COVID-19 mitigation policies and psychological distress in young adults

Online-only appendix

Contents

Methods. Further details on data and methodology

Measures of case counts and policy responsiveness

We produce measures of average weekly case counts (per 100,000 state residents) and average weekly policy response by state. Each survey cross-section is matched to the case counts and policy response that obtained as the survey went into the field (the date that a respondent filled out the survey is not recorded in the HPS, so it is not possible to match with any greater precision.) Case counts were used in preference to death counts because they are a better signal of perceived virus risk at the time of the survey, even if those case counts are inaccurate. At the beginning of the pandemic it is likely that the case counts substantially underestimated the actual rate of infection. An alternative method, in which we matched each survey to deaths occurring a month later – a measure of prior levels of infection – showed substantively similar results: an increase in deaths from COVID-19 is associated with increases in mean GAD and PHQ scores.

Data on state COVID-19 policy responses come from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021). We include two separate policy indexes in our model: the containment and health index and the economic support index. Our primary research interest is in the containment and health index, as this captures the policy response with respect to virus mitigation. The indexes are calculated as averages of the component indicators:

Containment and health index (14 items)

- School Closures (C1)
- Workplace closing (C2)
- Cancel Public Events (C3)
- Restrictions on gatherings (C4)
- Public Transportation (C5)
- Stay at Home Order (C6)
- Restrictions on Internal Movement (C7)
- International Travel Controls (C8)
- Public Information Campaigns (H1)
- Testing Policy (H2)
- Contact tracing (H3)
- Facial coverings (H6)
- Vaccination policy (H7)
- Protection of elderly people (H8)

Economic support index (2 items)

- Income Support (E1)
- Debt/contract relief for households (E2)

Each component is reported as a 0-100 score. Further details on each component measure can be found in the OxCGRT codebook (OxCGRT, 2021a). In Table A3, we calculate an alternative containment and health "residual" index that is the average of 11 items (i.e., the index without the three items that are included as separate variables (items C1, C3, and C6).)

The state policy score captures the policy in place in a given state at a given time. Policy responses in the U.S. context are determined at both the state and federal level. The OxCGRT database assigns policy to states in a two stage process. First, state policies are captured for each of the components. Then, policy at the national level is considered. If national policy in a given domain applies to lower-level jurisdictions, and the national policies are more stringent than the state policies, the national policy is taken to prevail. Variation in policy responsiveness across states is thus largely determined by state level policy, while levels of policy within a given state are a function of both state and national policy (OxCGRT, 2021b).

Coefficients for our full models are included in tab.A1. Fig.2 in the paper shows predicted values and associated confidence intervals based on the full models. In Fig.A1 we present state scores on the containment and health index by week, and in Fig.A2 we present weekly case counts per 100,000 by state.

Imputation model

As we describe in the main text, Little's test indicated that the HPS data were not MCAR (Little, 1988). We therefore conducted multiple imputation using chained equations to impute values for those who had not responded to all questions (Rubin, 1996; Sterne et al., 2009). Ten datasets were imputed.

Missing values were most numerous for the income measures, and the GAD and PHQ measures. The variable capturing recent job loss also had some missing values, although only around half a percent of cases were missing. The age, race, ethnicity, gender, and state of residence measures contained no missing values; in the HPS, the Census Bureau uses information from other records to replace missing values on these variables. We impute values for income, the GAD and PHQ measures, and recent job loss; in other words, following standard practice, we impute both independent and dependent variables (Johnson and Young, 2011). Our imputation model also includes race and ethnicity, gender, age, state of residence, education, and survey week (the latter two variables are auxiliary variables that do not appear in our regression analyses.) We use logit and multinomial logit models for our imputed variables, and the imputation is carried out using weights. Our imputation contains many categorical variables, and as a consequence, the problem of perfect prediction arises. We therefore use the approach proposed by White, Daniel, and Roston (White et al., 2010), in which a small number of observations are added to the data, to estimate the models.

In Tab.A2 we provide a comparison of the imputed and complete case analyses. The code to replicate our imputation model (including seed) is included in our OSF folder (https://osf.io/kzfqh/).

Measurement of age-groups

In fig.A3 we present results for an alternative age-group measure, which breaks out the 26-65-year-old category into smaller subcategories. We see evidence for an age effect: levels of anxiety are lower as we work from the younger to older cohorts. There is also evidence that those aged 26-35 are more similar to the young adults than to the adults aged 36-45. Note that the increase in categories reduces precision in the estimates.

The reduction in precision becomes a problem when we turn to the regression model examining the effects of policy. It is not, in fact, even possible to run the multiple imputation models in Stata using the finer-grained categories, as in some imputations, some (control variable) effects cannot be identified. For the purpose of providing as much information as possible to the reader, we implemented a workaround: the model was run on each imputed dataset separately, and we then calculated the coefficients and standard errors for the policy*age-group interactions by hand, using Rubin's formula. This is an analysis that comes with a substantial health warning: because in some models not all effects are identified, the coefficients and standard errors are not strictly comparable across the ten imputed datasets, even for those effects that *are* calculable. With that in mind, the results for the containment policy by age-group interactions are as follows:

	Coeff.	s.e.	p.
Containment and health index	-0.0140	0.0022	0.000
Containment and health index*26-35 years	0.0045	0.0025	0.069
Containment and health index*36-45 years	0.0058	0.0024	0.014
Containment and health index*46-55 years	0.0077	0.0024	0.002
Containment and health index*56-65 years	0.0083	0.0021	0.000
Containment and health index*66+ years	0.0062	0.0024	0.012

Two features are of interest in this table. First, there is evidence of an age effect: older adults are less responsive to policy than younger adults. But at the same time, the 66+ group shows a stronger response to policy (i.e., a smaller coefficient) than some of the younger age-groups. Second, the gap between the young adults and the 26-35-year-olds is bigger than the gaps between the other age-groups, suggesting that there might be a step change in policy response between the young adults and older adults (although note that the p. value for this effect falls outside the p<.05 level.)

Given the power problems, a safer approach is to respecify the model using an age measure that preserves degrees of freedom. Here, we fit the same model, but with age, or age and age-squared replacing the age-groups.

Model 1: Age	Coeff.	s.e.	p.
Containment and health index	-0.011692	0.002009	0.000
Containment and health index*age	0.000076	0.000035	0.036

Model 2: Age plus age-squared			
Containment and health index	-0.021334	0.005598	0.001
Containment and health index*age	0.000500	0.000230	0.040
Containment and health index*age-squared	-0.000004	0.0000022	0.075

These specifications of the age effect show that GAD scores in young adults are most strongly associated with containment policy, and that this association grows weaker for older adults. According to the first model, a 20-year-old has a predicted reduction in GAD score of 0.010 for each point on the containment index, as compared to a 30-year-old who has a predicted reduction of 0.009, and a 50-year-old who has a predicted reduction of .008. According to the second model, a 20-year-old has a predicted reduction in GAD score of 0.013 for each point on the containment index, as compared to a 30-year-old who has a predicted reduction of 0.010, and a 50-year-old who has a predicted reduction of .006.

Taking the descriptive results and the regression analyses together, we draw two conclusions. First, with respect to average levels, young adults appear to experience the highest levels of anxiety throughout 2020, but it is important to acknowledge that other age-groups also experienced high levels of anxiety, and that a finer-grained measure of age-group might pick up differences on a large enough sample. Second, with respect to the policy effect, young adults look different from the older age-groups, but there is also variation within the 26-65-year-old category. In combining age-groups into one large 26-65-year-old group and reporting mean values, we are certainly masking variation, but it is not clear that we are introducing bias (although we of course cannot rule this out). Given the substantive interest in comparing young adults to the non-elderly adult population – the implied reference category in most public discussions of young adults during the pandemic – we present results using the three-category age-group measure in the paper.

Changes in mean levels of psychological distress by sociodemographic subgroups

During the COVID-19 pandemic, there has been much discussion of whether psychological distress differs by gender and race. Although our paper focuses on psychological distress in young adults at the population level, we here present results for sociodemographic subgroups. In Figures A4&A7 we show mean GAD and PHQ scores by gender. Mean scores on the GAD and PHQ scales are higher for young women than for young men throughout the time series, but the pattern of over-time volatility is very similar by gender. In Figs.A5&A8, we present mean GAD and PHQ scores by race/ethnicity. The race-specific analyses rest on relatively small samples in the case of Black, Asian, and Hispanic young adults, but we nevertheless see similar patterns of cross-month variation in levels of psychological distress. An interesting feature of Figs.A5&A8 is the apparent increase in levels of psychological distress for Black young adults during May and June, albeit with wide confidence bands. This was the period when Black Lives Matter and racial justice protests swept the country; young adults were particularly likely to be engaged in these protests (Parker et al., 2020). Prior research has documented the costs of increasing the salience of racial discrimination to the mental wellbeing of people of color (Williams, 2018). We unfortunately lack the statistical power to provide a detailed assessment of trends in psychological distress during the BLM protests, but a recent study provides confirmatory evidence showing an increase in psychological distress following the BLM protests (Eichstaedt et al., 2021).

Figure A1. State scores on the containment and health index; New York and North Dakota highlighted in green and red, respectively, alongside average of state policy responsiveness index scores (unweighted) in purple.

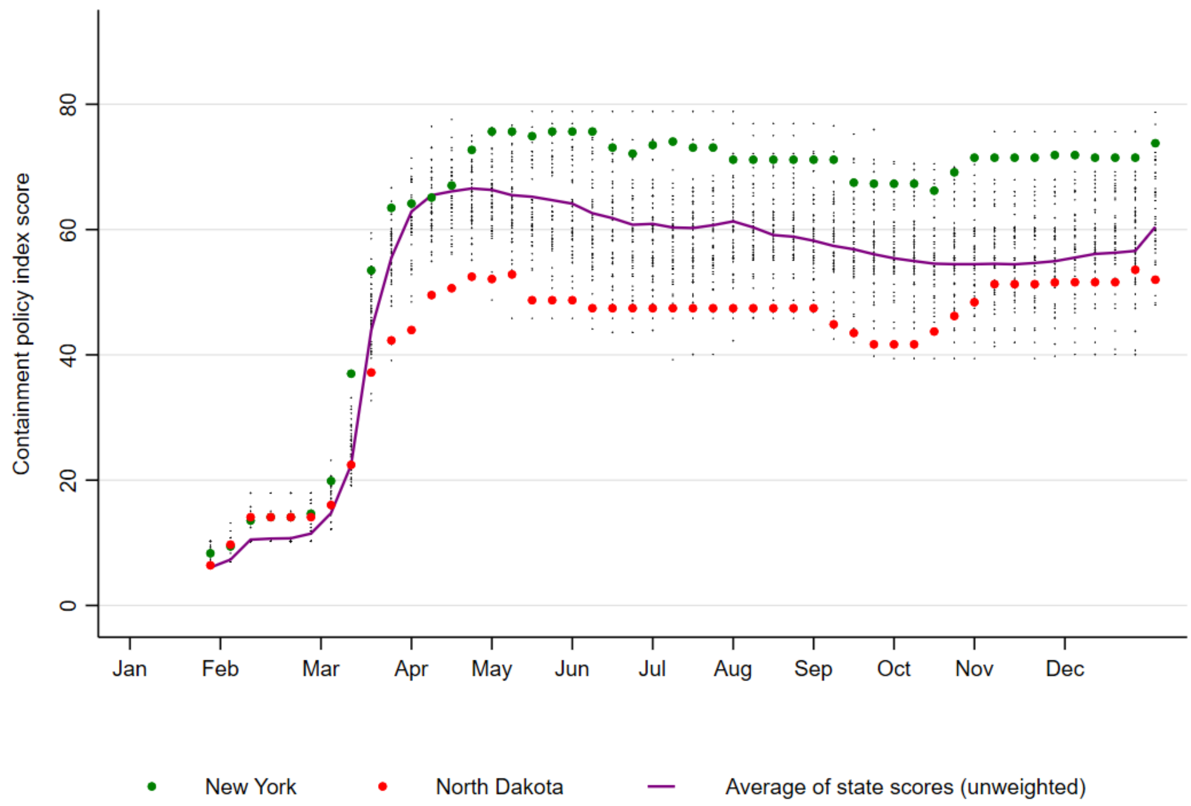


Figure A2. State weekly cases per 100,000; New York and North Dakota highlighted in green and red, respectively, alongside average of state weekly cases (unweighted) in purple.

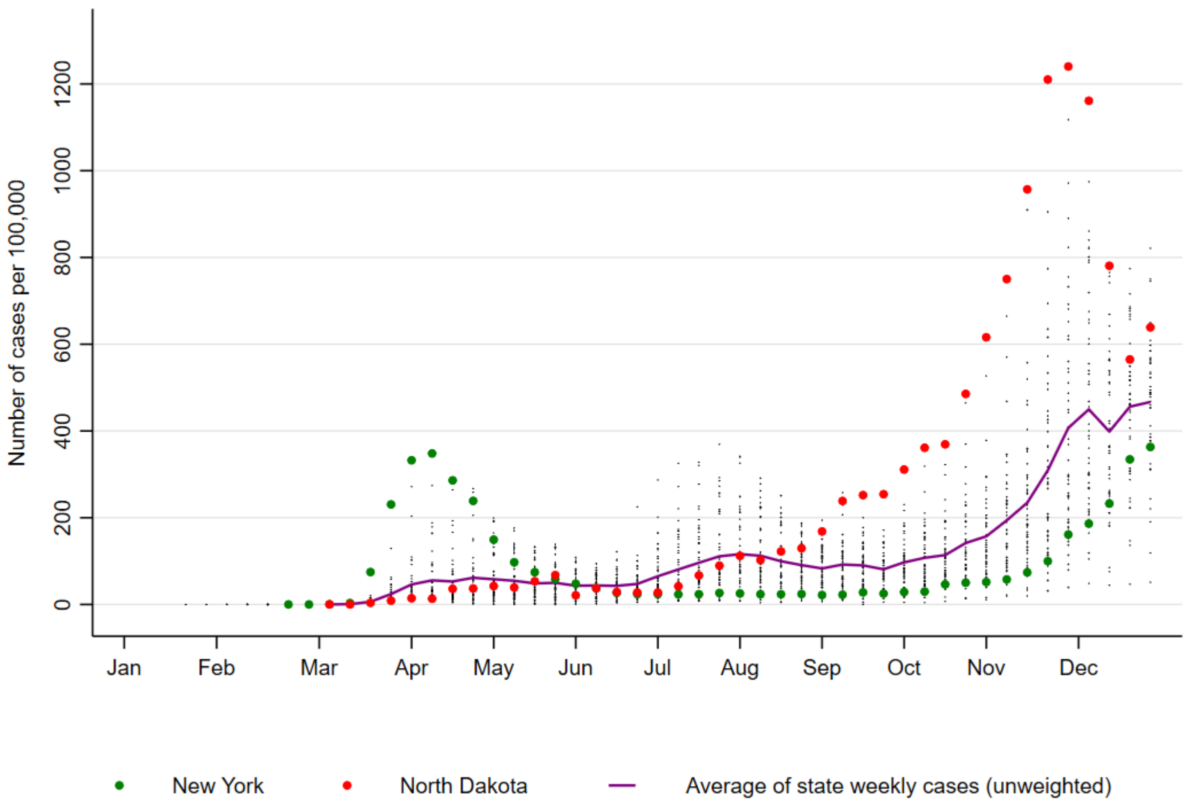
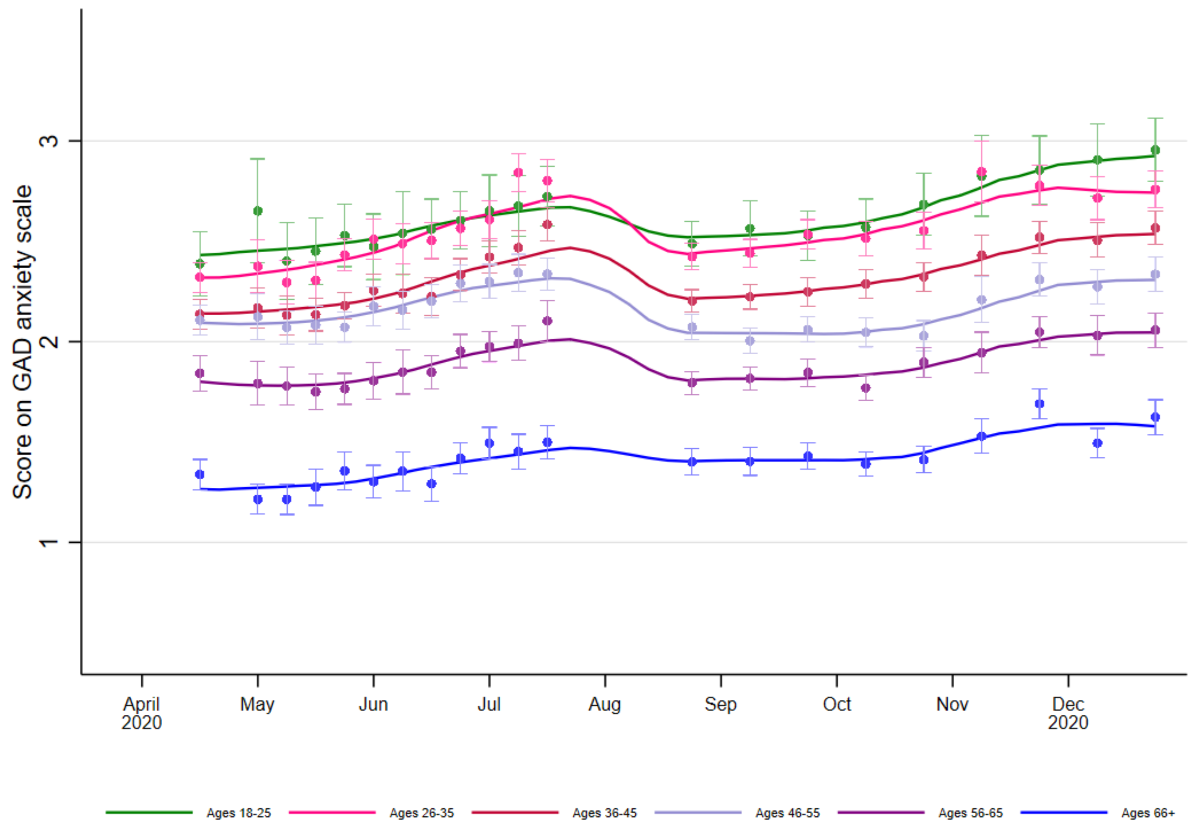
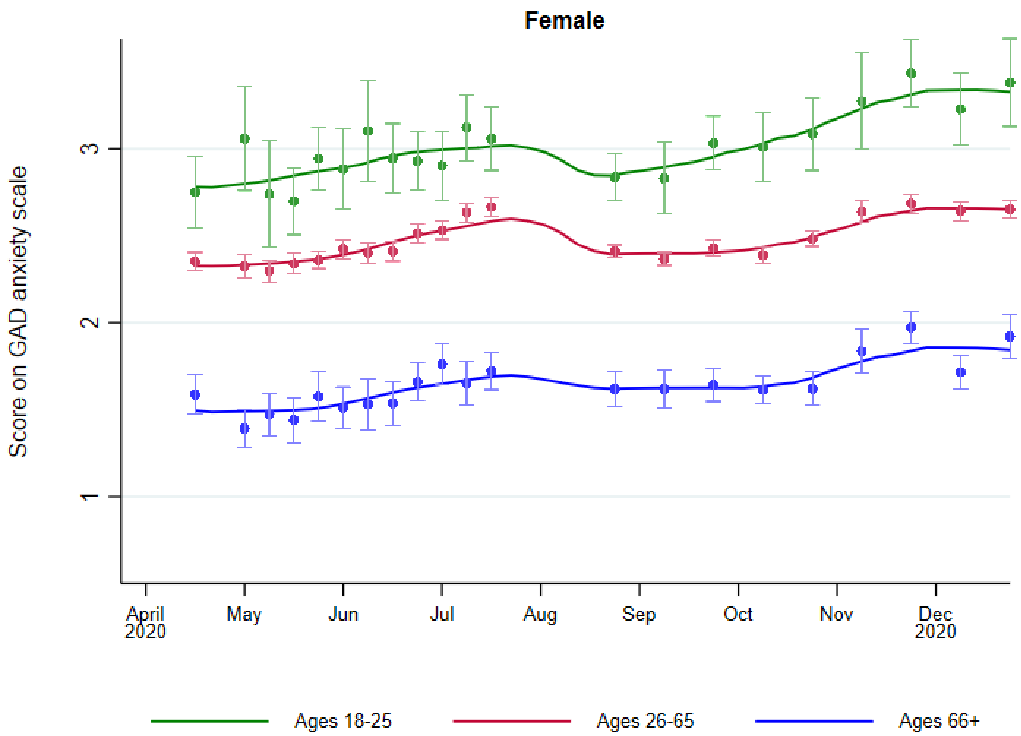


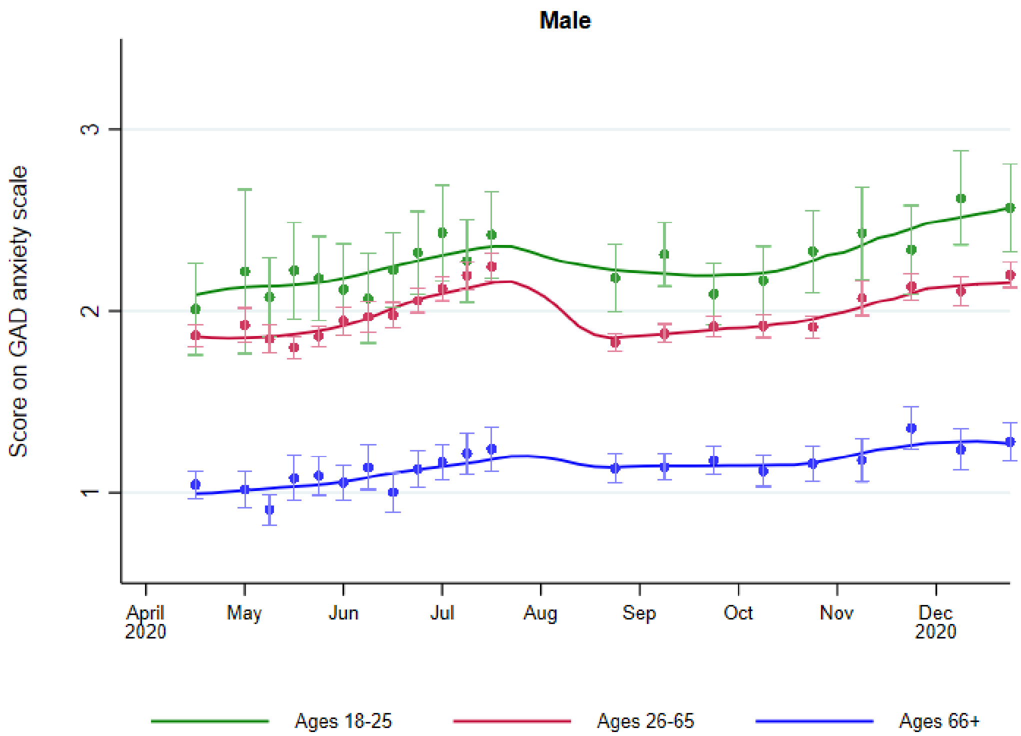
Figure A3. Score on the HPS GAD anxiety scale; mean scores by age-group and gender, with 95% confidence intervals (alternative age-group measure).



Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

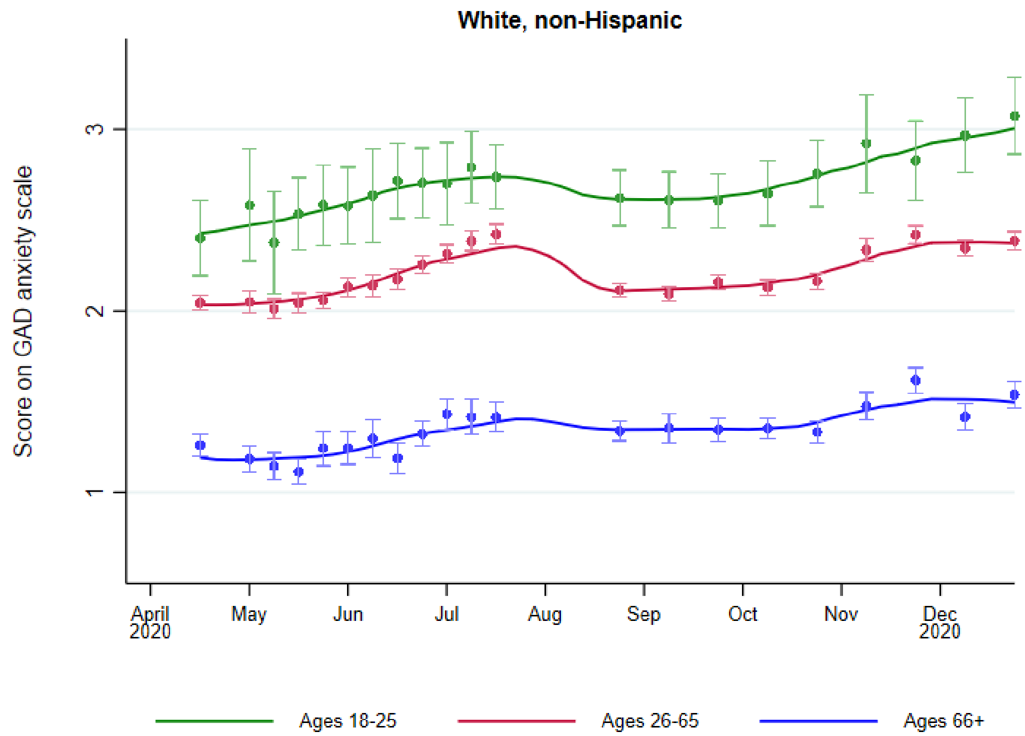
Figure A4. Score on the HPS GAD anxiety scale; mean scores by age-group and gender, with 95% confidence intervals.

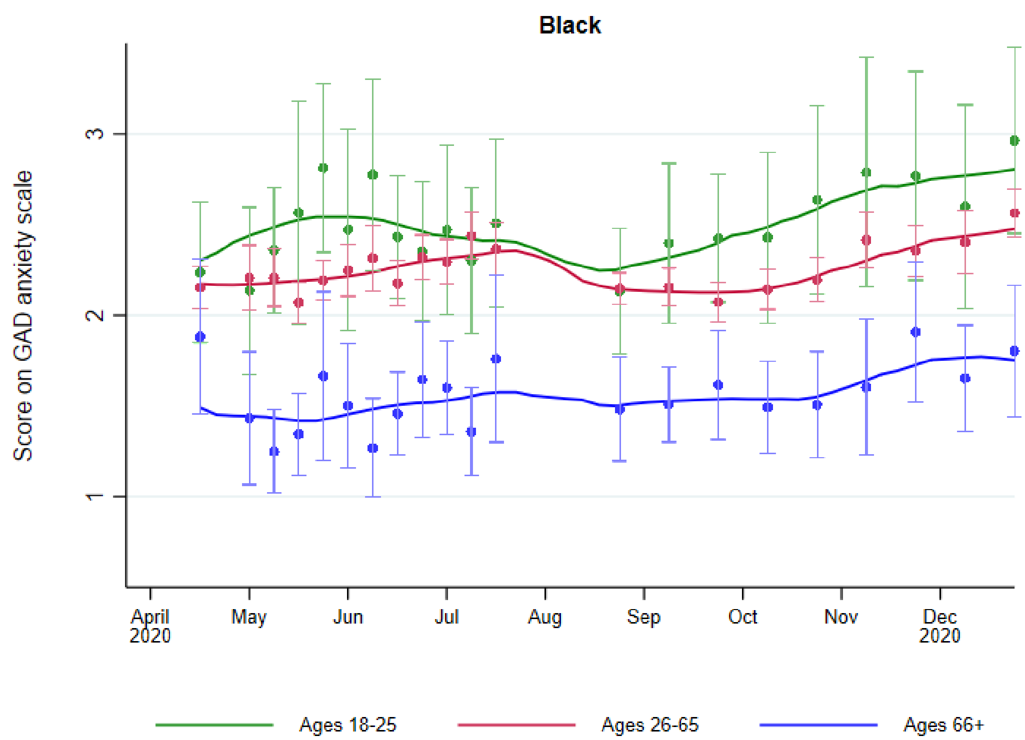


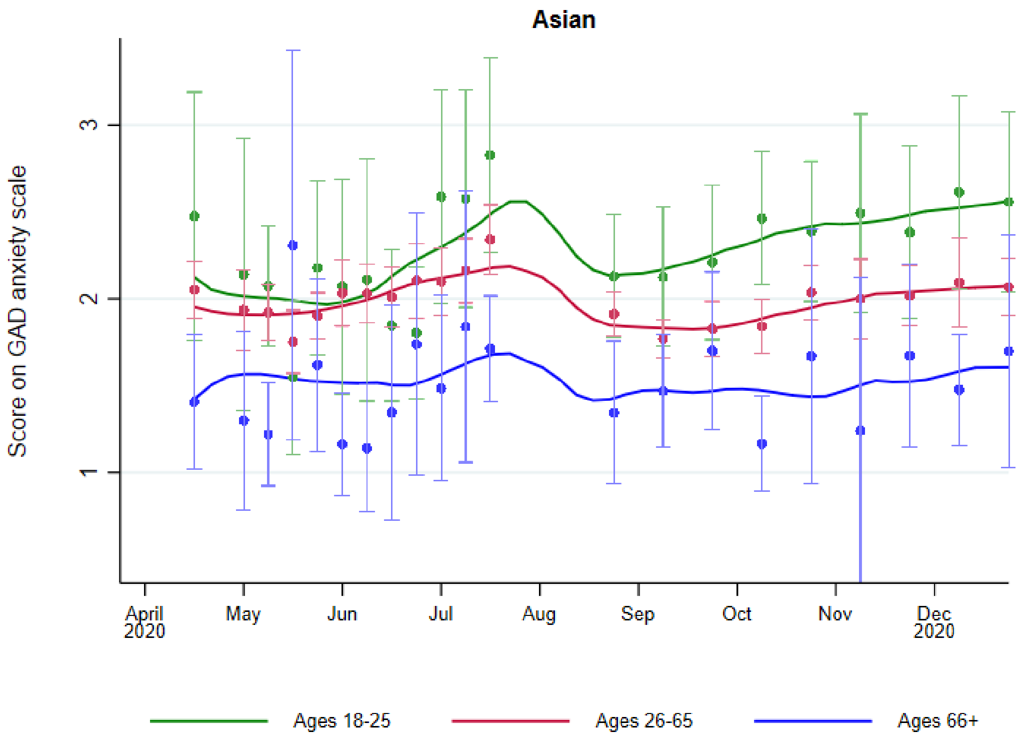


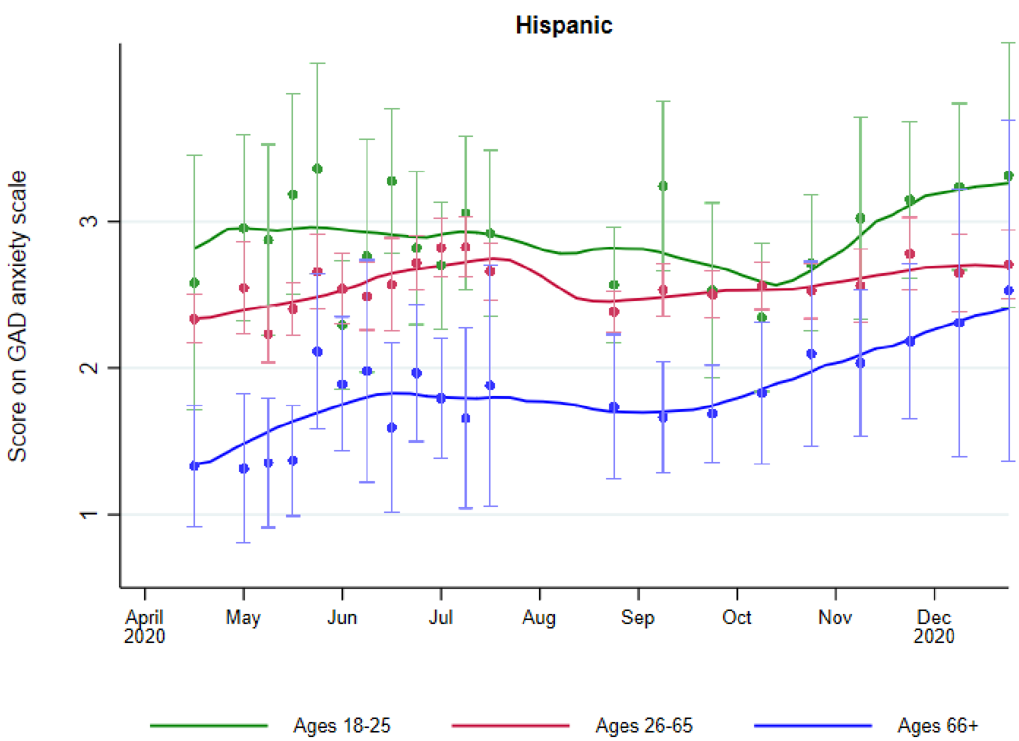
Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

Figure A5. Score on the HPS GAD anxiety scale; mean scores by age-group and race/ethnicity, with 95% confidence intervals.



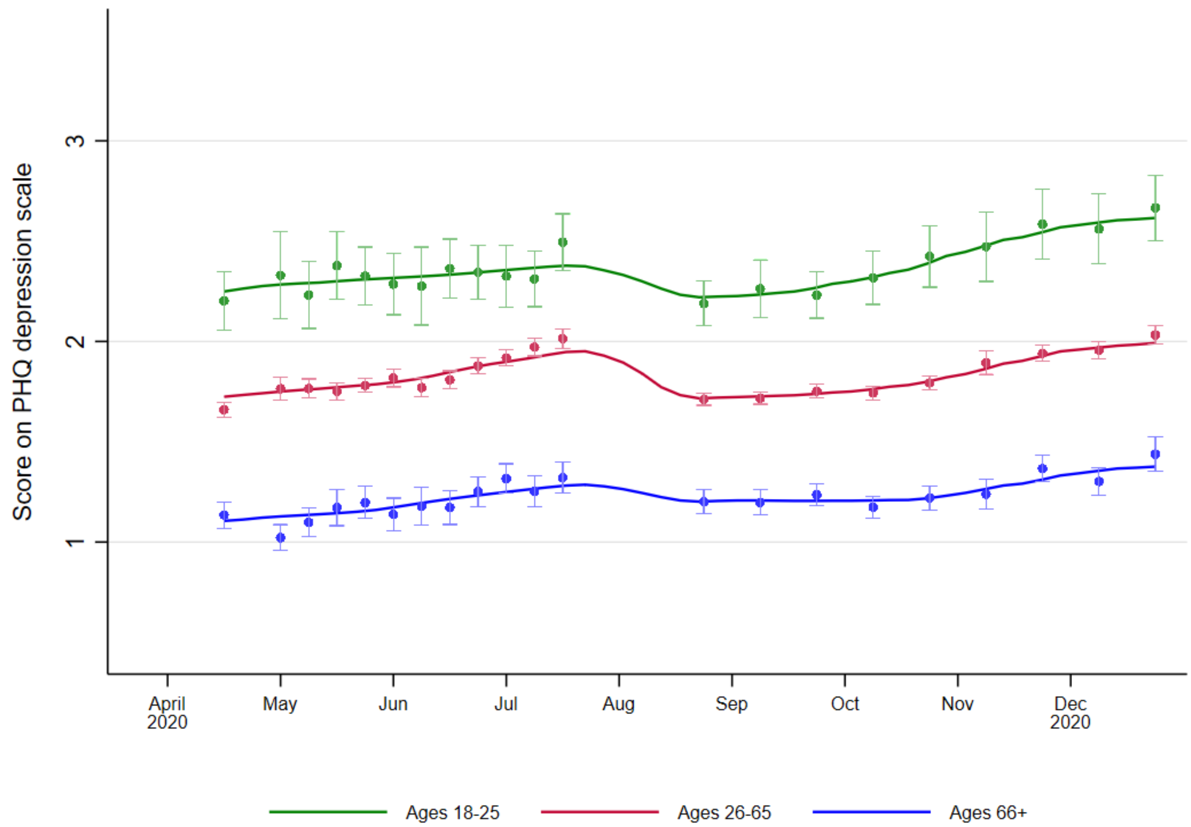






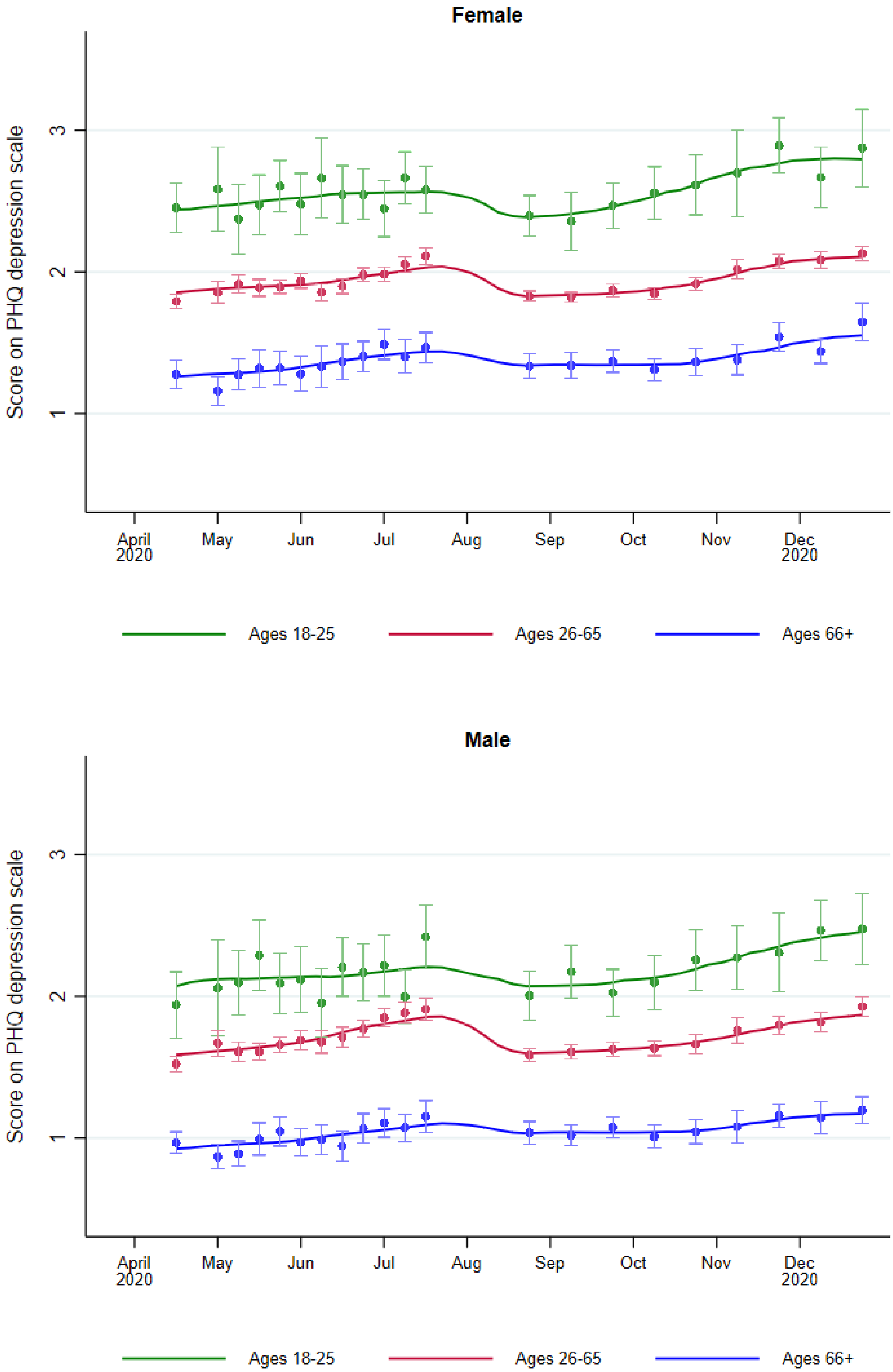
Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

Figure A6. Score on the HPS PHQ depression scale; mean scores by age-group, with 95% confidence intervals.



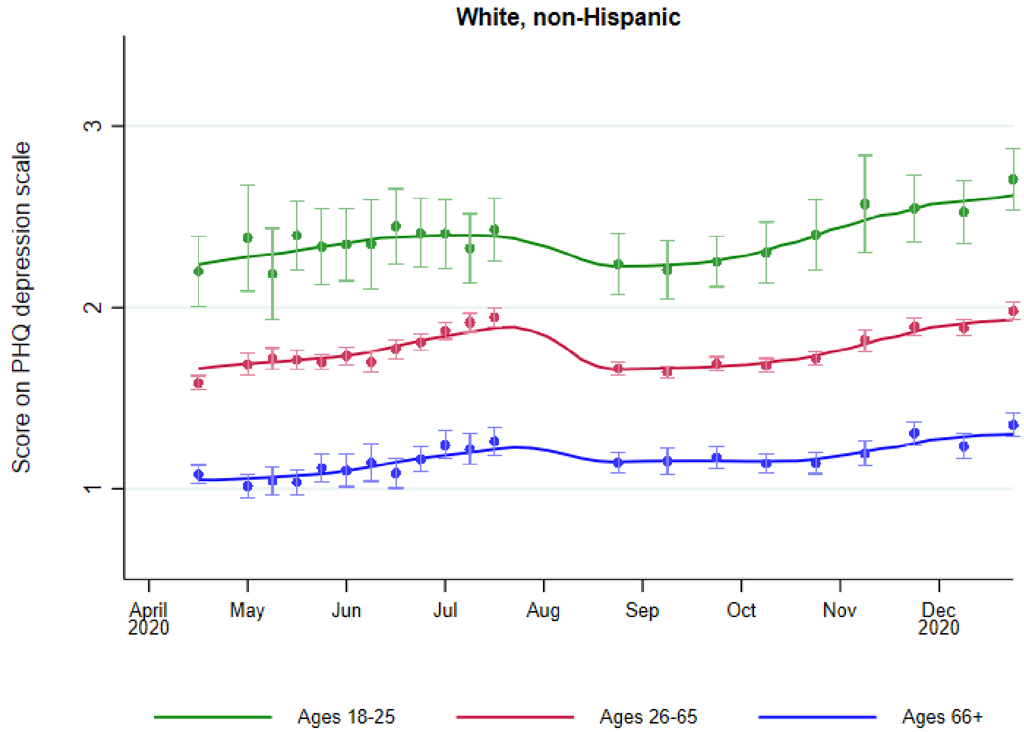
Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

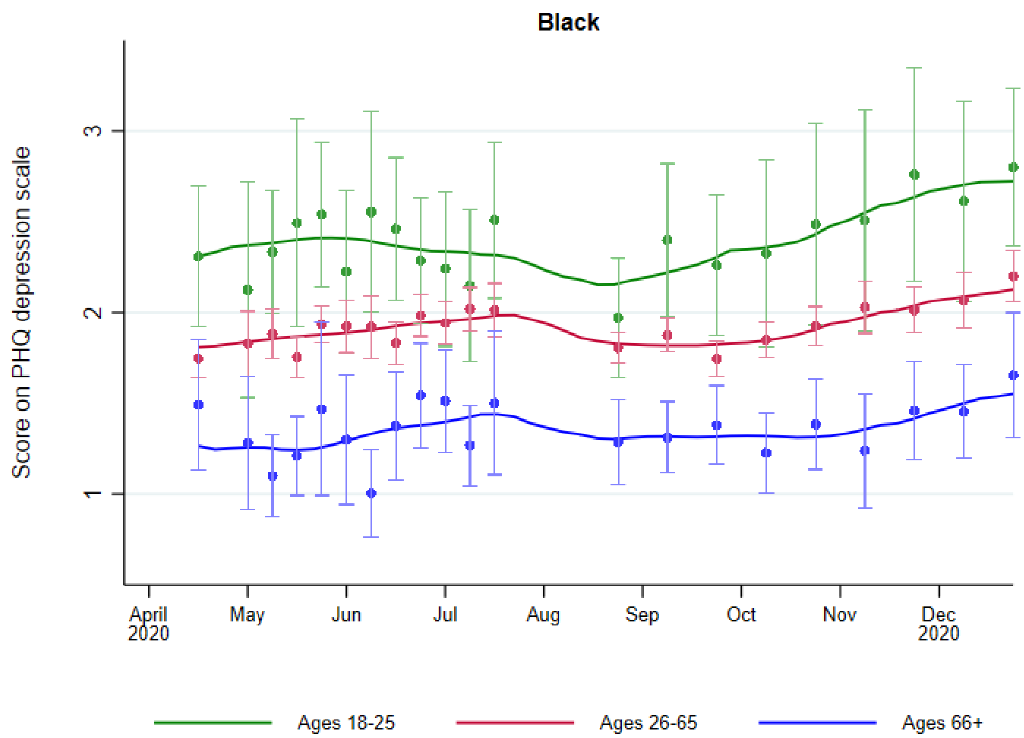
Figure A7. Score on the HPS PHQ depression scale; mean scores by age-group and gender, with 95% confidence intervals.

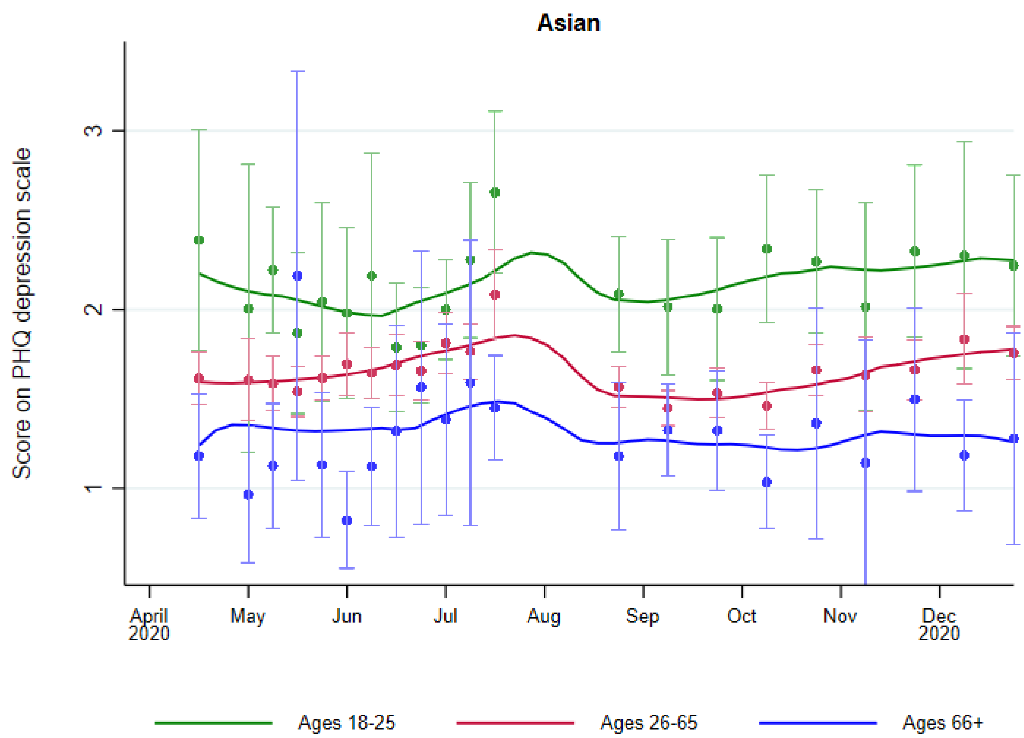


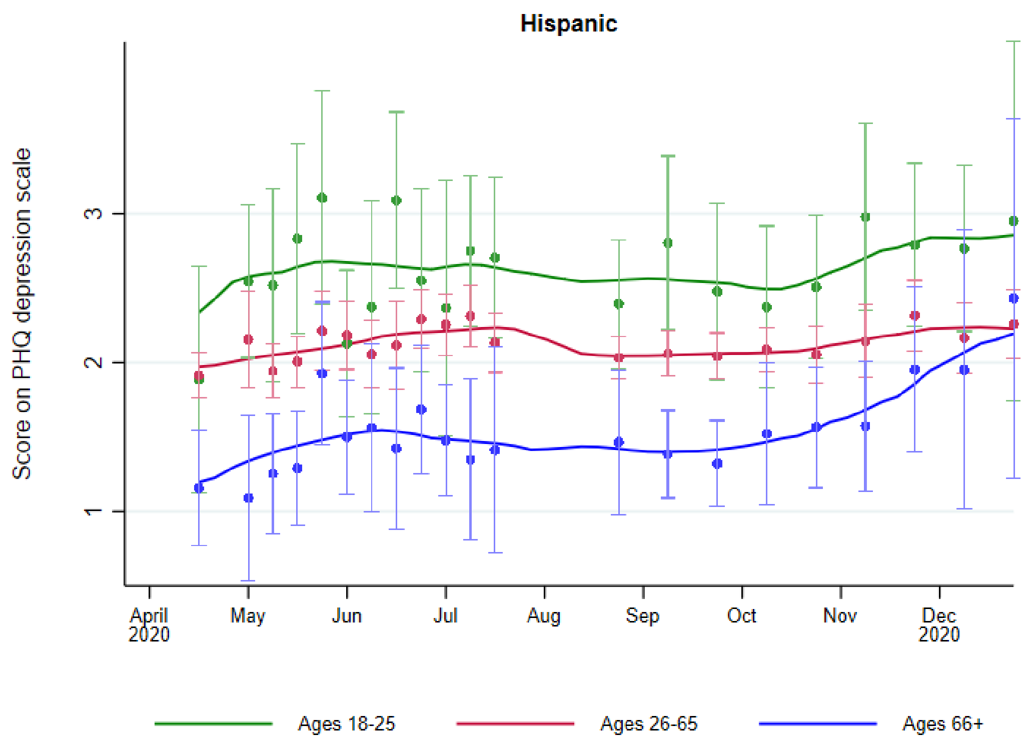
Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

Figure A8. Score on the HPS PHQ depression scale; mean scores by age-group and race/ethnicity, with 95% confidence intervals.









Note: Trend lines are fitted using local polynomial smoothing (all bandwidths set at 2).

Table A1: Coefficients (s.e.) for the model used to create predictions in Figure 2; GAD and PHQ measures. Coefficients significant to the p<.05 level are bolded.

	GAD measure	PHQ measure
26-65 years old	-0.33 (0.160)	**-0.35** (0.132)
66+ years old	**-1.07** (0.162)	**-0.93** (0.147)
Female	**0.67** (0.036)	**0.31** (0.043)
Female*26-65 years	**-0.25** (0.037)	**-0.16** (0.043)
Female*66+ years	**-0.24** (0.041)	-0.06 (0.046)
Black	**-0.34** (0.063)	**-0.16** (0.053)
Asian	**-0.45** (0.067)	**-0.29** (0.062)
Other	**0.11** (0.053)	**0.13** (0.060)
Black*26-65 years	0.10 (0.064)	-0.01 (0.055)
Black*66+ years	**0.32** (0.071)	**0.13** (0.059)
Asian*26-65 years	**0.23** (0.059)	**0.16** (0.054)
Asian*66+ years	**0.49** (0.068)	**0.30** (0.083)
Other*26-65 years	0.02 (0.056)	0.00 (0.061)
Other*66+ years	**0.18** (0.076)	0.11 (0.088)
Hispanic	**-0.30** (0.050)	**-0.26** (0.039)
Hispanic*26-65 years	**0.15** (0.049)	**0.11** (0.041)
Hispanic*66+ years	**0.50** (0.051)	**0.39** (0.053)
Job loss	**0.88** (0.058)	**0.81** (0.056)
Job loss*26-65 years	-0.05 (0.041)	**-0.09** (0.040)
Job loss*66+ years	**-0.12** (0.042)	**-0.17** (0.037)
$25,000 - $34,999 income	-0.08 (0.059)	-0.11 (0.053)
$35,000 - $49,999 income	**-0.11** (0.056)	**-0.19** (0.056)
$50,000 - $74,999 income	**-0.21** (0.057)	**-0.30** (0.056)
$75,000 - $99,999 income	**-0.38** (0.061)	**-0.50** (0.055)
$100,000 - $149,999 income	**-0.42** (0.069)	**-0.53** (0.067)
$150,000 - $199,999 income	**-0.54** (0.075)	**-0.65** (0.067)
$200,000 and above income	**-0.72** (0.079)	**-0.87** (0.086)
$25,000 - $34,999 income*26-65 years	**-0.20** (0.072)	**-0.21** (0.071)
$25,000 - $34,999 income*66+ years	**-0.19** (0.072)	**-0.19** (0.070)
$35,000 - $49,999 income*26-65 years	**-0.27** (0.060)	**-0.27** (0.058)
$35,000 - $49,999 income*66+ years	**-0.34** (0.074)	**-0.35** (0.060)
$50,000 - $74,999 income*26-65 years	**-0.31** (0.063)	**-0.35** (0.062)
$50,000 - $74,999 income*26-65 years	**-0.36** (0.067)	**-0.37** (0.068)
$75,000 - $99,999 income*26-65 years	**-0.30** (0.071)	**-0.34** (0.061)
$75,000 - $99,999 income*66+ years	**-0.26** (0.076)	**-0.26** (0.069)
$100,000 - $149,999 income*26-65 years	**-0.40** (0.060)	**-0.48** (0.061)
$100,000 - $149,999 income*66+ years	**-0.30** (0.078)	**-0.35** (0.067)
$150,000 - $199,999 income*26-65 years	**-0.40** (0.077)	**-0.52** (0.073)
$150,000 - $199,999 income*66+ years	**-0.23** (0.090)	**-0.28** (0.076)

	GAD measure	PHQ measure
$200,000 and above income*26-65 years	**-0.34** (0.100)	**-0.43** (0.098)
$200,000 and above income*66+ years	-0.09 (0.083)	-0.10 (0.096)
Plus a set of state coefficients and constant (not shown)		
Economic support index	**0.0012** (0.0005)	**0.0019** (0.0004)
Economic support index*job loss	**-0.0016** (0.0007)	**-0.0016** (0.0006)
Cases per 100,000	**0.0006** (0.0001)	**0.0006** (0.00005)
Containment and health index	**-0.0137** (0.0027)	**-0.0112** (0.0023)
Containment and health index*26-65 years	**0.0064** (0.0027)	**0.0056** (0.0023)
Containment and health index*66+ years	**0.0060** (0.0028)	0.0049 (0.0027)

Table A2: Comparison of cases and policy coefficients from imputed and complete case analyses; GAD and PHQ measures; coefficients (s.e.), coefficients significant to the p<.05 level are bolded.

	GAD measure	PHQ measure
Imputed		
Cases per 100,000	**0.0006** (0.0001)	**0.0006** (0.0000)
Containment and health index	**-0.0137** (0.0027)	**-0.0112** (0.0023)
Containment and health index*26-65 years	**0.0064** (0.0027)	**0.0056** (0.0023)
Containment and health index*66+ years	**0.0060** (0.0028)	0.0049 (0.0027)
Complete case		
Cases per 100,000	**0.0007** (0.0001)	**0.0006** (0.0000)
Containment and health index	**-0.0175** (0.0033)	**-0.0145** (0.0026)
Containment and health index*26-65 years	**0.0096** (0.0033)	**0.0084** (0.0025)
Containment and health index*66+ years	**0.0092** (0.0034)	**0.0081** (0.0028)

Table A3. Coefficients for cases and policy variables, where school closings, restrictions on gatherings, and stay at home policies are separated from the composite containment and health index; GAD and PHQ measures; coefficients (s.e.), coefficients significant to the p<.05 level are bolded.

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	GAD measure	**PHQ measure**
Economic support index	**0.0025** (0.0006)	**0.0027** (0.0005)
Economic support index*job loss	**-0.0017** (0.0006)	**-0.0016** (0.0006)
Cases per 100,000	**0.0006** (0.0001)	**0.0006** (0.0000)
School closings	**-0.0032** (0.0008)	**-0.0021** (0.0008)
School closings*26-65 years	**0.0020** (0.0007)	0.0014 (0.0008)
School closings*66+ years	0.0010 (0.0008)	0.0007 (0.0009)
Restrictions on gatherings	**-0.0018** (0.0006)	-0.0008 (0.0007)
Restrictions on gatherings*26-65 years	0.0006 (0.0006)	0.0001 (0.0007)
Restrictions on gatherings*66+ years	0.0001 (0.0006)	-0.0005 (0.0006)
Stay at home requirements	**-0.0041** (0.0013)	**-0.0028** (0.0013)
Stay at home requirements*26-65 years	0.0012 (0.0013)	0.0004 (0.0013)
Stay at home requirements*66+ years	0.0018 (0.0015)	0.0011 (0.0017)
Containment and health residual index	-0.0010 (0.0042)	-0.0051 (0.0042)
Containment and health residual index*26-65 years	0.0024 (0.0033)	0.0048 (0.0036)
Containment and health residual index*66+ years	0.0048 (0.0042)	0.0065 (0.0047)

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