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Associations of Small Business Closure and Reduced Urban Mobility with Mental Health Problems in COVID-19 Pandemic: a National Representative Sample Study

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Abstract It is suggested that the nationwide social distancing due to coronavirus disease 2019 (COVID-19) has adverse mental health consequences despite its necessity. We investigated the associations of social distancing measures with mental health problems. Using national representative sample of 509,062 adults in the USA, we examined the associations of small business closure and reduced urban mobility with generalized anxiety disorder (GAD) and major depression disorder (MDD). Multilevel regression models were fitted with individual, household, and state-level covariates, in addition to state and census-region-level random effects. Living in state with the highest quartile of small business closures was associated with increased prevalence of GAD (OR: 1.06; CI: 1.03–1.11) compared to lowest quartile, but had no association with MDD. Living in the highest quartile of urban mobility was associated with lower prevalence of both GAD (OR: 0.88; CI: 0.85–0.93) and MDD (OR: 0.90; CI: 0.86–0.95) relative to the lowest quartile. Our findings suggest that small business closures and reduced mobility during COVID-19 pandemic were negatively associated with the two mental health outcomes in the USA, despite their important roles in preventing the infection.

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Introduction

During the coronavirus disease 2019 (COVID-19) pandemic, physical and social distancing measures have been implemented across states in the USA to prevent the transmission of disease. These statewide and local interventions range from mandatory quarantine to voluntary self-isolation and have come at a cost of isolating citizens from social activities, potentially increasing risks of development, and/or aggravation of mental health problems [1–5]. Recent surveys of national representative samples showed the adverse mental health consequences during COVID-19 lockdown [6, 7]. For example, in mid-June 2020, prevalence of anxiety (25.5%) and depression (24.3%) was substantially higher than national estimates from the 2019 US National Health Interview Survey (6.6% for anxiety and 8.2% for depression) [6, 8]. Also, the rates of anxiety or depression during COVID-19 showed clear gradient and even worsening disparity across different demographic and socioeconomic groups, including a higher level of the mental disorders linked with younger age, female, race/ethnicity other than nonHispanic white and nonHispanic Asian, lower education, and lower household income [6, 8].

In addition to the individual-level factors, supraindividual predictors, such as urban and spatial contexts, may play important roles in the mental health consequences of COVID-19 [9, 10]. Business districts and socializing places have been affected by the closure of numerous small businesses such as restaurants, pubs, and sports facilities, resulting in sharp reductions of routine going-out and changes in behavioral patterns in the USA. [3] A national survey suggested that 41.4% of small businesses experienced temporary closures due to COVID-19 at least 1 day in late April [11]. For the same period, daily going-out was 32.0% lower than prepandemic normal days [12, 13]. Despite the public health crisis, however, the impacts of such contextual and behavioral changes on mental health problems still remain unclear [9]. Thus, we hypothesize that, during COVID-19 pandemic, states with a higher closure rate of small businesses and a lower level of urban mobility may experience increased prevalence rates of mental health outcomes, measured as generalized anxiety disorder (GAD) and major depression disorder (MDD).

Methods

Data

Main data is the Household Pulse Survey (HPS), a national representative survey deployed by the US Census Bureau jointly with the US National Center for Health Statistics (NCHS), which measures health impacts of COVID-19 pandemic on adult in the USA [14] The HPS comprises with three phases in the year of 2020: phase 1 (12 surveys during April 23rd–July 21st), phase 2 (5 surveys during August 19th–Oct 26th), and phase 3 (4 surveys during Oct 28th–December 21st). Due to data availability at the time of the analysis, we used the Public Use Data File of the phase 1 of HPS which contains the 12 surveys.

The structure of HPS dataset has a unique property, as it is a combination of longitudinal and cross-sectional compositions. Upon participants' consents, the US Census Bureau collected responses from the same participants up to three times, to achieve the sample size required for a valid national representative survey design [14]. Thus, some of the respondents participated more than once—for either two or three consecutive weeks (longitudinal composition)—while other participants were single-time respondents (cross-sectional composition). The multiple-time respondents (i.e., more than one participation) accounted for a relatively small portion of the total responses—among all participants of the phase 1 survey, 20.6% responded twice, and 7.1% responded three times (see Supplemental Table 1 for count of responses by week and response round). Due to the complex survey design, several different analytic approaches have been proposed to address the data structure, but the results were not substantially different from each other [15].

For this analysis, we addressed this unique data structure by dropping the second or third-time responses of the multiple-time respondents and built a pooled cross-sectional dataset that consists of 398,413 first-time responses (79.4% of all responses). This approach allowed large sample sizes across states and survey waves. As one of sensitivity tests, we build a separate longitudinal sample that consists of 24,361 respondents who interviewed fully three times and test whether the longitudinal data suggest the same or different results.

Statistical Analysis

We performed all analyses with Stata/MP 13.1 software (StataCorp, College Station, TX). We conducted separate analyses for GAD and MDD. Multilevel modeling was employed with adult individual and household-level characteristics at level-1, states at level-2, and census regions at level-3. We used multilevel mixed-effects logistic regression models (*melogit* in Stata/MP 13.1) to estimate the associations of small business closures and reduced mobility with GAD and MDD in a random intercept model, with adjustment for individual and household-level variables and state-level COVID-19 conditions (For a detailed discussion of multilevel mixed-effects logistic models, see Raudenbush and Bryk, 2002 [16], and StataCorp, 2019 [17]).

Mental Health Outcomes

Two self-reported measures of GAD and MDD were utilized: PHQ-2[18] and GAD-2 [18]. The two questionnaire measures frequencies of depression and anxiety symptoms over the last 7 days. The stem question of both PHQ-2 and GAD-2 is "over the last two weeks, how often have you been bothered by any of the following problems?", and the two items of PHQ-2 are "little interest or pleasure in doing things" and "feeling, down, depressed, or hopeless"; and the questions of GAD-2 are "feeling nervous, anxious or on edge" and "not being able to stop or control worrying". For each item, the answers were assigned numeric values: not at all = 0, several days = 1, more than half the days = 2, and nearly every day = 3, and scores from each questionnaire were summed and classified for binary diagnoses: more than three points from PHQ-2 as MDD and more than three points from GAD-2 as GAD. The cutoff points of the PHQ-2 and GAD-2 has been validated for diagnosed MDD and GAD [11, 18, 19].

Statewide Small Business Closure and Mobility Measures

We used SBPS—another new and nationally representative survey administered by the US Census Bureau—which measures the changes in small business (1–499 employees) conditions aggregated for all sectors across the same weeks of HPS [11]. We first define the state-level closure rate of small businesses as percentage of businesses that temporarily closed any of their locations for at least 1 day in the past week. The continuous measure is then used to specify quartile distribution of 50 states and the District of Columbia on a weekly basis.

Urban mobility was measured by an open-source smartphone data in a similar way as the CDC's COVID-19 Data Tracker does [13]. Descartes Labs, a geospatial data provider, quantifies the level of daily urban mobility aggregated at the state level. We define the rate of urban mobility as percentage of the prepandemic normal level (100% in the first week of March 2020) and daily measures are averaged to match individual weeks of HPS. It is utilized to identify quartile distribution on a weekly basis.

Statewide COVID-19 Cases and Reopening Policy

First, statewide COVID-19 cases per 100 population was retrieved from the CDC's COVID-19 Data Tracker [12]. During our analytic period (April 23–June 30), daily count of new cases in the nation gradually declined from 31,760 cases on April 23 to the lowest of 17,027 cases on June 8 but then sharply increased and added 47,717 cases on June 30, though the trend and pace varied across states. Daily counts are averaged to match individual weeks of HPS data, and the averaged count is divided by time-invariant population and multiplied by 100.

Second, we used an Indiana University's open-source data on state reopening policies [20]. The data define individual state's reopening date as the earliest date at which that state issued a reopening policy of any type. By June 1, all states and the District of Columbia had reopened in some form (see Supplemental Table 2 for variations in statewide reopening by state and week). We define state reopening policy as a binary variable which equates one if a respondent resides in state that executed at least the first phase of reopening and zero otherwise.

Individual and Household-Level Covariates

Potential individual and household-level confounding covariates are derived from HPS data, including demographic characteristics, socioeconomic status, self-rated health and health care access, and other COVID-19 hardships. Demographic characteristics consist of age, gender, race/ethnicity, marriage, household size, and number of children. Socioeconomic status includes education, household income, and tenure of residence. To control for health-related covariates, we consider self-rated health and insurance status, in addition to coronavirus-specific variables such as incidence of delay and missing of medical care due to COVID-19.

A wide range of socioeconomic hardships during the pandemic may affect mental health, which were controlled by three individual-level covariates: employment income loss [21], food insufficiency [22], and housing instability [23]. Income loss was measured from respondent answers that he/she or anyone in his/her household experienced a loss of employment income since March 13. Respondent reports that he/she did not have an enough of the kinds of food he/she wanted to eat for the last 7 days. Lastly, housing instability was measured whether respondent replies that he/she did not pay his/her last month's rent or mortgage on time.

Spatiotemporal Effects

To detect the temporal variations during the analytic period, we included the wave indicator as a continuous covariate starting from 1 to 9. A further time-invariant fixed-effect added in the model is residency in one of the 15 largest metropolitan statistical areas. We considered the metropolitan fixed-effect to control for additional differences in mental health outcomes across the nation's largest metropolitan areas beyond state-level variations.

Results

Table 1 shows the prevalence of GAD during COVID-19 pandemic increased gradually over weeks from

Table 1 Descriptive statistics: Household Pulse Survey, April 23–June 30, 2020

Variable	Full sample ($n = 398{,}413$), % or mean ± SD	Generalized anxiety disorder (GAD)		Major depression disorder (MDD)	
		Yes ($n = 128{,}254$), % or mean ± SD	No ($n = 270{,}159$), % or mean ± SD	Yes ($n = 90{,}327$), % or mean ± SD	No ($n = 308{,}086$), % or mean ± SD
Demographic characteristics					
Age					
18–24 (Ref)	9.5	11.1	8.6	13.4	8.1
25–34	25.6	29.4	23.6	29.3	24.3
35–44	21.0	21.4	20.8	19.7	21.5
45–54	17.1	16.9	17.2	15.9	17.6
55–64	14.7	12.9	15.7	12.9	15.4
65 +	12.0	8.3	14.0	8.8	13.2
Gender					
Female (Ref)	51.3	57.9	47.8	55.3	49.9
Male	48.7	42.2	52.2	44.7	50.1
Race/ethnicity					
NonHispanic White (Ref)	57.5	56.7	58.0	54.5	58.7
Non-Hispanic Black	13.7	13.7	13.7	14.6	13.4
NonHispanic A&PI	5.3	4.3	5.8	4.7	5.5
NonHispanic other	4.0	4.8	3.6	4.9	3.7
Hispanic	19.5	20.6	18.9	21.4	18.7
Marital status					
Unmarried (Ref)	47.8	54.6	44.1	59.4	43.5
Married	52.2	45.4	55.9	40.5	56.5
Children in household					
No child (Ref)	55.2	54.1	55.8	56.6	54.7
One or more children	44.8	45.9	44.2	43.4	45.3
Household size					
Single person (Ref)	7.2	7.0	7.3	7.7	7.0
2-person	26.4	25.0	27.2	25.4	26.8
3-person	20.3	20.8	19.9	20.6	20.1
4-person	20.5	20.9	20.3	19.8	20.8
5-person	11.9	12.2	11.7	12.0	11.8
6 or more persons	13.8	14.1	13.6	14.5	13.5
Socioeconomic status (SES)					
Education					
Less than high school (Ref)	8.9	9.6	8.5	10.7	8.2
High school	31.1	31.0	31.2	33.7	30.2
Some college and AA	31.4	34.0	30.1	34.6	30.3
BA+	28.5	25.4	30.1	21.0	31.3
Household income					
Less than $25,000 (Ref)	16.7	22.0	13.9	24.6	13.8
$25,000–49,999	25.4	27.8	24.0	30.1	23.6
$50,000–74,999	18.0	18.1	18.0	17.7	18.1
$75,000–99,999	13.2	11.8	13.9	11.1	13.9
$100,000–$149,999	14.4	11.7	15.9	9.8	16.1

Table 1 (continued)

Variable	Full sample ($n = 398{,}413$), % or mean ± SD	Generalized anxiety disorder (GAD)		Major depression disorder (MDD)	
		Yes ($n = 128{,}254$), % or mean ± SD	No ($n = 270{,}159$), % or mean ± SD	Yes ($n = 90{,}327$), % or mean ± SD	No ($n = 308{,}086$), % or mean ± SD
$150,000 and above	12.3	8.6	14.3	6.7	14.4
Tenure of residence					
Rental housing unit (Ref)	43.3	50.9	39.2	53.8	39.4
Owner housing unit	56.7	49.1	60.8	46.2	60.6
Self-rated health and health care access					
Self-rated health					
Excellent (Ref)	19.1	11.1	23.3	9.5	22.6
Very good	33.3	26.4	36.9	24.0	36.7
Good	30.3	33.9	28.4	34.1	28.9
Fair	14.1	22.2	9.8	24.8	10.2
Poor	3.2	6.4	1.6	7.6	1.6
Insurance status					
Private (Ref)	52.7	48.8	54.8	45.9	55.2
Public	14.7	16.9	13.5	18.2	13.4
Both private and public	14.7	13.4	15.4	13.6	15.2
Other	6.1	6.2	6.0	6.5	6.0
None	11.8	14.6	10.3	15.9	10.3
Delayed medical care due to pandemic					
Yes (Ref)	40.5	53.6	33.4	53.4	35.7
No	59.5	46.4	66.6	46.6	64.3
Did not get medical care due to pandemic					
Yes (Ref)	32.9	45.9	26.0	46.7	27.8
No	67.1	54.1	74.0	53.2	72.1
COVID-19 hardship					
Employment income loss					
No (Ref)	48.5	37.9	54.1	37.1	52.6
Yes	51.5	62.2	45.9	62.9	47.3
Food insufficiency					
No (Ref)	56.2	39.7	65.0	36.0	63.6
Yes	43.8	60.4	35.0	64.0	36.4
Housing instability					
No (Ref)	87.4	81.5	90.6	80.2	90.1
Yes	12.6	18.5	9.4	19.8	9.9
Spatiotemporal effects					
MSA (% of nonMSA or MSA)					
NonMSA (Ref)	100.0	34.5	65.5	26.6	73.4
MSA	100.0	35.6***	64.4	27.7***	72.3
Week (% of weekly sample)					
Week 1: April 23–May 5 (Ref)	100.0	32.4	67.6	24.5	75.5
Week 2: May 7–12	100.0	31.7**	68.3	25.6***	74.4
Week 3: May 14–19	100.0	29.9	70.1	25.6**	74.4
Week 4: May 21–26	100.0	31.1*	68.9	25.6+	74.4

Table 1 (continued)

Variable	Full sample ($n = 398{,}413$), % or mean ± SD	Generalized anxiety disorder (GAD)		Major depression disorder (MDD)	
		Yes ($n = 128{,}254$), % or mean ± SD	No ($n = 270{,}159$), % or mean ± SD	Yes ($n = 90{,}327$), % or mean ± SD	No ($n = 308{,}086$), % or mean ± SD
Week 5: May 28–June 2	100.0	32.6+	67.4	26.8***	73.2
Week 6: June 4–9	100.0	33.0*	67.0	27.3	72.7
Week 7: June 11–16	100.0	33.6***	66.4	26.1***	73.9
Week 8: June 18–23	100.0	33.4***	66.6	27.2***	72.8
Week 9: June 25–30	100.0	35.2***	64.8	28.7***	71.3
Statewide COVID-19 conditions and reopening policy (mean and SD)					
% small business closure	29.65 (11.78)	29.32 (11.85)	29.82 (11.74)	29.4 (11.88)	29.74 (11.74)
% outdoor mobility	46.47 (23.22)	46.85 (23.2)	46.28 (23.22)	46.84 (23.23)	46.34 (23.21)
State reopening policy	0.88 (0.33)	0.89 (0.33)	0.88 (0.34)	0.89 (0.33)	0.88 (0.34)
COVID-19 cases per 100 people	0.52 (0.49)	0.53 (0.49)	0.52 (0.48)	0.53 (0.49)	0.52 (0.48)

A&PI Asian and Pacific Islander. *MSA* metropolitan statistical area. Two-sample *t* test was used to check statistical significance of mean-differences for MSA and week. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, +$p < 0.10$

32.4% in late April (week 1) to 35.2% in late June (week 9), and the prevalence of MDD also increased from 24.5 to 28.7% for the same period. A greater share of urban residents living in one of the largest 15 MSAs suffered from GAD (35.6%) and MDD (27.7%) than nonMSA residents (34.5% and 26.6% for GAD and MDD, respectively). Two-sample *t* test results show that, for both GAD and MDD, statistically significant differences exist depending on survey week and location of residence. Also, prevalence of GAD and MDD varied substantially across demographic characteristics, socioeconomic status, self-rate health and health care access, and other COVID-19 hardships.

GAD Model Results

Table 2 shows the results of multilevel mixed-effects logistic models that estimated associations of small business closure and reduced mobility with GAD adjusting for abovementioned individual, household, and state-level covariates.

Living in state with mass small business closures (highest-quartile state) was associated with increased rate of GAD (OR: 1.07; CI: 1.04–1.12) compared to living in state with least closures (lowest-quartile state). However, this was not a linear relationship as visually displayed in Fig. 1. The column graph shows odds ratio of GAD and MDD on *y*-axis and six categorized closure rates of small business on *x*-axis, with 95% confidence interval (vertical line at the top of each column) by which we can be 95% certain that the interval range contains the true mean of the population. Adult Americans who were categorized as living in states with closures of 0–10% had the lowest odds of GAD. A relatively small increase in small business closure to 10.01–20% and to 20.01–30% led to the smallest increase in the odds ratio for GAD; however, the odds ratio (relative to the 20.01–30% closure) rose more for small business closures of 30.01–40% and 40.01–50%; beyond 50%, increases in small business closure led to the greatest increase in the odds ratio for GAD.

Urban mobility was negatively associated with the rate of GAD. Living in one of the most mobile (highest quartile) states was associated with decreased prevalence of GAD (OR: 0.88; CI: 0.85–0.93) relative to living in one of the least mobile (lowest quartile) states. As shown in Fig. 2, adults who were categorized as living in states with mobility of 0–20% had the highest odds of GAD. A relatively small increase in mobility to 20.01–40% and all the way up to 100% (= prepandemic normal level of mobility) led to the smallest decrease in the odds ratio for GAD.

Odds ratios estimated for individual-level factors were also shown in Table 2. Most of the level-1 covariates emerge as significant predictors of GAD during the pandemic, mostly consistent with the previous research on pandemic mental disorders. Key demographic and socioeconomic predictors of a higher level of GAD

Table 2 Multilevel mixed effects logistic model results: US Census Bureau's Household Pulse Survey, April 23–June 30, 2020

	Generalized anxiety disorder (GAD)			Major depression disorder (MDD)		
	OR	(95% CI)	*P*	OR	(95% CI)	*P*
Statewide COVID-19 conditions and reopening policy						
% small business closure						
Bottom Q1 state (Ref)	1.00			1.00		
Q2 state	1.05	(1.02, 1.08)	0.001	1.01	(0.98, 1.04)	0.640
Q3 state	1.07	(1.04, 1.11)	< 0.001	1.00	(0.98, 1.04)	0.796
Top Q4 state	1.07	(1.04, 1.12)	0.001	0.99	(0.95, 1.04)	0.733
% outdoor mobility						
Bottom Q1 state (Ref)	1.00			1.00		
Q2 state	0.98	(0.95, 1.01)	0.127	0.96	(0.94, 1)	0.043
Q3 state	0.91	(0.88, 0.96)	< 0.001	0.92	(0.88, 0.97)	< 0.001
Top Q4 state	0.88	(0.85, 0.93)	< 0.001	0.90	(0.86, 0.95)	< 0.001
State reopening policy	0.95	(0.93, 0.99)	0.007	1.00	(0.97, 1.05)	0.940
COVID-19 cases per 100 people	0.98	(0.94, 1.03)	0.301	1.02	(0.97, 1.09)	0.458
Demographic characteristics						
Age						
18–24 (Ref)	1.00			1.00		
25–34	0.92	(0.89, 0.97)	< 0.001	0.74	(0.71, 0.78)	< 0.001
35–44	0.76	(0.74, 0.8)	< 0.001	0.59	(0.57, 0.62)	< 0.001
45–54	0.61	(0.59, 0.65)	< 0.001	0.51	(0.49, 0.54)	< 0.001
55–64	0.48	(0.47, 0.51)	< 0.001	0.42	(0.4, 0.44)	< 0.001
65+	0.33	(0.32, 0.36)	< 0.001	0.31	(0.3, 0.33)	< 0.001
Gender						
Female (Ref)	1.00			1.00		
Male	0.71	(0.7, 0.72)	< 0.001	0.91	(0.9, 0.93)	< 0.001
Race/ethnicity						
NonHispanic White (Ref)	1.00			1.00		
NonHispanic Black	0.69	(0.68, 0.72)	< 0.001	0.77	(0.75, 0.8)	< 0.001
NonHispanic A&PI	0.69	(0.67, 0.72)	< 0.001	0.94	(0.91, 0.99)	0.007
NonHispanic other	0.98	(0.95, 1.02)	0.303	1.04	(1.01, 1.09)	0.048
Hispanic	0.86	(0.84, 0.89)	< 0.001	0.89	(0.87, 0.92)	< 0.001
Marital status						
Unmarried (Ref)	1.00			1.00		
Married	0.88	(0.87, 0.9)	< 0.001	0.80	(0.78, 0.82)	< 0.001
Children in household						
No child (Ref)	1.00			1.00		
One or more children	0.99	(0.97, 1.02)	0.411	0.87	(0.85, 0.9)	< 0.001
Household size						
Single person (Ref)	1.00			1.00		
2-person	1.03	(1.01, 1.06)	0.009	0.93	(0.91, 0.96)	< 0.001
3-person	0.99	(0.96, 1.03)	0.501	0.89	(0.86, 0.92)	< 0.001
4-person	0.95	(0.92, 0.99)	0.005	0.85	(0.83, 0.89)	< 0.001
5-person	0.88	(0.85, 0.92)	< 0.001	0.83	(0.8, 0.87)	< 0.001
6 or more persons	0.81	(0.78, 0.85)	< 0.001	0.78	(0.75, 0.82)	< 0.001

Table 2 (continued)

	Generalized anxiety disorder (GAD)			Major depression disorder (MDD)		
	OR	(95% CI)	*P*	OR	(95% CI)	*P*
Socioeconomic status (SES)						
Education						
Less than high school (Ref)	1.00			1.00		
High school	1.05	(1, 1.11)	0.108	1.02	(0.97, 1.08)	0.533
Some college and AA	1.15	(1.1, 1.22)	< 0.001	1.04	(0.99, 1.1)	0.160
BA+	1.28	(1.22, 1.35)	< 0.001	0.99	(0.94, 1.05)	0.808
Household income						
Less than $25,000 (Ref)	1.00			1.00		
$25,000–49,999	0.94	(0.92, 0.98)	< 0.001	0.95	(0.93, 0.98)	< 0.001
$50,000–74,999	0.94	(0.92, 0.98)	< 0.001	0.92	(0.9, 0.96)	< 0.001
$75,000–99,999	0.91	(0.89, 0.95)	< 0.001	0.86	(0.84, 0.9)	< 0.001
$100,000–$149,999	0.88	(0.86, 0.92)	< 0.001	0.80	(0.78, 0.84)	< 0.001
$150,000 and above	0.89	(0.86, 0.93)	< 0.001	0.75	(0.73, 0.79)	< 0.001
Tenure of residence						
Rental housing unit (Ref)	1.00			1.00		
Owner housing unit	0.90	(0.89, 0.92)	< 0.001	0.90	(0.89, 0.93)	< 0.001
Self-rated health and health care access						
Self-rated health						
Excellent (Ref)	1.00			1.00		
Very good	1.43	(1.41, 1.47)	< 0.001	1.45	(1.42, 1.49)	< 0.001
Good	2.15	(2.11, 2.21)	< 0.001	2.35	(2.29, 2.42)	< 0.001
Fair	3.69	(3.59, 3.8)	< 0.001	4.22	(4.09, 4.36)	< 0.001
Poor	6.65	(6.33, 7)	< 0.001	7.67	(7.3, 8.07)	< 0.001
Insurance status						
Private (Ref)	1.00			1.00		
Public	0.97	(0.95, 1)	0.019	1.03	(1.01, 1.07)	0.036
Both private and public	0.90	(0.88, 0.93)	< 0.001	0.93	(0.91, 0.96)	< 0.001
Other	0.96	(0.93, 0.99)	0.011	0.97	(0.94, 1.01)	0.114
None	1.13	(1.1, 1.17)	< 0.001	1.20	(1.17, 1.25)	< 0.001
Delayed medical care due to pandemic						
Yes (Ref)	1.00			1.00		
No	0.66	(0.65, 0.67)	< 0.001	0.73	(0.72, 0.75)	< 0.001
Did not get medical care due to pandemic						
Yes (Ref)	1.00			1.00		
No	0.71	(0.71, 0.73)	< 0.001	0.70	(0.69, 0.72)	< 0.001
COVID-19 hardship						
Employment income loss						
No (Ref)	1.00			1.00		
Yes	1.48	(1.46, 1.51)	< 0.001	1.37	(1.35, 1.4)	< 0.001
Food insufficiency						
No (Ref)	1.00			1.00		
Yes	1.84	(1.81, 1.87)	< 0.001	1.94	(1.91, 1.98)	< 0.001

Table 2 (continued)

	Generalized anxiety disorder (GAD)			Major depression disorder (MDD)		
	OR	(95% CI)	*P*	OR	(95% CI)	*P*
Housing instability						
No (Ref)	1.00			1.00		
Yes	1.41	(1.38, 1.46)	< 0.001	1.38	(1.35, 1.42)	< 0.001
Spatiotemporal effects						
15 largest metropolitan areas						
None (Ref)	1.00			1.00		
New York	1.13	(1.06, 1.22)	0.001	1.10	(1.02, 1.19)	0.018
Los Angeles	1.14	(1.07, 1.22)	< 0.001	1.16	(1.08, 1.25)	< 0.001
Chicago	1.18	(1.1, 1.28)	< 0.001	1.17	(1.07, 1.28)	0.001
Dallas	1.00	(0.93, 1.08)	0.905	1.09	(1.01, 1.18)	0.045
Houston	1.03	(0.96, 1.12)	0.394	1.13	(1.04, 1.23)	0.005
Washington, D.C.	1.13	(1.07, 1.2)	< 0.001	1.13	(1.06, 1.21)	0.001
Miami	1.11	(1.03, 1.2)	0.007	1.09	(1.01, 1.19)	0.037
Philadelphia	1.13	(1.07, 1.21)	< 0.001	1.08	(1.01, 1.16)	0.029
Atlanta	1.12	(1.03, 1.22)	0.013	1.08	(0.98, 1.19)	0.133
Phoenix	1.14	(1.05, 1.25)	0.003	1.19	(1.09, 1.32)	< 0.001
Boston	1.03	(0.97, 1.11)	0.357	1.02	(0.94, 1.1)	0.714
San Francisco	1.17	(1.1, 1.26)	< 0.001	1.12	(1.04, 1.22)	0.006
Riverside	0.98	(0.91, 1.06)	0.569	0.99	(0.91, 1.08)	0.787
Detroit	0.95	(0.88, 1.05)	0.292	1.00	(0.91, 1.11)	0.987
Seattle	1.13	(1.05, 1.23)	0.002	1.16	(1.07, 1.27)	0.001
Survey week	1.02	(1.02, 1.03)	< 0.001	1.00	(1, 1.01)	0.053
Constant	0.51	(0.48, 0.57)	< 0.001	0.44	(0.4, 0.49)	< 0.001
Number of observations	398,413		398,413			
Wald chi-squared	53,531		51,087			
Log likelihood	− 216,922	< 0.001	− 181,880	< 0.001		
Likelihood-ratio test						
Chi-squared	78.46	< 0.001	104.08	< 0.001		
Intraclass correlation (ICC)						
Census region	0.0000	(0.0000, 1.0000)		0.0003	(0.0000, 1.0000)	
State	0.0009	(0.0006, 0.0016)		0.0013	(0.0008, 0.0025)	

OR odds ratio; *CI* confidence interval; *A&PI* Asian and Pacific Islander; The sample size was $n = 398{,}413$

include younger age, female, unmarried status, smaller household size, lower household income, and renting versus owning a home. Contrary to expectations, nonHispanic white and a higher level of education were associated with a higher risk of GAD, which is likely due to other socioeconomic covariates such as household income and tenure of residence. A higher risk of GAD was also associated with worse self-rated health status, no insurance in any type, and delayed (or missed) medical care due to the pandemic. A further set of important predictors is socioeconomic hardships during the COVID-19 pandemic, suggesting a higher level of GAD associated with employment income loss (OR: 1.48; CI: 1.46–1.51), food insufficiency (OR: 1.84; CI: 1.81–1.87), and delayed housing payment (OR: 1.41; CI: 1.38–1.46).

As for spatiotemporal effects, the results show that urban residents who live in some largest

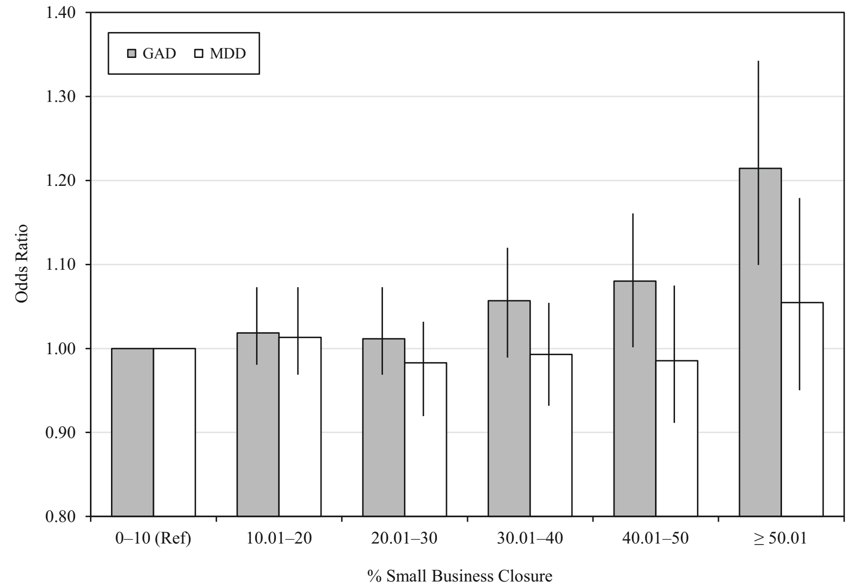

Fig. 1 Odds ratio of GAD and MDD among adult Americans during the COVID-19 pandemic, by small business closure rate: US Census Bureau's Household Pulse Survey, April 23–June 30, 2020

metropolitan areas such as New York and Los Angeles are more likely to suffer from GAD than nonmetropolitan residents. Also, the incidence rate of GAD increases by 2% per week (OR: 1.02; CI: 1.02–1.03) during the analytic period (April 23–June 30, 2020) even after controlling for all the other covariates. These findings from the spatio-temporal effects imply that the risk of GAD is higher in the most urbanized areas as the pandemic prolongs over weeks.

MDD Model Results

Unlike the results of GAD, neither small business closure nor state reopening policy was associated with MDD. However, there was a strong negative association between urban mobility and MDD. Living in one of the most mobile (highest quartile) states was associated with lower prevalence of MDD (OR: 0.90; CI: 0.86–0.95) relative to living in one of the least mobile (highest quartile) states.

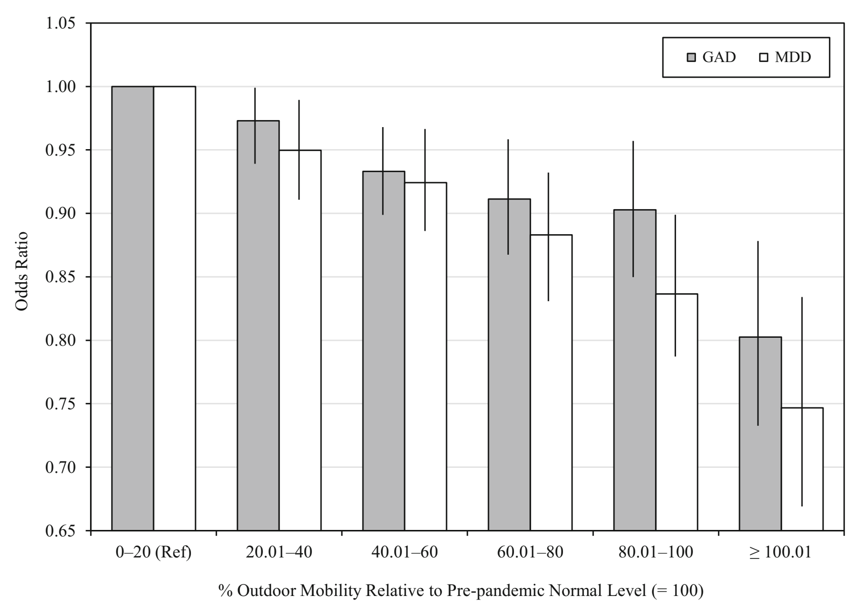

Fig. 2 Odds of GAD and MDD among adult Americans during the COVID-19 pandemic, by urban mobility rate relative to the pre-pandemic normal level: US Census Bureau's Household Pulse Survey, April 23–June 30, 2020

Also, Fig. 2 shows that the highest odds ratio for MDD in states with mobility of 0–20%. Relative to the 0–20% category, a continued decrease in odds of MDD was found for adults living states with mobility of 20.01–40%, 40.01–60%, 60.01–80%, and 80.01–100%; beyond 100%, increases in mobility led to the greatest decline in the odds ratio for MDD.

Sensitivity Analyses

As noted earlier, there are a set of critical assumptions inherent in the analysis that warrant sensitivity analyses and additional evidence on their robustness.

The first test concerns the unique data structure of HPS which is mixture of cross-sectional composition and longitudinal one, as discussed in the data section. While the pooled cross-sectional data allowed us to observe different respondents in different survey weeks, the longitudinal data can deal with repeated responses from the same respondents (identified by *scram* in HPS microdata) across weeks (maximum 3 weeks). To test if longitudinal data suggest different estimation results than those from the pooled cross-sectional data, we build and run conditional fixed-effects panel logistic regression and random-effects panel logistic regression for GAD and MDD, respectively (see Supplemental Table 3 for the full panel model results). The results for key covariates in the panel models are substantively unchanged, suggesting that both cross-sectional composition and longitudinal composition of HPS data show a consistent relationship between small business closure and reduced urban mobility and mental health outcomes during the COVID-19 pandemic.

Second, there might be some concerns about aggregating different types of small business. This is because a closure of some sectors that serve health care and social assistance may have a detrimental impact on health status of local residents. Also, small stores that provide locations for gathering and chatting may substantially limit socializations and therefore influence mental health outcomes. To partly reflect the sectoral variations, we repeated the main analysis with four SBPS-based covariates that measure weekly closure rate of small businesses in (i) retail (NAICS 2-digit code 44), (ii) health care and social assistance (62), (iii) arts, entertainment, and recreation (71), and (iv) accommodation and food services (72), respectively (see Supplemental Table 4). Note that we use nationwide measure due to unavailability of state-level sectoral data. We find that a greater closure rate of health care stores and social assistance businesses is related with an increased risk of both GAD and MDD across the nation. Estimated coefficients for other sectors were not significant except for the positive association between accommodation and food services closure and MDD, which is contrary to expectations.

Third, we recognize that the specification of a particular state in a particular survey week as locked down and reopened is subject to data source. To test whether an alternative specification might influence the results, we use Raifman et al.'s (2020) COVID-19 US State Policy (CUSP) database to determine lockdown and reopening in each week across states (see Supplemental Table 5). The signs and magnitudes of estimated coefficients are quite similar, showing a lower risk of GAD in reopened states while no relations between state reopening and MDD. It suggests that the measure of statewide lockdown and reopening is robust across alternative specifications.

An additional set of sensitivity tests is conducted with regard to alternative dependent and independent variables, different standard errors, and other model specifications. We substituted a comorbidity of GAD and MDD or at least one of the two disorders instead of existing separate measures and found that the model estimations are stable in alternative measures (see Supplemental Table 6). Alternatively, continuous measures of GAD and MDD were tested with the same set of covariates by multilevel mixed effects generalized linear models (*meglm* in Stata/MP 13.1), suggesting robust estimation results (see Supplemental Table 7). As key covariates of our interest, small business closures and urban mobility were estimated to have coefficients that are consistent with signs and significance of their quartile measures (see Supplemental Table 8). We also find minimal differences for model estimates when robust standard errors and clustered (clustered by state) standard errors were adopted instead of standard errors (see Supplemental Table 9). Lastly, we estimated weighted logistic models weighted by person-level weight variable (*pweight* in HPS microdata) for GAD and MDD, respectively, and confirmed that the estimated coefficients in the weighted models were largely unchanged (see Supplemental Table 10).

Discussion

COVID-19 and Urban Health Implications

Our findings suggest that social distancing interventions and consequently limited access to socialization locations measured as small business closures and the reduced urban mobility inevitably increased the incidence of anxiety and/or depression among Americans during the COVID-19 pandemic. It is consistent with early findings from other countries such as China, Italy, and Netherland [24–26]. Despite the protective effect of social distancing measures on transmission of the virus, the adverse mental health consequences should be considered from urban health perspectives. As the World Health Organization (WHO) and the UK have issued guidance on the management of mental health aspects of COVID-19 [27, 28], it is necessary to provide a set of individual, community, and state-level interventions for the inevitability of loneliness and its sequelae [3, 29]. Extra efforts should be made to ensure mental health of marginalized populations, such as racial/ethnic minorities, elderly, homeless individuals, and those with serious chronic mental illness [3, 5, 30, 31]. Lastly, existing free and confidential hotlines can be extended to provide immediate mental health supports for vulnerable populations during the pandemic, including children [32], pregnant women [33], health care workers [24, 34], and physicians [35].

An equally important finding is that a wide range of social and economic hardships during the pandemic—including employment income loss, food insufficiency, and housing payment delay—is closely related with the prevalence of anxiety and depression. These findings may suggest needs for interdisciplinary disaster management plans across different policy arenas. This interconnected policy frame is vital to formulating COVID-19 policies and mental health system and also to building the broad citizen support required for any reforms to be successful [36, 37]. Public understanding about these policy interconnections needs to be illuminated and fostered with timely studies on COVID-19 [38].

Strengths, Limitations, and Conclusions

To the best of knowledge, this is the first study on the associations of small business closure and reduced urban mobility with GAD and MDD during COVID-19 pandemic. The national representative sample of HPS data joined with SBPS and smartphone data allowed us to examine the overall picture of adverse mental health outcomes due to reduced socializations.

Our analysis is not without limitations. HPS data are limited in scope, and we were unable to control for a full-range of individual and household-level factors. The contextual and behavioral changes measured from HPS were aggregated to state-level and susceptible to the modifiable areal unit problem (MAUP) [39], which means that the results may change when a different geographic area (e.g., county) other than state is adopted. Our state-level analysis may also suffer from ecological fallacy [40], because the associations from state-aggregated data may not directly translate into associations for individuals who reside in different states. Despite the use of state-level random effects in our models, some state-level covariates (e.g., rurality of each state) may relate to both urban mobility and mental health outcomes, which might lead to over or underestimation of the coefficient of urban mobility. We recognize that the statewide lockdown and reopening were a complicated administrative and policy process, with multiple phases and dimensions to be considered, and therefore our binary specification of state reopening is subject to oversimplification of the reality. Measures of state reopening can be detailed by developing an alternative measure—for example, ordinal measure (e.g., reopening phase of 1, 2, and 3) or categorical measure (e.g., reopening of school/daycare, restaurant/bars, sporting venue, and/or place of worship) instead of the binomial form as adopted in this paper—to reflect multiple aspects and varying degree of state reopening policy. Lastly, we did not examine other mental illnesses such as trauma- and stressor-related disorder (TSRD) and seriously considered suicide related to COVID-19. Despite these limitations, this study can shed new light on the role of small business conditions and urban mobility in explaining the increased prevalence of mental illness during COVID-19 pandemic. Further research is needed on longitudinal analysis and individual-level mobility measures, in addition to analysis at lower geographic scales.

Overall conclusion is that, for GAD, both a higher level of small business closures and a lower level of urban mobility were associated with increased prevalence rate of GAD during COVID-19 pandemic. For MDD, however, an increased level of small business closure had no association with the prevalence rate of

MDD while a reduced level of mobility was strongly associated with increased prevalence of MDD.

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