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Mental Health, Material Possessions, and Social Capital During COVID-19: A Study of the United States Urban Working-Age Population

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Abstract

This study evaluates the associations between the urban working-age population's mental health, material possession, and social capital during the COVID-19 pandemic. The specific stressors examined in this empirical analysis are income level, food insecurity, and virtual psychological support. This paper further examines the differences across the employed and unemployed population groups. We obtained data from the COVID-19 Household Impact Survey and constructed four measures of mental health conditions: Nervous, Depressed, Lonely, and Hopeless. Our empirical analyses use an ordinal regression model that takes both time and regional factors into consideration to control for potential time effects and time-invariant confounders that only vary between regions. For the employed group, the main results suggest that lower income and food insecurity is correlated with a higher frequency of mental health symptoms, while virtual psychological support predicts a better mental health status. For the unemployed group, food insecurity is negatively associated with mental health, and virtual psychological might help alleviate nervousness and depression.

Keywords Food Insecurity · Income Level · Virtual Psychological Support, Mental Health · Urban Population · COVID-19

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Introduction

Studies have reported a high prevalence of psychological distress and disorder among U.S. adults (Iranpour et al., 2022). These mental health issues can lead to long-term post-traumatic stress symptoms, such as drug addiction, alcoholism, and suicide, which can harm both individuals and society as a whole (Moore et al., 2016). Further, mental health issues are associated with other comorbid conditions, such as cardiovascular disease, obesity, and diabetes (Stunkard et al., 2003; Suls & Bunde, 2005). It is evident that mental issues are associated with an increased mortality risk, which is associated with reduced physical activity, physical illnesses, and compromised cognitive functioning of patients (White et al., 2015).

Meanwhile, the COVID-19 pandemic has profoundly changed our daily lives in many ways, especially in terms of the population's mental health. In the US, mental issues increased noticeably from 2017 to 2020 following the emergence of the COVID-19 pandemic (Brooks et al., 2020; Rajkumar, 2020). A large body of literature suggests that there is a negative correlation between COVID-19 and mental health status. Earlier research suggests that mental health illness is higher relative to pre-COVID-19 levels (Ettman et al., 2020a, 2020b; Liu et al., 2020; McGinty et al., 2020). Existing studies on the association between COVID-19 and mental health have examined the impacts of layoffs and government assistance programs (Fan & Nie, 2020), low assets, and financial stressors (Ettman et al., 2021), and decreased physical activity (Creese et al., 2021). But we do not know which specific population groups experience the consequence of COVID-19 more than others, or what are the roles of losing jobs and incomes in shaping this risk.

This study, therefore, specifically investigates the impacts of food insecurity, income levels, and virtual psychological support on the urban working-age population's mental health during COVID-19. This research will focus on the urban working-age population during the pandemic. Densely inhabited urban areas are targeted as potential epicenters of infectious diseases, so more draconian policies, such as curfew, social distancing in public spaces, working from home, quarantine, and bars/clubs closing, are implemented in these areas. These control measures significantly affect the urban working-age population by curbing their face-to-face interactions within workplaces and social gatherings. To a certain extent, the COVID-19 pandemic removes the physical psychological support for urban working-age employees, which is achieved through physical or face-to-face interactions with colleagues and friends. Furthermore, existing empirical research highlights differences in dealing with depressive symptoms between urban and non-urban populations(Guo et al., 2018; Li et al., 2016; Norstrand & Xu, 2012; Vogelsang, 2016). Therefore, the empirical exercises in this study primarily focused on urban working-age employees.

This study specifically examines two forms of stressors. The first type of stressor is material possessions, which are proxied by income levels and food insecurity. Existing research finds that the stressors for mental disorders usually include financial losses and inadequate supplies (Pfefferbaum & North, 2020). A large volume of the literature suggests that income inequalities (Erdem et al., 2016; Fryers et al., 2005; Golberstein, 2015; Lorant et al., 2003; Pabayo et al., 2014, 2016; Zimmerman & Bell, 2006) and financial difficulties (Erdem et al., 2016; Ettman et al., 2020a, 2020b) contribute to mental disorders and depressive symptoms. Empirical analyses demonstrate that people with low income (Oh et al., 2018), low levels of education (Chrzastek et al., 2021; Lorant et al., 2003; Peyrot et al., 2013), or no job (Cygan-Rehm et al., 2017; Tefft, 2011; Zivin et al., 2011) are at an increased risk of depression. These inequalities can be explained by limited access to care for poor Americans (Dickman et al., 2017), lack of social support leading the rich to withdraw support for public services (Kawachi et al., 1999), feelings of insecurity and shame (Wilkinson & Pickett, 2006), and unhealthy behaviors (Stansfeld et al., 2003). An existing study focusing on non-elderly adults in the U.S. finds that income increases lead to improvements in depressive symptoms (Ettner, 1996).

During a crisis such as COVID-19, people are at the risk of being exposed to food insecurity due to job loss or reduced income (Wolfson & Leung, 2020). Since mid-March 2020, numerous surveys have documented unprecedented levels of food insecurity that eclipse anything seen in recent decades in the United States, including during the Great Recession. Existing empirical analyses across the globe have demonstrated that food insecurity is associated with poorer mental health and specific psychosocial stressors, independent of socioeconomic status (Jones, 2017). This result has been shown to hold in high-income countries (Maynard et al., 2018). Furthermore, food insecurity can provoke feelings of aggravation, worry, and depression concerning the ability to maintain food supplies or acquire sufficient food in the future (Campbell, 1991; Kessler, 1997; Whitaker et al., 2006). Although more prevalent in low-income countries (Weaver & Hadley, 2009), food insecurity has become a growing and persistent concern in high-income countries. In North America, for example, rates of household food insecurity have remained stable or even increased in the last several years (Maynard et al., 2018). The limited access to food caused by economic and financial losses during COVID-19 puts individuals and families under the same stress. As the Food and Agriculture Organization of the United Nations stated in June, 2020, although globally there is enough food for everyone, the significant decline in economic growth due to the pandemic has translated into an issue of access to food (FAO, 2020).

The second potential stressor is social capital. According to Putnam (1993), social capital is the "*features of social organization, such as trust, norms, and networks that can improve the efficiency of society by facilitating coordinated actions.*" At the individual level, Glaeser et al. (2002) highlight social capital as the individual's social characteristics including social skills, charisma, and material possessions that enable non-market returns via interaction with others. Social capital can also involve membership in groups and networks to secure benefits (Sobel, 2002). Prior empirical research shows that higher social capital has protective effects on depressive symptoms (Nummela et al., 2008; Takagi et al., 2013). Economic research using U.S. data finds that a higher degree of individual social capital is associated with higher objective social status (Bucciol et al., 2019). Individuals care about social status as a distinctive feature within society (Truyts, 2010), which is strongly correlated with psychological functioning and other important health-related factors (Lorant et al., 2003; Macleod et al., 2007; Sakurai et al., 2010; Singh-Manoux et al., 2005).

Moreover, social network theory suggests that one's social capital includes social status, social contact, and opportunity for control (Atkinson et al., 1987; Jahoda, 1982; Warr, 1994), which is the enabling mechanism for social participation (Almedom, 2005; Putnam, 1995). In addition, income and feelings of financial security are significant predictors of subjective social status (Singh-Manoux et al., 2003). On top of that, people with a lower social status generally have lower levels of social capital, and that lack of social capital is related to reduced health status (Uphoff et al., 2013, p. 8). This relationship is supported by strong evidence from empirical studies conducted in the United States (Dean & Sharkey, 2011; German & Latkin, 2011; Kawachi et al., 1997). Based on these findings, social capital could be further divided into three categories—physical psychological support through direct interaction with others, like work-related social participation, virtual psychological support through indirect interaction with people, such as phone calls and text messages, and income levels that reflect one's social status.

Given the above explanation, material possessions and social capital can be divided into the stressors of food insecurity, income level, virtual psychological support, and physical psychological support. For material possessions, the specific stressors are income level and food insecurity, which are fundamentally related to social capital. Regarding social capital, the specific stressors include income level, virtual psychological support, and physical psychological support. As illustrated in Fig. 1a, quarantine policies, layoffs, and furloughs could remove physical psychological support related to work-based social networks (Goldman-Mellor et al., 2010). This will reduce an individual's resilience to mental health conditions (Koltai, 2018). Figure 1b illustrates how unemployed and furloughed individuals in the urban population are further deprived of their typical income level.

Our research brings a contribution to the current studies on mental health during Covid-19, which adds to the existing studies that have examined the associations between income, social capital, and mental health (Cygan-Rehm et al., 2017; Golberstein, 2015; Jones, 2017; Maynard et al., 2018; Sorsdahl et al., 2011; Takagi et al., 2013; Tefft, 2011). However, these studies tend to focus on limited stressors. For example, Wolfson and Leung (2020), Fang et al. (2021), and McAuliffe et al. (2021) only investigated the effects of food insecurity. Ettman et al. (2021) only focused on the influences of asset and financial stressors on depression. Creese et al. (2021) focused on reduced physical activities but the mental health measurement is limited to only loneliness. Liu et al. (2020) discussed the significance of family and social support to mental health, but their scope is focused on young adults instead of the working population. Fan and Nie (2020) studied the mental health of the urban working population yet the stressors focus on income losses and government assistance programs. Our study integrated both food insecurity, financial stressors, as well as social support in the investigation, providing a more comprehensive picture of the association between the stressors and mental health.

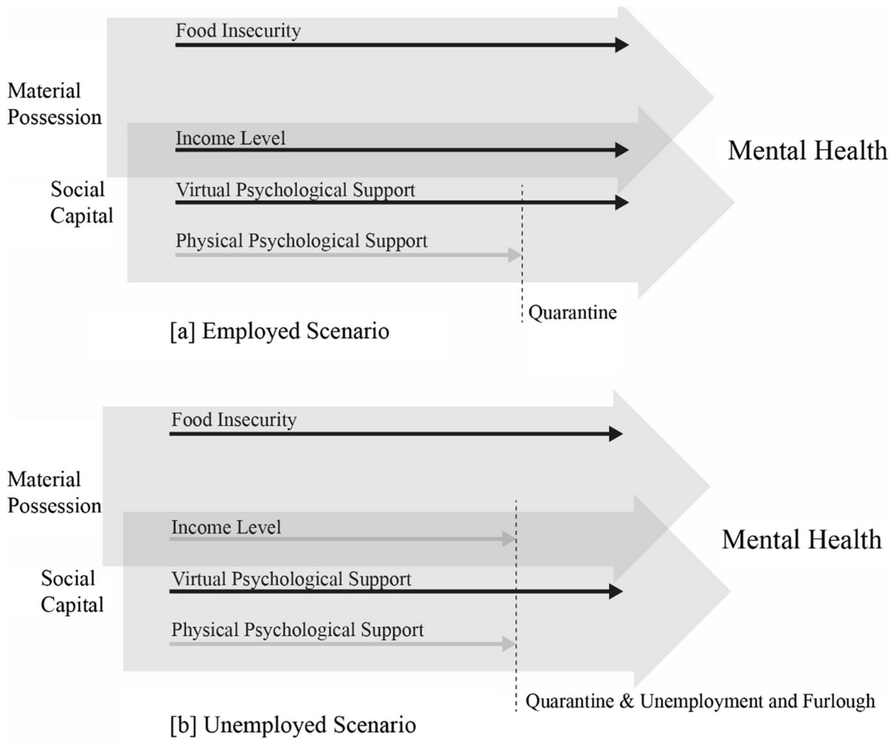

Fig. 1 **a**. Impacts of Material Possessions and Social Capital on the Mental Health of the Employed **b**. Impacts of Material Possessions and Social Capital on the Mental Health of the Unemployed and Furloughed

This empirical study evaluates the impacts of food insecurity, income level, and virtual psychological support during COVID-19 on the urban working-age population's mental health. In order to differentiate the impact of income level from the impacts of food insecurity and virtual psychological support, we stratify the analysis by the employed urban population and the unemployed and furloughed urban population.

Data, Variables, and Methods

Data Source

The data source for this study is the COVID-19 Household Impact Survey, which is a philanthropic project funded by the Data Foundation and conducted by the University of Chicago's National Opinion Research Center (NORC) (Wozniak et al., 2020). The survey was originally based on a proposal developed by the Federal Reserve Bank of Minneapolis and further applied by advisors to the COVID-19 Household

Impact Survey project. The survey includes three core modules—physical health, social and mental health, and economic and financial health. For the physical health module, questions include symptoms related to COVID-19, relevant existing conditions, and health insurance coverage. In the social and mental health module, questions are designed to align with the current population survey, focusing on communication with friends and family, volunteerism, and anxiety. The last module on economic and financial health prioritizes questions about government cash assistance, employment, and food security. The survey also collects important demographic characteristics, such as age, gender, race, and household income.

The survey targets two types of samples—a nationally representative sample of adults ages 18 and above in the United States and a regional representative sample of adults ages 18 and older living in 18 different geographic areas, including 10 states and 8 Metropolitan Statistical Areas (MSAs). These states include California, Colorado, Florida, Louisiana, Minnesota, Missouri, Montana, New York, Oregon, and Texas, while the MSAs include Atlanta-Sandy Springs-Alpharetta, Georgia; Baltimore-Columbia-Towson, Maryland; Birmingham-Hoover, Alabama; Chicago-Naperville-Elgin, Illinois-Indiana-Wisconsin; Cleveland-Elyria, Ohio; Columbus, Ohio; Phoenix-Mesa-Chandler, Arizona; and Pittsburgh, Pennsylvania. These regions are fixed effects in the empirical analysis because interregional income and socioeconomic status inequalities exist across the U.S. (Pabayo et al., 2014; Rey, 2018). NORC employs two sampling techniques—AmeriSpeak, a probability-based panel designed to be representative of the U.S. household population, and a Multi-mode Address Based Sample (ABS), which is a sampling frame based on an extract of the U.S. Postal Service delivery-sequence file. The field reports on the COVID Impact Survey official website provide details on both techniques.

As of June, three waves of the samples have been collected and made available with survey field periods of April 20–26, May 4–10, and May 30-June 8. These samples contain 25,269 observations with completed interviews with 34.79% (8,790) from the first wave, 35.51 (8,974) from the second wave, and 29.7% (7,505) from the third wave, consisting of 92.64% (23,408) web interviews and 7.36% (1,861) phone interviews. Among these samples, 74.38% (18,794) are sampled through the ABS approach and 25.62% (6,475) are sampled through the AmeriSpeak approach.

Urban Working-Age Employees

As mentioned earlier, the urban working-age population is affected by shutting down face-to-face interactions within workplaces and social gatherings, like bars and clubs. It removes the source of physical psychological support for urban working-age employees. This lays a good foundation for the study to differentiate the association of virtual psychological support and income level with mental health. Virtual conversations with friends and family members by phone or text could relieve pressure and provide social support(Almedom, 2005; Atkinson et al., 1987; Jahoda, 1982; Putnam, 1995; Warr, 1994). In this analysis, we use the change in frequency of communication with friends and family by phone, text, email, app, or the Internet to represent virtual psychological support.

After cleaning the raw data, the three survey waves include 7,295 non-retired, non-self-employed urban working individuals ages 18 and above within specified geographic areas. None of these individuals have been diagnosed with mental health conditions, infected with or recovered from COVID-19, isolated due to COVID-19 exposure, or lived with and cared for someone infected by the virus. In the 7 days prior to the field interview, the sampled individuals have not felt hot, feverish, chilly, cold, or bad chills. To investigate "precisely" the correlations between mental health and income levels and food insecurity during COVID-19, those who had not worked any hours before March 1st, 2020 (when the virus started spreading in the U.S.) are dropped from the relevant sample. The samples are described with sensitivity across four dimensions—layoff status, income levels, food insecurity status, and age intervals. In the relevant sample, 22.81% are laid off during the virus outbreak, 13.13% experienced food insecurity, 3.74% are aged 18–22, 86.22% are aged 23–64, and 10.03% are aged 65 and above. For the income levels (individual total pre-tax income in 2019 from all sources including wages, salaries, tips, business, interest, and alimony), 25.3% report earning more than \$125 k, 38.17% report earning \$60 k to less than \$125 k, 21.51% report earning \$30 k to less than \$60 k, and 15.01% report earning less than \$30 k. These cut-offs are based on the original dataset of NORC. Fig. 2 in the Appendix shows more details.

Mental Health

We construct four measures of mental health conditions based on the survey question SOC5—Nervous, Depressed, Lonely, and Hopeless. In this question, interviewees were asked to report the frequency of feeling these four emotions in the 7 days prior to the survey. The responses range from not at all or less than 1 day, 1–2 days, 3–4 days, to 5–7 days. Out of the 7,295 observations among the urban working-age population, 64% of the interviewees did not have the symptoms at all or experienced them less than 1 day, 23–24% experience them for 1–2 days, 8.37–8.82% had them for 3–4 days, and 4.3–4.77% had them for 5–7 days. Refer to Fig. 3 in the Appendix for the distributions of the four specific symptoms.

Covariates

We compile 11 covariates that are indexed at the individual and regional levels. The 3 major independent variables include income level, food insecurity, and virtual psychological support, which is represented by the probability of increased virtual communication frequency with friends and family. The income level, which reports 2019 annual pre-tax income from all sources (including wages, salaries, tips, business, interest, and so on), ranges from more than \$125 k, \$60 k to less than \$125 k, \$30 k to less than \$60 k, to less than \$30 k. Food insecurity evaluates if the two phrases "urban employees worried the food would run out before getting money to buy more" and "the food that urban employees bought just did not last, and they did not have money to get more" are often true or sometimes true.

The probability of increased virtual communication with friends and family is constructed following Hayes (1973), where the frequency of events is dependent on the number of intervals that are Poisson-distributed. Based on the two questions in the survey, "During a typical month prior to March 1, 2020, when COVID-19 began spreading in the United States, how often did you communicate with friends and family by phone, text, email, app, or using the Internet" and "In the past month, how often did you communicate with friends and family by phone, text, email, app, or using the Internet", we naturally have two-time frames—the first is the one month prior to March and the second is the one month before the field interview. The frequency expected in the second period is based on the occurrences in the first period. This refers to the mean of the Poisson distribution for the events happening in the second time window, which is m in the below equation. According to the potential responses, we categorize "basically every day" as 30 times, "a few times a week" as 16 times, "a few times a month" as 4 times, "once a month" as 1 time, and "not at all" as 0 times. We use the standard Poisson formula

$$f(x) = \frac{e^{-m} m^x}{m!},$$

where $f(x)$ is the expected frequency or probability of exactly x occurrences, e is the natural base of logarithms (2.71828…), m is the number of occurrences expected in the second time window, and x is the number of occurrences observed in the second time window. Instead of only calculating the exact probability of x occurrences for the second time window, we compute the probability that an individual communicated virtually with his or her friends and family at least x times based on the expected number of occurrences in the second time window and the actual number of occurrences observed in the second time window, which captures the change in willingness to virtually communicate. Fig. 4 in the Appendix illustrates the Poisson distributions with different means.

The other 8 control variables include general self-rated health (ranging from excellent, very good, good, fair, to poor), age categories (divided into 18–29, 30–44, 45–59, 60+), gender, education (ranging from no high school diploma, high school graduate or equivalent, some college, to the bachelor of arts or above), marital status (whether single, including widowed, divorced, separated, and never married, or married), race (African American or not), insurance (whether covered by health insurance), and household size (including children).

Method

Our statistical analysis uses an ordinal regression model (ordered logit model) that implements both week and region fixed effects. This model appropriately captures the ordinal frequency of the four mental health condition measures, as reflected by the number of days those interviewees felt nervous, depressed, lonely, or hopeless during the outbreak of COVID-19. By adding both time and region factors, we can account for the potential time effects and time-invariant confounders that only vary between regions. Standard errors are clustered at the regional level. The estimating equation is specified as.

$$ln(\theta_j) = \alpha_j + \beta E_{iwr} + XControl + \mu_w + \delta_r + \epsilon_{iwr},$$

where θ_j defines the odds of feeling nervous, depressed, lonely, or hopeless for fewer days than in category j for individual i in week w residing in region$r$, ***Control*** is a vector of control variables, μ_w is the time fixed effects, δ_r is region fixed effects, and ϵ_{iwr} is the error term. E_{iwr} is one of the three major independent variables,$FoodInsecurity_{iwr}$,$IncomeLevel_{iwr}$, and $VirtualComm_{iwr}$, measured by whether or not an individual has money to buy food, four levels of 2019 annual total pre-tax income, and the probability of increasing virtual communication with friends and family, respectively. To reduce the potential influence among the independent variables, for example, low-income families might be more likely to have food insecurity and lack of psychological support, we only test one major independent variable in each regression analysis.[1] In addition, due to data availability, only 2019 pre-tax income information is collected for both employed and unemployed individuals. To identify the difference in income caused by individuals becoming unemployed in 2020, we include an interaction term $IncomeLevel_{iwr} * Laidoff_{iwr}$ that nullifies the income of individuals who are still employed in 2020. The parallel lines assumption for the ordinal regression model assumes three different intercepts for each category, but a constant slope across categories.

Based on theory, material possessions encompass food insecurity and income level, while social capital encompasses income level, physical psychological support, and virtual psychological support. To further identify the "clean" impacts of income level, we take advantage of the quarantine and social distancing policies implemented primarily in urban areas, which basically cut off physical interactions with others, especially work-related and face-to-face psychological support. We divide the urban working-age population sample into two groups— the employed group and the unemployed group, which includes individuals who are laid off and furloughed. We do this to remove the effects of income for the unemployed group, so the effects of material possessions and social capital can be clearly distinguished.

Results

Table 1 outlines how material possessions and social capital are associated with the frequency of feeling nervous, depressed, lonely, and hopeless through waves 1, 2, and 3 with both week and regional fixed effects. The results are controlled for individual characteristics, including health status, age, gender, education, marital status, race, insurance, and household size.[2] Significant differences are identified

[1] Table 12 reports the results of mental health symptoms for the full sample by ignoring potential collinearity among major independent variables. The coefficients for income level and the interactive term income level * laid off are consistently smaller in magnitude than in Table 1, and the coefficients for food insecurity and virtual communication are consistently larger in magnitude than in Table 1. It indicates potential multicollinearity in the empirical analysis.

[2] The initial prevalence of feeling nervous, depressed, lonely, and hopeless in each category of the four major variables (income level, unemployed, food insecurity, and expected occurrences in the 2nd time window) are illustrated in Tables 7, 8, 9, and 10.

Table 1 Fixed Effects Results of Mental Health Symptoms for Full Sample

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
Income Level	1.058	0.988	0.982	1.068								
	[0.998,1.121]	[0.930,1.049]	[0.922,1.045]	[0.982,1.161]								
Income Level*Laid off	1.051*	1.026	1.068**	1.057*								
	[1.009,1.096]	[0.983,1.072]	[1.025,1.113]	[1.011,1.104]								
Food Insecurity					1.498***	1.301*	1.375**	1.568***				
					[1.234,1.820]	[1.045,1.619]	[1.112,1.702]	[1.312,1.873]				
Virtual Comm									0.654***	0.684***	0.823*	0.721**
									[0.517,0.827]	[0.568,0.823]	[0.682,0.994]	[0.587,0.886]
N	7069	7067	7046	7055	6754	6753	6733	6741	7198	7196	7175	7184
Log pseudo-likelihood	-6738.938	-6757.792	-6699.297	-6663.636	-6336.792	-6367.662	-6292.705	-6279.399	-6854.341	-6891.678	-6825.467	-6796.699

Each column reports estimates from a separate regression. Coefficients estimates are only reported for income level, income level*laid off, food insecurity, and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Table 11 in the appendix reports the full table results. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

between the employed and unemployed groups in columns (1), (3), and (4). The odds ratios show that feeling nervous, lonely, and hopeless may not be significantly associated with changes in income for employed individuals but could be positively correlated with income level if an individual is laid off. Columns (5)-(8) shows that food insecurity has a significant and strong association with mental health (Nervous: $\beta = 1.498$, 95% CI: 1.234, 1.820[3]). In columns (9)-(12), the odds ratios on the probability of increasing virtual communication with family and friends are significant and less than one, indicating the beneficial correlation with mental health (Nervous: $\beta = 0.654$, 95% CI: 0.517, 0.827).

Since we are using the same independent variable to identify the association with the survived dependent variables, it might raise the issue of type-I error that rejects the null hypothesis with mistakes by applying the standard 0.05 significance level. For example, income level could directly make an unemployed individual feel nervous, and the symptom of feeling nervous could as well lead to feeling lonely or hopeless. To identify what symptoms are more significantly related to the independent variables when they are logically or statistically related in our analysis, we further our analysis by restricting the significance level to 0.01. The results are reported in Table 15. The dependent variables that are more significantly related to income level, food insecurity, and virtual communication are loneliness, nervousness and hopelessness, and depression, respectively. This indicates that for an unemployed individual, a reduced income level leads to feeling loneliness, which could also lead to nervousness or hopelessness. Food insecurity leads to feeling nervousness and hopelessness, which then could lead to experiencing depression or loneliness. The lack of virtual communication leads to feelings of depression, which then could make the person feel nervous, lonely, and hopeless.[4]

Tables 2 and 3 exhibit the results after dividing the urban working-age population into employed and unemployed groups, which include individuals both being laid off and furloughed during COVID-19. Specifically, in columns (1)-(4) of Table 2, lower income levels could predict an increase in the frequency of feeling nervous and hopeless (Nervous: $\beta = 1.102$, 95% CI: 1.025, 1.184). In columns (5), (7), and (8), food insecurity is significantly associated with more days of feeling nervous, lonely, and hopeless (Nervous: $\beta = 1.455$, 95% CI: 1.199, 1.766). Columns (9)-(12) show that talking to family and friends over the phone has a significant negative correlation with the frequency of expressing mental health issues (Nervous: $\beta = 0.658$, 95% CI: 0.519, 0.836).

In Table 3, columns (1), (2), and (3) display the significant associations between food insecurity and deteriorated status of feeling nervous, depressed, and lonely. This pattern is similar to the pattern expressed by the employed group (Nervous: $\beta = 1.558$, 95% CI: 1.101, 2.204). Table 13 shows the Wald test on equality of coefficients for food insecurity between the employed and unemployed individuals, and we fail to reject the equality at the 10% level. On the other hand, being different from the employed individuals, the odds ratios reveal that virtual communication

[3] Only coefficients and confidence intervals on Nervous regressions are presented in the parentheses.

[4] We thank the anonymous reviewer for pointing this out.

Table 2 Fixed Effects Results of Mental Health Symptoms for Employed Individuals

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
Income Level	1.102**	1.027	1.029	1.122**								
	[1.025,1.184]	[0.952,1.109]	[0.957,1.107]	[1.035,1.216]								
Food Insecurity					1.455***	1.171	1.286*	1.641***				
					[1.199,1.766]	[0.991,1.384]	[1.010,1.639]	[1.350,1.994]				
Virtual Comm									0.658***	0.687***	0.717***	0.723**
									[0.519,0.836]	[0.581,0.812]	[0.605,0.850]	[0.586,0.892]
N	5453	5455	5432	5439	5252	5254	5232	5240	5510	5511	5488	5496
Log pseudolikelihood	-5097.758	-5153.104	-5051.225	-5038.772	-4861.502	-4918.848	-4810.875	-4812.670	-5149.662	-5228.887	-5114.877	-5109.882

Each column reports estimates from a separate regression. Coefficients estimates are only reported for income level, food insecurity, and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 3 Fixed Effects Results of Mental Health Symptoms for Unemployed Individuals

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless
Food Insecurity	1.558*	1.539*	1.467*	1.401				
	[1.101,2.204]	[1.046,2.264]	[1.023,2.105]	[0.968,2.027]				
Virtual Comm					0.704	0.703	1.232	0.763
					[0.485,1.024]	[0.491,1.005]	[0.769,1.973]	[0.538,1.080]
N	1445	1442	1444	1444	1623	1620	1622	1623
Log pseudolikelihood	-1414.423	-1386.275	-1419.552	-1407.079	-1630.167	-1585.827	-1633.817	-1613.807

Each column reports estimates from a separate regression. Coefficients estimates are only reported for food insecurity and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

has no significant association with the mental health status of unemployed individuals, as presented in columns (5)-(8) (Nervous: $\beta = 0.704$, 95% CI: 0.485, 1.024). However, in Table 13, the Wald test cannot reject the difference in the magnitude of coefficients between the two groups at the 10% significance level except for the coefficient for virtual communication regressing on the odds of being lonely.

Robustness Analysis

Considering that the fixed-effects analysis examines the relationship between changes in both material possessions and social capital on mental health symptoms across survey waves, we assume that respondents who participated in the survey in all three waves lost their work-based social networks of psychological support due to quarantine policies. As a robustness check, we use the occupation information collected by the AmeriSpeak approach. Out of the 476 individuals who reported their job information, the essential workers who are most likely to continue to have face-to-face interactions at work are dropped. These include the community and social service occupations, healthcare support occupations, healthcare practitioners and technicians, sales and related occupations, food preparation and serving related occupations, and transportation and material moving occupations. Table 4 shows that the robustness analysis results are qualitatively similar to the main results: the direction and magnitude of the associations remain similar, whereas only some associations become statistically significant under the new sample.

In our main sample, about 78% of the individuals are employed and 22% are unemployed. This might lessen the comparability of the two groups in Tables 2 and 3 because a smaller unemployed sample size might mean greater variability around the mean and lower odds of achieving significance. To reduce the discrepancy between these two groups, we first apply propensity score matching with Mahalanobis distance using individual characteristics. Next, we randomly draw a sample size of 1,500 from the employed group to match the sample size of the unemployed group. Tables 5 and 6 report the robustness analysis results. Compared to the results in Tables 2 and 3, for the employed group, the robustness results show that food insecurity significantly aggravates nervous, depressed, and hopeless feelings, but not the lonely feeling, and contacting family and friends over the phone significantly helps improve symptoms of those negative feelings. For the unemployed group, similar to the results in Table 3, food insecurity significantly worsens the frequency of feeling nervous, depressed, and lonely. Virtual communication helps alleviate nervousness and depression but not lonely and hopeless, while in Table 3, the coefficients for virtual communication are insignificant for all symptoms.

Limitations

This paper uses data from the COVID-19 Household Impact Survey. However, the dataset does not collect information on individuals' access to health care facilities or physicians, either physically or over the phone. This could be one limitation because

Table 4 Robustness Analysis of Mental Health Symptoms Excluding Essential Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Nervous	Depressed	Lonely	Hopeless	Nervous	Depressed	Lonely	Hopeless	Nervous	Depressed	Lonely	Hopeless
Income Level	0.825*	0.729***	0.847	0.802								
	[0.703,0.969]	[0.630,0.844]	[0.623,1.153]	[0.637,1.010]								
Income Level*Laid off	1.316*	1.298**	1.126**	1.424***								
	[1.067,1.621]	[1.096,1.537]	[1.044,1.215]	[1.307,1.551]								
Food Insecurity					1.773*	1.701	2.459**	2.015				
					[1.020,3.080]	[0.816,3.547]	[1.256,4.813]	[0.978,4.149]				
Virtual Comm									0.314**	0.320**	0.342***	0.251
									[0.134,0.737]	[0.150,0.684]	[0.213,0.550]	[0.059,1.064]
N	342	341	340	341	304	304	303	304	340	339	338	339
Log pseudo-likelihood	-298.968	-293.921	-269.651	-287.993	-250.766	-255.180	-224.099	-249.438	-297.654	-292.879	-265.374	-288.058

Each column reports estimates from a separate regression. Coefficients estimates are only reported for income level, income level*laid off, food insecurity, and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 5 Propensity Score Matching Robustness Analysis of Mental Health Symptoms for Employed Individuals

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
Income Level	1.122*	1.058	0.963	1.114*								
	[1.003,1.255]	[0.964,1.161]	[0.846,1.096]	[1.014,1.225]								
Food Insecurity					1.813**	1.496**	1.184	1.837***				
					[1.202,2.735]	[1.105,2.026]	[0.774,1.814]	[1.394,2.421]				
Virtual Comm									0.612*	0.504***	0.577***	0.535***
									[0.420,0.892]	[0.358,0.711]	[0.436,0.762]	[0.385,0.743]
N	1473	1474	1465	1469	1405	1407	1398	1402	1483	1484	1474	1479
Log pseudolikelihood	-1385.254	-1413.057	-1357.100	-1358.938	-1303.744	-1337.560	-1277.362	-1265.482	-1393.808	-1424.777	-1362.090	-1367.679

Each column reports estimates from a separate regression. Coefficients estimates are only reported for income level, food insecurity, and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 6 Propensity Score Matching Robustness Analysis of Mental Health Symptoms for Unemployed Individuals

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless
Food Insecurity	1.524*	1.430*	1.520**	1.330				
	[1.081,2.148]	[1.031,1.983]	[1.106,2.090]	[0.964,1.834]				
Virtual Comm					0.659*	0.667*	1.180	0.745
					[0.454,0.957]	[0.472,0.943]	[0.711,1.959]	[0.526,1.057]
N	1312	1309	1312	1311	1479	1476	1479	1479
Log pseudolikelihood	-1289.072	-1265.328	-1299.416	-1290.905	-1490.258	-1448.593	-1503.658	-1483.985

Each column reports estimates from a separate regression. Coefficients estimates are only reported for food insecurity and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

the compromised access to health care services could be a potential stressor that affects individuals' mental health status, especially during a pandemic. Secondly, there are limitations in the dataset when describing mental health conditions. The mental health status of the participants before COVID-19 is not described and other potential confounders such as personality traits that could influence both psychological support levels and feelings of loneliness are also not identified. The measurement of mental health status could also be subjective, for example, compared to the outcomes from validated depression or anxiety screeners, and single-item measures of mental health are not strong. Thirdly, the dataset only describes income levels in the pre-COVID time in 2019. Lastly, future studies could explore the mechanism behind material possessions and social capital that influence the population's mental well-being. Although this study identifies the associations between mental health and food insecurity, income level, and virtual psychological support, more detailed data could help to find out the channels through which these variables work.

Discussion

The existing literature on this topic examines the simple correlation between a crisis and an individual's mental health. This study contributes to the literature by examining the comparative associations between the working-age urban population's mental well-being during the pandemic and income level, food insecurity, and virtual psychological support. These results could provide policymakers with novel perspectives on how to prioritize policy goals during a crisis. Our results show that food insecurity has a significant and strong correlation with mental health, which is consistent with previous findings that food supply worries contribute to worse mental well-being (Campbell, 1991; Kessler, 1997; Whitaker et al., 2006). The odds ratios on the virtual communication variable are significant and less than one, indicating the beneficial mental health effects of virtual contact. This finding confirms our theoretical assumption that communicating with friends and family provides psychological support (Almedom, 2005; Warr, 1994).

Furthermore, we compared the results across the three survey waves, April 20–26, May 4–10, and May 30-June 8 (see Table 16 in the Appendix). We found that food insecurity remains a significant determinant of mental health. Moreover, we found the benefits of virtual communication vary across the three windows. It significantly reduces the symptoms of feeling depressed and lonely during the first window when lockdown and quarantine policies substantially changed people's lifestyles, alleviates nervousness and loneliness in the second window when people worry about the consequences of the pandemic and perhaps access to health care, and relieves depression in the third window when people were more used to being alone but generally frustrated about the longevity of the pandemic.

In addition, we as also found that people at a younger age or with a higher education level are more prone to mental health issues. This could be caused by the sudden lifestyle change by the Covid outbreak. On the one hand, children and university students are prone to Covid-related mental health issues (Elharake et al., 2022; Hawrilenko et al., 2021). Compared to the elderlies, youth is especially sensitive to lockdown and school closure (Viner et al., 2022). At the same time, the working population is also more easily affected by the deprivation of physical connection with work-related individuals and environments compared to the elderly. On the other hand, people with higher education levels are more likely to engage in office- or lab-related work environments, therefore they are more vulnerable to the sudden physical disconnection with work environments caused by quarantine policies compared to the population with lower education levels.

When we stratify the sample by the employed and unemployed population, the analyses exhibit quite different results. For the employed population, which is now deprived of physical psychological support, the results are qualitatively similar to those of the entire population. For income levels, explanations can be from both material possessions and social capital. From the perspective of material possessions, higher income ensures access to material supplies (Ettner, 1996) and access to care (Dickman et al., 2017). In regards to social capital, higher income alleviates feelings of insecurity (Wilkinson & Pickett, 2006) and could improve one's self-perceived subjective social status (Bucciol et al., 2019). However, the compounding impact of income level is weaker than the impacts of food insecurity and virtual psychological support. Food insecurity can provoke feelings of anxiety and depression (Campbell, 1991; Kessler, 1997; Whitaker et al., 2006) about the ability to maintain food supplies or acquire sufficient food in the future. Even when the employed population earns their typical income level, they nevertheless worry about their access to food. On the other hand, virtual psychological support can significantly improve the employed population's mental well-being because it is a form of social support and enabling environment for social participation (Almedom, 2005; Putnam, 1995), which together have protective effects on depressive symptoms (Nummela et al., 2008; Takagi et al., 2013).

For the unemployed population, the empirical results differ dramatically. Food insecurity remains the primary stressor, with the most significant effect on increased frequencies of feeling nervous, depressed, and lonely. However, the mitigating effect of virtual psychological support is compromised for the unemployed group feeling lonely and hopeless, although it remains helpful for alleviating nervous and depressed feelings. This is because of the protective effects of virtual psychological support on depressive symptoms, as suggested by existing theory and prior empirical results. But food insecurity is still the primary concern of this group. This has an important conceptual implication regarding the differentiation between the employed and unemployed groups. In Figs. 1a and b, a major difference in mental health stressors for the employed and unemployed groups is income level. Covid-19 removes income for the unemployed group, therefore, compared to the employed group whose material possession could be assured by a sustained income, food insecurity could translate into a more extreme condition of food insufficiency for the unemployed group due to being unable to afford food (Sorsdahl et al., 2011).

Food insufficiency refers to when household members do not have enough to eat and is comparable to "food insecurity with hunger" (Alaimo et al., 1998). Under extreme food insufficiency that could threaten survival, people could feel hopeless, and virtual psychological support as a form of social capital is unable to cause a meaningful change. Other recent studies have also suggested similar results that food insecurity, which may result from job loss, is associated with mental issues (Fang et al., 2021; McAuliffe et al., 2021). It is interesting to note, however, that for unemployed individuals, loneliness and hopelessness are not alleviated by virtual psychological support either in this case, which a lot of studies assume otherwise. In addition, food insecurity itself is not significantly correlated with hopelessness for the unemployed group, meaning that this group may feel hopeless not because of the present status of being unable to afford food, but rather the unpredictable future of staying unable to afford food. Therefore, instead of psychological support, material sustenance is still the primary concern of households without income sources during a crisis.[5]

Conclusion

In conclusion, this paper uses current data collected during COVID-19 to explore the impacts of material possessions and social capital on the urban working-age population's mental well-being. The specific stressors examined in the empirical analyses are income level, food insecurity, and virtual psychological support. The main findings align with those of the existing literature, while important novel findings are identified to complement the existing literature. First, food insecurity has an adverse association with mental health for the unemployed urban populations. Second, virtual psychological support, while significantly mitigating mental issues for the employed population, might only have a significant correlation with the nervous and depressed feelings in the unemployed population. In general, the unemployed group mainly worries about their access to food. Third, income level has a significantly moderate mitigating association with the employed population's mental well-being, although this correlation disappears for the unemployed. These findings can help policymakers better understand how to prioritize the needs of the urban population during a crisis. While virtual psychological support should be prioritized in alleviating mental issues of the employed urban population, the material substance is the priority for the unemployed urban population. Policies targeting this population group could consider granting them various forms of material support, including but not limited to reoccurring small amount checks or food coupons that could assure them a forceable guaranteed survival.

Appendix

Table 11 outlines the full table results of Table 1. This table reports the odds ratio coefficients for the 8 control variables, including general self-rated health (ranging from excellent, very good, good, fair, to poor), age categories (divided

[5] One of the coauthors of this study experienced the strict lockdown in Shanghai during Spring 2022 that shut every store including food supplies, and his anxiety that was caused by food insecurity due to nowhere to get food for the incoming days provides personal evidence for this argument.

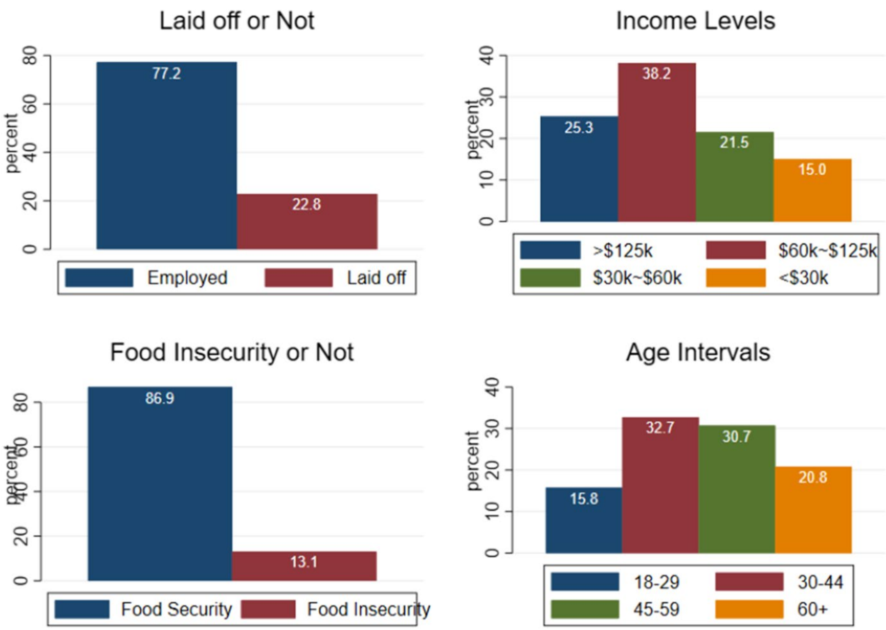

Fig. 2 The Distributions of Urban Working-Age Population Across 4 Dimensions

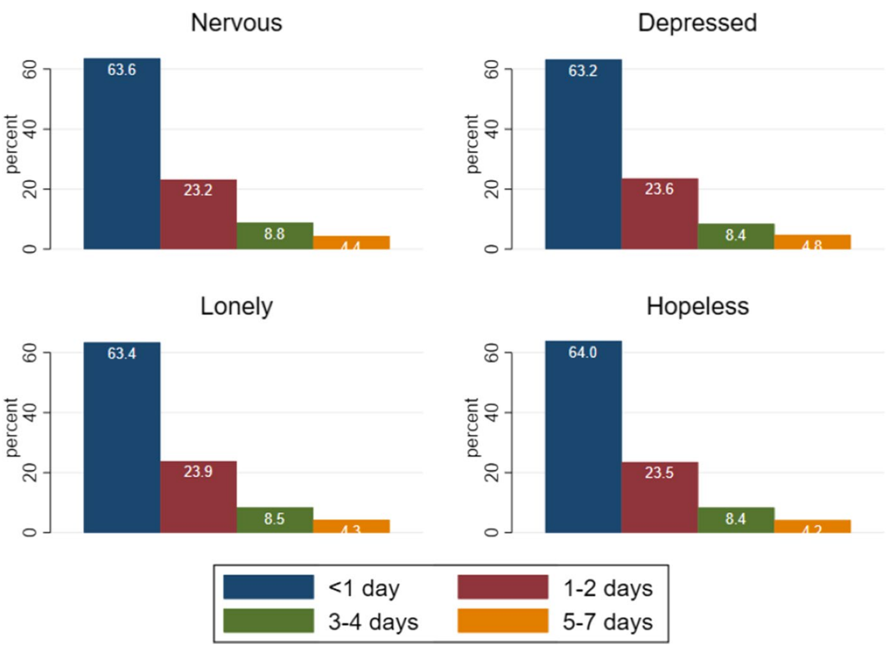

Fig. 3 The Distributions of Mental Health Conditions

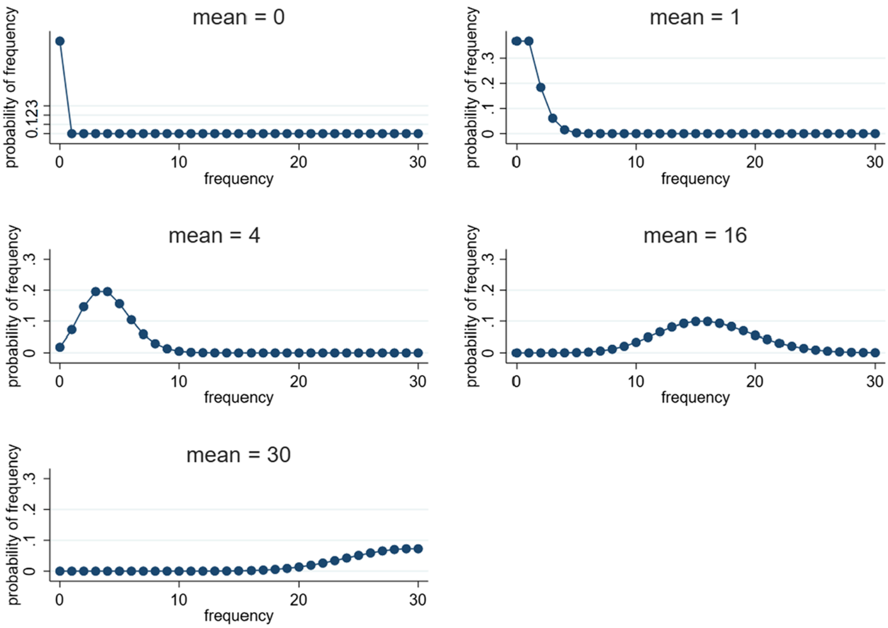

Fig. 4 Poisson Distributions with Different Means

into 18–29, 30–44, 45–59, 60+), gender, education (ranging from no high school diploma, high school graduate or equivalent, some college, to the bachelor of arts or above), marital status (whether single, including widowed, divorced, separated, and never married, or married), race (African American or not), insurance (whether covered by health insurance), and household size (including children).

African Americans show a lower frequency of having mental health issues than other races. As one's self-rated health status deteriorates, her/his mental health declines as well. Older people are having less mental health symptoms than younger people, which might imply that as individual ages, it could be better to deal with mental health status during a crisis like the pandemic. Females are significantly reporting worse symptoms than males. More educated people might exhibit more days of feeling nervous, depressed, lonely, and hopeless, but this pattern is not significant for all regressions. The marital status of being single reports insignificant coefficients with mental health. Health insurance might help alleviate the feeling of nervousness, depression, and hopelessness during the pandemic. Household size is significantly and negatively associated with days of having mental health issues, which might suggest the importance of physical psychological support within a family.

Table 14 shows the full table results for the full sample, employed individuals, and unemployed individuals. This table reports the odds ratio coefficients for both the major independent variables and the 8 control variables. Similar to Tables 1, 2, and 3, the significant coefficient for the interactive term income level and laid

Table 7 Initial Prevalence of Feeling Nervous in Each Category of the Four Major Variables

Nervous	Income Level				Unemployed		Food Insecurity		Expected Virtual Communication Occurrences in the 2nd Time Window				
	< \$30 k	\$30 k-\$60 k	\$60 k-\$125 k	> \$125 k	0	1	0	1	0	1	4	16	30
< 1 day	61.25	61.59	62.13	68.47	64.32	60.95	65.58	56.53	64.29	60.00	63.02	64.30	63.27
1–2 days	22.60	23.37	24.18	21.85	23.11	23.72	22.81	22.86	14.29	20.00	24.56	23.40	23.05
3–4 days	9.34	11.07	9.36	6.08	8.57	9.55	7.79	12.73	7.14	13.00	7.99	8.65	8.96
5–7 days	6.82	3.97	4.33	3.60	4.00	5.78	3.82	7.88	14.29	7.00	4.44	3.65	4.72
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 8 Initial Prevalence of Feeling Depressed in Each Category of the Four Major Variables

	Income Level				Unemployed		Food Insecurity		Expected Virtual Communication Occurrences in the 2nd Time Window				
Depressed	< $30 k	$30 k-$60 k	$60 k-$125 k	> $125 k	0	1	0	1	0	1	4	16	30
< 1 day	65.11	61.47	61.42	66.02	63.28	62.64	64.78	58.80	71.43	61.00	64.16	63.68	62.68
1–2 days	19.03	24.84	25.07	23.30	24.01	22.43	23.54	22.23	10.71	18.00	22.57	24.04	23.76
3–4 days	9.24	8.74	8.77	7.19	8.33	8.96	7.51	11.40	10.71	11.00	9.14	8.44	8.25
5–7 days	6.62	4.95	4.74	3.49	4.38	5.97	4.16	7.56	7.14	10.00	4.13	3.85	5.30
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 9 Initial Prevalence of Feeling Lonely in Each Category of the Four Major Variables

	Income Level				Unemployed		Food Insecurity		Expected Virtual Communication Occurrences in the 2nd Time Window				
Lonely	< $30 k	$30 k-$60 k	$60 k-$125 k	> $125 k	0	1	0	1	0	1	4	16	30
< 1 day	62.56	62.62	62.53	65.22	64.14	60.56	65.09	57.55	67.86	66.00	63.56	64.26	62.58
1–2 days	21.57	23.29	24.92	24.35	23.84	24.04	23.66	24.10	21.43	18.00	24.44	24.13	23.84
3–4 days	9.34	9.13	8.60	7.32	8.08	9.92	7.46	11.49	3.57	7.00	7.70	8.00	9.01
5–7 days	6.54	4.96	3.95	3.11	3.95	5.48	3.79	6.87	7.14	9.00	4.30	3.61	4.57
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 10 Initial Prevalence of Feeling Hopeless in Each Category of the Four Major Variables

	Income Level				Unemployed		Food Insecurity		Expected Virtual Communication Occurrences in the 2nd Time Window				
Hopeless	< \$30 k	\$30 k-\$60 k	\$60 k-\$125 k	> \$125 k	0	1	0	1	0	1	4	16	30
< 1 day	62.53	61.55	63.15	67.63	64.62	61.50	65.92	56.31	71.43	59.00	65.63	64.14	63.52
1–2 days	21.99	24.67	23.98	23.10	23.41	23.91	22.81	25.68	21.43	18.00	22.37	25.12	22.93
3–4 days	9.69	8.75	9.12	6.16	8.25	9.00	7.57	11.82	0.00	16.00	8.15	7.95	8.57
5–7 days	5.78	5.03	3.75	3.11	3.73	5.60	3.70	6.19	7.14	7.00	3.85	2.79	4.99
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 11 Full Table Regression Results of Full Sample

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
Income Level	1.058	0.988	0.982	1.068								
	[0.998,1.121]	[0.930,1.049]	[0.922,1.045]	[0.982,1.161]								
Income Level*Laid off	1.051*	1.026	1.068**	1.057*								
	[1.009,1.096]	[0.983,1.072]	[1.025,1.113]	[1.011,1.104]								
Food Insecurity					1.498***	1.301*	1.375**	1.568***				
					[1.234,1.820]	[1.045,1.619]	[1.112,1.702]	[1.312,1.873]				
Virtual Comm									0.654***	0.684***	0.823*	0.721**
									[0.517,0.827]	[0.568,0.823]	[0.682,0.994]	[0.587,0.886]
African American	0.672***	0.648***	0.651***	0.622***	0.587***	0.573***	0.586***	0.571***	0.670***	0.637***	0.654***	0.647***
	[0.562,0.802]	[0.573,0.734]	[0.581,0.729]	[0.519,0.746]	[0.484,0.711]	[0.508,0.646]	[0.513,0.670]	[0.460,0.708]	[0.565,0.795]	[0.563,0.720]	[0.582,0.734]	[0.540,0.775]
Self-Rated Health	1.319***	1.348***	1.334***	1.241***	1.300***	1.315***	1.309***	1.232***	1.336***	1.337***	1.340***	1.255***
	[1.242,1.401]	[1.271,1.429]	[1.241,1.433]	[1.164,1.323]	[1.225,1.380]	[1.243,1.391]	[1.219,1.404]	[1.153,1.316]	[1.260,1.416]	[1.258,1.420]	[1.245,1.442]	[1.179,1.335]
Age	0.703***	0.691***	0.683***	0.730***	0.707***	0.705***	0.695***	0.740***	0.697***	0.688***	0.688***	0.719***
	[0.671,0.738]	[0.659,0.725]	[0.660,0.707]	[0.699,0.762]	[0.668,0.748]	[0.668,0.745]	[0.670,0.720]	[0.702,0.780]	[0.664,0.731]	[0.656,0.722]	[0.667,0.710]	[0.684,0.755]
Female	1.467***	1.474***	1.456***	1.403***	1.486***	1.441***	1.446***	1.382***	1.498***	1.475***	1.493***	1.440***
	[1.312,1.639]	[1.386,1.567]	[1.330,1.595]	[1.293,1.523]	[1.327,1.664]	[1.325,1.567]	[1.313,1.593]	[1.277,1.497]	[1.329,1.687]	[1.379,1.578]	[1.360,1.638]	[1.328,1.562]
Education	1.188***	1.220***	1.195***	1.241***	1.185***	1.244***	1.238***	1.256***	1.129***	1.200***	1.173***	1.173***
	[1.119,1.260]	[1.138,1.309]	[1.104,1.292]	[1.153,1.335]	[1.099,1.277]	[1.159,1.335]	[1.141,1.343]	[1.158,1.361]	[1.063,1.198]	[1.119,1.287]	[1.086,1.266]	[1.094,1.258]
Single	0.994	0.910	1.090	1.049	1.018	0.967	1.133	1.084	0.988	0.943	1.119	1.048
	[0.646,1.528]	[0.568,1.456]	[0.784,1.516]	[0.854,1.289]	[0.679,1.528]	[0.598,1.562]	[0.803,1.599]	[0.866,1.357]	[0.649,1.506]	[0.585,1.520]	[0.796,1.572]	[0.875,1.256]
Insurance	0.787**	0.746**	0.827	0.796*	0.889	0.843	0.895	0.896	0.720***	0.715***	0.784*	0.728**
	[0.665,0.932]	[0.616,0.903]	[0.651,1.052]	[0.641,0.987]	[0.713,1.108]	[0.658,1.082]	[0.680,1.179]	[0.724,1.109]	[0.601,0.863]	[0.590,0.866]	[0.620,0.991]	[0.599,0.884]
Household Size	0.946**	0.924***	0.920***	0.927**	0.915***	0.922***	0.926***	0.915***	0.933**	0.923***	0.928***	0.916***
	[0.908,0.986]	[0.888,0.961]	[0.889,0.951]	[0.882,0.974]	[0.874,0.958]	[0.884,0.962]	[0.892,0.961]	[0.869,0.963]	[0.894,0.974]	[0.889,0.960]	[0.896,0.961]	[0.874,0.960]

Table 11 (continued)

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
N	7069	7067	7046	7055	6754	6753	6733	6741	7198	7196	7175	7184
Log pseudo-likelihood	-6738.938	-6757.792	-6699.297	-6663.636	-6336.792	-6367.662	-6292.705	-6279.399	-6854.341	-6891.678	-6825.467	-6796.699

Each column reports estimates from a separate regression. Regressions control for both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 12 Results of Mental Health Symptoms for Full Sample by Ignoring Potential Collinearity among Major Independent Variables

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless
Income Level	1.031	0.961	0.948	1.042
	[0.972,1.093]	[0.898,1.027]	[0.889,1.012]	[0.974,1.115]
Income Level*Laid off	1.026	1.013	1.050*	1.033
	[0.983,1.071]	[0.970,1.057]	[1.004,1.099]	[0.987,1.082]
Food Insecurity	1.571***	1.489***	1.568***	1.719***
	[1.259,1.961]	[1.197,1.854]	[1.267,1.940]	[1.452,2.035]
Virtual Comm	0.698**	0.710***	0.802*	0.751**
	[0.543,0.898]	[0.582,0.866]	[0.664,0.969]	[0.606,0.929]
African American	0.585***	0.582***	0.587***	0.570***
	[0.487,0.702]	[0.512,0.662]	[0.513,0.671]	[0.462,0.703]
Self-Rated Health	1.293***	1.317***	1.316***	1.223***
	[1.222,1.368]	[1.242,1.396]	[1.226,1.413]	[1.141,1.311]
Age	0.708***	0.697***	0.687***	0.741***
	[0.671,0.747]	[0.659,0.737]	[0.662,0.714]	[0.703,0.780]
Female	1.440***	1.419***	1.437***	1.339***
	[1.285,1.613]	[1.315,1.532]	[1.305,1.582]	[1.236,1.451]
Education	1.192***	1.222***	1.219***	1.279***
	[1.100,1.291]	[1.143,1.306]	[1.118,1.329]	[1.187,1.377]
Single	1.041	0.958	1.140	1.093
	[0.697,1.553]	[0.592,1.550]	[0.808,1.609]	[0.871,1.371]
Insurance	0.902	0.834	0.891	0.930
	[0.719,1.130]	[0.654,1.063]	[0.666,1.194]	[0.741,1.166]
Household Size	0.918***	0.912***	0.916***	0.919**
	[0.878,0.959]	[0.874,0.953]	[0.881,0.952]	[0.870,0.971]
N	6522	6521	6501	6509
Log pseudolikelihood	-6128.865	-6149.919	-6093.103	-6068.450

Each column reports estimates from a separate regression. Regressions control for both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

off reveals the difference between employed and unemployed groups in column (1), and as income level decreases, the symptoms of having mental health issues are getting worse for the employed individuals in column (4). Food insecurity is consistently and significantly associated with the deteriorated status of mental well-being but talking to family and friends over the phone could ease those nervous, depressed, lonely, and hopeless feelings.

Table 15 reports the results of mental health symptoms for the full sample by restricting the significance level to 0.01 and below, and the p values for those coefficients are in the parentheses for easy comparison. The purpose of this estimation is to identify which symptoms are relatively significant. As shown in the

Table 13 Wald Test on Equality of Coefficients to Employed and Unemployed Individuals Estimations

		Nervous	Depressed	Lonely	Hopeless
H_0 :[Employed]Food Insecurity = [Unemployed]Food Insecurity	Chi2(1)	0.19	2.57	0.51	0.53
	Prob > chi2	0.6663	0.1091	0.4742	0.4654
H_0 :[Employed]Virtual Comm = [Unemployed]Virtual Comm	Chi2(1)	0.13	0.02	5.28***	0.09
	Prob > chi2	0.7201	0.8843	0.0216	0.7652

The chi-squared distribution statistic values give the results of Wald tests on equality of coefficients for both food insecurity and virtual communication when regressing the odds of being nervous, depressed, lonely, and hopeless. The rejection significance level is 0.05 ***

Table 14 Results of Mental Health Symptoms by Using Mental Health Scale as Dependent Variable

	Full Sample			Employed Individuals			Unemployed Individuals	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income Level	1.017			1.060*				
	[0.968,1.068]			[1.004,1.119]				
Income Level*Laid off	1.060**							
	[1.021,1.100]							
Food Insecurity		1.513**			1.424***		1.576*	
		[1.130,2.026]			[1.159,1.751]		[1.069,2.322]	
Virtual Comm			0.644***			0.621***		0.746*
			[0.547,0.757]			[0.527,0.731]		[0.557,1.000]
African American	0.602***	0.506***	0.573***	0.568***	0.485***	0.534***	0.557**	0.662*
	[0.537,0.675]	[0.440,0.582]	[0.502,0.655]	[0.490,0.658]	[0.419,0.562]	[0.461,0.618]	[0.364,0.852]	[0.474,0.925]
Self-Rated Health	1.384***	1.325***	1.355***	1.410***	1.344***	1.362***	1.285***	1.330***
	[1.300,1.474]	[1.248,1.407]	[1.274,1.441]	[1.318,1.508]	[1.264,1.430]	[1.283,1.445]	[1.170,1.411]	[1.211,1.461]
Age	0.655***	0.660***	0.650***	0.661***	0.659***	0.648***	0.654***	0.645***
	[0.628,0.684]	[0.628,0.694]	[0.621,0.681]	[0.626,0.698]	[0.622,0.699]	[0.614,0.684]	[0.596,0.717]	[0.587,0.708]
Female	1.587***	1.562***	1.586***	1.637***	1.624***	1.626***	1.376***	1.465***
	[1.470,1.713]	[1.437,1.697]	[1.458,1.725]	[1.509,1.775]	[1.501,1.758]	[1.508,1.755]	[1.150,1.647]	[1.245,1.724]
Education	1.312***	1.079	1.058	1.384***	1.046	1.040	1.233*	1.210**
	[1.233,1.397]	[0.734,1.586]	[0.863,1.298]	[1.233,1.553]	[0.912,1.199]	[0.953,1.135]	[1.046,1.453]	[1.074,1.363]
Single	1.021	1.144	1.079	1.043	1.149	1.077	1.086	1.032
	[0.697,1.494]	[0.766,1.708]	[0.745,1.562]	[0.834,1.304]	[0.883,1.493]	[0.875,1.326]	[0.540,2.182]	[0.480,2.220]
Insurance	0.759*	0.989	0.787	0.718**	0.918	0.796	1.044	0.825
	[0.614,0.938]	[0.713,1.370]	[0.603,1.026]	[0.575,0.896]	[0.699,1.205]	[0.619,1.022]	[0.717,1.522]	[0.613,1.111]
Household Size	0.918***	0.904***	0.908***	0.928***	0.912***	0.913***	0.887**	0.892***
	[0.890,0.948]	[0.874,0.935]	[0.880,0.937]	[0.899,0.958]	[0.885,0.939]	[0.886,0.941]	[0.820,0.959]	[0.838,0.949]

Table 14 (continued)

	Full Sample			Employed Individuals			Unemployed Individuals	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N	7001	6687	7127	5398	5198	5453	1432	1609
Log pseudolikelihood	-13,272.101	-12,529.722	-13,522.016	-10,100.361	-9662.444	-10,228.714	-2748.743	-3150.362

Each column reports estimates from a separate regression. Regressions control for both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15 Fixed Effects Results of Mental Health Symptoms for Full Sample to Identify Significant Dependent Variables

	(1) Nervous	(2) Depressed	(3) Lonely	(4) Hopeless	(5) Nervous	(6) Depressed	(7) Lonely	(8) Hopeless	(9) Nervous	(10) Depressed	(11) Lonely	(12) Hopeless
Income Level	1.058	0.988	0.982	1.068								
	(0.0575)	(0.6897)	(0.5574)	(0.1260)								
Income Level * Laid Off	1.051	1.026	1.068*	1.057								
	(0.0183)	(0.2408)	(0.0016)	(0.0142)								
Food Insecurity					1.498***	1.301	1.375*	1.568***				
					(0.0000)	(0.0188)	(0.0033)	(0.0000)				
Virtual Comm									0.654**	0.684***	0.823	0.721*
N	7069	7067	7046	7055	6754	6753	6733	6741	7198	7196	7175	7184
Log pseudolikelihood	-6738.938	-6757.792	-6699.297	-6663.636	-6336.792	-6367.662	-6292.705	-6279.399	-6854.341	-6891.678	-6825.467	-6796.699

Each column reports estimates from a separate regression. Coefficients estimates are only reported for income level, income level*laid off, food insecurity, and virtual communication, but regressions control for individual characteristics as well as both week and regional fixed effects. Standard errors are clustered at the region level. P-values are in parentheses; * $p < 0.01$, ** $p < 0.001$, *** $p < 0.0001$

Table 16 Fixed Effects Results of Mental Health Symptoms for Full Sample across the Three Survey Waves

	Survey Wave 1				Survey Wave 2				Survey Wave 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Nervous	Depressed	Lonely	Hopeless	Nervous	Depressed	Lonely	Hopeless	Nervous	Depressed	Lonely	Hopeless
Income Level	1.076	0.902	0.940	1.087*	1.006	1.010	0.939	1.080	1.010	0.973	0.960	0.957
	[0.959,1.206]	[0.794,1.024]	[0.855,1.033]	[1.001,1.179]	[0.926,1.092]	[0.912,1.118]	[0.822,1.073]	[0.921,1.266]	[0.890,1.147]	[0.877,1.080]	[0.864,1.067]	[0.842,1.087]
Income Level * Laid Off	1.023	1.063	1.071	1.028	1.001	0.979	1.007	1.033	1.049	0.995	1.067	1.030
	[0.934,1.120]	[0.971,1.164]	[0.999,1.149]	[0.956,1.105]	[0.935,1.071]	[0.905,1.059]	[0.930,1.089]	[0.935,1.140]	[0.982,1.121]	[0.924,1.071]	[0.980,1.162]	[0.964,1.101]
Food Insecurity	1.566*	1.624**	1.563**	1.514**	1.578**	1.343	1.714**	1.737***	1.708***	1.635**	1.546*	2.026***
	[1.087,2.256]	[1.204,2.189]	[1.123,2.177]	[1.109,2.066]	[1.150,2.165]	[0.940,1.919]	[1.205,2.438]	[1.320,2.286]	[1.287,2.265]	[1.158,2.308]	[1.051,2.275]	[1.417,2.896]
Virtual Comm	0.732	0.719*	0.670*	0.759	0.541***	0.766	0.661**	0.730	0.948	0.641**	1.298	0.793
	[0.489,1.097]	[0.528,0.980]	[0.470,0.955]	[0.531,1.084]	[0.388,0.755]	[0.564,1.041]	[0.483,0.905]	[0.504,1.057]	[0.653,1.375]	[0.476,0.863]	[0.983,1.713]	[0.550,1.143]
N	2216	2217	2212	2212	2302	2302	2294	2298	2004	2002	1995	1999
Log pseudolikelihood	-2115.012	-2101.941	-2058.114	-2052.972	-2104.952	-2139.882	-2133.203	-2150.584	-1878.357	-1873.123	-1871.144	-1840.580

Each column reports estimates from a separate regression. Regressions control for both week and regional fixed effects. Standard errors are clustered at the region level. 95% confidence intervals in brackets; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

table, if an individual is laid off, feeling lonely is still significantly associated with changes in income. Food insecurity reveals significant correlations with symptoms of nervousness and hopelessness. Virtual communication with family and friends exhibits a significant association with feeling depressed. As the results indicate, the symptoms that the three independent variables significantly predict are different. Besides the direct correlation between independent variables and mental health symptoms, another possible path is that the symptoms significantly affected by the independent variables could as well affect the other symptoms that are not significantly affected after restricting the p values.

In Table 16, we include all the four major independent variables in each regression for comparison across the three survey waves, April 20–26, May 4–10, and May 30-June 8. The results in general report a similar pattern as in Table 1. The odds ratios show that feeling symptoms may not be significantly correlated with changes in income across those three survey windows. Food insecurity exhibits a strong and significant association with mental health. As an individual or a family facing the issue of a shortage of food under the shock of COVID-19, his/her frequency of having symptoms rises. The odds ratios on the probability of increasing virtual communication with family and friends show different patterns across the three waves. During the first window when the early diagnosed cases emerged, talking to family and friends significantly reduce the symptoms of feeling depression and loneliness. In the second window, virtual communication is significantly associated with less frequency of nervousness and loneliness, but merely significantly benefits for relieving depression in the third window.

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Declarations

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