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Elevated serious psychological distress, economic disruption, and the COVID-19 pandemic in the nonmetropolitan American West

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ABSTRACT

In this study we examined the psychological distress, self-rated health, COVID-19 exposure, and economic disruption of a sample of the nonmetropolitan western U.S. population and labor force one year after the start of the COVID-19 pandemic. Using novel primary survey data from non-metropolitan counties in the eleven contiguous western United States collected from February 28 until April 3, 2021 ($n = 1203$), we descriptively analyzed variables and estimated binomial and multinomial logit models of the association between economic disruption, COVID-19 exposure, self-rated health, and psychological distress. Results showed there was widespread presence of psychological distress, COVID-19 exposure, and economic disruption among the overall sample and members of the labor force. There was extremely high incidence of serious psychological distress (14.8% CI [12.1,17.8] of the weighted sample), which was heightened among the labor force (16.6%, CI [13.0,20.9] of those in the labor force). We found economic disruption was associated with severe psychological distress, but exposure to infection was not. Comparatively, overall self-rated health was at similar levels as prior research and was not significantly associated with economic disruption or COVID-19 exposure. COVID-19, particularly its associated economic effects, had a significant relationship with serious psychological distress in this sample of adults in the nonmetropolitan western United States.

1. Introduction

The COVID-19 pandemic has disrupted nearly every aspect of U.S. society since March 2020. An ongoing crisis of this magnitude has been unmatched in recent history and has caused the U.S. population to contend with high levels of uncertainty and economic disruption. Since the outset of the pandemic, there have been concerns regarding the heightened vulnerability to the pandemic and its associated impacts faced by nonmetropolitan residents of the United States (Dearinger, 2020; Henning-Smith, 2020; Peters, 2020). Nonmetropolitan areas have less accessible health care (Peters, 2020), higher rates of poverty (Tickamyer et al., 2017), more vulnerable labor markets (Mueller, 2021), older populations (Johnson, 2020), a greater share of health-comprised individuals (Henning-Smith, 2020; Peters, 2020), higher mortality rates (Brooks et al., 2020), and lower usage of available mental health care than their metropolitan counterparts (Crumb et al., 2019; Stewart et al., 2015). Further, although there has been a widespread expansion of telehealth across nonmetropolitan areas during the COVID-19 pandemic, nonmetropolitan residents have accessed these services less than their metropolitan counterparts (Pierce and Stevermer, 2020). These vulnerabilities have resulted in notable health-related and economic impacts from the pandemic in nonmetropolitan areas throughout the country (Brook et al., 2021; Cheng et al., 2020; Karim and Chen, 2021; Mueller et al., 2021).

However, the scope and extent of these impacts are still unfolding. Due largely to a lack of data, we still do not fully understand the impact of the pandemic on many indicators of well-being historically collected via survey research, such as self-rated health and psychological distress. It is necessary to address this absence in understanding due to the vulnerabilities of nonmetropolitan residents generally, as well as the nonmetropolitan labor force specifically. In this study, we used novel survey data to address this need by examining self-rated health and psychological distress approximately one year after the onset of the COVID-19 pandemic in the nonmetropolitan counties—meaning

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counties defined by the US Office of Management and budget as those counties with a core population of less than 50,000 and less than 25% of labor commuting to core metropolitan counties (Office of Management and Budget, 2010)—of the eleven contiguous western United States.

Similar to other outbreaks like Severe Acute Respiratory Syndrome, Swine Flu, and Ebola, recent literature has noted the mental health impacts of the COVID-19 pandemic, including anxiety, stress, and depression (Brown and Schuman, 2020; Gardner and Moallef, 2015; Huremović, 2019; Mak et al., 2009; Monteith et al., 2020; Serrano-Ripoll et al., 2020). Additionally, a nationally representative survey conducted in April 2020 found that 41% of Americans anticipated there would be mental health consequences from the pandemic (Piltch-Loeb et al., 2021). Those who lived in states with high rates of mortality or infection due to COVID-19 and those anticipating negative economic impacts from the pandemic were more likely to expect negative mental health consequences (Piltch-Loeb et al., 2021). More recently, researchers have begun to explore how the health and economic impacts of the pandemic have been unequally experienced by particular segments of the population, especially those in the labor force—meaning those either actively employed or unemployed but looking for work (Brown and Schafft, 2019).

Evidence is mounting that particular segments of the labor force have experienced greater health and economic consequences than others. This includes racial and ethnic minority workers (Fairlie et al., 2020), healthcare workers (Greenberg et al., 2020), essential workers (van Zoonen and Ter Hoeven, 2021), lower-income households (Rothwell and Smith, 2021), and women (Collins et al., 2021). Although a large amount of this research has focused on the impacts of the pandemic on metropolitan laborers, there has been less scholarship on the nonmetropolitan labor force. Although not on the labor force specifically, existing nonmetropolitan-focused work suggests there have likely been high levels of unemployment, and decreases in overall life satisfaction, mental health, and economic outlook as a result of the COVID-19 pandemic (Brook et al., 2021; Mueller et al., 2021). Further, nonmetropolitan laborers were likely particularly vulnerable to the consequences of the pandemic due to nonmetropolitan areas' economic reliance on natural resource extraction, tourism, and manufacturing industries like meatpacking, which are industries that depend on in-person contact (Peters, 2020; Mueller, 2021).

In this study we analyzed the self-rated health, psychological distress, and economic disruption of a sample of the nonmetropolitan U.S. western population during the spring of 2021, one year after the COVID-19 pandemic began in earnest in the United States. We did so to understand the consequences of the pandemic itself, as well as the economic disruption stemming from efforts to control its spread. Using data from a novel purposive poll of adults living in the nonmetropolitan western United States, we tested whether negative health outcomes are greater than historically observed, and whether these outcomes are poorer for members of the labor force. Drawing on the impacts and vulnerabilities outlined above, we tested two hypotheses:

H1: Poor self-rated health, psychological distress, and economic disruption will be greater in this sample of nonmetropolitan residents than was observed in similar adult populations prior to the pandemic. This difference will be exacerbated for members of the nonmetropolitan labor force due to their central place in the experience of pandemic-related disruption.

H2: COVID-19 exposure and economic disruption will be associated with higher rates of poor self-rated health and both mild/moderate and serious psychological distress in this nonmetropolitan sample. These associations will be stronger for members of the nonmetropolitan labor force.

2. Methods

2.1. Data collection and weighting

The data for this study came from a primary purposive poll in the nonmetropolitan counties of the eleven contiguous western United States designed to have a sampling error of ±3.1% at the 95% confidence level. Data were collected in a manner similar to conventional political polls designed to quickly generate data on time-sensitive topics across the population. This was done via a dual-mode phone and internet survey of a sample collected by drawing a random sample of households from the United States Postal Service Delivery Sequence File. After drawing the sample, a survey-research firm, FM3, matched addresses against public records to discern contact information of residents. Residents were first contacted via phone and email, with postcards being sent if neither of those methods were successful. Data were collected from February 28 to April 3, 2021. Data collection utilized a method common in conventional polling where a desired N (1,000) was specified in advance with soft-quotas set for hard to reach groups. Sampling continued until the desired N was reached or we reached the end of our survey window—whichever came last. Soft-quotas were used to ensure a representative sample after weighting. Quotas included sex, age, Latino/a, Native American, and state. These soft-quotas were designed to result in a sample within +/− 3% of the population proportion. To keep our survey in-line with a prior effort (Mueller et al., 2021), we kept the survey open for five weeks and a total of 1203 completed surveys were collected. Responses came from all contact modes, with 478 via email, 500 via phone, 18 via postcard, and 207 via text.

Due to the use of a purposive sample and poll-style data collection, the results presented here should be considered equivalent to a political poll and not a traditional social scientific survey. The 'blast' nature of our sampling procedure, as well as our abbreviated sampling window, make relying upon a conventional response rate dubious—especially when considering the mixed support for response rates as indicators of data reliability (Groves and Peytcheva, 2008). That said, our contact and response rates were similar to both prior work in the disaster context as well as on COVID-19 in this population (Mueller et al., 2021; Piltch-Loeb et al., 2019). Using the most conservative rates from the American Association of Public Opinion Research (The American Association for Public Opinion Research, 2016), our Contact Rate 1 (the proportion of cases where a member of a housing unit was successfully reached) was 2.5%. This corresponds to an AAPOR Cooperation Rate 1 (total completed interviews among those contacted) of 38.1% and a Response Rate 1 (completed interviews relative to the entire sample regardless of successful contact) of 0.9%. Although these rates are lower than what many have historically considered desirable in survey research, it is not unexpected due the study design which was selected to ensure the rapid collection of timely data. Further, as detailed below, our use of soft quotas and poststratification via rake weighting reduce the limitations imposed by this level of response (Kulas et al., 2018). All of this said, due to the polling nature of our approach, further studies using more traditional techniques are needed to validate and verify our findings.

We applied weights to our data along the dimensions of sex, age, education, Latino/a, Native American, and state of residence. Weights were generated via raking to Census statistics. Due to the inability to obtain more recent census data in-line with our 18-year-old cut-off for this sample for educational groupings, we had to generate our weights via 2010 Census estimates. The procedures of the study were reviewed and approved by Yale University's Human Research Protection Program under exemption determination ID#2000027941.

2.2. Dependent variables

We focused on two dependent variables: self-rated health and non-specific psychological distress. Self-rated health was asked on the conventional five-point scale ranging from poor to excellent. Similar to other work using this measure (Blakely et al., 2002; Mueller et al., 2019), we dichotomized the five-point self-rated health measure into poor (fair/poor) and good (good/very good/excellent) self-rated health due to distributional issues within the five-point scale, which is generally skewed toward better health. Our measure of psychological distress was the widely used Kessler K6 non-specific psychological distress scale (Kessler et al., 2002; Prochaska et al., 2012; Tomitaka et al., 2019). This scale asks respondents to rate how often during the past 30 days they felt six different symptoms: nervous, hopeless, restless or fidgety, so depressed that nothing could cheer you up, that everything was an effort, and worthless. These items are rated on a five-point scale ranging from 0 – None of the time to 4 – All of the time. We then summed these six items to create an index of psychological distress. In-line with prior work and convention (Prochaska et al., 2012; Tomitaka et al., 2019), we evaluated this measure at the validated cut-offs for mild/moderate psychological distress—where the scale is greater than or equal to 5—and severe psychological distress—where the index is greater than or equal to 13.

2.3. Predictor variables

Our predictor variables were in three sets: demographic covariates, COVID-19 exposure indicators, and economic disruption indicators. The demographic covariates were variables likely to influence health outcomes via social determinants of health, as well as exposure to COVID-19 and economic disruption. These included sex, age, education, and Latino/a—we did not include detailed race because of limited variation within our sample and the study population. The categorical breakdown for each of these demographic covariates, as well as other relevant demographic characteristics can be seen in Table 1.

Our COVID-19 exposure indicators mirrored those used by Mueller et al. (Mueller et al., 2021) and included three binary measures related to direct exposure to the COVID-19 virus. These included whether or not the respondent contracted coronavirus (i.e. COVID-19) or showed symptoms, whether or not one of the respondent's family members contracted coronavirus or showed symptoms, or whether or not one of the respondent's friends or acquaintances contracted coronavirus or showed symptoms.

Economic disruption in our models was comprised of several measures. These measures included both perceived impacts and self-reported objective impacts. We included both perceived and objective impacts to capture the relative and absolute nature of economic impacts, wherein the perception of a local area may impact health regardless of experiencing a direct impact such as loss of employment. The perceived impacts mirrored items used by Mueller et al. (Mueller et al., 2021) and included two measures of perceived impact of the COVID-19 pandemic on the respondent's overall life and personal finances. Respondents were asked to rate how each of these items were impacted by the pandemic from 1 – Extreme Negative Impact to 10 – Extreme Positive Impact. We also included a measure of perceived economic health of the respondent's county for the month prior to the survey rated from 1 – Extremely Poor to 7 – Extremely Good. The self-reported objective measures focused on issues of employment, income, and housing. These included whether or not a respondent was unemployed or received unemployment insurance in the month prior to the survey; whether or not a respondent had to move out of their residence or have someone move into their residence due to the pandemic; or whether or not the respondent experienced any income loss due to the pandemic. All survey question language is included in the supplemental materials.

2.4. Analytic approach

Our analysis occurred in two steps. First, we evaluated the descriptive prevalence of model variables due to the novelty of this dataset and the time period under study. In doing so, we compared each of our variables between the overall sample and members of the labor force—meaning the portion of our sample either employed full-time or part-time, or temporarily unemployed (Brown and Schafft, 2019)—to evaluate if members of the labor force experienced greater hardship and disruption from the pandemic than adults generally. As we did not have a direct pre-pandemic sample to draw from to test elements of Hypothesis 1, we referred to recent literature and publicly available data to compare the observed prevalence of our outcomes and indicators to pre-pandemic levels of similar populations. In this descriptive analysis we report statistics for all cases which responded to the variable in question.

Second, we estimated a set of weighted models for both the overall sample and the labor force predicting poor self-rated health with a binary logistic model and different levels of psychological distress with a multinomial logistic model. In each case, we estimated four models: (1) a base model with only our demographic covariates, (2) a model with just COVID-19 exposure and demographic covariates, (3) a model with

Table 1
Demographic characteristics of sample and target population.

Variable	Levels	Sample		Adult Population[a]	
		N	Weighted Percent[b,c]	Non-Metro West	Non-Metro United States
				Percent[c]	Percent[c]
Sex	Male	624	51.0	50.7	49.7
	Female	551	49.0	49.3	50.3
Age	18–29	106	12.8	19.5	19.3
	30–39	143	21.2	15.5	14.8
	40–49	195	15.5	14.2	14.9
	50–64	341	28.9	26.1	26.6
	65+	404	21.7	24.7	24.3
Education[d]	Less than high school	29	3.7	11.4	13.7
	High School or GED	150	19.7	28.7	35.6
	Some College	326	41.1	26.1	21.5
	Bachelors or Associates	406	22.0	25.2	22.1
	Graduate or Professional Degree	278	13.5	8.6	7.1
Latino/a	Latino/a	109	15.0	15.0	7.1
	Not Latino/a	1054	85.0	85.0	92.9
Race	White	988	82.3	86.1	85.4
	Black	13	1.4	1.1	8.1
	Asian	13	0.9	1.2	1.0
	Native American	31	4.2	5.5	2.0
	Hawaiian or Pacific Islander	3	0.2	0.2	0.14
	Other	47	5.5	3.5	1.6
	Mixed race	49	5.5	2.4	1.7
State	Arizona	51	5.0	5.4	–
	California	215	14.0	13.9	–
	Colorado	129	12.0	11.6	–
	Idaho	105	9.0	8.7	–
	Montana	119	11.0	11.0	–
	Nevada	80	4.0	4.5	–
	New Mexico	67	11.0	10.7	–
	Oregon	142	11.0	10.9	–
	Utah	74	5.0	4.8	–
	Washington	147	12.0	12.2	–
	Wyoming	74	6.0	6.4	–
Total N		1203	–	4,840,699	36,026,729

[a] Population percentages pulled from 2015 to 2019 American Community Survey and are out of the entire population, as opposed to the sample which was restricted to only those 18 and older.
[b] Percent calculated using proportional weights by sex, age, education, Latino/a, Native American, and state.
[c] Values may not equal 100% due to rounding.
[d] Census totals are for only those over the age of 25.

just our economic disruption measures and demographic covariates, and (4) a full model with all covariates. To ensure consistent inference across models, we removed cases with any missing model variable data from all models ($n = 126$), resulting in a final modeling sample of 1077. All models and estimates used the previously discussed weights and were estimated using Taylor linearized robust standard errors. All indication of statistical significance is $p < .05$ and all confidence intervals are 95%.

3. Results

The final working descriptive sample was comprised of 1203 respondents and after weighting was generally representative of the nonmetropolitan U.S. west (Table 1). The exception is education, where our sample was over-representative of those with some college even after weighting. However, it is likely this disconnect is at least partially a product of the difference between census age thresholds for this data (25+) and our sample (18+).

While overall self-reported health remained relatively high, we found the presence of widespread psychological distress, COVID-19 exposure, and economic disruption (Table 2). With regard to self-rated health, we found that the majority of our sample was in good self-rated health, but a large portion—about a fifth—reported a poor level of self-rated health. This is similar to pre-pandemic data on this measure. For example, using data from the Behavioral Risk Factor Surveillance System (BRFSS) for 2019, we estimate that 18.7% CI [17.8,19.7] of adults in the nonmetropolitan West reported poor self-rated health. This stability of self-rated health is sharply in contrast to psychological distress. Diverging from the generally stable pre-pandemic estimates of serious psychological distress of about 3% to 5% (Tomitaka et al., 2019), a total of 14.8% CI [12.1,17.8] of our weighted sample reported serious psychological distress. Further, an additional 35.1% CI [31.6,38.7] of our sample reported mild/moderate psychological distress, meaning almost 50% of our weighted sample reported at least mild/moderate psychological distress (Table 1). These estimates are not only much larger than pre-pandemic data, but are also greater than recently published data on psychological distress during the early stages of the pandemic (May 2020) at the national level (Breslau et al., 2021).

Exposure to COVID-19 was widespread in our sample, with 14.9% CI [12.4,17.8] of respondents contracting the virus themselves, 35.6% CI [32.1,39.3] reporting a family member experienced infection, and 44.0% CI [40.4,47.7] reporting a friend or acquaintance was infected. Although not directly comparable due to question wording, infection in this sample (14.9% CI [12.4,17.8]) was higher than reported for the national population by the CDC at time of survey close (9.2%) (Centers for Disease Control and Prevention, 2021). These values are far larger than prior data on this population from June of 2020, where Mueller et al. (Mueller et al., 2021) found that only about a third of all nonmetropolitan westerners had any direct exposure to the virus (e.g. self, family, or friends); in this sample that percentage was 72.9% CI [69.7,76.0]. We also found that members of the labor force were more likely to have contracted COVID-19 themselves, with a 3.7 percentage point difference between members of the labor force and our overall sample (18.6% CI [15.0,22.9] vs. 14.9% CI [12.4,17.8], respectively).

Economic disruption due to COVID-19 was notable in our sample. A total of 13.4% CI [10.3,17.3] of those in the labor force reported they were temporarily unemployed, which is more than double the 6.0% reported by the Bureau of Labor Statistics for the nation during the same time period. Further, 9.6% CI [7.7,12.0] of the overall sample and 11.8% CI [9.1,15.1] of the labor force had someone in their household receiving unemployment benefits. We also found COVID-19 resulted in notable migration, with 6.1% CI [4.4,8.4] moving out due to COVID-19 and 10.3% CI [8.0,13.2] having someone move into their house due to the pandemic. These numbers were greater among the labor force, with members of the labor force both moving out of their residence due to COVID-19 and having people move in due to COVID-19 at greater rates than adults overall. In-line with our prior evidence of disruption, we also found that a large portion of our weighted sample, 35.3% CI [31.8,38.9], had lost income in 2020 due to the pandemic. This was more pronounced among the labor force, with 38.9% [34.3,43.8] losing income in 2020 from the pandemic.

Table 2
Descriptive statistics of model variables.

Categorical variables	Levels	Weighted percent[b,c] [95% CI] All adults	Labor force
Self-Rated Health	Excellent	13.4 [11.1,16.0]	14.9 [11.9,18.5]
	Very Good	30.0 [26.9,33.4]	29.4 [25.3,33.8]
	Good	34.8 [31.3,38.5]	37.2 [32.5,42.2]
	Fair	16.5 [13.9,19.5]	15.3 [12.1,19.2]
	Poor	5.3 [3.8,7.2]	3.3 [1.8,6.0]
Poor Self Rated Health	Good/Very Good/ Excellent	78.2 [75.0,81.1]	81.4 [77.2,85.0]
	Fair/Poor	21.8 [18.9,25.0]	18.6 [15.0, 22.8]
Non-Specific Psychological Distress	No Distress	50.2 [46.5,53.9]	48.0 [43.1,52.9]
	Mild/Moderate Distress	35.1 [31.6,38.7]	35.4 [30.9,40.3]
	Serious Distress	14.8 [12.1,17.8]	16.6 [13.0,20.9]
COVID-19 Exposure	Myself	14.9 [12.4,17.8]	18.6 [15.0,22.9]
	Family	35.6 [32.1,39.3]	35.2 [30.6,40.0]
	Friends	44.0 [40.4,47.7]	46.6 [41.8,51.5]
Unemployed	Yes	8.3 [6.3,10.8]	13.4 [10.3,17.3]
	No	91.7 [89.2,93.7]	86.6 [82.7,89.7]
Receiving Unemployment Insurance	Yes	9.6 [7.7,12.0]	11.8 [9.1,15.1]
	No	90.4 [88.0,92.3]	88.2 [84.9,90.9]
Moved Out due to COVID-19	Yes	6.1 [4.4,8.4]	7.0 [4.7,10.4]
	No	93.9 [91.6,95.6]	93.0 [89.6,95.3]
Moved In due to COVID-19	Yes	10.3 [8.0,13.2]	12.4 [9.2,16.6]
	No	89.7 [86.8,92.0]	87.6 [83.4,90.8]
Lost Income due to COVID-19	Yes	35.3 [31.8,38.9]	38.9 [34.3,43.8]
	No	64.7 [61.1,68.2]	61.1 [56.2,65.7]
Labor Force	Yes	61.9 [58.4,65.3]	–
	No	38.1 [34.7,41.6]	–
Continuous Variables	Scale	Mean [95% CI]	
Overall Life Impact	1 – Extreme Negative to 10 – Extreme Positive	4.3 [4.2,4.5]	4.3 [4.1,4.5]
Financial Impact	1 – Extreme Negative to 10 – Extreme Positive	4.7 [4.5,4.8]	4.6 [4.4,4.9]
County Economic Health	1 – Extremely Poor to 7 Extremely Good	3.5 [3.3,3.6]	3.5 [3.3,3.7]

[b] Percent calculated using proportional weights by sex, age, education, Latino/a, Native American, and state.
[c] Values may not equal 100% due to rounding.

4. Modeling

Similar to the stability we observed when comparing our descriptive statistics of overall self-rated health to recent data, our models of self-rated health suggest there is not a strong relationship between COVID-19 exposure, economic disruption, and poor self-rated health (Table 3). Our base model showed expected significant relationships via known social determinants of health, validating the data, but the indicators for COVID-19 exposure and economic disruption had no consistent relationship with the outcome.

The models of psychological distress were more dynamic and suggest that economic disruption from the COVID-19 pandemic is associated with elevated levels of psychological distress, while direct exposure to the virus is not Table 4. Again, the base model showed expected demographic relationships, validating the data. Our three indicators of COVID-19 exposure were not associated with either mild/moderate or serious psychological distress. When looking at economic disruptions, we found the only economic indicator associated with mild/moderate distress was household use of unemployment insurance. Findings differed when assessing serious psychological distress. Serious psychological distress was associated with household use of unemployment insurance, lost income due to COVID-19, individuals moving into a household due to COVID-19, and perceptions of worse county economic health.

Our models limited to those in the labor force in the month prior to the survey did not vary notably from the models of the entire sample. For that reason, we only describe them here and present the tabular results in the supplemental materials. The only differences observed in the labor force models were that mild/moderate psychological distress was associated with a friend or acquaintance contracting COVID-19, while household unemployment insurance usage was not. In the case of serious psychological distress, perceived county economic health did not have an association with serious psychological distress in the labor force models.

5. Discussion

In this study we found high levels of mild/moderate and serious psychological distress, but generally stable and positive levels of overall self-rated health, among a purposive sample of nonmetropolitan western U.S. residents living through the COVID-19 pandemic. Alongside this distress, we found significant exposure to the COVID-19 virus and high levels of economic disruption. These outcomes were greater than observed pre-pandemic in the nonmetropolitan population of the U.S. west and the overall national population, and many outcomes were observably worse for members of the labor force. These findings, with the exception of self-rated health, confirm our first hypothesis and suggest significant impacts of the pandemic on this sample. Although our study design limits generalizability, these results highlight the importance of continued research on this population.

When it comes to the models presented in this paper, the evidence for our second hypothesis was mixed. Our results suggest a nuanced relationship between economic disruption and psychological distress, no observable relationships with self-rated health, and no clear connection between exposure to the COVID-19 virus and psychological distress. The findings regarding the relationship between direct exposure to the COVID-19 virus and psychological distress may be driven by the generally infrequent incidence of prolonged and serious infection. Had we utilized a more detailed question on personal infection, a relationship may have been observed.

That we find a relationship between economic disruption and psychological distress is not especially surprising. However, given the high levels of psychological distress observed in this study, it is essential that we understand which forms of disruption are possibly driving these adverse outcomes. Somewhat surprisingly, we did not find a strong relationship between economic disruption and mild/moderate distress—indicating that other factors, possibly related to cultural change or perhaps the degree of isolation in these areas, may be driving this outcome. Serious psychological distress was more strongly correlated with economic impacts, however, not all indicators were significant.

Table 3
Logistic Regression of COVID-19 exposure and poor self-rated health.

	Base Model		COVID-19 Exposure		Economic Disruption		Full Model	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Female [Ref. = Male]	0.98	[0.67,1.43]	0.99	[0.68,1.45]	0.94	[0.63,1.39]	0.93	[0.63,1.38]
Age [Ref. = 18–29]								
30–39	**0.36**	**[0.18,0.71]**	**0.35**	**[0.18,0.71]**	**0.35**	**[0.17,0.71]**	**0.35**	**[0.17,0.72]**
40–49	**0.28**	**[0.14,0.58]**	**0.28**	**[0.14,0.58]**	**0.28**	**[0.14,0.56]**	**0.28**	**[0.14,0.57]**
50–64	**0.45**	**[0.25,0.82]**	**0.45**	**[0.25,0.81]**	**0.44**	**[0.24,0.81]**	**0.44**	**[0.24,0.81]**
65+	**0.29**	**[0.16,0.53]**	**0.28**	**[0.15,0.51]**	**0.30**	**[0.16,0.56]**	**0.29**	**[0.16,0.55]**
Education [Ref. = Bachelors or Associates]								
Less than High School	**6.84**	**[2.51,18.64]**	**6.95**	**[2.54,19.04]**	**5.85**	**[2.13,16.01]**	**6.02**	**[2.19,16.53]**
High School/GED	0.91	[0.47,1.75]	0.89	[0.46,1.72]	0.92	[0.47,1.80]	0.91	[0.47,1.79]
Some College	**2.14**	**[1.32,3.47]**	**2.15**	**[1.32,3.48]**	**1.99**	**[1.21,3.26]**	**1.99**	**[1.21,3.27]**
Graduate or Professional Degree	1.61	[0.94,2.75]	1.61	[0.94,2.78]	1.66	[0.95,2.92]	1.64	[0.93,2.89]
Non-Latino/a [Ref. = Latino/a]	1.44	[0.76,2.73]	1.45	[0.76,2.76]	1.47	[0.73,2.98]	1.44	[0.71,2.91]
COVID-19 Exposure [Ref. = No]								
Myself			0.95	[0.55,1.64]			0.83	[0.47,1.47]
Family			0.92	[0.61,1.39]			0.96	[0.62,1.47]
Friends or Acquaintances			0.91	[0.62,1.34]			1.00	[0.68,1.48]
Unemployed [Ref. = No]					0.62	[0.28,1.40]	0.60	[0.27,1.36]
Unemployment Insurance [Ref. = No]					1.40	[0.72,2.71]	1.42	[0.73,2.75]
Lost Income due to COVID-19 [Ref. = No]					0.94	[0.62,1.43]	0.94	[0.62,1.43]
Moved Out due to COVID-19 [Ref. = No]					0.82	[0.33,2.04]	0.82	[0.33,2.04]
Moved in due to COVID-19 [Ref. = No]					1.29	[0.69,2.42]	1.31	[0.69,2.47]
Overall Life Impact					0.95	[0.85,1.06]	0.95	[0.85,1.06]
Financial Impact					0.90	[0.81,1.01]	0.90	[0.81,1.01]
County Economic Health					**0.87**	**[0.77,0.98]**	**0.87**	**[0.77,0.98]**
Constant	0.29	[0.12,0.71]	0.31	[0.13,0.77]	0.96	[0.28,3.22]	1.04	[0.31,3.42]
N, McFadden Psuedo-R^2, BIC	1077, 0.06, 1101.27		1077, 0.06, 1121.58		1077, 0.08, 1128.45		1077, 0.08, 1148.60	

Exponentiated coefficients; Significant coefficients ($p < .05$) in bold.

Table 4
Multinomial Logistic Regression of COVID-19 exposure and psychological distress

A

Mild/Moderate Psychological Distress [Base Outcome = No Distress]	Base Model		COVID-19 Exposure		Economic Disruption		Full Model	
	RRR	95% CI	RRR	95% CI	RRR	95% CI	RRR	95% CI
Female [Ref. = Male]	**1.42**	**[1.00,1.99]**	1.40	[0.99,1.98]	1.38	[0.98,1.94]	1.36	[0.96,1.92]
Age [Ref. = 18–29]								
30–39	0.80	[0.38,1.69]	0.81	[0.38,1.70]	0.90	[0.42,1.92]	0.91	[0.43,1.93]
40–49	**0.44**	**[0.22,0.89]**	**0.44**	**[0.22,0.90]**	**0.44**	**[0.22,0.90]**	**0.44**	**[0.22,0.90]**
50–64	**0.41**	**[0.21,0.77]**	**0.42**	**[0.22,0.81]**	**0.40**	**[0.21,0.78]**	**0.42**	**[0.22,0.81]**
65+	**0.23**	**[0.12,0.43]**	**0.23**	**[0.12,0.46]**	**0.25**	**[0.13,0.50]**	**0.26**	**[0.13,0.52]**
Education [Ref. = Bachelors or Associates]								
Less than High School	1.50	[0.53,4.26]	1.48	[0.51,4.35]	1.36	[0.50,3.68]	1.36	[0.49,3.78]
High School/GED	**0.56**	**[0.32,0.97]**	0.57	[0.33,1.00]	0.62	[0.36,1.07]	0.64	[0.37,1.11]
Some College	1.10	[0.75,1.63]	1.11	[0.75,1.63]	1.03	[0.69,1.53]	1.03	[0.69,1.53]
Graduate or Professional Degree	1.12	[0.73,1.72]	1.08	[0.71,1.66]	1.20	[0.78,1.84]	1.14	[0.74,1.76]
Non-Latino/a [Ref. = Latino/a]	0.82	[0.46,1.49]	0.80	[0.44,1.44]	0.88	[0.47,1.65]	0.84	[0.45,1.58]
COVID-19 Exposure [Ref. = No]								
Myself			0.97	[0.59,1.58]			0.87	[0.52,1.47]
Family			1.02	[0.71,1.48]			0.99	[0.68,1.45]
Friends or Acquaintances			1.32	[0.93,1.87]			1.39	[0.97,2.00]
Unemployed [Ref. = No]					0.44	[0.18,1.05]	0.43	[0.18,1.04]
Unemployment Insurance [Ref. = No]					**2.98**	**[1.50,5.90]**	**3.07**	**[1.54,6.15]**
Lost Income due to COVID-19 [Ref. = No]					1.44	[0.97,2.12]	1.45	[0.98,2.14]
Moved Out due to COVID-19 [Ref. = No]					1.64	[0.68,3.95]	1.58	[0.66,3.79]
Moved in due to COVID-19 [Ref. = No]					1.77	[0.91,3.44]	1.78	[0.91,3.47]
Overall Life Impact					0.98	[0.90,1.07]	0.99	[0.91,1.08]
Financial Impact					0.93	[0.85,1.01]	0.92	[0.84,1.01]
County Economic Health					0.98	[0.88,1.09]	0.97	[0.87,1.09]
Constant	1.59	[0.71,3.57]	1.42	[0.63,3.18]	1.94	[0.65,5.78]	1.80	[0.60,5.43]

B

Serious Psychological Distress [Base Outcome = No Distress]	Base Model		COVID-19 Exposure		Economic Disruption		Full Model	
	RRR	95% CI	RRR	95% CI	RRR	95% CI	RRR	95% CI
Female [Ref. = Male]	**2.52**	**[1.46,4.36]**	**2.59**	**[1.51,4.45]**	**2.75**	**[1.58,4.81]**	**2.75**	**[1.59,4.76]**
Age [Ref. = 18–29]								
30–39	1.93	[0.72,5.13]	1.90	[0.73,4.96]	2.11	[0.81,5.51]	2.13	[0.82,5.50]
40–49	0.75	[0.28,2.03]	0.74	[0.28,1.99]	0.63	[0.24,1.66]	0.64	[0.24,1.67]
50–64	0.41	[0.16,1.08]	0.40	[0.15,1.04]	**0.36**	**[0.14,0.94]**	**0.37**	**[0.14,0.94]**
65+	**0.17**	**[0.06,0.48]**	**0.17**	**[0.06,0.47]**	**0.20**	**[0.07,0.58]**	**0.21**	**[0.08,0.59]**
Education [Ref. = Bachelors or Associates]								
Less than High School	3.58	[0.81,15.75]	3.40	[0.76,15.12]	2.61	[0.47,14.35]	2.50	[0.45,14.06]
High School/GED	0.97	[0.43,2.18]	0.96	[0.42,2.18]	1.03	[0.43,2.47]	1.05	[0.44,2.50]
Some College	**2.99**	**[1.62,5.50]**	**3.01**	**[1.63,5.57]**	**2.36**	**[1.23,4.53]**	2.37	[1.24,4.53]
Graduate or Professional Degree	0.80	[0.37,1.75]	0.83	[0.38,1.82]	0.84	[0.36,1.98]	0.85	[0.36,2.00]
Non-Latino/a [Ref. = Latino/a]	0.83	[0.35,1.99]	0.88	[0.37,2.09]	0.89	[0.35,2.25]	0.90	[0.35,2.31]
COVID-19 Exposure [Ref. = No]								
Myself			1.26	[0.62,2.54]			1.07	[0.54,2.13]
Family			1.02	[0.60,1.75]			1.09	[0.61,1.94]
Friends or Acquaintances			0.89	[0.54,1.49]			1.10	[0.64,1.87]
Unemployed [Ref. = No]					1.28	[0.49,3.33]	1.33	[0.52,3.38]
Unemployment Insurance [Ref. = No]					**3.90**	**[1.70,8.96]**	**3.79**	**[1.66,8.66]**
Lost Income due to COVID-19 [Ref. = No]					**1.86**	**[1.02,3.38]**	**1.87**	**[1.02,3.41]**
Moved Out due to COVID-19 [Ref. = No]					1.89	[0.57,6.27]	1.88	[0.58,6.14]
Moved in due to COVID-19 [Ref. = No]					**3.27**	**[1.53,6.99]**	**3.20**	**[1.49,6.86]**
Overall Life Impact					0.93	[0.80,1.09]	0.93	[0.80,1.09]
Financial Impact					0.91	[0.77,1.06]	0.91	[0.78,1.06]
County Economic Health					**0.80**	**[0.68,0.95]**	**0.80**	**[0.68,0.95]**
Constant	0.19	[0.06,0.59]	0.18	[0.06,0.56]	0.43	[0.09,1.96]	0.39	[0.08,1.88]
N, McFadden Pseudo-R^2, BIC	1077, 0.08, 2104.67		1077, 0.08, 2139.96		1077, 0.14, 2095.39		1077, 0.14, 2131.01	

Exponentiated coefficients; Significant coefficients ($p < .05$) in bold.

These results suggest psychological distress may be heightened across the nonmetropolitan U.S. west, and it is imperative future research, particularly that using traditional survey techniques, tracks this issue to inform the preparation of policy solutions to emerging public health issues from the COVID-19 pandemic.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ypmed.2021.106919.

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