar time. Observations weighted with the population in each cell. Standard errors in parentheses, clustered at the municipality level. * $p < .10$, ** $p < .05$, *** $p < .01$.

(mental health care only) to construct a cell-quarter level panel data set with quarterly data on consultation rates, analogous to those in our main estimation sample. Children are assigned their parents' work loss variables. We estimate separate models of maternal and paternal work losses. More details on sample selection and supplementary results are presented in Appendix C.

Pandemic-induced work losses could have differential impact for workers with minor children. However, when we estimate our event study model from equation (1) separately by couple status and parental status, we find that effects are of similar magnitude for parents and non-parents (Appendix Figure C3). Figure 4 presents the estimated event study models of spillovers on children. Table 5 presents the corresponding difference-in-differences estimates.

Table 5: Difference-in-difference estimates for children. Mental and somatic health

	(1) Father, mental	(2) Mother, mental	(3) Father, somatic	(4) Mother, somatic
Post × Parent's Q2	0.00119	-0.000340	0.000432	-0.00146
	(0.00378)	(0.00527)	(0.00213)	(0.00298)
Post × Parent's Q3	0.00250	0.00527	0.00190	-0.00314
	(0.00380)	(0.00552)	(0.00211)	(0.00304)
Post × Parent's Q4	-0.000479	-0.000654	-0.00241	-0.00353
	(0.00388)	(0.00458)	(0.00221)	(0.00272)
N	723240	518080	723240	518080
ymean	0.131	0.120	0.343	0.332

Note: Table shows estimated effects of parental work loss, estimated on a sample of children aged 6-16, where the predictor is the father's (col. 1 and 3) and mother's (col. 2 and 4) risk of work loss. Population-weighted estimates. Standard errors are clustered at the group level. * $p < .10$, ** $p < .05$, *** $p < .01$

For children´s mental health, the estimated event study coefficients do not appear to shift after the onset of the pandemic. This holds both for maternal and paternal work loss. The 95% confidence intervals for estimates from equation (2) allow us to rule out increases greater than 4% relative to the sample mean (Table 5). For maternal work loss, limited precision means we are unable to rule out relatively large effects (13% of the sample mean). In other words, parents' increased risk of work can only explain a very minor part of the increase in children's mental health consultations during the pandemic.

Figure 4: Spillovers to children

(a) Mental health (primary and specialist) by paternal work loss

(b) Mental health (primary and specialist) by maternal work loss

(c) Somatic health (primary) by paternal work loss

(d) Somatic health (primary) by maternal work loss

Note: Figure shows estimated effects of parents' work loss on children's consultation rates. Models are estimated on a sample of children (6-16). Population-weighted estimates. Standard errors are clustered at the group level.

Parental work loss could also have spillovers on children's somatic health. On the one hand, parental stress could contribute to child neglect and even maltreatment. On the other hand, work losses could leave parents with more time available to supervise their children. Our models suggest the latter channel could dominate: Figure 4, panel (d) is a tendency of a transient reduction in somatic consultations for children whose mothers are more exposed to work loss, driven entirely by reductions during the period of initial school closures.

5 Discussion

Our analyses document adverse mental health impacts from the the economic disruptions brought about by the COVID-19 pandemic and its countermeasures. Employees in jobs more exposed to work losses during the pandemic had significantly larger increases in mental health consultation rates, compared to workers in less affected jobs. To better make sense of these findings, we begin by reviewing some potential underlying mechanisms. Next, we consider the magnitudes of our estimated effects and how they compare to the existing literature.

Mechanisms

One potential mechanism linking job loss and mental health is the loss of income. Studies exploiting lottery wins to identify the causal effect of income shocks show no or very small effects on consultation frequency or use of medications (Cesarini et al. 2016), albeit somewhat more positive effects for self-reported mental health (Apouey & Clark (2015), Gardner & Oswald (2007), Lindqvist et al. (2020), but see Raschke (2019) for a counterexample). Even if the positive effects of unexpected income increases are modest, an income loss could have a substantial detrimental effect on mental health. Sullivan & Von Wachter (2009) find that increases in mortality risk were concentrated among those losing more income, suggesting that income loss is an important mechanism linking job displacement and mortality. In that paper, displaced workers have substantial income losses, with average estimated income losses of approximately 40%. A natural question then is whether income loss is a credible mechanism in our setting, where income losses are largely buffered by a generous unemployment insurance.

To assess the plausibility of the income loss hypothesis, we carry out simple auxiliary analyses linking health impacts and income losses. In this exercise, we estimate our empirical models on quarterly income, defined as the sum of wage earnings and transfers. Defining the outcome this way, we ensure that our income measure includes any unemployment insurance benefits.

Workers with the greatest exposure to work loss did see larger income losses (see Appendix Figure A4). Our difference-in-difference models of log quarterly income find statistically significant negative effects for third and fourth quartile workers. Our models suggest that pandemic induced work losses reduced the incomes of third quartile workers by less than 1%, while the effect for fourth quartile workers was just over 3%. These effects are small relative to the average work losses in each quartile (5% and 17% respectively), consistent with a robust social safety net and expanded unemployment insurance limiting the direct economic consequences of the pandemic for affected workers. For the fourth quartile workers, these numbers together imply that a worker experiencing complete work loss after the onset of the pandemic has an expected income loss of 19%.

Meanwhile, there is substantial variation in estimated income losses across subsamples. Younger workers, women, and workers living in Oslo tend to have larger estimated negative effects on income. To see how the estimated income losses line up with estimated effects of health care utilization, we follow Hoynes et al. (2015) and plot the difference-in-difference estimates for consultation rates against the estimates for log income. Results from this exercise indicate a significant and substantial correlation between the estimated income losses and the increase in consultation numbers across subgroups (see Appendix Figure A5, panel (a)). There are also some differences in pandemic work loss between the subsamples of fourth quartile workers. However, these differences are significantly smaller, and the positive association between subsample workloss and estimated increases in consultation rates is less pronounced, suggesting the correlation with income losses is not primarily driven by within-quartile differencesd in exposure across groups (see Appendix Figure A5, panel (b)). Overall, these patterns indicate that we are not able to rule out income effects as a contributing mechanism, even if a modest income loss of 3% for the most affected can hardly explain a 6% increase in mental health consultations.

The labor market situation during the COVID-19 pandemic might arguably also have triggered worries about employment security among those not losing work. Worries about job loss and changes to one's own economic situation might in and of itself have negatively affected their mental health, even in the absence of actual job loss (Avdic et al. 2021, Watson & Osberg 2018). We estimate significant increases for second and third quartile workers, where realized work losses are modest. This suggests that an uncertain job, even in the absence of actual job loss, affected mental health during the pandemic.

Effect size and external validity

In order to compare our results with estimates from the literature, we first perform a simple back-of-the-envelope calculation, scaling our estimated effects by the average excess work loss for fourth quartile workers. Results from this exercise are presented in Table 6. Relative to pre-pandemic means, fourth quartile workers saw a 6% increase in consultation volumes while they experienced work losses of 16 percentage points greater than what workers in the first quartile did. Taken at face value, a simple calculation scaling these two numbers implies that a complete loss of employment between March and December 2020 leads to a 38% increase in consultations for mental health.

In a related exercise, we scale our estimates by the estimated income losses. To be clear, this calculation does not reflect that we believe that the estimated health effects operate primarily through the income effect. Rather, this exercise serves as a starting point for comparing our effect sizes to existing studies of job loss. With that caveat, our estimates suggest that work losses that are associated with a 10% reduction in income correspond to a 19% increase in mental health consultations.

One comparable study might be Browning & Heinesen (2012)'s analysis of effects of plant closures in Denmark on hospitalizations and related outcomes.[7] The authors found a 63% increase in hospitalizations for mental health in the year after displacement. Crucially, most displaced workers in their sample find new employment immediately; on average, 20% of displaced workers experience unemployment in the first year after displacement, and the associated income losses are estimated at 13%. While we do not estimate effects on hospitalizations as such, our models of specialist care represent a natural comparison point. Based on our estimates for fourth quartile workers, the simple

[7] Moreover, the institutional context in Denmark, with universal healthcare and a comprehensive social safety net, is similar to our setting.

Table 6: Fourth quartile effects scaled by work loss

	(1) All mean	(2) Men mean	(3) Women mean	(4) Primary mean	(5) Specialist mean
1. Estimated coefficient	0.009	0.005	0.013	0.001	0.008
2. Pre-mean	0.142	0.106	0.211	0.068	0.075
3. Rel effect	0.062	0.045	0.062	0.016	0.104
4. Excess work loss (WL)	0.165	0.163	0.166	0.165	0.165
5. Rel effect - full WL	0.378	0.275	0.376	0.100	0.630
6. Income loss	-0.031	-0.025	-0.040	-0.031	-0.031
7. Income loss scaled full WL	-0.190	-0.155	-0.238	-0.190	-0.190
8. Rel effect - 10% inc loss	-0.199	-0.178	-0.158	-0.053	-0.331

Note: Table shows estimated effects relative to the sample mean, scaled by work loss and income loss. Rows 1 and 6 are estimates from equation (2) of effects on consultations and income. Row 2 is the pre-pandemic sample average consultation rates. Row 3 - the relative effect - is row 1 scaled by row 2. Rows 5 and 7 are relative effects on consultations and income scaled by mean work loss (row 4). Row 8 is relative effects on consultations scaled by 10% income loss.

scaling exercises presented in Table 6 imply that work losses that are associated with a 10% income loss would increase specialist consultations by 33% relative to pre-pandemic means. That is, our estimated effects appear to be somewhat smaller than the impacts of Browning & Heinesen (2012).

In contrast, neither Mörk et al. (2020) nor Kuhn et al. (2009) find significant effects of job loss due to plant closure on hospitalization for mental health causes, using data from Sweden and Austria respectively[8]. Our finding of no significant spillovers for children's consultations for mental health are qualitatively consistent with Mörk et al. (2020).

Our estimated effects on consultations do not necessarily correspond one-to-one with an increase in the underlying health problems. More frequent consultations could partly reflect changes in healthcare-seeking behaviors. The interpretation that our results are driven by deteriorating mental health would be in line findings for self-reported mental health (Farré et al. (2018), Marcus (2013), Schaller & Stevens (2015), but see Schmitz (2011), Salm (2009)) and prescription drug use (Kuhn et al. 2009). Results from a US sample suggest that self-reported health is more easily moved than consultations: Schaller & Stevens (2015) find that albeit self-reported mental health deteriorated, consultations re-

[8]Mörk et al. (2020) estimates that displacement increases unemployment by 8% in the first year post displacement, with a 6% associated income loss. Kuhn et al. (2009) does not report estimates of associated income losses or unemployment. Kuhn et al. (2009) does find an increase in spending on prescription drugs for mental diagnoses, suggesting that less severe and more common mental health outcomes, like consultations, may be more easily moved by job loss than hospitalizations.

lated to mental health were unmoved.[9] In our setting, there is no evidence suggesting that healthcare-seeking in and of itself should be moved by job loss. Generally, we might expect consultations to be more easily moved in a context with universal public health care, at low or no cost, than in the US system, where consultations are contingent on insurance and income.

6 Conclusions

The COVID-19 pandemic and its countermeasures have led to a significant drop in economic activity with differential impact across industries and regions. Our findings indicate that work loss during the pandemic lead to a significant increase in the demand for healthcare, with a substantial impact on consultations for psychological conditions.

Our results suggest that the pandemic augmented health inequality. Groups with high risk of job loss also had low income and frequent mental health consultations before the onset of the pandemic. When their mental health deteriorates, the social gradient in mental health becomes more pronounced.

While these findings establish early evidence of adverse health impacts of pandemic-related work loss, several important questions remain for further research. The impacts of work loss on health are likely to be context-dependent and our results reflect a setting of a generous near-universal unemployment insurance and universal access to free healthcare. To the extent that an extensive social security net mitigates any negative effects of job loss, our results may constitute a lower bound.

[9] Among those who relied on employer-sponsored health insurance, healthcare utilization did decline after displacement.

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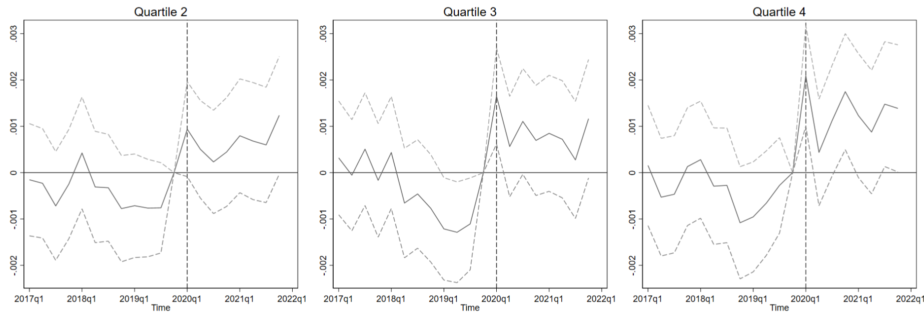
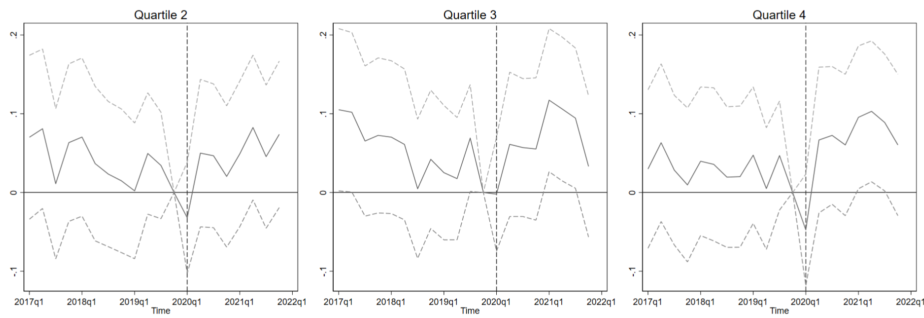
Appendix A: Supplementary findings

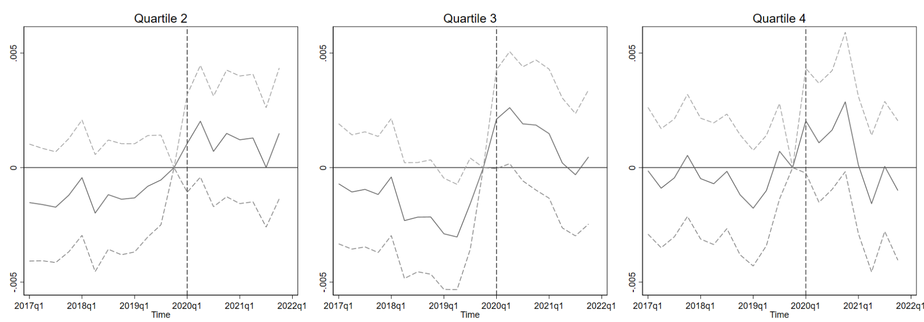
Figure A1: Event study estimates - additional outcomes



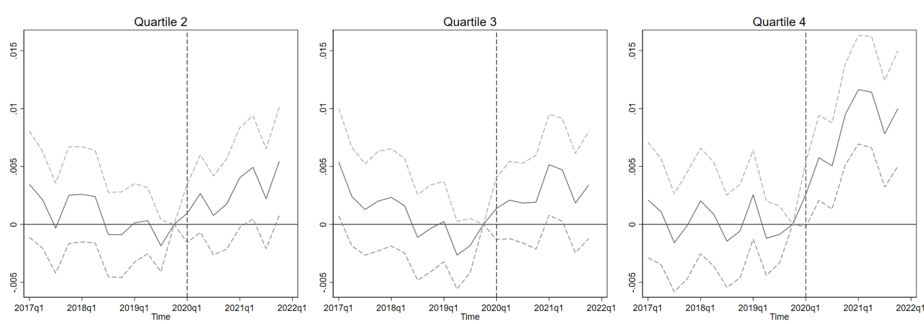
(a) Consultations (any)



(b) Consultations per patient



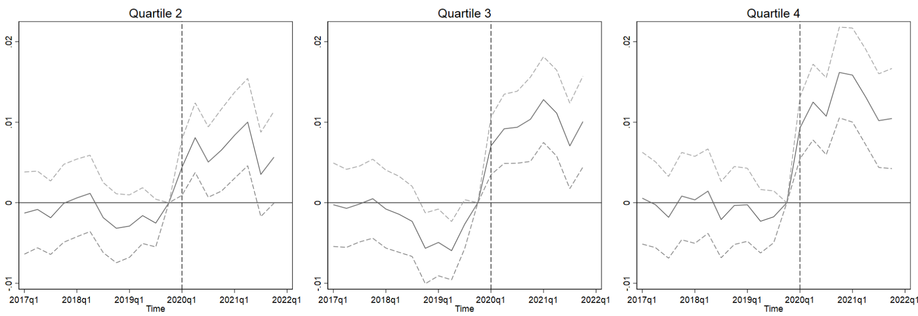
(c) Primary



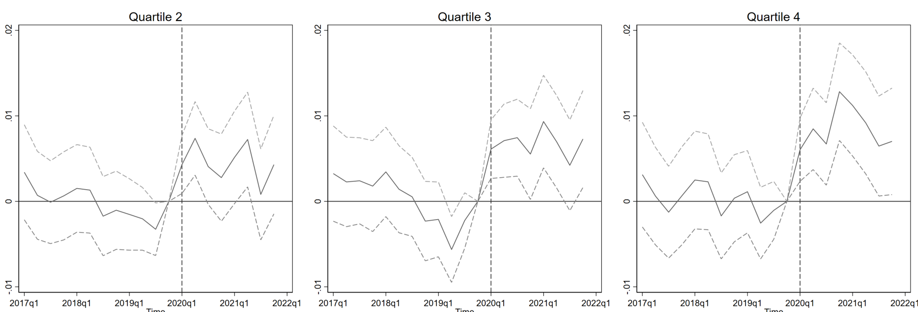
(d) Specialist

Note: Figure shows the estimates of $\rho^{t\tau}$ in Equation (1), with 95% confidence intervals. Dependent variable in panel (a) is the average number of quarterly consultations per worker, in panel (b) the fraction of workers with at least one consultation during the quarter, in panel (c) the average number of quarterly consultations conditional on being seen at least once, and in panels (d) and (e) the average number of primary care and specialist care consultations per worker, respectively. Cell-population-weighted estimates. Standard errors are clustered at the group level.

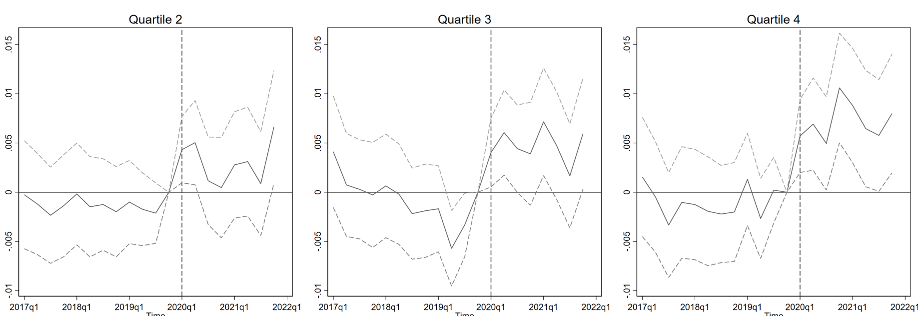
Figure A2: Event study estimates - alternative work loss definitions



(a) Any work loss



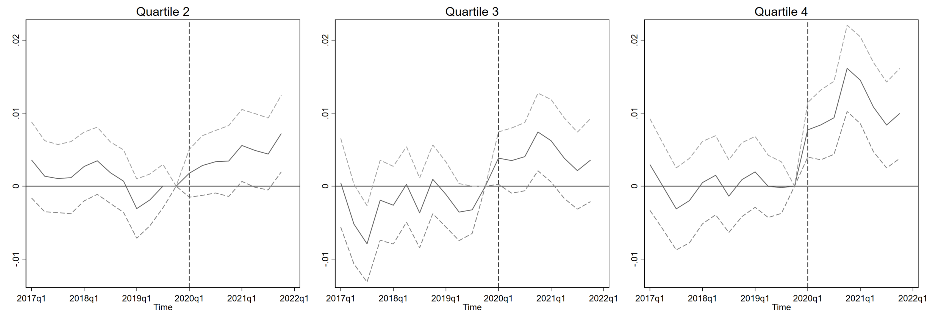
(b) Share 10%+ work loss



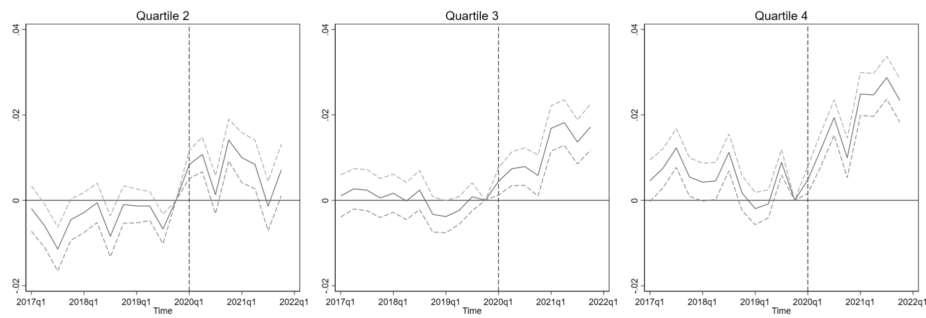
(c) Share 20%+ work loss

Note: Figure shows the estimates of $\rho^{t\tau}$ in Equation (1), with 95% confidence intervals. Cell-population-weighted estimates. Standard errors are clustered at the group level.

Figure A3: Event study estimates - robustness



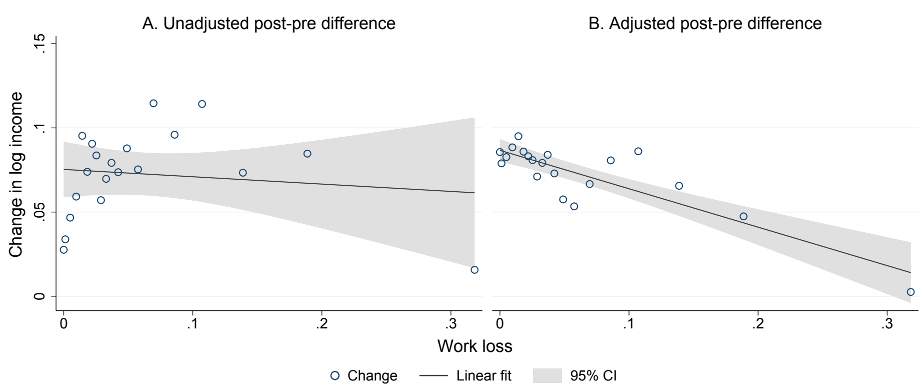
(a) Cells defined by occupation



(b) Including public sector employees

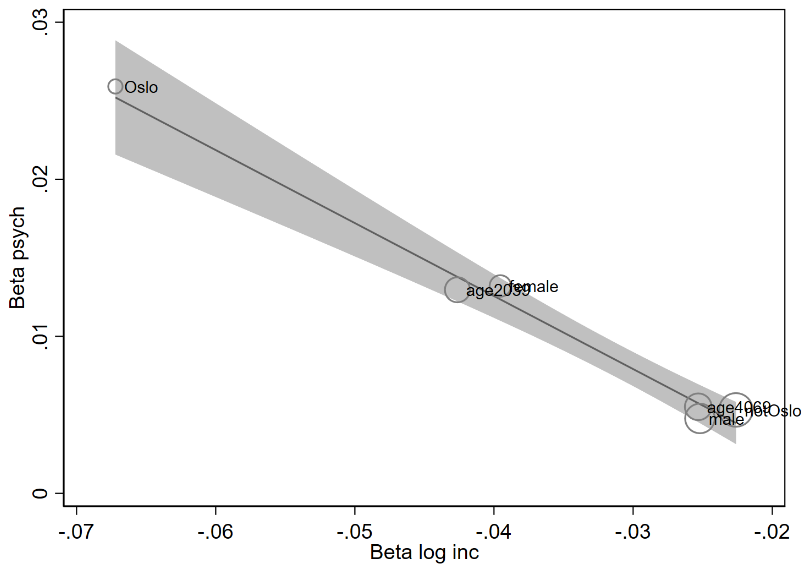
Note: Figure shows the estimates of $\rho^{t\tau}$ in Equation (1), with 95% confidence intervals. Standard errors are clustered at the group level.

Figure A4: Change in income by work loss

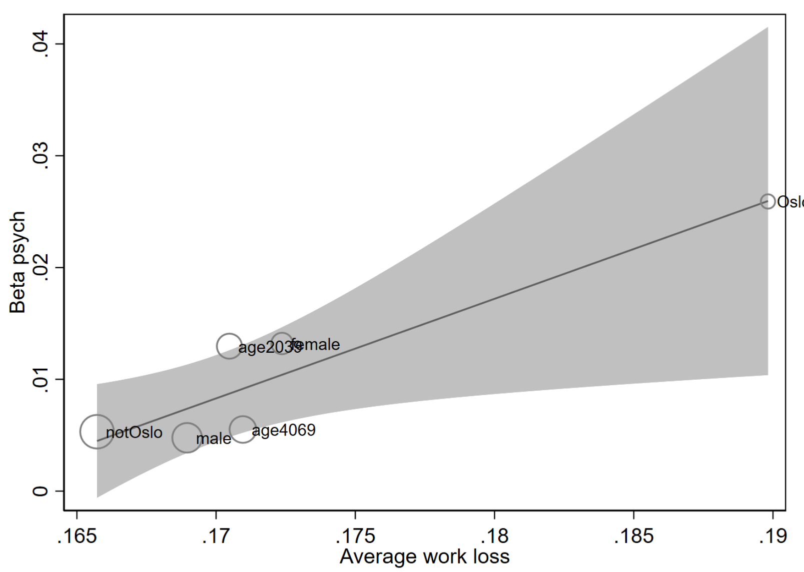


Note: Figure plots changes in average quarterly income (defined as wage earnings and transfers) from pre-pandemic baseline 2017-2019 to 2020-2021 against the ventiles of the work loss distribution. Panel (a) plots raw changes, panel (b) plots residualized changes controlling for age, gender and county.

Figure A5: Fourth quartile workers' work losses, estimated income losses and consultation increases



(a) Income losses



(b) Work losses

Note: Figure plots estimated effects for fourth quartile workers from equation (2) estimated on demographic subgroups. In panel (a), the x-axis shows the difference-in-difference estimate for quarterly income (defined as wage earnings and transfers). In panel (b), the x-axis shows subgroup average pandemic work losses. In both panels, the y-axis shows the difference-in-differences estimate for psychological consultations. The size of the circles reflect the number of workers in each group.

Appendix B: Somatic conditions

In this appendix, we present results for somatic diagnoses. This includes all consultations in primary and specialist care that are not coded with an ICPC-2 P-code (primary care) or an ICD-10 F-code (specialist care).

Summary statics on healthcare utilization are presented in Table B1. First and fourth quartile workers have similar rates of somatic consultations pre-pandemic, while second and third quartile workers have somewhat lower consultation rates.

Figure B1 plots trends in somatic consultations over time by quartile of the work loss distribution. Pre-pandemic, there are significant level differences between quartiles; lines appear to move in parallel. After the onset of the pandemic, gaps in consultation rates tend to widen, that is, there is a divergence in the indexed consultation rates (panel b). This divergence is monotonic in quartiles of the work loss distribution, similar to the pattern for mental health consultations.

Figure B2 plots changes in consultation rates before and after the pandemic against ventiles of the work loss distribution. Similar to the results for mental health consultations, these figures point to a positive, non-linear association. This holds for both raw and residualized data, suggesting the relationship cannot be fully explained by differential impacts of the pandemic by age, gender or geography.

Figure B3 presents our estimated event study models. The estimated pre-trends are mostly not statistically significantly different from zero, though they are consistently negative, suggesting a slight upward trend in healthcare utilization in the years leading up to the pandemic for high exposure workers. Event time coefficients jump significantly at the start of 2020 for all three quartiles, though the estimated coefficients in the post period exhibit more volatility than what we found for mental health consultations.

Table B2 summarizes the models of equation (2). Our main specification (col 1) suggest the pandemic increased quarterly consultation rates for fourth quartile workers by 0.044 consultations per capita, or a 5.1% increase relative to the pre-pandemic sample mean.

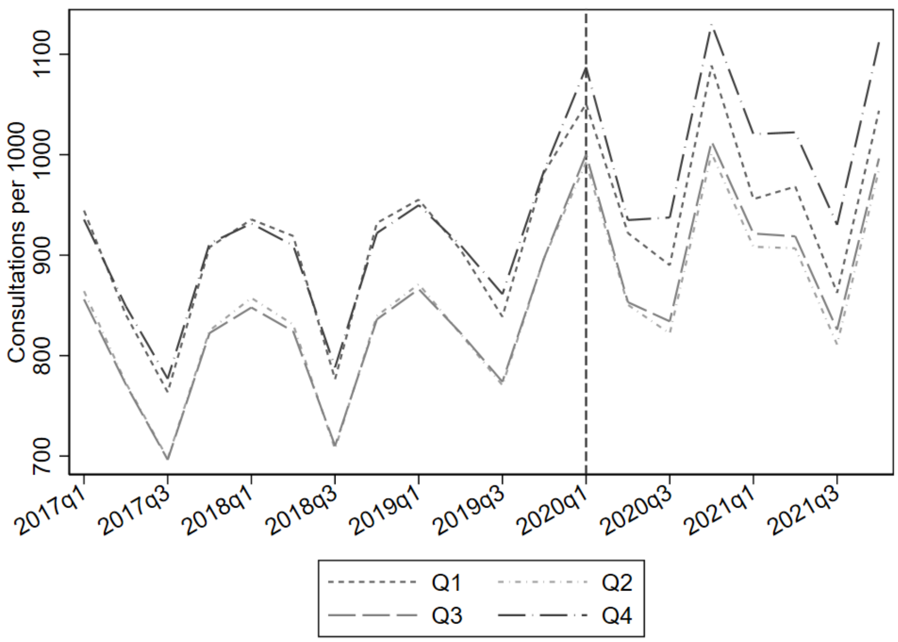
Table B3 summarizes results from various robustness tests. The positive effect on somatic consultations is qualitatively consistent across specifications.

Table B1: Somatic health care utilization

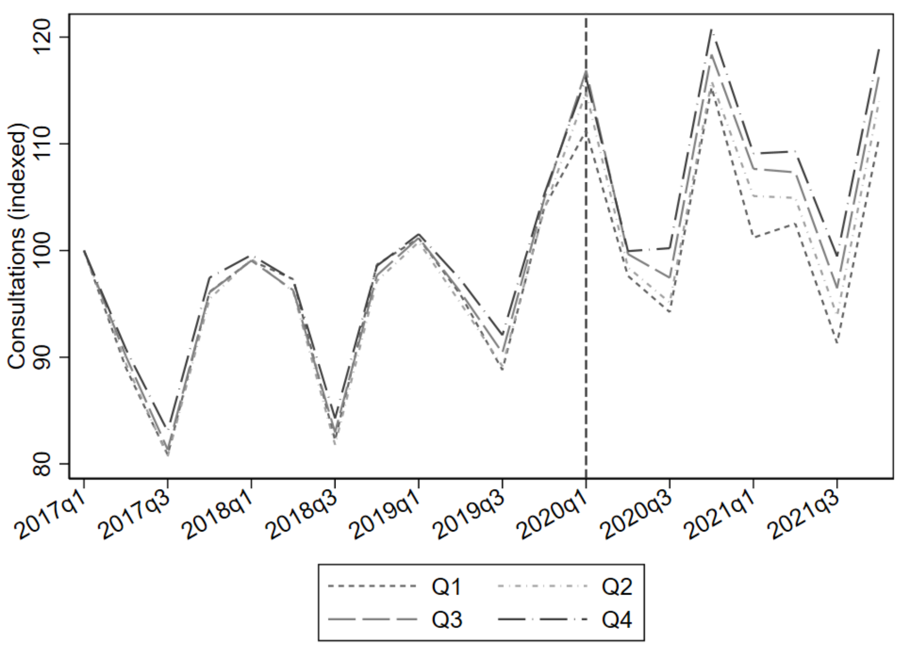
	(1)	(2)	(3)	(4)	(5)
All consultations	0.894	0.924	0.852	0.854	0.945
	(0.410)	(0.481)	(0.341)	(0.367)	(0.427)
All, 2017-2019	0.852	0.892	0.813	0.810	0.894
	(0.390)	(0.460)	(0.324)	(0.347)	(0.407)
All, 2020-2021	0.956	0.973	0.910	0.920	1.022
	(0.429)	(0.506)	(0.358)	(0.385)	(0.444)
Primary care consultations	0.584	0.590	0.558	0.563	0.625
	(0.260)	(0.299)	(0.215)	(0.233)	(0.277)
Primary care, 2017-2019	0.543	0.556	0.519	0.520	0.576
	(0.236)	(0.276)	(0.194)	(0.210)	(0.251)
Primary care, 2020-2021	0.645	0.640	0.615	0.627	0.699
	(0.280)	(0.323)	(0.232)	(0.251)	(0.298)
Specialist consultations	0.310	0.335	0.294	0.292	0.320
	(0.221)	(0.278)	(0.172)	(0.191)	(0.226)
Specialist, 2017-2019	0.309	0.336	0.294	0.291	0.318
	(0.219)	(0.275)	(0.170)	(0.189)	(0.226)
Specialist, 2020-2021	0.311	0.333	0.295	0.293	0.323
	(0.224)	(0.282)	(0.176)	(0.194)	(0.226)
Workers	1,578,488	394,672	394,822	394,408	394,586
Observations	737,240	312,540	87,700	127,500	209,500

Note: Population-weighted averages. Column (1) presents summary statistics on somatic healthcare utilization for the full sample; columns (2)-(5) show the corresponding figures by quartile of the job loss distribution. Q1-Q4: quartiles of the work loss distribution. Cells defined by combinations of age (10-year brackets), gender, municipality, and industry of employment.

Figure B1: Quarterly somatic consultations by quartile of work loss distribution



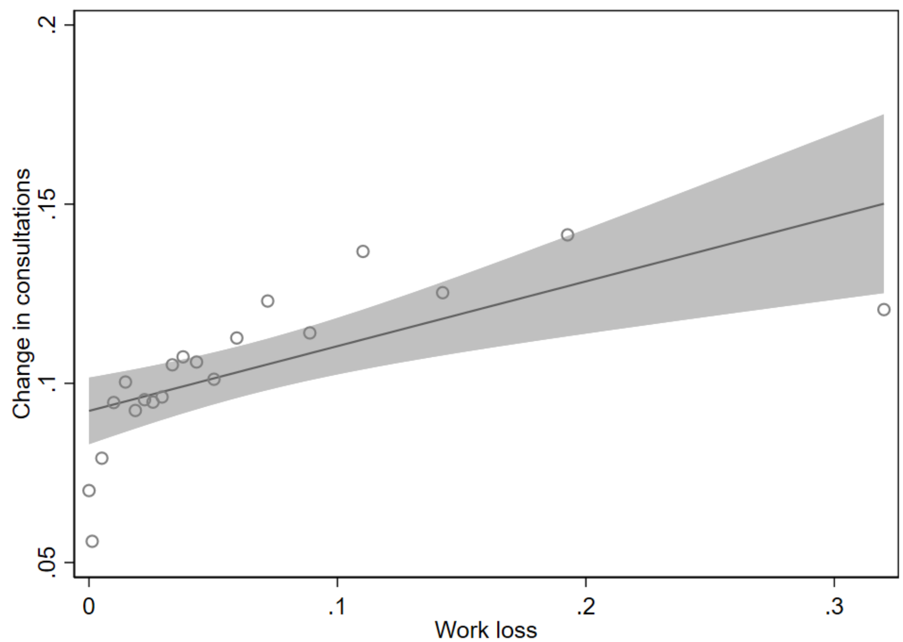
(a) Consultations per 1,000 workers



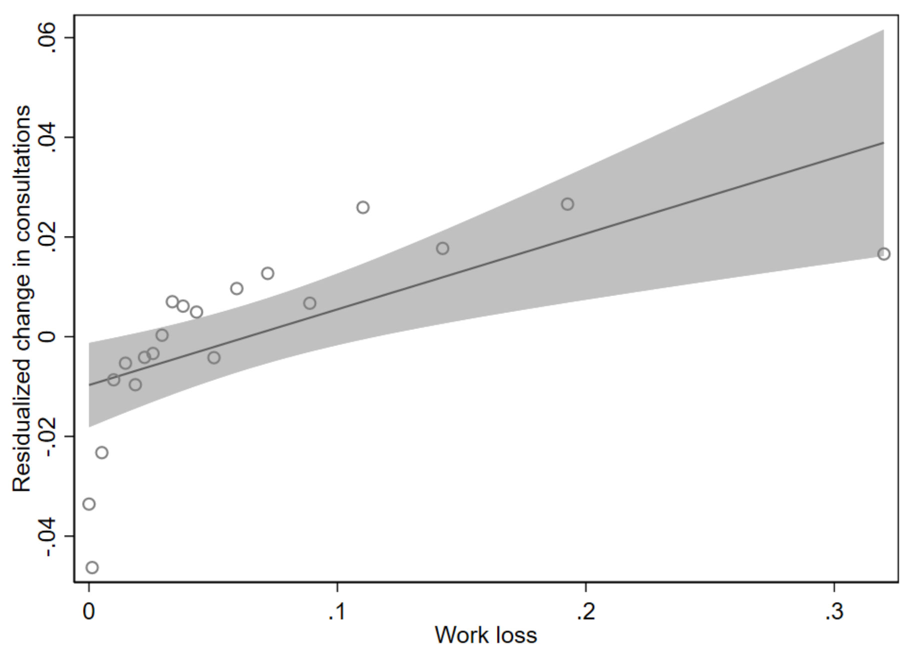
(b) Consultations (indexed)

Note: Figure shows average quarterly somatic consultations per 1,000 workers by quartile of the work loss distribution.

Figure B2: Change in somatic consultation volumes by work loss



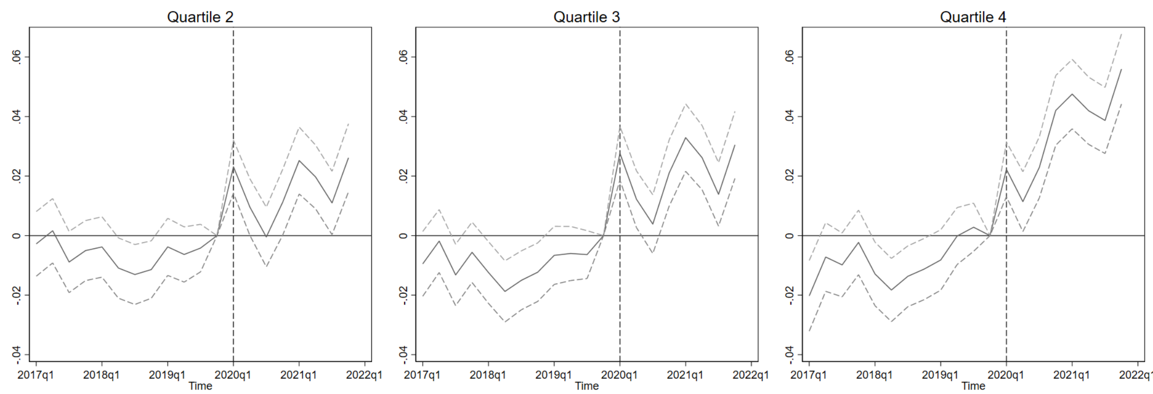
(a) Raw changes



(b) Residualized changes

Note: Figure plots changes in average quarterly consultation rates from pre-pandemic baseline 2017-2019 to 2020-2021 against the ventiles of the work loss distribution. Panel (a) plots raw changes, panel (b) plots residualized changes controlling for age, gender and county.

Figure B3: Event study estimates - somatic conditions



Note: Figure shows the estimates of $\rho^{t\tau}$ in Equation (1), with 95% confidence intervals. Cell-population-weighted estimates. Standard errors are clustered at the group level.

Table B2: Somatic conditions - difference-in-difference estimates

	(1)	(2)	(3)	(4)	(5)
	All cons	Cons (any)	Cons per patient	Primary	Specialist
Post × Q2	0.0214***	0.00484***	0.0249***	0.0168***	0.00461**
	(0.00345)	(0.000827)	(0.00566)	(0.00222)	(0.00195)
Post × Q3	0.0300***	0.00858***	0.0249***	0.0253***	0.00475**
	(0.00342)	(0.000832)	(0.00567)	(0.00221)	(0.00192)
Post × Q4	0.0438***	0.0139***	0.0286***	0.0321***	0.0117***
	(0.00371)	(0.000966)	(0.00562)	(0.00242)	(0.00200)
N	737240	737240	649436	737240	737240
Pre mean	0.852	0.388	2.150	0.543	0.309
Rel effect Q2	0.0251	0.0125	0.0116	0.0309	0.0149
Rel effect Q3	0.0352	0.0221	0.0116	0.0465	0.0154
Rel effect Q4	0.0514	0.0358	0.0133	0.0591	0.0378

Note: Table presents estimates from equation (2). Models include calendar time and cell fixed effects, and covariates (age, gender, county) interacted with calendar time. Observations weighted with the population in each cell. Standard errors in parentheses, clustered at the group level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B3: Robustness - somatic conditions

	(1) Any WL	(2) 10%+ WL	(3) 20%+ WL	(4) Occup	(5) With public sector	(6) Reweight
Post × Q2	0.0267***	0.0218***	0.0196***	0.0170***	0.0254***	-0.00174
	(0.00349)	(0.00346)	(0.00346)	(0.00354)	(0.00545)	(0.00729)
Post × Q3	0.0387***	0.0327***	0.0298***	0.0296***	0.0206***	0.0299***
	(0.00344)	(0.00340)	(0.00338)	(0.00390)	(0.00502)	(0.00730)
Post × Q4	0.0424***	0.0432***	0.0426***	0.0458***	0.0204***	0.0320***
	(0.00367)	(0.00370)	(0.00367)	(0.00397)	(0.00516)	(0.00574)
N	737240	737240	737240	607360	804060	737240

Note: Table presents estimates from equation (2). All models include calendar time and cell fixed effects. Models (1)-(5) include covariates (age, gender, county) interacted with calendar time. Columns (1) - (3) assigns cells to quartiles using share of workers with (1) any registered work loss, (2) share lost 10% or more of pre-pandemic hours, (3) share of workers lost 20% or more of pre-pandemic hours. Column (4): sample where cells defined by 4-digit occupation instead of 4-digit industry classifiers. Column (5) shows models estimated on expanded sample including public sector employees. Column (6) shows estimates from propensity score reweighting. Observations weighted with the population in each cell. Standard errors in parentheses, clustered at the group level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Appendix C: Effects on children and by parental status - additional results

Construction of child sample. To test for spillover effects to children, we also estimate effects for children who turned 6-16 years in 2020. Children are linked to their parents using an unique (encrypted) personal identifier, and to their parents' risk of work loss as defined above. We estimate models for both paternal and maternal work loss. For the child sample, we have data on primary and specialist consultations for psychological conditions, but from primary care only for somatic conditions. Descriptive statistics are shown in Table C1 for the paternal job loss sample and Table C2 for the maternal job loss sample.

Results for children. Trends in healthcare utilization for children by parents' risk of work loss in quartiles are shown in Figure C1. Overall, the plots suggest that trends are broadly parallel both before and after the onset of the pandemic, with similar increases in consultations for mental health during the pandemic for children of parents with high and low exposure to work loss. To net out any impact of compositional changes, we estimate event study models (results in Figure 4). Overall, the models find no consistent evidence that paternal or maternal work losses affected children's consultation rates for somatic or mental health conditions. For consultations for mental health conditions, there is a slight tendency of a decrease in the high-risk versus the low risk group in the pre-periods, but differences are rarely statistically significant. There is no significant differential emerging after the onset of the pandemic. For somatic conditions there are also no significant increases following the pandemic.

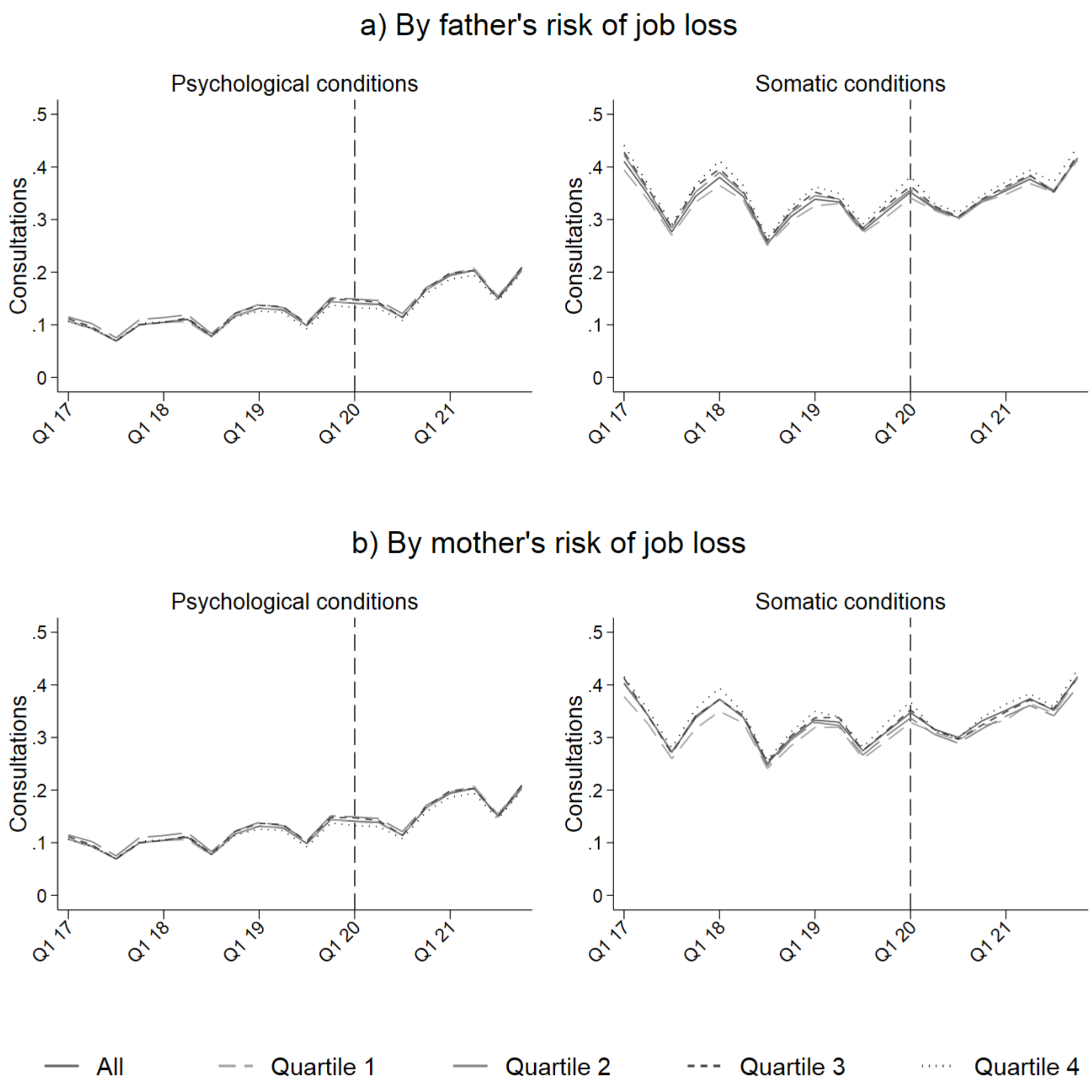
Difference-in-difference estimates are shown in Table C3 for somatic outcomes. (Results for mental health outcomes are shown in Table 5 and discussed in the main text.[10]) In the pooled model, somatic outcomes are not significantly affected.

For robustness, we have estimated the models separately by gender and by age (6-12 vs 13-16) (available upon request). Subsample analysis shows a tendency of a reduction in somatic consultation due to maternal job loss, concentrated among sons. Beyond this, the models fail to find any effects beyond what one should expect from chance at this significance level.

[10] For maternal work loss, the second quartile is statistically different from the first quartile in the difference-in-difference model ($p<0.1$). Given the many tests we perform, and the lack of evidence of a clear trend deviation in the event study models, we refrain from giving this a substantive interpretation.

Effects for the subsample of workers that are parents. Finally, we show that estimated effects of work loss on own health care utilization are similar for parents with dependent children and other fourth quartile workers (Figure C3). These results indicate that parents of the children we study experienced a worsening of health linked to increased risk of job loss during the pandemic. That is, the estimated increases in consultation rates of affected workers are not driven exclusively by non-parents.

Figure C1: Children's consultations by parent's risk of work loss



Note: Figure shows average quarterly consultations for children per by quartile of the work loss distribution of the parent.

Table C1: Summary statistics for child sample paternal job loss

	(1)	(2)	(3)	(4)	(5)
Work loss	0.0562	0.00535	0.0265	0.0526	0.162
	(0.0708)	(0.00556)	(0.00530)	(0.0122)	(0.0900)
Oslo	0.101	0.0948	0.0737	0.0961	0.150
	(0.302)	(0.293)	(0.261)	(0.295)	(0.357)
Female	0.484	0.506	0.358	0.487	0.609
	(0.500)	(0.500)	(0.479)	(0.500)	(0.488)
Age	43.25	44.48	43.10	42.59	42.71
	(7.192)	(7.114)	(7.069)	(7.227)	(7.204)
Child's age	10.96	11.15	10.94	10.89	10.81
	(2.680)	(2.701)	(2.658)	(2.675)	(2.671)
Psychological consultations	0.131	0.128	0.139	0.133	0.123
	(0.304)	(0.350)	(0.247)	(0.274)	(0.343)
Psychological, 2017-2019	0.109	0.105	0.121	0.111	0.0978
	(0.266)	(0.299)	(0.226)	(0.242)	(0.296)
Psychological, 2020-2021	0.164	0.163	0.166	0.168	0.160
	(0.351)	(0.412)	(0.273)	(0.311)	(0.400)
Somatic consultations	0.343	0.331	0.336	0.347	0.361
	(0.229)	(0.263)	(0.177)	(0.205)	(0.263)
Somatic, 2017-2019	0.334	0.320	0.330	0.339	0.352
	(0.216)	(0.247)	(0.168)	(0.195)	(0.248)
Somatic, 2020-2021	0.356	0.347	0.346	0.359	0.375
	(0.246)	(0.285)	(0.189)	(0.219)	(0.283)
countemp	17734720	233396	232608	234374	186358
	(0)	(0)	(0)	(0)	(0)
Observations	1446480	533000	224000	295520	393960

Note: Population-weighted averages, standard deviations in parantheses. Column (1) presents summary statistics on somatic healthcare utilization for the full sample; columns (2)-(5) show the corresponding figures by quartile of the job loss distribution for the father. Cells defined by combinations of parents' age (10-year brackets), gender, municipality, and industry of employment.

Table C2: Summary statistics for child sample maternal job loss

	(1)	(2)	(3)	(4)	(5)
Work loss	0.0772	0.00573	0.0253	0.0546	0.180
	(0.0913)	(0.00553)	(0.00539)	(0.0128)	(0.0916)
Oslo	0.128	0.131	0.105	0.136	0.137
	(0.334)	(0.337)	(0.307)	(0.342)	(0.344)
Female	0.490	0.500	0.437	0.460	0.534
	(0.500)	(0.500)	(0.496)	(0.498)	(0.499)
Age	40.73	42.35	40.49	40.45	39.79
	(6.616)	(6.399)	(6.492)	(6.654)	(6.611)
Child's age	10.95	11.15	10.90	10.91	10.86
	(2.711)	(2.748)	(2.683)	(2.707)	(2.694)
Psychological consultations	0.120	0.116	0.122	0.125	0.119
	(0.357)	(0.371)	(0.327)	(0.390)	(0.344)
Psychological, 2017-2019	0.0982	0.0947	0.102	0.101	0.0968
	(0.317)	(0.314)	(0.328)	(0.339)	(0.300)
Psychological, 2020-2021	0.153	0.149	0.151	0.161	0.152
	(0.407)	(0.441)	(0.324)	(0.455)	(0.400)
Somatic consultations	0.332	0.319	0.326	0.334	0.343
	(0.264)	(0.286)	(0.222)	(0.278)	(0.263)
Somatic, 2017-2019	0.322	0.306	0.320	0.325	0.334
	(0.248)	(0.266)	(0.211)	(0.262)	(0.246)
Somatic, 2020-2021	0.346	0.339	0.336	0.347	0.357
	(0.286)	(0.313)	(0.237)	(0.300)	(0.286)
countemp	8940240	114912	97050	87054	147996
	(0)	(0)	(0)	(0)	(0)
Observations	1036160	329840	161360	219360	325600

Note: Population-weighted averages, standard deviations in parantheses. Column (1) presents summary statistics on somatic healthcare utilization for the full sample; columns (2)-(5) show the corresponding figures by quartile of the job loss distribution for the mother. Cells defined by combinations of parents' age (10-year brackets), gender, municipality, and industry of employment.

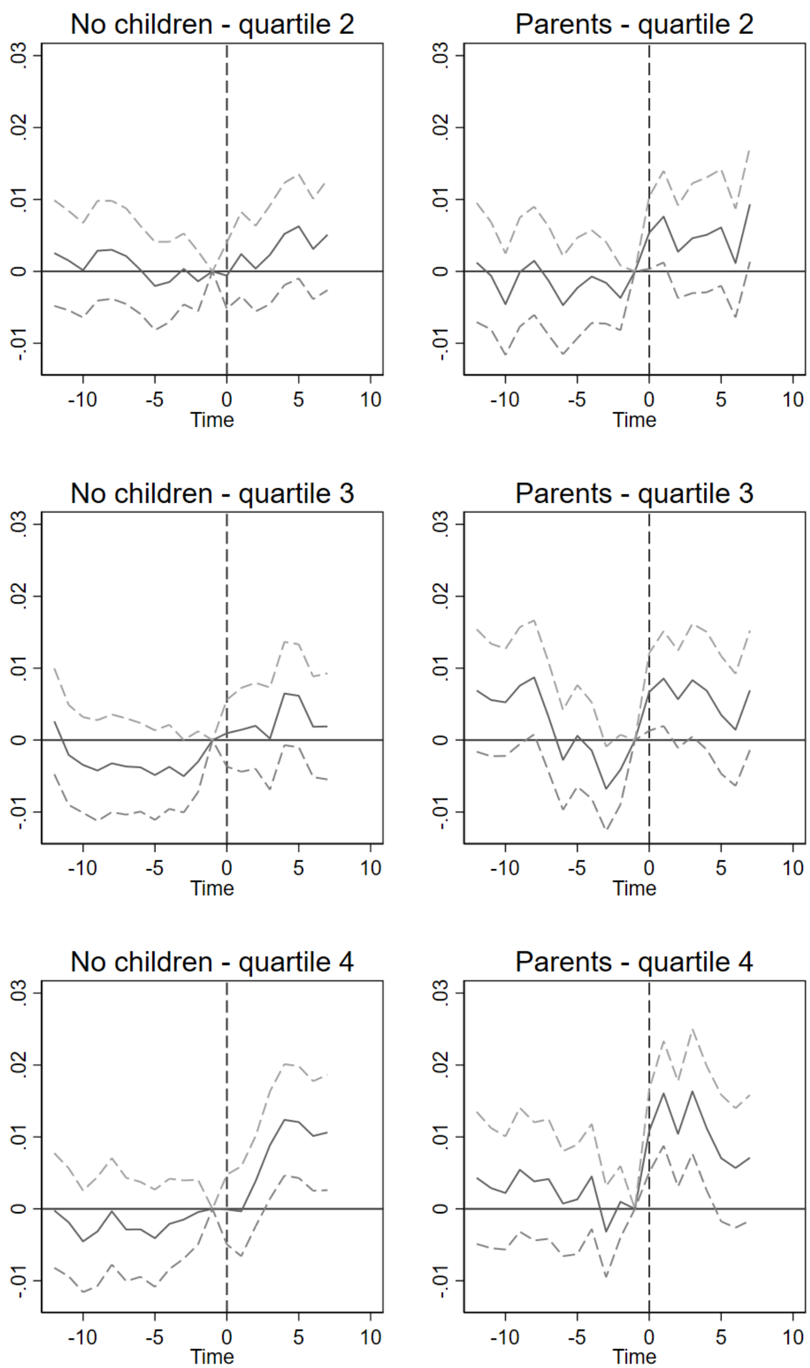
Figure C2: Change in psychological consultation volumes by parent's work loss

(a) Raw changes

(b) Residualized changes

Note: Figure plots changes in average quarterly consultation rates from pre-pandemic baseline 2017-2019 to 2020-2021 against the ventiles of the work loss distribution. Panel (a) plots raw changes, panel (b) plots residualized changes controlling for age, gender and county.

Figure C3: Effects by parental status



Note: Figure shows the estimates of $\rho^{t\tau}$ for $\tau = 4$ in Equation (1), with 95% confidence intervals. Cells defined by occupation (four-digit code), age, gender, and county. Cell-population-weighted estimates. Standard errors are clustered at the group level.

Table C3: Difference-in-difference estimates for children. Somatic health

	(1) Father	(2) Mother
Post × Parent's Q2	0.000432	-0.00146
	(0.00213)	(0.00298)
Post × Parent's Q3	0.00190	-0.00314
	(0.00211)	(0.00304)
Post × Parent's Q4	-0.00241	-0.00353
	(0.00221)	(0.00272)
N	723240	518080
ymean	0.343	0.332

Note: Figure shows estimated effects of parental work loss. Estimates of Equation (1) with 95% confidence intervals, estimated on a sample of children (6-16), where the predictor is the father's (col. 1) and mother's (col. 2) risk of work loss. Population-weighted estimates. Standard errors are clustered at the group level.

* $p < .10$, ** $p < .05$, *** $p < .01$