Spatial mobility and mental health during COVID-19: Evidence from linked individual-level GPS data and health care records

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Abstract

Using de-anonymized smartphone GPS data in one large U.S. county, we connect the mobility patterns of approximately 1,500 individuals to administrative data on mental health care utilization. This linkage enables a study of the relationship between a person's level of spatial movement and their mental health experiences during the early months of COVID-19. Mobility levels declined sharply in the initial months of the pandemic, but returned to near pre-pandemic levels by June 2020. Mental health care consumption over this same period showed no increase from baseline trends and in some cases decreased. We find no association between a person's spatial mobility and their likelihood of receiving mental health care over a one-year period spanning the start of the pandemic. Our results contribute highly novel evidence on spatial movement as a determinant of psychological well-being, and on the social welfare effects of public health measures that constrain residents' mobility.

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1 Introduction

The COVID-19 pandemic brought a sudden and unprecedented disruption to individuals' daily travel patterns. People spent more time at home than usual due to mandatory stay-at-home orders and business closures, as well as out of personal efforts to maintain physical distance from others. These lockdown policies and changes in modes of social interaction raised concerns about adverse psychological effects on a mass scale. Mental health officials predicted that the combination of isolation and other stressors "will contribute to widespread emotional distress and increased risk for psychiatric illness" (Pfefferbaum & North, 2020). Clinicians similarly voiced a worry that social distancing policies would result in traumatic confinement and loneliness, fearing that "the lockdown is storing up problems which could then lead to a tsunami of referrals" (Roxby, 2020). A complete assessment of the social costs and benefits of public health-related mobility restrictions thus requires understanding the relationship between spatial movement, social isolation, and mental health.

In this paper, we leverage the sharp reduction in mobility that occurred in the early months of COVID-19 to examine the correlation between an individual's level of spatial movement and their likelihood of receiving mental health care. We analyze this correlation using a first-of-its-kind data linkage: We connect smartphone GPS data to administrative health care records at the individual level for a sample of phone users in one large county in the Midwestern United States. To do this, we start with a commercially-available data set that contains location data on approximately 33,000 cell phones within the county of study. Although the users of the phones are nominally deidentified, the data contains phone-level identifiers that enable the location tracking of each phone over time at a high level of spatial and temporal resolution. We use this longitudinal feature of the data to compare a phone's whereabouts in time and space with confidential government records of social service recipients in the same county. These government records often indicate the date and location where a social service was provided. By repeatedly matching the phone's location at a given point in time with a specific person's social service location at the same time, we identify approximately 1,500 individual owners of the phones with relatively high confidence. We then observe the Medicaid-funded mental health care claims for these phone-matched individuals during the same time period that is covered by the GPS data.

Our sample of smartphone users experienced a sharp drop in geospatial mobility in the first two months after the onset of the pandemic in March 2020. During this same period, their use of mental health services showed little deviation from prior trends. Regression results indicate that the drop in geospatial mobility between March and June 2020 was not correlated with an increase in mental health care consumption. The relationship between mobility and care usage also did not vary by whether the individual had a pre-COVID mental health diagnosis. We test the robustness of this relationship using several panel regression specifications that control for demographics and pre-COVID measures of care utilization. Although our analysis is descriptive in nature, it provides suggestive evidence that the temporary reduction in spatial movement in the early months of the pandemic did not by itself lead to adverse mental health outcomes. The relationship between spatial movement per se and mental health may be too causally complex to register a bivariate correlation.

Our study contributes to several knowledge gaps at the intersection of public health and spatial mobility. First, we provide highly novel evidence on psychological outcomes during the peak period of mobility restrictions early in the COVID-19 pandemic. Research has reached mixed conclusions on the extent to which mental health worsened in the early portion of the pandemic when mandatory lockdowns were in effect (Cenat et al., 2022; Organization et al., 2022; Prati & Mancini, 2021; A. B. Witteveen et al., 2023).[1] The heterogeneous findings on the mental health consequences of COVID-19 lockdowns are difficult to interpret in part because almost all studies relied on self-reported measures of isolation and psychological well-being. Such measures are susceptible to the typical issues of reporting accuracy and memory that arise when eliciting information about mental health status. We avoid this measurement concern by quantifying an individual's spatial mobility and mental health using non-subjective data sources. Despite gaps in the receipt of treatment among people with mental illness (Kessler et al., 2005; Walker et al., 2015), health care utilization (as measured by claims data) provides a reliable positive indication of adverse mental health experiences. Claims data also enables us to disaggregate types of care at a granular level, including crisis-oriented care, substance use-related treatment, and more routine preventive care such as counseling visits. Rates of mental health care utilization across the U.S. increased only modestly during COVID-19 compared with pre-pandemic levels, as sharp reductions in in-person care were offset by expanded telehealth care (Adepoju & Valdez, 2023;

[1]The complex social dynamics of lockdowns during a public health crisis make it unclear whether such policies can be expected to have a net positive or negative effect on mental health. On one hand, limited social contact has well-known negative effects on both physical and mental health (Hatcher & Stubbersfield, 2013; Kuiper et al., 2015; Pantell et al., 2013; Santini et al., 2015), and numerous studies have found that feelings of isolation contributed to mental health challenges during the pandemic (Kim & Jung, 2021; Morina et al., 2021; Murayama et al., 2021; Pieh et al., 2021). Home confinement during lockdowns also raised concerns about increased rates of intimate partner violence (Campbell et al., 2023; Uzoho et al., 2023). On the other hand, mobility restrictions may have supported mental health in the early stages of the pandemic by providing real or perceived safety from the spread of disease and by suspending the social pressures of everyday life (Soneson et al., 2023). Spending more time at home offered short-term relief for some individuals with social anxiety (Goh et al., 2023). The shared sacrifices of lockdowns even produced a unifying sense of social purpose in some settings (Bowe et al., 2021).

Asch et al., 2021; Cantor et al., 2023; McBain et al., 2023). Among Medicaid patients, the volume of mental health care consumption exhibited no change from pre-pandemic trends or even decreased by some measures (CMS, 2022; Kearly et al., 2024). At the same time, local shelter-in-place orders appear to have correlated with increased mental health care usage in the same place (Ferwana & Varshney, 2024). In contrast to this prior work, our study provides the first known *individual-level* analysis of spatial mobility and mental health care consumption during the pandemic. Our results corroborate the community-level evidence that lockdowns did not coincide with greater use of mental care. In our sample, people with larger drops in personal movement were no more likely to receive mental health treatment.

Furthermore, we build upon existing research that has used smartphone GPS data to explore the mental health consequences of mobility restrictions during COVID-19. Several studies have used such data to demonstrate that early lockdown measures caused mass reductions in spatial mobility and increased the amount of time people spent at home (McCrary & Sanga, 2021; Mizuno et al., 2021; Szocska et al., 2021). Others have analyzed these aggregate mobility changes together with contemporaneous longitudinal surveys to link the reductions in spatial movement to worse self-reported mental well-being (Burdett et al., 2021; Carpio-Arias et al., 2023; Chan et al., 2024; Lee et al., 2023). These aggregate analyses, while suggestive, do not speak to the individual-level relationship between a person's daily movements and their mental health. A small literature has examined individually-linked data on smartphone mobility and mental health outcomes early in the pandemic. Mack et al. (2021) and Wu et al. (2021) collected smartphone-based location data and mental health questionnaires from small samples of U.S. college students both before and during COVID-19. Both studies found a negative correlation between mobility levels and mental health symptoms before the pandemic, but the correlation became much weaker after the virus outbreak began. A case study in Massachusetts tracked the smartphone locations of seven patients with severe mental illness, finding that lockdowns led patients to move around less and report greater loneliness (Valeri et al., 2023). We extend this work by leveraging a much larger sample size of individually-linked mobility and mental health data, along with a more diverse sample in terms of age and mental health status. Our findings echo those from the above smaller-scale studies in that we find little to no relationship between spatial movement and mental health care usage early in the pandemic.

Beyond the context of COVID-19, our results also shed light on the more general relationship between a person's breadth and frequency of spatial movement and their risk of adverse mental health outcomes. An individual's travel behavior could influence their mental health in multiple ways. First, as feared during the pandemic, a lack of spatial movement may lead to social isolation, which in turn poses a strong risk factor for mental health issues.

An inability to meet one's travel needs could independently cause mental distress, although this may not translate into increased health care usage if the person faces transportation barriers to getting to the doctor.[2] Even if a person's physical movements do not correlate with social engagement, reduced mobility may harm mental health through other channels. To the extent that a person's movement is self-powered, walking and recreation are known to have positive psychological effects (Kelly et al., 2018; Lackey et al., 2021), and residents of neighborhoods with better pedestrian infrastructure tend to exhibit better mental health (Park et al., 2021). The experiential diversity that comes with visiting new places has also been linked to positive mental states (Heller et al., 2020). Having a limited range of mobility may also be a *consequence* of mental health challenges rather than a cause, as mentally ill individuals often travel less than the general population (Mackett, 2021). Furthermore, a person's travel patterns could result from other socioeconomic factors that independently affect mental health. Less frequent travel may indicate the loss of employment, for example, which was prevalent in the early months of the pandemic and is a common risk factor for mental distress (D. Witteveen & Velthorst, 2020).

While this paper's descriptive analyses do not disentangle the causal relationships mentioned above, our finding of no association between mobility and mental health care usage nonetheless provides a telling empirical result. Even if spatial movement has no relationship with social isolation, a sudden change to a person's normal mobility patterns often indicates a life disruption that could be accompanied by mental health challenges. Instead, we find no correlation between the depth of a person's COVID-related decrease in mobility and their propensity to consume mental health care. The relationship between these two behaviors is likely too complex and multifactorial to register a strong partial correlation in our observational regressions.

Finally, our paper makes a methodological contribution, in the form of a novel data-linking exercise, to the growing literature that uses smartphone GPS data to monitor economic activity and public health. To our knowledge, we are the first to attempt to link anonymous smartphone GPS data with government records of social service involvement. This linkage is highly exploratory in nature, and it serves as a proof of concept for researchers seeking to undertake similar work with the proper privacy and confidentiality safeguards. While research has begun to establish standardized methods of analyzing aggregate device location data (Barreras & Watts, 2024), there is little guidance to date on best practices for identifying individual phone users from such data (in the event that such

[2] A recent randomized controlled trial that provided mobility-enhancing public transit fare discounts found that free fares cause a 6.3% reduction in mental health care consumption relative to regular fare prices (Chizeck & Mbonu, 2024).

identification is warranted). Prior research has demonstrated the theoretical feasibility of re-identifying anonymous GPS traces (De Montjoye et al., 2013), but few real-world attempts at re-identification have detailed their methods and results in practice (Podlesny et al., 2023). Our results demonstrate both the possibilities and limitations of privacy maintenance in smartphone data. On one hand, our exercise confirms that ostensibly anonymous location data can indeed reveal a person's identity when paired with sufficient linked information for cross-validation. On the other hand, our relatively low phone-to-person match rate and the substantial uncertainty in many of the matches gives pause to the privacy concerns about commercially-available location data. We accessed a vast array of government records on a person's whereabouts that is far richer than the publicly-available records that are typically used in "linkage attacks" on mobility data, yet we were only able to identify 6.6% of phone users in our GPS sample with confidence. Our limited matching success suggests that improper re-identification attacks may be more difficult to implement than has previously been acknowledged.[3]

The early COVID-19 lockdowns and physical distancing policies helped to limit the spread of the virus and likely saved many lives. These measures, however, came with steep socioeconomic costs. Among a sample of approximately 1,500 lower-income residents of one large Midwestern U.S. county, we find that individuals who experienced larger declines in geospatial movement between March and June 2020 were no more likely to receive mental health care during this time period. For policymakers, our results imply that temporary government-ordered limits on travel may not pose a significant tradeoff between mental health and physical safety, at least in the context of a public health emergency.

2 Data and methods

Our analysis connects two sources of data at the individual level. The first is high-frequency geolocation data for a sample of smartphone devices. The second is Medicaid health care claims for the owners of the phones. This section briefly summarizes the two data sources. Additional details on the data and sample construction are in the Appendix.

We purchased commercially-available GPS data for 33,796 smartphones in one large U.S. county, covering the time period from September 1, 2019 to August 31, 2020. Each

[3]It must be noted that our highly sensitive and unusual linkage of anonymous smartphone data with confidential government records was approved by the Carnegie Mellon University institutional review board and was carried out with full awareness and approval from our government partner. The data matching with government records was covered by a data-sharing agreement with the public agency in question. While the ethical and legal dimensions of re-identifying personal GPS data lie beyond the scope of this paper, we in no way condone attempts to discern individuals' identities outside of formally-approved human subjects research studies with stringent data security measures in place.

device has at least 25 location pings in the data per day. See Appendix Section A for more information on the GPS data. We then used administrative records from a government social services agency in the same county to identify local residents who are the likely owners of the smartphones. This process involved searching for social service records that place an individual at the same location as a given smartphone at several points in time.

For example, we estimated each device's place of residence by observing the address where the device routinely stays between 1 am and 5 am on weeknights. We then searched for individuals in our government partner's social service records who live at that same address. As another example, we estimated the place where the device user goes to work by observing the location where the device travels to and from each day. We then searched for individuals in state unemployment insurance wage records who have an employer address that is at the same location where the device user is estimated to work. We searched for these types of time-and-space correspondences between devices and individuals across eight types of locations: 1) Home address 2) Place of employment 3) Medicaid-funded health care visit location 4) Location of hospital where a woman gave birth 5) Head Start early childhood program location 6) Child care facility location 7) Court hearings, and 8) School attendance location. The details of this matching process are described further in Appendix Section B.

We considered a smartphone to match to a certain individual with sufficiently high confidence if the match met three criteria. First, the device and person had to match on at least two out of the eight locational dimensions listed above. Second, the device had to match to only one unique person in our government partner's records on at least two locational dimensions. Third, the person had to match to only one unique device on at least two locational dimensions. The rationale for the first criterion is that if a device truly belongs to a certain person, then it should match the person's location in more than one social service data set. A locational match that is based on only one type of social service record does not provide strong evidence that the device truly belongs to the person. The rationale for the second criterion is that phones are mostly held by only one person at a time. Therefore, we should not expect a device to match to more than one individual. The rationale for the third criterion is that most people only possess one phone at a given time. It is therefore unlikely for a person to match to more than one phone in our GPS data.

Among the 33,796 smartphones in our sample, we matched 2,238 (6.6%) of them to an individual in government records with relatively high confidence. We then further limited the sample of 2,238 device-matched individuals to those who had been enrolled in Medicaid health insurance at some point between September 2019 and August 2020. We limited the results to Medicaid beneficiaries because we are only able to observe a person's health care utilization if the care is paid for by Medicaid. This leaves a resulting sample of 1,457 device-matched individuals, covering 4.2% of the devices in our sample. Among them, 282 were under age 18 as of January 1, 2020. It is plausible for a minor-age youth to have their own phone. However, many of the mobility patterns that we leveraged in the matching process could be trips taken by a parent and child together, such as trips to a doctor's appointment, which makes it difficult to discern the true owner of the phone. To account for the possibility that we erroneously matched the device to a child instead of their parent, we added to the study sample the biological mothers of the phone-matched individuals who were under age 18 as of January 1, 2020. We were able to locate the biological mothers of 198 of the youth matches, for a total sample size of 1,655 individuals.

To put our match rate in context, our government data-sharing partner's administrative database contains home addresses for the vast majority of the more than one million residents in the county of study. The database also contains the universe of Medicaid claims for the county, and 19% of residents in this county were on Medicaid as of March 15, 2020. Furthermore, our partner's database contains the universe of birth certificates for births that take place in the county, as well as the universe of county court hearings. If we assume that our sample of smartphone users is a random sample of county residents and that the government agency's records are accurate and complete for the eight location types that we use in our matching, then our match results would depend solely on the percentage of county residents who are enrolled in Medicaid and who appear in at least two of these locational sources; we would thus expect a match rate of around 19%. In practice, however, several factors serve to dampen our match rate. First, the anonymous smartphone data contains gaps in the frequency of its GPS traces and noise in the precision of its location coordinates. Second, the data on home addresses and places of employment in our partner's database is often out of date or not entirely accurate. Third, there are many Medicaid enrollees who rarely or never receive health care. This limits our ability to match them to a device based on their location of health care service receipt. Given these sources of incompleteness and uncertainty in our data, we interpret our 4.2% matching rate to be roughly in line with what we expected at the outset.

Table 1 describes the sample of phone-matched individuals. The sample is 68% female and 18% Black.[4] The sample is more socioeconomically disadvantaged than the average resident in the county of study. Over 37% of sample members received Supplemental Nutrition Assistance Program (SNAP) benefits at some point in the year prior to March 2020, compared with less than 15% of the countywide population. The employed adults in the sample

[4]The inclusion of youth sample members' biological mothers but not their biological fathers skews the sample more heavily towards females.

earned an average of \$7,379 from work between September and December 2019, compared with a per capita quarterly income of \$10,396 across all county residents.[5] The relative disadvantage of the sample is not surprising, because sample members were identified in part based on their involvement in social programs that tend to serve lower-income people. In terms of health care usage, two-thirds of the sample received some type of Medicaid-funded health care between March and August 2020. Nearly 35% had at least one claim for non-emergency room physical health care during this time period, and 20% had a claim for non-crisis-related mental health care. Over 48% of the sample was diagnosed with a chronic physical health condition prior to 2020, while 7.8% and 9% were diagnosed with anxiety and depression, respectively. The substantial rates of health care utilization during the early months of COVID-19 hint at the possibility that people sought care in response to the challenges of restricted mobility.

[5] Countywide per capita income is based on data from American Community Survey Table S1902 2019 1-year estimates.

Table 1: Description of device-matched study sample

(N = 1,655)	Mean
A. Demographics	
Age as of March 15, 2020 (years)	37.20
Female (%)	0.681
Black (%)	0.184
Under 18 years old as of March 15, 2020 (%)	0.071
Mother of device-matched youth (%)	0.135
B. Socioeconomic status	
Received public benefits in 12 months prior to March 2020 (%)	
Medicaid	0.962
Supplemental Nutrition Assistance Program (SNAP)	0.374
Supplemental Security Income (SSI)	0.085
Temporary Assistance for Needy Families (TANF)	0.018
Section 8 or public housing	0.079
Had paid employment in Q4 2019 (%; only among adults)	0.607
Mean earnings in Q4 2019 among those employed ($; only among adults)	7,379
C. Health status	
Died between March and August 2020 (%)	0.003
Diagnosed with health condition prior to March 2020 (%)	
Chronic physical health condition	0.481
Anxiety	0.078
Depression	0.090
Other mental health diagnosis	0.151
D. Health care utilization between March and August 2020	
Any health care	
Had at least one claim (%)	0.659
Days with a claim (N)	3.19
Physical health ER	
Had at least one claim (%)	0.052
Days with a claim (N)	0.115
Physical health non-ER	
Had at least one claim (%)	0.346
Days with a claim (N)	1.12
Mental health non-crisis	
Had at least one claim (%)	0.200
Days with a claim (N)	0.769
Mental health crisis	
Had at least one claim (%)	0.029
Days with a claim (N)	0.056
Substance use disorder	
Had at least one claim (%)	0.045
Days with a claim (N)	0.369

Notes: Calculations based on administrative data from our government data-sharing partner for the device-matched sample. The sample is limited to individuals who were enrolled in Medicaid for at least one month between September 2019 and August 2020.

2.1 Mobility measures

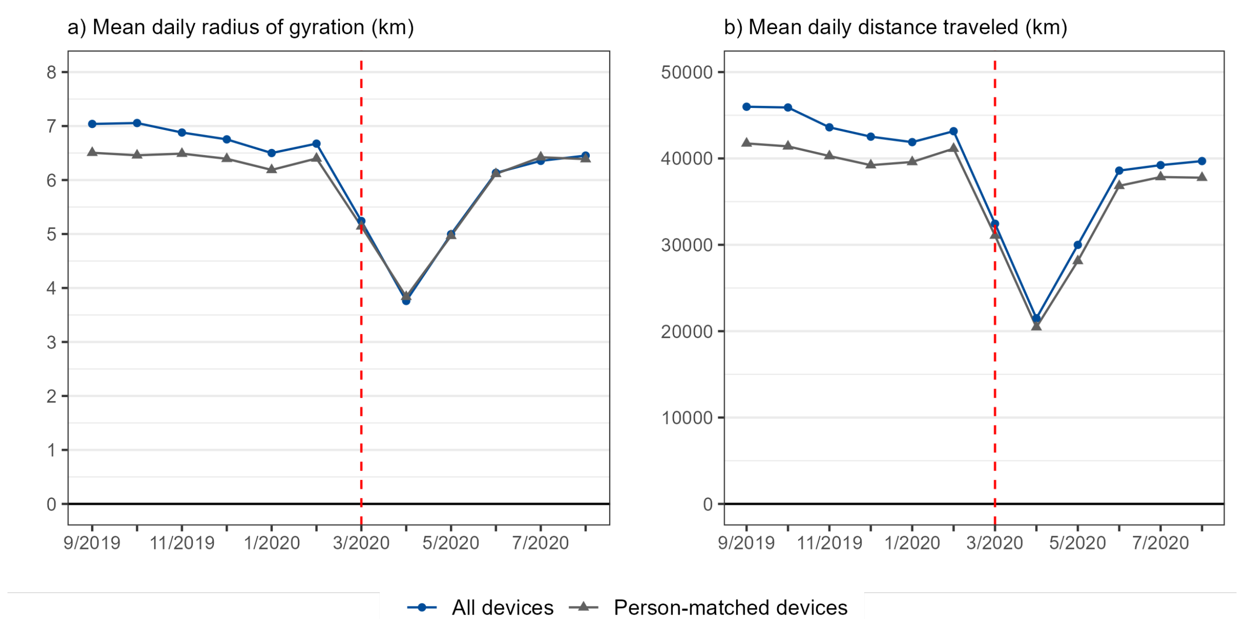
We use the smartphone geolocation data to measure each device user's level of geospatial mobility over time. Our primary measure of mobility is the user's radius of gyration in a given day. The daily radius of gyration is calculated as:

$$RoG = \sqrt{\frac{\sum_{k=1}^{N} D_k^2}{N}} \tag{1}$$

where N is the number of unique locations where the device was observed, and D is the distance in kilometers of each location from the device's home. Radius of gyration is commonly used to quantify the spatial dispersion of travel patterns (Gonzalez et al., 2008; Pappalardo et al., 2015; Song et al., 2010).

Figure 1 depicts the monthly geospatial mobility among all 33,796 mobile devices in our data set, and among the 1,457 devices that we matched to an individual. The device sample experienced a sharp drop in mobility in March 2020, corresponding to the beginning of COVID-19 in the United States. Mobility began to rebound in May and tapered off at near pre-pandemic levels by August 2020. Our person-matched sample of devices closely follows the mobility trends of the entire device sample. This suggests that our matched sample of smartphone users is fairly representative of the countywide population of phone users in terms of their changes in mobility during COVID-19. Compared with the full sample of devices, the slightly lower levels of mobility among the matched sample may stem from the lower socioeconomic status of the matched individuals. Some research has found that lower socioeconomic status is correlated with a smaller range of geographic mobility (Moro et al., 2021; Xu et al., 2018). Our main analyses, reported below, explore whether the steep reduction in mobility shown in Figure 1 was associated with increased use of mental health care among the matched sample of individuals.

Figure 1: Spatial mobility among entire smartphone device sample and person-matched sample



Notes: Calculations based on data from smartphone GPS data. Vertical dotted line marks the beginning of the COVID-19 pandemic in March 2020.

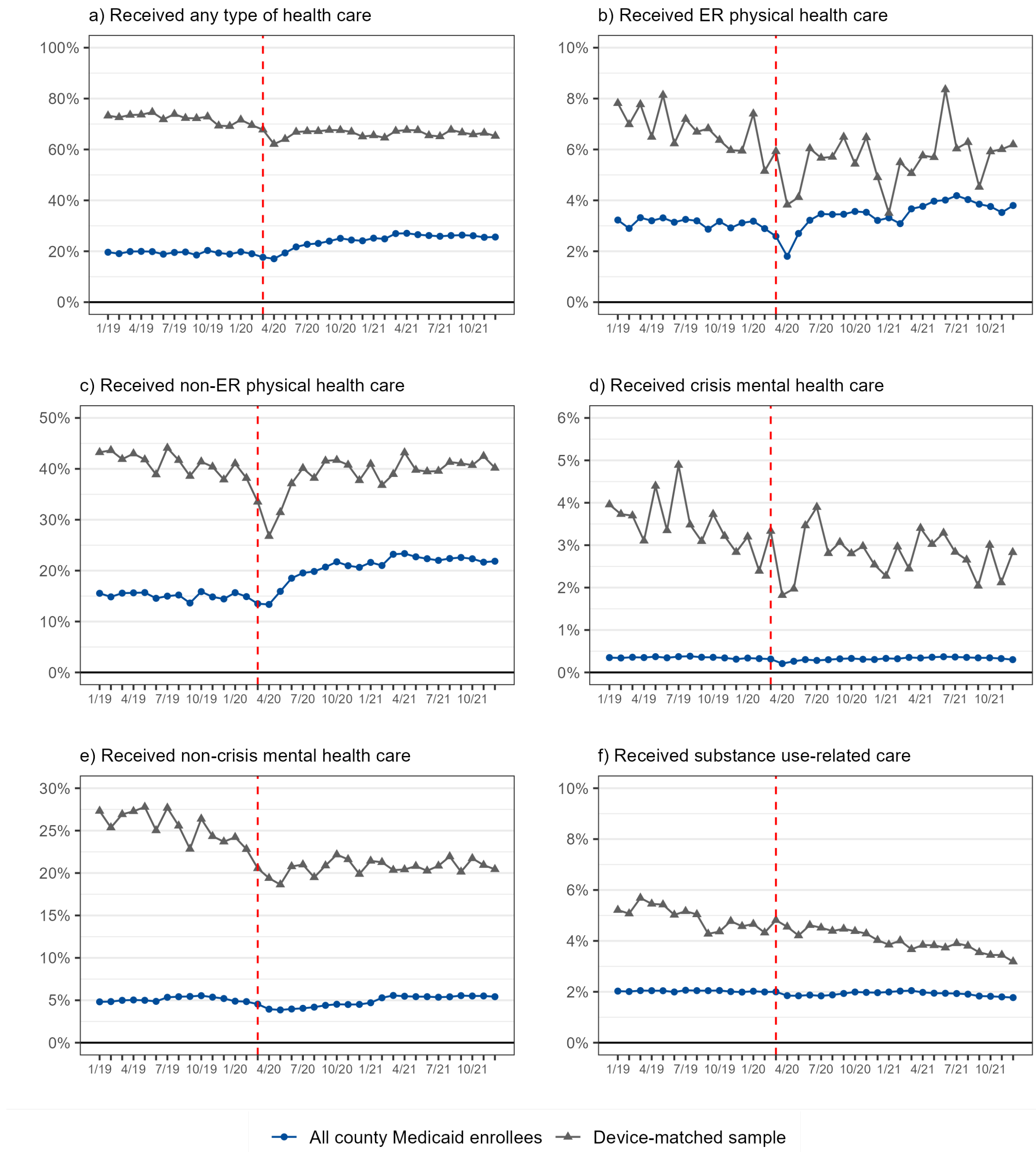
2.2 Health care use

We observe health care use for the matched sample using Medicaid managed care claims data that covers physical and mental health services, as well as pharmacy prescriptions. To place our analysis in context, Figure 2 presents the monthly trends in the likelihood of receiving health care among the sample and among the entire population of Medicaid beneficiaries in the county of study. Panel A shows that the rates of receiving any care in a given month hovered between 60% and 80% over the study period. For the countywide Medicaid population, this rate never exceeded 30% in a given month. The device-matched sample experienced a sharp temporary drop in the likelihood of receiving non-emergency room physical health care at the outset of the pandemic, while the countywide Medicaid sample exhibited no such drop. Monthly rates of non-crisis mental health care receipt were already decreasing in the months prior to the COVID-19 outbreak, then stabilized and showed no discernible trend in the first 18 months of the pandemic. These trends align with the limited nationwide increases in mental health care usage discussed in Section 1, suggesting that the challenges of COVID-19 did not translate into greater longer-term aggregate demand for mental health care.[6]

The device-matched sample had much higher monthly rates of care usage than the average Medicaid patient for all types of care shown in Figure 2. This is due to the fact that we used Medicaid health care claims as a key source of administrative service location data when matching smartphones to individuals. The device-matched sample is thus skewed towards Medicaid enrollees who visit the doctor relatively frequently.

[6] The mental health care data includes telehealth visits, which became much more prevalent after the onset of the pandemic. We do not present rates of telehealth care usage as its own category because Medicaid claims do not reliably indicate whether the care was delivered in person or virtually.

Figure 2: Likelihood of receiving health care, by month



Notes: Calculations based on Medicaid claims data from government data-sharing partner. Vertical dotted line marks the beginning of the COVID-19 pandemic in March 2020.

Despite the lack of a surge in health care usage during COVID-19, an aggregate-level comparison of spatial movement and health care consumption could mask a relationship between these two measures if, for example, the individuals who experienced the largest declines in mobility happened to have a below-average level of vulnerability to the mental health effects of reduced travel. We now investigate this relationship at the individual level using our matched sample of smartphones and phone owners.

3 Results

We construct a person-by-month panel data set using the matched sample of 1,457 smartphones and their respective owners, plus the 198 mothers of phone-matched youth under age 18. The panel spans from September 2019 to August 2020. We use the following regression model as a benchmark specification:

$$y_{it} = \beta_0 + \beta_1(\text{Mobility})_{it} + \beta_2 X_i + \epsilon_{it} \tag{2}$$

where y_{it} is a binary indicator that equals one if person i had at least one health care claim in month t, (Mobility) is person i's mean daily measure of spatial movement in month t, and X_i is a vector of time-invariant traits that include the person's gender, race, age as of March 15, 2020, and whether or not they had a mental health diagnosis prior to March 15, 2020. We control for the presence of a pre-COVID mental health diagnosis to test the possibility that having an existing mental health condition can make a person more susceptible to the negative psychological effects of immobility.

Table 2 presents the results. The presence of a pre-COVID mental health diagnosis increases the likelihood of having at least one non-crisis mental health care claim in a given month by 28.6 percentage points. A person's breadth of spatial movement in a given month, as measured by their mean daily radius of gyration, is associated with small yet statistically significant reductions in the probability of receiving health care in the same month. In particular, a one-kilometer increase in mean daily movement is associated with a 0.5 percentage-point reduction in the probability of receiving any health care, and a 0.4 percentage-point reduction in the probability of receiving both non-crisis mental health care and non-ER physical health care. These partial correlations are consistent with the notion that greater mobility lessens one's need for health care.

Table 2: Relationship between mean daily radius of gyration and monthly likelihood of receiving health care between September 2019 and August 2020

(N = 1,655)	Any type of care	ER physical health care	Non-ER physical health care	Crisis mental health care	Non-crisis mental health care	Substance use-related care
Intercept	0.466*** (0.033)	0.029*** (0.010)	0.220*** (0.028)	0.007 (0.007)	0.162*** (0.029)	-0.009 (0.015)
Mean daily radius of gyration (km)	-0.005*** (0.002)	<0.001 (<0.001)	-0.004*** (0.001)	<0.001 (<0.001)	-0.004*** (0.001)	<0.001 (0.001)
Had pre-covid mental health diagnosis	0.155*** (0.019)	0.021*** (0.006)	0.020 (0.016)	0.024*** (0.004)	0.286*** (0.016)	0.093*** (0.012)
Had pre-covid chronic physical health condition	0.182*** (0.021)	0.027*** (0.006)	0.141*** (0.017)	0.017*** (0.005)	0.059*** (0.017)	0.004 (0.012)
Female	0.011 (0.020)	-0.007 (0.007)	0.048*** (0.018)	<0.001 (0.005)	-0.041** (0.018)	-0.021* (0.013)
Black	-0.088*** (0.023)	0.034*** (0.008)	-0.005 (0.019)	0.003 (0.005)	-0.048*** (0.018)	-0.022** (0.010)
Mom of device-matched child	-0.012 (0.032)	-0.003 (0.010)	-0.069*** (0.024)	-0.004 (0.006)	0.012 (0.028)	0.020 (0.022)
Age as of 3/15/2020 (years)	0.002*** (<0.001)	<0.001 (<0.001)	0.001** (<0.001)	<0.001 (<0.001)	-0.002*** (<0.001)	<0.001** (<0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

The partial correlation between mobility and the likelihood of receiving non-crisis mental health care remains relatively stable when using alternative measures of mean daily mobility, such as total daily distance traveled and daily farthest distance from home (see Appendix Table A1). The coefficient also does not vary significantly when looking across certain sample subgroups, such as females, Black individuals, and those who received mental health care in the two months prior to the start of COVID-19 (see Appendix Table A2). Beyond the likelihood of receiving any care, we also examine the outcome of the monthly number of days on which the person received care. This alternative measure better captures a person's intensity of care utilization. These results are shown in Appendix Table A3. A one-kilometer increase in mean daily radius of gyration is associated with 0.046 fewer days of health care receipt per month. This mobility measure has no discernible relationship with the number of days with crisis or non-crisis mental health care per month.

The regression results in Table 2 capture the average relationship between mobility and health care usage across the entire observed time period (September 2019 to August 2020). The results are thus influenced by individuals who had both low levels of mobility and poor mental health in the six months prior to the pandemic. To focus more closely on the effect of the pandemic-related mobility shock on care usage, we next control for the individual's mobility levels in the months prior to COVID-19.

Table 3 presents the regression results when focusing on the pandemic-related mobility shock. The main coefficient of interest is the pre to post-covid change in the person's mean daily radius of gyration. This time-invariant measure is the difference between the person's mean radius of gyration from September 2019 through February 2020 and their mean radius of gyration from March 2020 through August 2020. The mobility shock coefficient is statistically insignificant for all types of health care shown in Table 3. A person's pre to post-COVID change in spatial mobility relative to their pre-pandemic baseline has no discernible relationship with their likelihood of using a mental health service in a given month. This non-relationship persists when using alternative measures of daily mobility (see Appendix Table A4). Among people who were already engaged in mental health care in the months prior to COVID-19, a one kilometer decrease in the size of the negative mobility shock led to a statistically significant 0.4 percentage point increase in the monthly likelihood of receiving crisis mental health care (Appendix Table A5). The negative mobility shock also correlates very weakly with the number of days per month that a person received crisis mental health care. In particular, a one kilometer decrease in the size of the negative mobility shock led to a 0.003-day increase in the number of days per month with a crisis mental health claim.

The lack of a strong relationship between the mobility shock and mental health care usage is not an artifact of low baseline mobility levels among those with mental health conditions. As shown in Figure 3, the sample members with a pre-COVID mental health diagnosis exhibited very similar levels of baseline mobility as the individuals who did not have a diagnosis. These two groups also experienced similar absolute reductions in mobility after the onset of the pandemic. Appendix Figure A1 shows a similar result when disaggregating pre-pandemic mental health diagnoses by category. In fact, some diagnosis categories had *higher* mean levels of pre-pandemic mobility than those with no diagnosis.

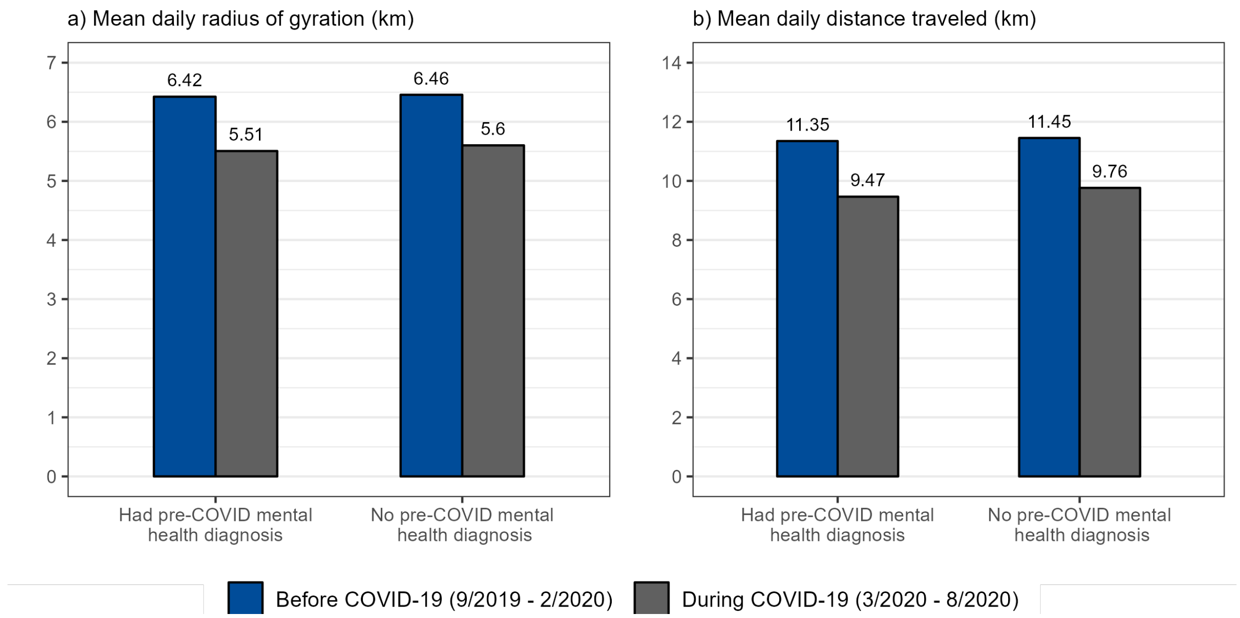
Additionally, the non-relationship between the early-pandemic mobility shock and mental health care usage does not appear to stem from service capacity limits in the mental health system. As evidence for this, we observe small regression-adjusted correlations between mobility and emergency room physical health care usage. This type of care is likely less capacity-constrained than mental health care and thus may better reflect true underlying levels of community need. Service constraints do not appear to drive the unresponsiveness of health care to the drop in spatial movement in our sample.

Table 3: Relationship between pre to post-covid change in mean daily radius of gyration and monthly likelihood of receiving health care between September 2019 and August 202

(N = 1,655)	Any type of care	ER physical health care	Non-ER physical health care	Crisis mental health care	Non-crisis mental health care	Substance use-related care
Intercept	0.450*** (0.032)	0.028*** (0.009)	0.199*** (0.027)	0.008 (0.007)	0.140*** (0.028)	-0.011 (0.014)
Pre to post-covid Δ in mean daily radius of gyration (km)	0.004 (0.003)	<0.001 (<0.001)	0.002 (0.002)	<0.001 (<0.001)	0.002 (0.002)	-0.002 (0.001)
Had pre-covid mental health diagnosis	0.153*** (0.019)	0.022*** (0.006)	0.021 (0.016)	0.025*** (0.004)	0.288*** (0.017)	0.093*** (0.012)
Had pre-covid chronic physical health condition	0.175*** (0.021)	0.027*** (0.006)	0.139*** (0.017)	0.018*** (0.005)	0.062*** (0.017)	0.003 (0.012)
Female	0.006 (0.020)	-0.007 (0.007)	0.044** (0.018)	<0.001 (0.005)	-0.044** (0.018)	-0.022* (0.013)
Black	-0.093*** (0.024)	0.034*** (0.008)	-0.010 (0.020)	0.002 (0.005)	-0.051*** (0.019)	-0.022** (0.011)
Mom of device-matched child	<0.001 (0.032)	-0.002 (0.010)	-0.062** (0.025)	-0.004 (0.007)	0.019 (0.028)	0.022 (0.023)
Age as of 3/15/2020 (years)	0.002*** (<0.001)	<0.001 (<0.001)	0.002** (<0.001)	<0.001 (<0.001)	-0.002*** (<0.001)	<0.001** (<0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Figure 3: Mobility levels before and during COVID-19, by presence of pre-COVID mental health diagnosis



Notes: Calculations based on smartphone GPS data and Medicaid claims records from government data-sharing partner.

4 Discussion

We used individually-linked smartphone GPS data and Medicaid claims to examine the relationship between a person's level of spatial mobility and their use of mental health care in the early months of COVID-19. Mobility levels plummeted in March 2020 and returned to near pre-pandemic levels by June 2020. However, we find no evidence that this temporary drop in movement led to greater use of mental health care among a sample of residents of one large U.S. county. In particular, individuals with larger reductions in mobility were no more likely to use mental health services when holding constant certain demographic characteristics and their pre-COVID mental health care usage.

This analysis has limitations that may partly explain the absence of an observed relationship between mobility and mental health care usage. First, health care utilization does not fully reflect the prevalence of mental health issues. Mental health care volume did not spike in the early months of COVID-19 even as surveys indicated worsening mental health conditions (CMS, 2021; Panchal et al., 2020). Public health officials noted a worrying disparity between the prevalence of psychological distress and the accessibility of mental health services during the pandemic, both in the U.S. (Altiraifi & Rapfogel, 2020) and around the world (WHO, 2020). Second, the process of matching anonymous smartphone GPS data to government records likely produced some false positive and false negative matches. We describe the matching process in more detail in Appendix section B. Third, we observe geospatial mobility through August 2020, which only covers the first five months of the pandemic. It is possible that trends after August 2020 would reveal a longer-term relationship between mobility and mental health. The stresses of social isolation, for example, may take more than a few months to translate into mental health challenges. More broadly, our empirical strategy is purely descriptive. We do not purport to identify a causal relationship between spatial movement and health care usage. A person's deviation from their normal travel patterns in the early months of COVID-19 could have been both a cause and a consequence of myriad other factors that independently affect their mental health.

Regarding the external validity of our work, our data covers one county that could differ from other regions of the U.S. in the relationship between spatial mobility, social isolation, and mental health care usage. Our study sample also consists solely of Medicaid beneficiaries who are socioeconomically disadvantaged. Some research has found that lower-income people were at greater risk of anxiety and depression during the pandemic (Shevlin et al., 2020). At the same time, lower-income residents are of particular interest for studying mobility and mental health, as this segment of society tends to be difficult to reach in public health surveys. The generalizability of our analysis is supported by the fact that our person-matched phones exhibited similar time trends in mobility as the entire sample of smartphones in our county of study.

Our results motivate several directions for future study. The quality of our matched sample of smartphone users depends on how accurately we were able to match anonymous smartphone data to individuals in a confidential social services database. Little research exists to date that offers guidance on best practices for re-identifying phone location traces using external data linkages. As anonymized smartphone data becomes more prevalent in academic research, future work could build upon our methods and refine the process of identifying unique individuals within the data. We emphasize again, however, that such de-anonymization exercises must adhere to human subjects research standards, with stringent data security measures and careful consideration of the ethical and legal implications for phone users' privacy (De Montjoye et al., 2013; Frith & Saker, 2020; Thompson & Warzel, 2019).

Additional research is also warranted on the relationship between geospatial mobility and mental health. A person's ability to move around in space may influence their mental health through a variety of mechanisms, either positively or negatively. Being constantly on the move could signal that a person is avoiding a stressful or dangerous situation at home.

On the other hand, a homebound individual may still enjoy rich social connectedness by having guests and visitors keep them company. The spatial extent of a person's mobility may not matter for mental health as much as the types of specific places they are visiting. The rise of working from home introduces a further complication, since staying at home no longer reliably indicates a lack of employment. More research on these aspects of mobility and mental health will help gauge the full social costs of policies that limit citizens' movement for public health and safety purposes. The psychological and emotional consequences of such policies are more difficult to quantify than the economic costs, yet are no less important for society's well-being.

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Spatial mobility and mental health during COVID-19: Evidence from linked individual-level GPS data and health care records

Online Appendix

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A Description of smartphone GPS data

We obtained a sample of high-frequency geospatial data from a commercial data vendor for a sample of smartphones within one large Midwestern U.S. county. The location data was collected using GPS technology from more than 400 commonly used mobile applications from both Android and iOS devices in a General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA)-compliant manner. Depending on the application and the operating system of the smartphone that collects the data, the GPS location traces are recorded either in five to 20 minute intervals or whenever the mobile device moves more than 100 meters. Each location record contains a unique device ID, timestamp, speed, longitude, and latitude of the location.

To create a uniform sample of individuals whose mobility patterns can be observed in the context of COVID-19, our study only includes individuals who appear within the boundaries of the county of study with at least 25 GPS traces per day (a GPS "trace" is a location data point). We also limit our sample to individuals who appear in the data for least 10 days a month for each of the eight months from January 2020 through August 2020. These filters leave a resulting data set of over 2.5 billion GPS traces from 33,796 unique smartphones.

We identify mobility patterns for each smartphone based on the phone's daily "stay-points". We cluster the raw GPS traces by space and time such that no two traces within a cluster are more than 100 meters apart and that there are at least 10 traces in a cluster. This is a standard method of parsing raw GPS data, and it reflects the fact that individual GPS traces can be measured with error. Our clustering methodology limits the impact of measurement error on our mobility analyses. We use the resulting clusters of GPS traces as stay-points. A home location for a phone is defined as the modal stay-point where the phone resides between 1 am and 5 am on weekdays. If there are no data between 1 am and 5 am, we consider the home location to be the modal stay-point where the phone spends greater than 12 hours in a day. The specific coordinates of the location were computed using the centroid of the stay-point.

B Methodology for matching smartphones to individuals

We constructed a matched sample of smartphone devices and their users by matching the device sample to Medicaid recipients in the same county who exist in administrative records held by our government data-sharing partner. The matching process was based on the idea of correspondence in time and space: If a person and a device were in many of the same places at the same time, then we inferred that the device belongs to that person. In particular, we searched for matches using eight different sources of administrative social services data that indicate a person's geospatial location at a given point in time to varying degrees of accuracy. We considered the evidence for a device-to-person match to be sufficiently strong if it met three criteria: 1) The device and person matched on at least two out of the eight potential match dimensions 2) The device matched to only one unique person on at least two out of eight match dimensions 3) The person matched to only one unique device on at least two out of eight match dimensions. The matches on each of the eight locational dimensions were determined as follows:

B.1 Home location

To match devices to individuals based on their home location, we first used the smartphone GPS data to estimate the potential home locations of each device as described before. We then searched for individuals in our data-sharing partner's records that matched to the device on home location. We considered a person to match to a device if the person has a home address that falls within a small radius of the device's potential home location. Our partner's home address records are derived from many different administrative data sets, and the partner uses a proprietary algorithm to decide on a person's most likely current address at a given time. We ran a separate version of the match using every permutation of five parameters:

1. Using a radius tolerance of 100 meters, 75 meters, 50 meters, or 25 meters

2. Using only the individual's most recent home address record held by our partner, or using the individual's entire history of home address records.

3. Counting all individuals who fall within the radius tolerance for a given device, or only counting the individual whose home address lies closest to the device (allowing for ties if multiple individuals lie equally close to the device)

4. Counting or not counting individuals as a match if their home address is a multi-unit building. We determined whether a individual's home address is part of a multi-unit dwelling by spatial joining the address to property tax parcel data in the county of study. The parcel data indicates the type of building on the parcel, including the number of units in each residential dwelling. The rationale for not counting individuals who live in multi-unit dwellings is that multi-unit dwellings can contain many residents,

and this increases the chance of matching the device to the wrong resident, even when requiring a match on other dimensions such as place of work. For example, there can be several people who live in the same large apartment building and work at the same employer location.

5. Including or not including device home location estimates that are based on devices that have GPS data on less than 15 days in the sample and for which the device is at the home location on less than half of the observed days. Some of the devices had GPS pings on only a few days and only matched to the estimated home location on a small fraction of those days. We ran versions of the match in which we disregarded the home location estimates that are based on a relatively small amount of GPS data.

We ended up with 64 different versions of home location match results based on these five parameters.

B.2 Work location

To match individuals to devices based on their work location, we first used the smartphone GPS data to estimate the work locations of each device. We estimated a device's work location as the non-home stay-point where the device spends four to 10 hours per day at least three days per week. We considered the device's workplace to be the Google Maps point of interest (POI) that is closest to the stay-point.

We then identified people in our partner's administrative records that matched to the device based on the place of employment. The administrative data used in this match comes from unemployment insurance (UI) wage records.

We considered a person to match to the device if the person had a UI wage record at some point between January 1, 2020 and August 31, 2020 that is associated with an employer address that lies within 100 meters of the device's estimated work location. The UI wage data has two limitations for identifying a person's place of employment. One is that the data is missing addresses for some employers. The second is that the employer's address in the data may not represent the physical location where the person actually works; it sometimes represents the corporate headquarters of the employer or a tax filing address. We therefore augmented the employer addresses in the UI data with two additional sources of information. First, we searched the employer's name in the business entity database for our state of study and pulled any addresses associated with the employer that lie in our county of study. Second, we searched the employer's name on Google Maps and extracted any addresses that were associated with the employer.

B.3 School location

We identified youth in our partner's administrative records who were enrolled in certain local public schools at some point between January 1, 2020 and August 31, 2020. This information comes from data that our partner receives from certain school districts in our county of study. We took the list of unique schools from this data and identified smartphones whose user appeared to be attending one of these schools. We considered a device user to be attending a certain school if it spent more than two hours between 8 am and 6 pm within 100 meters of the school for at least three days per week.

B.4 Health care location

We identified individuals in our partner's records who received any Medicaid-funded health care between January 1, 2020 and August 31, 2020. This information comes from Medicaid managed care claims data that covers the universe of Medicaid enrollees in our county of study. The claims data indicates the date of service and the location where the service took place. We searched for devices that visited the same health care facility on the same date as the patient's visit. We considered a device user to have visited a health care facility if the device spent at least 30 consecutive minutes within a 100 meter radius of the facility at any time of the day.

Given that individuals often have more than one health care visit in the claims data, we used three different "miss rate" thresholds to determine a sufficiently strong device-to-person match:

1. Least stringent: The individual had at least one health care visit during the study period, and the device matched to at least one of the individual's visits.

2. More stringent: The individual had a health care visit on at least 10 distinct days during the study period, and the device failed to match to less than 25 percent of the individual's total visit-days on days when the device had sufficient GPS data.

3. Most stringent: The individual had a health care visit on at least 15 distinct days during the study period, and the device failed to match to less than 10 percent of the individual's total visit-days on days when the device had sufficient GPS data.

We considered a device to have sufficient GPS data on a given day if it had traces in at least 11 unique hours between 9 am and 9 pm, and it had at least six traces per hour during this time window.

One limitation with our health care location matching exercise is that the addresses in the Medicaid claims data do not always represent the location where the service took place. Sometimes the address represents a billing address that is separate from the actual place of service. There is no simple way to discern the true place of service in the data. A second limitation is that the Medicaid claims data does not indicate the time of day that the service occurred. This may reduce the accuracy of the device-to-person match since the device user's visit to the health care facility may have occurred at a different time of day than the person's visit.

B.5 Birthing location

We identified women in our partner's records who were listed as the birth mother on a birth certificate that was issued in our county of study between January 1, 2020 and August 31, 2020. The birth certificate lists the date and location of the birth, thus indicating the birth mother's presence at a certain place on a certain date.

We then took the list of distinct birthing facilities that appear in the birth certificate data and searched for smartphone devices that spent a significant amount of time at the same facility on the same date as the woman's childbirth. We considered a device user to have "given birth" at a facility if the device spent at least four consecutive hours per day within a 500 meter radius of the facility on two consecutive days. We also removed devices that spent this much time at a birthing facility on more than one occasion between January 1, 2020 and August 31, 2020, to rule out the possibility of giving birth more than once in eight months. We used a 500 meter radius tolerance because most of the birth certificate locations were large hospitals that have a sizable geographic footprint.

B.6 Head Start location

We identified adults in our partner's records who were listed as the primary caregiver of a child that was enrolled in the Head Start early childhood education program at some point during the 2020-2021 school year (which includes our study period). We then took the list of distinct Head Start facility locations that appear in our partner's data and searched for smartphone devices that visited the location in a manner that resembles dropping off a child in the morning and picking up the child in the evening. In particular, we considered a device user to have visited the location if it spent between five and 60 consecutive minutes at the location between 7 and 9 am and again between 4 and 6 pm within a 100 meter radius of the facility on one day.

B.7 Child care location

We identified people in our partner's records who were listed as the primary caregiver of a child that was receiving state-subsidized child care at some point between January 1, 2020 and August 31, 2020. We then took the list of distinct child care facility locations that appear in the data and searched for devices that visited the location in a manner that resembles dropping off a child in the morning and picking up the child in the evening. In particular, we considered a device user to have visited the location if it spent between five and 60 consecutive minutes at the location between 7 and 9 am and again between 4 and 6 pm within a 100 meter radius of the facility on one day.

B.8 County court hearing location

We identified people in our partner's records who were listed as the defendant in a court hearing in our county of study at some point between January 1, 2020 and March 15, 2020. These hearings all took place at a large central county courthouse building. We limited the analysis to this time period because court hearings became mostly virtual starting in mid-March due to COVID-19. We then searched for smartphone devices that spent at least 60 consecutive minutes within the county courthouse building boundary on the same date as the person's court hearing.

B.9 Determining final matched sample

The combined results of these eight locational matches yielded 970,468 unique individuals who matched to 33,395 unique devices on at least one of the eight dimensions. In other words, 99 percent of the devices in our sample of smartphone GPS data matched to at least one person on at least one of the above locational dimensions. Moreover, the 970,468 unique individuals represent a large fraction of the entire population of our county of study as of 2019. These initial match results suggest that the eight location types yielded many false positives when considering each locational dimension in isolation.

To determine the final matched sample of devices and people, we dropped from the match results any people who were deceased as of January 1, 2020, assuming that a phone cannot plausibly match to a deceased person. We then considered a smartphone to match to a certain individual with sufficiently high confidence if the match met three criteria. First, the device and person had to match on at least two out of the eight locational dimensions listed above. Second, the device had to match to only one unique person in our government partner's records on at least two locational dimensions. Third, the person had to match to only one unique device on at least two locational dimensions. The rationale for the first criterion is that if a device truly belongs to a certain person, then it should match the person's location in more than one social service data set. A locational match that is based on only one type of social service record does not provide strong evidence that the device truly belongs to the person. The rationale for the second criterion is that phones are mostly held by only one person at a time. Therefore, we should not expect a device to match to more than one individual. The rationale for the third criterion is that most people only possess one phone at a given time. It is therefore unlikely for a person to match to more than one phone in our GPS data.

Finally, we limited the match results to individuals who had been enrolled in Medicaid health insurance in our county of study at some point between September 2019 and August 2020. We limited the results to Medicaid recipients because we are only able to observe a person's health service use if they are on Medicaid.

We ran 192 versions of this device-to-person matching exercise, each using a different permutation of methods (five parameters for the home location match and three parameters for the health care location match). We deemed the "best" version of the match to be the one that maximized the number of unique individuals that had a sufficiently strong match with a device. These 192 versions of the matching process yielded 924 to 1,457 matched Medicaid beneficiaries.

Our preferred version of the match results, the one that yielded the maximum result of 1,457 matches, used a 100 meter radius tolerance for the home location match, based only on the individual's current home address record, including all home address matches that fall within the radius tolerance, not including home addresses in multi-unit dwellings, including device home location estimates that are based on few GPS pings, and keeping only the health care visit matches for which the person has at least 10 distinct visit-days and the device has a "miss" rate of less than 25 percent.

Among the 1,457 matched device-individual pairs, 99.4 percent of the matches were based on only two locational dimensions. Only 43 percent of the matches included a match on home location, 59 percent included a match on work location, 61 percent included a match on health care location, and 28 percent included a match on school location. Additionally, one percent of the matched individuals were under age 5 as of 1/1/2020, six percent were under age 10, and 35 percent were under age 18. The presence of very young children in our preferred version of the matched sample likely indicates some degree of erroneous matches.

B.10 Interpreting the device-to-person match rate

We took a sample of 33,796 smartphones in one U.S. county and matched them against a government database that contains records for over 500,000 unique individuals who received Medicaid at some point during the study period. Given the large number of candidate matches in our partner's records, it may be surprising that we obtained only around 1,500 matched individuals that met our criteria for a sufficiently strong match. There are two primary reasons why we were able to match only 4.2% of our sample devices to a Medicaid patient. First, only 19% of residents in our county of study were enrolled in Medicaid at the start of COVID-19. Taking the 33,796 smartphones as a random sample of county residents, we would only expect to match a maximum of 19% of the smartphones to a Medicaid recipient.

Second, and more importantly, there were sources of uncertainty at every stage of the matching process. On the smartphone GPS side, the data contains a maximum margin of error of 100 meters and an average margin of error of 10 meters in its location tracking. A 100 meter margin of error can encompass several home addresses in a dense urban neighborhood, which creates uncertainty in the accuracy of the home matches. Also, many of the location estimates that we derive from the GPS data are based on a relatively small number of traces. This adds some degree of inaccuracy to our GPS-based estimates of the device's home location, work location, and other locations used in the device-to-person matching. There are also many sources of noise in our partner's administrative records. For one, the service recipients' home addresses may be out of date, as people and families relocate without notifying public agencies. Many people live in multi-unit dwellings and large apartment buildings. This raises the possibility of a false match based on home location. The locations in the Medicaid claims data contain uncertainty because the addresses in the data do not necessarily represent the place of service, and the data does not indicate the time of day of the visit. The employer addresses in UI wage records also may not represent the physical location where the individual goes to work.

Together, these sources of uncertainty cause most phones in the sample to match to several unique individuals on each match dimension. These matches drop out as invalid when we limit the matched pairs to those that match on at least two locational dimensions, which significantly whittles down the number of strong matches.

C Health services use

We measure mental health service use using the universe of Medicaid claims data for our county of study. The claims data contains all billed services related to physical health, mental health, and pharmacy prescriptions. Providers submit the claims to local managed care organizations to be paid for their services.

C.1 Physical health care categories

We classify physical health care into four categories:

1. Emergency room inpatient: Care episodes that begin with a visit to the emergency room and result in an inpatient hospital stay.

2. Non-emergency room inpatient: Care that occurs during an inpatient hospital stay that did not begin with a visit to the emergency room. This includes pre-planned surgeries and other inpatient procedures.

3. Emergency room outpatient: Care that occurs during a visit to the emergency room that does not result in an inpatient hospital stay.

4. Non-emergency room outpatient: Care that occurs in outpatient settings outside of the emergency room. This category includes routine primary and specialist care, well-visits, and other preventative visits.

C.2 Mental health care categories

We classify mental health care into three categories: crisis, non-crisis, and substance use disorder.

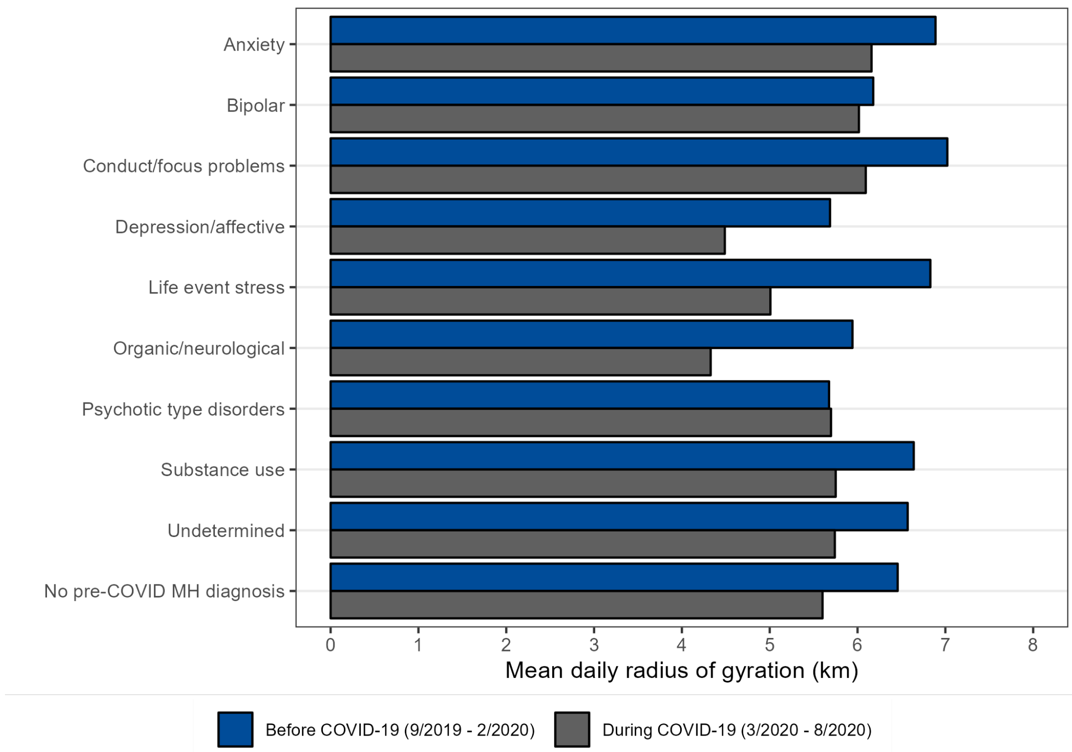
1. Crisis services include inpatient stays at a hospital or treatment facility, calls to a hotline for mental health crisis intervention and stabilization services, mobile crisis response services, emergency room visits at the county's primary psychiatric hospital, and emergency room visits at non-psychiatric hospitals that result in a mental health-related diagnosis. We identified mental health-related diagnoses in the emergency room claims based on the ICD-10 codes.

2. Non-crisis services include services such as individual and group psychotherapy, clinical psychiatric evaluations, diagnostic interviews, and case management. These services include both in-person and telehealth visits.

3. Substance use disorder services include services such as needs assessments, clinical treatment, individual and group therapy, case management, and peer recovery support. These services include both in-person and telehealth visits.

D Additional tables and figures

Figure A1: Mean daily radius of gyration before and during COVID-19, by type of pre-COVID mental health diagnosis



Notes: Calculations based on smartphone GPS data and Medicaid claims records from government data-sharing partner. Diagnoses represent the individual's most recent diagnosis as of March 15, 2020.

Table A1: Robustness of relationship between mobility and monthly likelihood of receiving mental health care between September 2019 and August 2020, by measure of mobility

(N = 1,655)	Mean daily radius of gyration (km)	Mean daily max distance from home (km)	Mean daily distance traveled (km)
A. Likelihood of receiving crisis mental health care			
Intercept	0.007 (0.007)	0.008 (0.007)	0.009 (0.007)
GPS-based measure of mobility	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
Had pre-covid mental health diagnosis	0.024*** (0.004)	0.024*** (0.004)	0.024*** (0.004)
Had pre-covid chronic physical health condition	0.017*** (0.005)	0.016*** (0.005)	0.016*** (0.005)
Female	<0.001 (0.005)	<0.001 (0.005)	<0.001 (0.005)
Black	0.003 (0.005)	0.004 (0.005)	0.003 (0.005)
Mom of device-matched child	-0.004 (0.006)	-0.004 (0.006)	-0.004 (0.007)
Age as of 3/15/2020 (years)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
B. Likelihood of receiving non-crisis mental health care			
Intercept	0.162*** (0.029)	0.167*** (0.029)	0.164*** (0.028)
GPS-based measure of mobility	-0.004*** (0.001)	-0.003*** (<0.001)	<0.001*** (<0.001)
Had pre-covid mental health diagnosis	0.286*** (0.016)	0.285*** (0.017)	0.285*** (0.016)
Had pre-covid chronic physical health condition	0.059*** (0.017)	0.059*** (0.017)	0.059*** (0.017)
Female	-0.041** (0.018)	-0.041** (0.018)	-0.041** (0.018)
Black	-0.048*** (0.018)	-0.049*** (0.018)	-0.047*** (0.018)
Mom of device-matched child	0.012 (0.028)	0.011 (0.028)	0.012 (0.028)
Age as of 3/15/2020 (years)	-0.002*** (<0.001)	-0.002*** (<0.001)	-0.002*** (<0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Table A2: Heterogeneity across sample subgroups in relationship between mean daily radius of gyration and monthly likelihood of receiving mental health care between September 2019 and August 2020

(N = 1,655)	Full sample	Female	Black	Received mental health care in Jan or Feb 2020
A. Likelihood of receiving crisis mental health care				
Intercept	0.007 (0.007)	0.010 (0.008)	0.026* (0.014)	0.026 (0.022)
Mean daily radius of gyration (km)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)	0.001 (0.001)
Had pre-covid mental health diagnosis	0.024*** (0.004)	0.023*** (0.005)	0.021** (0.009)	<0.001 (0.013)
Had pre-covid chronic physical health condition	0.017*** (0.005)	0.016*** (0.005)	0.014* (0.008)	0.030** (0.013)
Female	<0.001 (0.005)		-0.012 (0.011)	0.004 (0.012)
Black	0.003 (0.005)	<0.001 (0.006)		-0.010 (0.013)
Mom of device-matched child	-0.004 (0.006)	-0.004 (0.006)	-0.001 (0.012)	-0.006 (0.017)
Age as of 3/15/2020 (years)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
B. Likelihood of receiving non-crisis mental health care				
Intercept	0.162*** (0.029)	0.094*** (0.030)	0.084 (0.058)	0.479*** (0.069)
Mean daily radius of gyration (km)	-0.004*** (0.001)	-0.005*** (0.002)	-0.005** (0.002)	-0.003 (0.004)
Had pre-covid mental health diagnosis	0.286*** (0.016)	0.272*** (0.020)	0.250*** (0.034)	0.265*** (0.039)
Had pre-covid chronic physical health condition	0.059*** (0.017)	0.042** (0.019)	0.098*** (0.028)	0.004 (0.039)
Female	-0.041** (0.018)		-0.040 (0.038)	-0.097*** (0.036)
Black	-0.048*** (0.018)	-0.039* (0.021)		-0.027 (0.044)
Mom of device-matched child	0.012 (0.028)	0.008 (0.028)	0.058 (0.059)	0.088 (0.054)
Age as of 3/15/2020 (years)	-0.002*** (<0.001)	<0.001 (<0.001)	<0.001 (0.001)	-0.002 (0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Table A3: Relationship between mean daily radius of gyration and monthly number of days with health care between September 2019 and August 2020

(N = 1,655)	Any type of care	ER physical health care	Non-ER physical health care	Crisis mental health care	Non-crisis mental health care	Substance use-related care
Intercept	1.13*** (0.398)	0.021 (0.023)	0.261 (0.215)	0.006 (0.017)	1.02*** (0.284)	-0.108 (0.141)
Mean daily radius of gyration (km)	-0.046* (0.024)	-0.002 (0.002)	-0.020* (0.011)	<0.001 (<0.001)	-0.016 (0.021)	-0.001 (0.009)
Had pre-covid mental health diagnosis	2.03*** (0.239)	0.043 (0.027)	-0.136 (0.107)	0.046*** (0.011)	1.16*** (0.175)	0.747*** (0.127)
Had pre-covid chronic physical health condition	1.04*** (0.248)	0.015 (0.029)	0.364*** (0.115)	0.029*** (0.010)	0.101 (0.184)	0.039 (0.132)
Female	-0.602** (0.270)	-0.060** (0.024)	-0.023 (0.137)	-0.012 (0.013)	-0.509** (0.207)	-0.103 (0.115)
Black	-0.484* (0.284)	0.088* (0.047)	-0.028 (0.122)	0.002 (0.011)	0.024 (0.236)	-0.253*** (0.095)
Mom of device-matched child	0.036 (0.418)	0.095 (0.089)	-0.322** (0.159)	-0.010 (0.016)	0.009 (0.250)	0.531 (0.351)
Age as of 3/15/2020 (years)	0.034*** (0.009)	0.002** (<0.001)	0.023*** (0.006)	<0.001 (<0.001)	-0.010* (0.006)	0.005 (0.003)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Table A4: Relationship between pre to post-covid change in mean daily radius of gyration and monthly likelihood of receiving mental health care between September 2019 and August 2020

(N = 1,655)	Radius of gyration (km)	Total distance traveled (km)	Max distance from home (km)
A. Likelihood of receiving crisis mental health care			
Intercept	0.008 (0.007)	0.007 (0.007)	0.008 (0.007)
Pre to post-covid Δ in daily mobility measure	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
Had pre-covid mental health diagnosis	0.025*** (0.004)	0.025*** (0.004)	0.024*** (0.004)
Had pre-covid chronic physical health condition	0.018*** (0.005)	0.018*** (0.005)	0.017*** (0.005)
Female	<0.001 (0.005)	<0.001 (0.005)	<0.001 (0.005)
Black	0.002 (0.005)	0.002 (0.005)	0.003 (0.005)
Mom of device-matched child	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.007)
Age as of 3/15/2020 (years)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
B. Likelihood of receiving non-crisis mental health care			
Intercept	0.140*** (0.028)	0.140*** (0.028)	0.141*** (0.028)
Pre to post-covid Δ in daily mobility measure	0.002 (0.002)	<0.001 (<0.001)	<0.001 (0.001)
Had pre-covid mental health diagnosis	0.288*** (0.017)	0.288*** (0.017)	0.289*** (0.017)
Had pre-covid chronic physical health condition	0.062*** (0.017)	0.061*** (0.017)	0.061*** (0.017)
Female	-0.044** (0.018)	-0.044** (0.018)	-0.044** (0.019)
Black	-0.051*** (0.019)	-0.052*** (0.019)	-0.052*** (0.019)
Mom of device-matched child	0.019 (0.028)	0.018 (0.029)	0.018 (0.028)
Age as of 3/15/2020 (years)	-0.002*** (<0.001)	-0.002*** (<0.001)	-0.002*** (<0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Table A5: Heterogeneity across sample subgroups in relationship between pre to post-covid change in mean daily radius of gyration and monthly likelihood of receiving mental health care between September 2019 and August 2020

(N = 1,655)	Full sample	Female	Black	Received mental health care in Jan or Feb 2020
A. Likelihood of receiving crisis mental health care				
Intercept	0.008 (0.007)	0.009 (0.007)	0.019 (0.014)	0.037* (0.020)
Pre to post-covid Δ in mean daily radius of gyration (km)	<0.001 (<0.001)	<0.001 (<0.001)	-0.001 (0.001)	0.004** (0.002)
Had pre-covid mental health diagnosis	0.025*** (0.004)	0.023*** (0.005)	0.020** (0.009)	<0.001 (0.013)
Had pre-covid chronic physical health condition	0.018*** (0.005)	0.017*** (0.005)	0.015* (0.008)	0.031** (0.013)
Female	<0.001 (0.005)		-0.015 (0.011)	0.005 (0.012)
Black	0.002 (0.005)	-0.002 (0.006)		-0.009 (0.013)
Mom of device-matched child	-0.004 (0.007)	-0.004 (0.007)	-0.004 (0.011)	-0.008 (0.017)
Age as of 3/15/2020 (years)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)	<0.001 (<0.001)
B. Likelihood of receiving non-crisis mental health care				
Intercept	0.140*** (0.028)	0.067** (0.029)	0.047 (0.056)	0.464*** (0.066)
Pre to post-covid Δ in mean daily radius of gyration (km)	0.002 (0.002)	0.003 (0.003)	<0.001 (0.003)	0.004 (0.005)
Had pre-covid mental health diagnosis	0.288*** (0.017)	0.274*** (0.020)	0.251*** (0.035)	0.265*** (0.039)
Had pre-covid chronic physical health condition	0.062*** (0.017)	0.044** (0.020)	0.103*** (0.029)	0.002 (0.039)
Female	-0.044** (0.018)		-0.046 (0.040)	-0.096*** (0.036)
Black	-0.051*** (0.019)	-0.044** (0.021)		-0.025 (0.044)
Mom of device-matched child	0.019 (0.028)	0.015 (0.028)	0.052 (0.060)	0.088 (0.054)
Age as of 3/15/2020 (years)	-0.002*** (<0.001)	<0.001 (<0.001)	<0.001 (0.001)	-0.002 (0.001)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1

Table A6: Relationship between pre to post-covid change in mean daily radius of gyration and monthly number of days with health care between September 2019 and August 2020

(N = 1,655)	Any type of care	ER physical health care	Non-ER physical health care	Crisis mental health care	Non-crisis mental health care	Substance use-related care
Intercept	0.870** (0.397)	0.009 (0.023)	0.158 (0.195)	0.002 (0.015)	0.947*** (0.310)	-0.145 (0.126)
Pre to post-covid Δ in mean daily radius of gyration (km)	0.007 (0.031)	<0.001 (0.002)	0.015 (0.025)	0.003* (0.002)	0.014 (0.013)	-0.018 (0.014)
Had pre-covid mental health diagnosis	2.02*** (0.243)	0.041 (0.027)	-0.130 (0.109)	0.044*** (0.010)	1.17*** (0.178)	0.737*** (0.127)
Had pre-covid chronic physical health condition	0.998*** (0.255)	0.013 (0.030)	0.353*** (0.118)	0.029*** (0.010)	0.105 (0.191)	0.013 (0.135)
Female	-0.668** (0.275)	-0.054** (0.024)	-0.042 (0.142)	-0.005 (0.011)	-0.526** (0.211)	-0.129 (0.116)
Black	-0.519* (0.287)	0.087* (0.047)	-0.060 (0.122)	<0.001 (0.011)	0.019 (0.237)	-0.242** (0.095)
Mom of device-matched child	0.136 (0.423)	0.100 (0.091)	-0.290* (0.162)	-0.008 (0.016)	0.031 (0.252)	0.564 (0.357)
Age as of 3/15/2020 (years)	0.036*** (0.009)	0.002** (<0.001)	0.023*** (0.006)	<0.001 (<0.001)	-0.010* (0.006)	0.006* (0.003)

Notes: Calculations using matched sample of smartphone devices and Medicaid enrollees. Robust standard errors are in parentheses and are clustered at the person level. ***p <0.01, **p <0.05, *p <0.1