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## Supplementary Information for

3 Evidence and Theory for Lower Rates of Depression in Larger U.S. Urban Areas
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6 This PDF file includes:
Figs. S1 to S6 (not allowed for Brief Reports)
Tables S1 to S8 (not allowed for Brief Reports)


Fig. S1. Histograms of the detected change points for all window sizes in BRFSS data and Twitter19'. We used a covariate discriminant method (see Methods) to nonparametrically detect changes in the joint distribution of depression rates and population, under the assumption that BRFSS report methods might induce an artificial change. For the Twitter19' dataset, the detection of change points primarily at the edges of the population range is indicative of finite edge effects rather than a true change in the joint distribution of depression rates and city size. Compare to BRFSS data where change points are detected in the middle of the population range.


Fig. S2. Pooling BRFSS data across years for all cities results in a scaling exponent of $\beta=0.926$ ( $95 \% \mathrm{CI}=[0.903,0.950]$ ), consistent with lower depression rates in larger cities.


Fig. S3. Users with lower numbers of tweets are more likely to have depressive sentiment in their tweets. When using an exclusion criteria of less that 92 tweets a logistic regression model significantly distinguishes individuals with depressive sentiment from individuals without depressive sentiment.


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Fig. S4. QQ plots of the residuals of the OLS model. No significant deviations are observed indicating that the residuals are approximately normally distributed and the linear model is appropriate.


Fig. S5. Residuals from OLS models are not correlated with city size. In all datasets, residuals are not correlated with city size (Spearman-r minimum $p$-value $=0.44$ ). Thus no corrections to estimates of $\beta$ are required.


Fig. S6. OLS fit to each dataset. Sublinear scaling is observed across all datasets.

## Table S1. MSAs included in the analysis in the main text (Fig. 2.). Included MSAs are marked with an X.

| MSA | Twitter10' | BFRSS | NSDUH | Twitter19' | 2017 Population |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Albuquerque, NM | - | - | X | - | 912897 |
| Ann Arbor, MI | - | - | - | X | 369208 |
| Atlanta-Sandy Springs-Alpharetta, GA | X | X | X | - | 5874249 |
| Augusta-Richmond County, GA-SC | X | - | - | - | 600006 |
| Austin-Round Rock-Georgetown, TX | - | X | - | - | 2115230 |
| Baltimore-Columbia-Towson, MD | X | X | X | - | 2798587 |
| Birmingham-Hoover, AL | - | X | - | - | 1085750 |
| Boston-Cambridge-Newton, MA-NH | X | - | X | - | 4844597 |
| Bridgeport-Stamford-Norwalk, CT | - | X | - | - | 943457 |
| Buffalo-Cheektowaga, NY | - | X | - | - | 1129660 |
| Charlotte-Concord-Gastonia, NC-SC | - | X | - | - | 2549741 |
| Chicago-Naperville-Elgin, IL-IN-WI | X | X | X | X | 9520784 |
| Cincinnati, OH-KY-IN | X | X | - | X | 2202597 |
| Cleveland-Elyria, OH | X | X | X | X | 2058549 |
| Columbus, OH | - | X | - | - | 2082475 |
| Dallas-Fort Worth-Arlington, TX | X | - | X | X | 7340943 |
| Denver-Aurora-Lakewood, CO | - | X | X | - | 2892979 |
| Detroit-Warren-Dearborn, MI | X | - | X | X | 4321704 |
| Fresno, CA | - | - | - | X | 986542 |
| Grand Rapids-Kentwood, MI | - | X | - | - | 1063926 |
| Gulfport-Biloxi, MS | - | - | - | X | 412946 |
| Hartford-East Hartford-Middletown, CT | - | X | - | - | 1206719 |
| Houma-Thibodaux, LA | - | - | - | X | 209893 |
| Houston-The Woodlands-Sugar Land, TX | X | X | X | X | 6905695 |
| Indianapolis-Carmel-Anderson, IN | X | X | - | - | 2026723 |
| Jacksonville, FL | - | X | - | - | 1504841 |
| Kansas City, MO-KS | X | X | X | X | 2127259 |
| Lafayette, LA | - | - | - | X | 490107 |
| Las Vegas-Henderson-Paradise, NV | - | X | X | X | 2183310 |
| Lock Haven, PA | - | - | - | X | 38837 |
| Los Angeles-Long Beach-Anaheim, CA | X | X | X | X | 13298709 |
| Louisville/Jefferson County, KY-IN | - | X | - | - | 1260391 |
| Macon-Bibb County, GA | - | - | - | X | 229081 |
| Manchester-Nashua, NH | - | - | X | - | 413157 |
| Memphis, TN-MS-AR | - | X | - | - | 1339290 |
| Miami-Fort Lauderdale-Pompano Beach, FL | X | X | X | X | 6149687 |
| Milwaukee-Waukesha, WI | - | X | - | - | 1575151 |
| Minneapolis-St. Paul-Bloomington, MN-WI | - | X | X | X | 3577765 |
| Montgomery, AL | X | - | - | - | 374042 |
| Nashville-Davidson-Murfreesboro-Franklin, TN | - | X | X | - | 1875736 |
| New Orleans-Metairie, LA | X | X | X | X | 1270465 |
| New York-Newark-Jersey City, NY-NJ-PA | X | - | X | X | 19325698 |
| Oklahoma City, OK | - | X | - | - | 1383249 |
| Opelousas, LA | - | - | - | X | 83447 |
| Orlando-Kissimmee-Sanford, FL | X | X | - | - | 2512917 |
| Philadelphia-Camden-Wilmington, PA-NJ-DE-MD | X | - | X | X | 6078451 |
| Phoenix-Mesa-Chandler, AZ | - | X | X | X | 4761694 |
| Pittsburgh, PA | - | X | X | - | 2330283 |
| Portland-Vancouver-Hillsboro, OR-WA | - | X | X | X | 2456462 |
| Poughkeepsie-Newburgh-Middletown, NY | X | - | - | - | 673253 |
| Providence-Warwick, RI-MA | - | X | - | - | 1617057 |
| Raleigh-Cary, NC | - | X | - | - | 1334342 |
| Richmond, VA | X | X | - | X | 1269478 |
| Riverside-San Bernardino-Ontario, CA | X | X | - | X | 4570427 |
| Rochester, NY | - | X | - | - | 1071589 |
| Sacramento-Roseville-Folsom, CA | - | X | - | - | 2320381 |
| Salt Lake City, UT | - | X | X | X | 1205238 |
| San Antonio-New Braunfels, TX | - | X | - | - | 2474274 |
| San Diego-Chula Vista-Carlsbad, CA | - | X | X | X | 3325468 |


| San Francisco-Oakland-Berkeley, CA | - | X | X | X | 4710693 |
| :--- | :--- | :--- | :--- | :--- | ---: |
| San Jose-Sunnyvale-Santa Clara, CA | - | X | - | X | 1993582 |
| Seattle-Tacoma-Bellevue, WA | X | - | X | X | 3884469 |
| St. Louis, MO-IL | - | X | X | X | 2805850 |
| Tampa-St. Petersburg-Clearwater, FL | - | $X$ | X | - | 3091225 |
| Trenton-Princeton, NJ | - | - | - | X | 368602 |
| Tucson, AZ | - | X | - | - | 1027502 |
| Tulsa, OK | - | X | X | X | 991610 |
| Virginia Beach-Norfolk-Newport News, VA-NC | X | X | - | X | 1761305 |
| Warner Robins, GA | - | - | - | X | 180019 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | - | - | X | - | 6213246 |
| Worcester, MA-CT | - | $X$ | - | - | 942303 |

Table S2. Estimates of the scaling exponent made with BRFSS data from smaller cities that were below the estimated change point for each year.

| Dataset | $\beta$ | $95 \% \mathrm{Cl}$ | $R^{2}$ | n |
| :--- | :--- | :--- | :--- | ---: |
| BRFSS2011 | 1.000 | $[0.960,1.039]$ | 0.952 | 128 |
| BRFSS2012 | 1.001 | $[0.961,1.040]$ | 0.954 | 122 |
| BRFSS2013 | 1.020 | $[0.969,1.070]$ | 0.953 | 81 |
| BRFSS2014 | 1.034 | $[0.991,1.077]$ | 0.969 | 74 |
| BRFSS2015 | 1.044 | $[0.996,1.093]$ | 0.966 | 67 |
| BRFSS2016 | 0.967 | $[0.906,1.028]$ | 0.931 | 76 |
| BRFSS2017 | 1.010 | $[0.962,1.058]$ | 0.959 | 76 |

Table S3. Robustness of scaling exponent estimates made with BRFSS data to variation in the city size below which data was excluded.

| Dataset | $\beta$ | $95 \% \mathrm{CI}$ |
| :--- | :--- | :--- |
| BRFSS2011 | 0.88 | $[0.87,0.89]$ |
| BRFSS2012 | 0.85 | $[0.85,0.87]$ |
| BRFSS2013 | 0.86 | $[0.85,0.87]$ |
| BRFSS2014 | 0.83 | $[0.83,0.84]$ |
| BRFSS2015 | 0.83 | $[0.82,0.84]$ |
| BRFSS2016 | 0.83 | $[0.82,0.84]$ |
| BRFSS2017 | 0.83 | $[0.83,0.85]$ |

Table S4. Scaling exponent estimates for all BFRSS data. No cities below the change point are excluded.

| Dataset | $\beta$ | $95 \% \mathrm{Cl}$ | $R^{2}$ | n |
| :--- | :--- | :--- | :--- | ---: |
| BRFSS2011 | 0.966 | $[0.942,0.991]$ | 0.974 | 172 |
| BRFSS2012 | 0.956 | $[0.931,0.982]$ | 0.972 | 161 |
| BRFSS2013 | 0.951 | $[0.920,0.982]$ | 0.968 | 122 |
| BRFSS2014 | 0.959 | $[0.932,0.987]$ | 0.978 | 111 |
| BRFSS2015 | 0.961 | $[0.932,0.990]$ | 0.976 | 109 |
| BRFSS2016 | 0.941 | $[0.910,0.972]$ | 0.968 | 119 |
| BRFSS2017 | 0.965 | $[0.939,0.991]$ | 0.980 | 116 |

Table S5. Robustness of scaling exponent estimates to variation in the minimum number of tweets required for inclusion in the Twitter analyses.

| Minimum Tweets | $\beta$ | $95 \% \mathrm{Cl}$ | \# MSAs |
| :--- | :--- | :--- | :--- |
| 82 | 0.85 | $[0.75,0.96]$ | 31 |
| 83 | 0.85 | $[0.75,0.95]$ | 29 |
| 84 | 0.86 | $[0.75,0.96]$ | 29 |
| 85 | 0.87 | $[0.75,0.98]$ | 28 |
| 86 | 0.86 | $[0.75,0.98]$ | 28 |
| 87 | 0.83 | $[0.69,0.97]$ | 26 |
| 88 | 0.83 | $[0.68,0.98]$ | 25 |
| 89 | 0.80 | $[0.65,0.95]$ | 25 |
| 90 | 0.79 | $[0.63,0.94]$ | 24 |
| 91 | 0.80 | $[0.65,0.96]$ | 24 |
| 92 | 0.82 | $[0.67,0.97]$ | 24 |
| 93 | 0.85 | $[0.70,0.99]$ | 22 |
| 94 | 0.84 | $[0.69,0.98]$ | 22 |
| 95 | 0.83 | $[0.70,0.95]$ | 22 |
| 96 | 0.83 | $[0.70,0.97]$ | 22 |
| 97 | 0.84 | $[0.71,0.98]$ | 22 |
| 98 | 0.86 | $[0.71,1.00]$ | 22 |
| 99 | 0.84 | $[0.70,0.98]$ | 22 |
| 100 | 0.81 | $[0.65,0.97]$ | 22 |
| 101 | 0.86 | $[0.68,1.04]$ | 21 |

Table S6. Shapiro-Wilk test of normality on the OLS residuals for each dataset. The residuals from the BRFSS 2013 data fail this normality test due to one outlier city with an negative residual.

| Dataset | statistic | p-value | n |
| :--- | :--- | :--- | :--- |
| Twitter10' | 0.917 | $5.03 \mathrm{e}-02$ | 24 |
| NSDUH | 0.970 | $5.26 \mathrm{e}-01$ | 31 |
| Twitter19 | 0.948 | $9.26 \mathrm{e}-02$ | 36 |
| BRFSS2011 | 0.977 | $4.79 \mathrm{e}-01$ | 48 |
| BRFSS2012 | 0.951 | $8.96 \mathrm{e}-02$ | 39 |
| BRFSS2013 | 0.873 | $3.47 \mathrm{e}-04$ | 40 |
| BRFSS2014 | 0.964 | $2.54 \mathrm{e}-01$ | 38 |
| BRFSS2015 | 0.951 | $7.38 \mathrm{e}-02$ | 41 |
| BRFSS2016 | 0.969 | $2.95 \mathrm{e}-01$ | 43 |
| BRFSS2017 | 0.959 | $1.55 \mathrm{e}-01$ | 40 |

Table S7. Result of logistic regression models for each year of BRFSS data. In addition to city natural-log-population and the rate of population change from the previous year, we conditioned on income, race, and education. The income variable had 6 levels with a baseline of not reported or missing, followed by: less than $\$ 15 \mathrm{k}, \mathbf{\$ 1 5 - \$ 2 5 k}, \$ 25-\$ 35 \mathrm{k}, \mathbf{\$ 3 5 - \$ 5 5 k}$, and greater than $\$ 50 \mathrm{k}$. The education variable had 5 levels with a baseline of not reported followed by: no high-school, graduated high-school, attended college, and graduated college. The race variable had 4 levels with a baseline of White followed by: Black, Asian, and other/multi-racial.

|  | Dependent variable: |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | (2017) | (2016) | (2015) | $\begin{gathered} \text { dep } \\ (2014) \end{gathered}$ | (2013) | (2012) | (2011) |
| logpop | $\begin{gathered} -0.104^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.115^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.115^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.108^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.124^{* * *} \\ (0.008) \end{gathered}$ | $\begin{gathered} -0.092^{* * *} \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.118^{* * *} \\ (0.008) \end{gathered}$ |
| inc1 | $\begin{gathered} 1.062^{* * *} \\ (0.033) \end{gathered}$ | $\begin{gathered} 1.098^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 1.103^{* * *} \\ (0.033) \end{gathered}$ | $\begin{gathered} 1.125^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 1.102^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} 1.101^{* * *} \\ (0.034) \end{gathered}$ | $\begin{gathered} 1.111^{* * *} \\ (0.031) \end{gathered}$ |
| inc2 | $\begin{gathered} 0.583^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} 0.613^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} 0.679^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} 0.598^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} 0.588^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} 0.601^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 0.568^{* * *} \\ (0.030) \end{gathered}$ |
| inc3 | $\begin{gathered} 0.321^{* * *} \\ (0.033) \end{gathered}$ | $\begin{gathered} 0.288^{* * *} \\ (0.034) \end{gathered}$ | $\begin{gathered} 0.344^{* * *} \\ (0.034) \end{gathered}$ | $\begin{gathered} 0.270^{* * *} \\ (0.034) \end{gathered}$ | $\begin{gathered} 0.282^{* * *} \\ (0.034) \end{gathered}$ | $\begin{gathered} 0.292^{* * *} \\ (0.036) \end{gathered}$ | $\begin{gathered} 0.318^{* * *} \\ (0.034) \end{gathered}$ |
| inc4 | $\begin{gathered} 0.206 * * * \\ (0.031) \end{gathered}$ | $\begin{gathered} 0.174^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} 0.188^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 0.157^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} 0.189 * * * \\ (0.032) \end{gathered}$ | $\begin{gathered} 0.144^{* * *} \\ (0.035) \end{gathered}$ | $\begin{gathered} 0.164^{* * *} \\ (0.033) \end{gathered}$ |
| inc5 | $\begin{gathered} -0.093^{* * *} \\ (0.024) \end{gathered}$ | $\begin{gathered} -0.130^{* * *} \\ (0.025) \end{gathered}$ | $\begin{gathered} -0.055^{* *} \\ (0.025) \end{gathered}$ | $\begin{gathered} -0.114^{* * *} \\ (0.026) \end{gathered}$ | $\begin{gathered} -0.086^{* * *} \\ (0.027) \end{gathered}$ | $\begin{gathered} -0.138^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.112^{* * *} \\ (0.027) \end{gathered}$ |
| edu1 | $\begin{gathered} 0.626^{* * *} \\ (0.159) \end{gathered}$ | $\begin{gathered} 0.416^{* * *} \\ (0.151) \end{gathered}$ | $\begin{gathered} 0.786^{* * *} \\ (0.172) \end{gathered}$ | $\begin{gathered} 0.434^{* * *} \\ (0.105) \end{gathered}$ | $\begin{gathered} 0.460^{* * *} \\ (0.129) \end{gathered}$ | $\begin{gathered} 0.691^{* * *} \\ (0.168) \end{gathered}$ | $\begin{gathered} 0.167 \\ (0.136) \end{gathered}$ |
| edu2 | $\begin{gathered} 0.541^{* * *} \\ (0.157) \end{gathered}$ | $\begin{gathered} 0.238 \\ (0.149) \end{gathered}$ | $\begin{gathered} 0.686^{* * *} \\ (0.170) \end{gathered}$ | $\begin{gathered} 0.302^{* * *} \\ (0.102) \end{gathered}$ | $\begin{gathered} 0.302^{* *} \\ (0.128) \end{gathered}$ | $\begin{gathered} 0.587^{* * *} \\ (0.167) \end{gathered}$ | $\begin{gathered} 0.024 \\ (0.135) \end{gathered}$ |
| edu3 | $\begin{gathered} 0.755^{* * *} \\ (0.157) \end{gathered}$ | $\begin{gathered} 0.450^{* * *} \\ (0.149) \end{gathered}$ | $\begin{gathered} 0.923^{* * *} \\ (0.170) \end{gathered}$ | $\begin{gathered} 0.511^{* * *} \\ (0.102) \end{gathered}$ | $\begin{gathered} 0.551^{* * *} \\ (0.127) \end{gathered}$ | $\begin{gathered} 0.779^{* * *} \\ (0.167) \end{gathered}$ | $\begin{aligned} & 0.262^{*} \\ & (0.134) \end{aligned}$ |
| edu4 | $\begin{gathered} 0.534^{* * *} \\ (0.157) \end{gathered}$ | $\begin{aligned} & 0.261^{*} \\ & (0.149) \end{aligned}$ | $\begin{gathered} 0.718^{* * *} \\ (0.170) \end{gathered}$ | $\begin{gathered} 0.320^{* * *} \\ (0.102) \end{gathered}$ | $\begin{gathered} 0.345^{* * *} \\ (0.127) \end{gathered}$ | $\begin{gathered} 0.618^{* * *} \\ (0.167) \end{gathered}$ | $\begin{gathered} 0.123 \\ (0.135) \end{gathered}$ |
| rac2 | $\begin{gathered} -0.474^{* * *} \\ (0.027) \end{gathered}$ | $\begin{gathered} -0.509^{* * *} \\ (0.028) \end{gathered}$ | $\begin{gathered} -0.487^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.460^{* * *} \\ (0.027) \end{gathered}$ | $\begin{gathered} -0.497^{* * *} \\ (0.027) \end{gathered}$ | $\begin{gathered} -0.513^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.497^{* * *} \\ (0.028) \end{gathered}$ |
| rac3 | $\begin{aligned} & 0.116^{*} \\ & (0.063) \end{aligned}$ | $\begin{gathered} 0.108 \\ (0.068) \end{gathered}$ | $\begin{aligned} & -0.017 \\ & (0.069) \end{aligned}$ | $\begin{gathered} 0.029 \\ (0.068) \end{gathered}$ | $\begin{gathered} -0.014 \\ (0.069) \end{gathered}$ | $\begin{gathered} -1.186 * * * \\ (0.097) \end{gathered}$ | $\begin{gathered} -1.084^{* * *} \\ (0.086) \end{gathered}$ |
| rac4 | $\begin{gathered} -0.327^{* * *} \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.371^{* * *} \\ (0.030) \end{gathered}$ | $\begin{gathered} -0.392^{* * *} \\ (0.032) \end{gathered}$ | $\begin{gathered} -0.336^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} -0.335^{* * *} \\ (0.031) \end{gathered}$ | $\begin{gathered} -0.069^{* *} \\ (0.031) \end{gathered}$ | $\begin{gathered} -0.074^{* *} \\ (0.030) \end{gathered}$ |
| pop_change_rate | $\begin{gathered} -1.194 \\ (1.094) \end{gathered}$ | $\begin{gathered} -1.803^{*} \\ (0.944) \end{gathered}$ | $\begin{aligned} & -1.427 \\ & (1.017) \end{aligned}$ | $\begin{gathered} -1.874^{*} \\ (1.087) \end{gathered}$ | $\begin{gathered} -1.972 \\ (1.274) \end{gathered}$ | $\begin{gathered} -2.987^{* *} \\ (1.302) \end{gathered}$ | $\begin{gathered} 0.718 \\ (1.281) \end{gathered}$ |
| Constant | $\begin{gathered} -2.083^{* * *} \\ (0.157) \end{gathered}$ | $\begin{gathered} -1.949^{* * *} \\ (0.148) \end{gathered}$ | $\begin{gathered} -2.340^{* * *} \\ (0.170) \end{gathered}$ | $\begin{gathered} -1.937^{* * *} \\ (0.101) \end{gathered}$ | $\begin{gathered} -1.946^{* * *} \\ (0.127) \end{gathered}$ | $\begin{gathered} -2.260^{* * *} \\ (0.166) \end{gathered}$ | $\begin{gathered} -1.814^{* * *} \\ (0.134) \end{gathered}$ |
| Observations | 104,556 | 110,826 | 102,349 | 108,795 | 106,845 | 96,590 | 109,683 |
| Log Likelihood | -50,461.720 | -49,524.370 | -48,143.410 | -50,977.470 | -51,100.640 | -44,614.290 | -49,923.300 |
| Akaike Inf. Crit. | 100,953.400 | 99,078.740 | 96,316.820 | 101,985.000 | 102,231.300 | 89,258.580 | 99,876.610 |


|  | coef | std err | $\mathbf{t}$ | $\mathbf{P}>\|\mathbf{t}\|$ | $[\mathbf{0 . 0 2 5}$ | $\mathbf{0 . 9 7 5 ]}$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Twitter 2010 Ln Population | -0.2284 | 0.107 | -2.127 | 0.045 | -0.452 | -0.005 |
| Twitter 2010 Population Change \% | -184.8047 | 287.438 | -0.643 | 0.527 | -782.564 | 412.955 |
| Twitter 2019 Ln Population | -0.0846 | 0.022 | -3.842 | 0.001 | -0.129 | -0.040 |
| Twitter 2019 Population Change \% | -3.0574 | 4.446 | -0.688 | 0.496 | -12.102 | 5.987 |
| NSDUH Ln Population | -0.0952 | 0.045 | -2.108 | 0.044 | -0.188 | -0.003 |
| NSDUH Population Change \% | 67.5237 | 130.243 | 0.518 | 0.608 | -199.266 | 334.314 |

Table S8. Depression rates are not associated with year over year population change. Results from ordinary least squares fits with the rate of population change included.

