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Broadband internet access as a social determinant of health in the early COVID-19 pandemic in U.S. counties☆

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ABSTRACT

Recent work suggests that internet access was key in delivering life-saving health information about the COVID-19 pandemic. This paper expands on these findings by focusing on the early pandemic in the United States to examine the role of internet access on masking and COVID-19 incidence and mortality. Using county-level data from the American Community Survey, The New York Times, and other sources, weighted OLS regression models with state fixed-effects were used to predict the association of internet access on self-reported masking in July 2020 and COVID-19 incidence and mortality during multiple periods from July–October 2020. Results suggest that internet access is associated with a substantial decrease in a county's COVID-19 incidence and mortality. Most strikingly, models predict that counties with the highest internet access had less than 50% of the COVID-19 mortality as counties with the lowest internet access from July–October 2020. Meanwhile, though the association between internet access and masking is positive and significant, the effect size net of control variables is small. In sum, this paper finds that internet access is associated with COVID-19 outcomes in ways beyond information about masking alone.

1. Introduction

The COVID-19 pandemic was among the worst public health emergencies of the modern era. Across the globe, over 7 million deaths and at least 775 million infections from SARS-CoV-2, the virus responsible for the COVID-19 pandemic, have been reported as of December 2024 (World Health Organization, 2024). Public health agencies were tasked with releasing health guidance that could slow the virus' spread and save lives. The internet emerged as an important media for individuals to get information about the pandemic and rapidly changing health recommendations aimed at limiting its spread. Recommendations were prominent on the websites of national and local newspapers, press conferences were attended and streamed to millions on video-sharing websites, and public health entities published their recommendations on social media platforms for the world to see.

However, disparities in broadband internet access (BIA) suggest that information about the pandemic could have been unevenly spread, especially in the first months of the pandemic (Early & Hernandez, 2021). This is especially true in the United States, where BIA rates vary greatly by race, income, and other sociodemographic factors (Pew Research Center, 2024) along similar racial and socioeconomic lines that have given rise to disparities in the COVID-19 pandemic (Bui et al., 2020; Oster et al., 2020). This has led some researchers to suggest that internet access is a social determinant of health (Benda et al., 2020; Early & Hernandez, 2021; Sieck et al., 2021), but this claim remains under-studied (but see Li, 2022; Michaels et al., 2021).

This study tests the claim that BIA is a social determinant of health in the COVID-19 pandemic from July to October 2020. Though this period began five months into the pandemic, the public continued to seek guidance on COVID-19 recommendations. In doing so, this study addresses two questions: First, is access to the internet associated with adherence to public health measures, specifically masking behavior? Second, is access to the internet associated with COVID-19 incidence and mortality? This paper relies on a framework suggesting that internet access encourages the spread of information about the pandemic, which increases the uptake of public health protocols and subsequently decreases COVID-19 incidence and mortality. These questions are answered using existing data pooled from multiple publicly-available survey and administrative sources.

☆ This research has been deemed "exempt" by the institutional review board of the author's university.

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2. Background

In the context of digital inequality, internet *use* and internet *access* are two separate constructs. Both constructs have value for scholars of the "digital divide," who argue that access constitutes the first level of the digital divide, and use the second (Ragnedda, 2017). Internet *use* refers to the behavior that individuals engage in when online, including what websites they use and how much time they spend online. While this line of research predates the COVID-19 pandemic, a wealth of research during the pandemic emerged regarding how patterns of internet use shape knowledge about the pandemic and health outcomes (Hargittai, 2022).

However, studies of the effects of internet use on health can only draw conclusions about individuals who are connected to the internet. Compared to the wealth of studies investigating the COVID-19 health effects of internet *use*, there have been relatively fewer of studies focused on internet *access*, or whether an individual is able to connect to the internet at all (but see Li, 2022; Michaels et al., 2021). While most individuals in industrialized countries are online (Hargittai et al., 2019), recent estimates suggest that 2.9 billion people across the globe remain disconnected (International Telecommunication Union, 2021). In the U. S., around 20% of Americans remain disconnected as of 2024 (Pew Research Center, 2024). What is more, disparities in BIA persist by race/ethnicity, income, and other sociodemographic characteristics (Pew Research Center, 2024). Thus, by focusing on internet use, researchers draw conclusions about a group of individuals that are not representative of the entire country.

Information accessibility is a key mechanism that prior research suggests links internet access to pandemic health outcomes. Benda et al. (2020) propose a conceptual model where BIA is an upstream social determinant of health that impacts the information individuals can access to make health-related decisions. Without BIA, individuals were less able to use information on the internet to benefit their health in the pandemic. Empirical research has noted that the internet is one of several communication media through which individuals were able to become informed about the pandemic (Hargittai, 2022). The power of the internet as a social determinant of health may have been particularly great early in the pandemic when the public knew less about COVID-19.

Information about masking was especially critical in this period. Before the COVID-19 vaccine became available to the general public, wearing a face mask was one of the most effective tools for preventing incidence and mortality (Van Dyke et al., 2020). Details about best practices for masking were translated to the public through several means, including the websites of news organizations and public health agencies. Accessing up-to-date information was especially important as the perceived efficacy of masking has changed significantly during the pandemic, when masks were first not recommended before receiving the green light from the CDC in April 2020 (Fazio, 2021). Those connected to the internet were inundated with new recommendations and could fact-check claims about the virus from their homes.

While it is outside the scope of the current study to investigate other mechanisms linking technology to pandemic health outcomes, the link between technology and pandemic health outcomes is not exclusively through internet access and information about masking. It is well known that misinformation was widespread during the pandemic (Sule et al., 2023), which may downwardly bias potentially health protective effects of internet access. That said, past research has generally found that the public chose to engage with reliable news sources (Altay et al., 2022) which promoted disseminating and retaining health literacy related to the pandemic (but see Gerosa et al., 2021 for contrary evidence regarding social media use). The internet was also not the only way individuals gained information about the pandemic. Rather, the internet was one of several media where information about the pandemic was shared (Hargittai, 2022). The internet could have been useful ways beyond masking information, including by enabling work-from-home and social interactions (McClain et al., 2021). Some of these mechanisms may have been more useful in preventing mortality from COVID-19 than preventing infection, like learning about supportive care measures and locating a nearby hospital for further treatment.

BIA may also function as a structural characteristic of communities that allows individual-level benefits from BIA to extend to the broader communities. Neighborhood social cohesion may enable both the diffusion of preventative information about the pandemic outside of the internet alone and trigger enforcement of certain norms for use of preventative measures (Kawachi & Berkman, 2000). Within the context of the pandemic, prior work conducted in China found that COVID-19 was less prevalent among networks with high information diffusion (Lin et al., 2022). What is more, individuals were resistant to adopting novel preventative behaviors unless a certain critical mass of their community adopts the behavior (Morsky et al., 2023). Thus, a neighborhood or group of individuals who adopted a particular preventative measure in the pandemic may have implicitly encouraged others in their community to adopt that practice to maintain the status quo of the community. Additionally, areas with low internet access may have been not have had the flexibility to allow remote school or work, contributing to broader community spread (Barbour et al., 2021; Boerngen & Rickard, 2021; Jones et al., 2023).

3. Current study

The central goal of this study is to better understand the role that BIA played in COVID-19 outcomes in the U.S. early in the pandemic. To achieve this goal, this study builds on prior research in this area by focusing on an early period in the pandemic, the summer and fall of 2020. This period is advantageous because the virus was transitioning between different areas of the country, vaccines were not yet available to the general public, and information about the pandemic was less salient than in later periods. Drawing from previous research and evidence from the COVID-19 pandemic, this paper tests the following hypotheses:

Hypothesis 1. Internet access is positively associated with the uptake of masking at the county level.

Hypothesis 2. Internet access is negatively associated with COVID-19 incidence at the county level.

Hypothesis 3. Internet access is negatively associated with COVID-19 mortality at the county level.

4. Data/methods

4.1. Data

The county is the unit of analysis in this study. Counties are a common unit of analysis for studies during the COVID-19 pandemic (Albrecht, 2022; Jones et al., 2023; Kahane, 2021; Li, 2022) because of the policy relevance of counties and the widespread availability of county-level data.

Data on COVID-19 cases and deaths in most counties come from The New York Times (The New York Times, 2020). The dataset includes daily cumulative COVID-19 cases and deaths from January 2020 until March 2023. The New York Times aggregated the case and death counts in the five boroughs of New York City into one unit. For this reason, data for the five boroughs of city are obtained from the New York City Department of Health (NYC Health, 2023). These data are likely an undercount of the true COVID-19 incidence and mortality during the pandemic (Mullachery et al., 2022).

Data on mask use come from a July 2020 survey fielded by The New York Times and Dynata (Katz et al., 2020). 250,000 respondents were asked, "How often do you wear a mask in public when you expect to be within six feet of another person?" between July 2–14, 2020. To aggregate these data at the county level, The New York Times and

Dynata first assembled a weighted average of the 200 responses closest to individual Census tracts according to their ZIP Code, where respondents living closer to the Census tract were weighted more heavily than respondents living further away. Each Census tract was then population-weighted before assembling county-level averages. In the publicly available data, results are presented as the percentage of respondents in or around each county who responded to each of the five response categories. Importantly, these data may be subject to social desirability bias, as self-reported masking from this survey is somewhat higher than observed masking from the same period (Katz et al., 2020).

Demographic data come primarily from the 5-year American Community Survey 2015–2019 (U.S. Census Bureau, 2023). These demographic data are supplemented with election returns from the 2016 presidential election gathered by the MIT Election Data and Science Lab (MIT Election Data and Science Lab, 2022; Though 2020 election data may be more representative of a county's political leanings in summer 2020 compared to 2016 election data, 2020 election results were affected by the pandemic itself (Baccini et al., 2021), which may introduce bias into the analysis. County-level election data is not available for Alaska, so state-level election returns are used in place of county-level data (Cohen, 2020). County rural/urban classification comes from the U.S. Department of Agriculture (U.S. Department of Agriculture, 2023). Finally, county-level social capital measures are sourced from the Northeast Regional Center for Rural Development (NERCRD) (Rupasingha et al., 2006).

Of 3142 counties and county-equivalent areas in the 50 states and the District of Columbia, a total of 68 (2.2% of all counties) are dropped from the dataset. 3 (<0.1%) are dropped in listwise deletion procedures for missing data on election returns, metropolitan status, or social capital. A further 65 (2.1%) are dropped due to inconsistencies in reported COVID-19 data. These inconsistencies emerge either when a county reports fewer cases or deaths on August 11, September 8, and/or October 6 than on July 14 or when a county reports fewer cases or deaths in one period than a previous period. Considering that the cumulative prevalence of COVID-19 cases and deaths in a county cannot naturally decrease, negative COVID-19 data is most likely the result of data errors. 3074 counties (97.8% of total counties) remain in the final analytic sample.

4.2. Variables

4.2.1. Dependent variables

The first dependent variable, mask use, is an index assembled from the data collected by The New York Times and Dynata. Participants responded on a five-point Likert scale, with possible responses including "never," "rarely," "sometimes," "frequently," and "always." Prior research employs an index of these five response categories to ascertain the relative mask use in a given county (Kahane, 2021). Thus, Equation (1) constructs a similar mask index:

$$M_c = (0^*N_c) + (25^*R_c) + (50^*S_c) + (75^*F_c) + (100^*A_c) \tag{1}$$

where M is the mask index in county c from 0 to 100, with 0 meaning residents never masked when unable to social distance and 100 meaning residents always masked when within six feet of others outside their household. N, R, S, F, and A refer to the proportion of residents in county c who report masking never, rarely, sometimes, frequently, and always, respectively, when unable to social distance. This mask index is used as both a dependent and mediating variable, as described below.

COVID-19 outcomes across time are the second set of dependent variables. Summer to early fall 2020 was a dynamic time in the pandemic's trajectory (Smith & Allen, 2022). To examine temporal changes in COVID-19 incidence and mortality following the end of the masking survey, this study employs measures of new COVID-19 cases and deaths per 100,000 residents in the 4, 8, and 12 weeks after July 14, 2020, in counties. Prior research suggests that the widespread adoption of pandemic behaviors does not result in an immediate decrease in COVID-19 transmission or mortality but instead occurs over a longer period (Van Dyke et al., 2020). Thus, using overlapping periods in this study accounts for the momentum of the pandemic. Since longer periods result in higher COVID-19 incidence and mortality, these temporal incidence and mortality measures are divided by the number of weeks in each period to ease between-period comparisons.

4.2.2. Independent variable

BIA is operationalized as the percentage of households in a county with access to any form of internet that is faster than dial-up, including cellular data plans, fiber optic, DSL, and satellite. Access to the internet requires both that reliable internet is available in a household's geographic area and that the household has the financial means to purchase an internet subscription. Current research focuses on BIA because of its high speed and reliability in homes and communities with access (Tomer et al., 2020).

4.2.3. Control variables

Based on prior literature, the below models control for a battery of variables to capture competing mechanisms linking internet access and COVID-19 outcomes (Albrecht, 2022; Bui et al., 2020; CDC COVID-19 Response Team, 2020; Cohen, 2020; Danielsen et al., 2022; Fielding--Miller et al., 2020; Jones et al., 2023; Parolin & Lee, 2022; Pew Research Center, 2024; Zhuo & Harrigan, 2023). Race/ethnicity is measured the percentage of residents who identify as non-Hispanic Black or African American, non-Hispanic American Indian or Alaska Native, and Hispanic/Latino. Socioeconomic status is measured as the poverty rate of a county and the percentage of adults aged 25 or older with at least a bachelor's degree. Other sociodemographic control variables include the percentage of residents who are uninsured, female, or age 65 or older, as well as an indicator variable of whether the county is in a metropolitan statistical area (1) or not (0). To capture the political orientation of a county, models control for the percentage of votes for Trump in 2016 relative to all major party votes that year. Social capital is accounted for using the county-level social capital index constructed by NERCRD, which is centered at a mean of 0 and a standard deviation of 1. This paper controls for total COVID-19 cases and deaths per 100,000 residents as of July 14, 2020. This lagged measure is useful when considering the extent to which previous COVID-19 conditions in a county may have altered a county's culture surrounding prevention or if prior infections contributed to natural immunity in the county (Jones et al., 2023). Finally, state fixed-effects are a nominal indicator to account for unobserved characteristics of the state that a county is in.

4.3. Analytic strategy

Though this paper does not consider hypotheses related to time, it is important to note that summer and early fall 2020 was a dynamic time for the pandemic's trajectory, as a second wave of the pandemic moved across the U.S. before transitioning into a third wave (Smith & Allen, 2022). Additionally, point-in-time changes in behaviors and policies did not have an immediate effect on the population but instead had delayed impacts (Van Dyke et al., 2020). To account for possible temporal changes in the pandemic, a set of three overlapping periods — July 14 – August 11, July 14 – September 8, and July 14 – October 6, 2020 — gauges how the momentum of the pandemic may have been changed by health behaviors and policies.

After computing descriptive statistics, the paper computes three sets of OLS regression models, weighted by county population size to improve generalizability (Montez et al., 2022). The first set of models examines the association between internet access and county-level masking behaviors. Increasingly stringent models control for lagged COVID-19 cases and deaths, sociodemographic characteristics, and state fixed-effects. These models are represented by Equation (2):

$$M_c = \beta_0 + \beta_1 B_c + \beta_2 V_c + \beta_3 X_c + S_c + \varepsilon_c \quad (2)$$

where the main outcome variable, M, is the mask index of residents in county c, constructed from Equation (1) above. B is the percentage of households in county c with BIA, V is the vector of lagged COVID-19 cases and deaths per 100,000 population in county c as of July 14, 2020, and X is the vector of all other county-level control variates in county c. S refers to state fixed-effects. ε is the error term.

The second and third sets of models separately estimate how internet access is associated with the change in COVID-19 cases and deaths, respectively, in three overlapping periods as described above. This modeling strategy introduces the same control variables as above and includes the mask index as a mediating variable. For the sake of brevity, only three models are presented per period: the bivariate association between BIA and mean weekly COVID-19 cases or deaths; a fully controlled model that includes the bivariate association plus all controls and state fixed-effects; and the fully controlled model plus masking as a mediator. These models take the form of Equation (3):

$$\frac{IM_{ct}}{w_t} = \beta_0 + \beta_1 B_c + \beta_2 V_c + \beta_3 X_c + \beta_4 M_c + S_c + \varepsilon_{ct} \quad (3)$$

Where IM is new COVID-19 cases or deaths per 100 thousand residents in county c between July 14 and the end date of period t. w is the number of weeks between July 14 and the end date of period t. Taken together, $\frac{IM_{ct}}{w_t}$ is the mean number of new cases or deaths per 100 thousand residents per week in county c between July 14 and the end of period t. For example, imagine a hypothetical county that reported 600 COVID-19 cases per 100 thousand residents in the 8 weeks between July 14 – September 8, 2020. The value for $\frac{IM_{ct}}{w_t}$ in this county during the 8-week period would be $\frac{600}{8}$, or 75 mean weekly cases per 100 thousand residents. All other terms in Equation (3) are the same as in Equation (2).

5. Results

5.1. Descriptive results

Table 1 depicts descriptive statistics for all study variables, weighted by county population. On average, 82.62% of households in U.S. counties have BIA. The mean mask index in early July 2020 was 83.60, suggesting that masking outside the home was high in early July 2020. Counties in the U.S. reported a mean of 133.98, 113.51, and 106.72 weekly new cases per 100 thousand residents in the 4, 8, and 12 weeks, respectively, after July 14, 2020. This scales to a mean of 535.92, 908.08, and 1280.64 total new cases per 100 thousand residents through the whole duration of each period, respectively. Patterns for COVID-19 mortality across these periods were similar to patterns of COVID-19 incidence. The average county reported a mean of 2.23, 2.09, and 1.94 new COVID-19 deaths per 100 thousand residents in the 4, 8, and 12 weeks after July 14, respectively. Considering the whole period, this translates to 8.92, 16.72, and 23.28 total new COVID-19 deaths across

Table 1
Descriptive statistics.

	Mean	SD	Median
% Broadband [a]	82.62	6.71	83.70
Mask index	83.60	8.29	86.55
Weighted cases per 100K residents [b]			
July 14 – August 11, 2020	133.98	108.04	104.27
July 14 – September 8, 2020	113.51	78.31	98.73
July 14 – October 6, 2020	106.72	64.62	95.25
Weighted deaths per 100K residents [b]			
July 14 – August 11, 2020	2.23	2.68	1.28
July 14 – September 8, 2020	2.09	2.35	1.29
July 14 – October 6, 2020	1.94	2.03	1.30
Cumulative cases per 100K residents [c]	1023.39	718.61	923.90
Cumulative deaths per 100K residents [c]	37.77	51.57	18.34
% Non-Hispanic Black	12.46	12.74	7.90
% Non-Hispanic American Indian/Alaska Native	0.68	3.16	0.20
% Hispanic	18.27	17.31	11.60
% Age 65+	15.59	4.00	14.90
% Female	50.75	1.25	50.80
% Poverty	13.61	4.93	13.70
% Uninsured	9.02	4.37	8.40
% Bachelor's degree	31.75	11.13	31.70
% 2016 Trump votership	48.66	18.34	47.14
Social capital index	−0.59	0.79	−0.61
Metro status (Ref. = nonmetro)	0.85	0.35	1.00

N = 3074 counties. Descriptive statistics weighted by population size of county.
[a] Broadband internet access measured among households.
[b] Effect sizes adjust for the number of weeks in the respective period to facilitate comparisons between periods. Effect sizes are divided by 4 in models 1a-1c, 8 in models 2a-2c, and 12 in models 3a-3c.
[c] Cases and deaths per 100K residents on July 14, 2020, the last day of the masking survey.

each period, respectively (See Figs. S1, S2, S3a-S3c, and S4a-S4c in the Supplemental Materials for the geographic distributions of these variables.).

5.2. Internet access and mask use

Table 2 demonstrates support for Hypothesis 1 that BIA is associated with mask use (See Table S1 in the supplement for the full, unabridged table.). In Model 1, a 1 percentage point increase in BIA is associated with a 0.52 unit increase ($p < 0.001$) in the mask index. Accordingly, the mask index in counties at the 90th percentile for internet access is predicted to be 8.12 points higher than counties at the 10th percentile. After controlling for prior COVID-19 incidence and mortality in Model 2, the effect size of BIA on mask index remains virtually unchanged (0.552; $p < 0.001$). The effect size of BIA on masking attenuates considerably after controlling for sociodemographic characteristics in Model 3 (0.114; $p < 0.001$). From this model, the mask index in a county at the 90th percentile for BIA is predicted to be 1.77 points higher than a county at the 10th percentile for BIA, net all other variables in the model. The association between BIA and masking decreases, but not entirely, in Model 4 after including state fixed-effects (0.086; $p < 0.001$).

5.3. Internet access and COVID-19 cases

Table 3 finds support for Hypothesis 2 that BIA is associated with lower COVID-19 incidence across all periods of interest, though this association becomes weaker as periods grow longer (See Supplemental Table S2 for the full table.) Models 1a through 1c depict the association between BIA and COVID-19 cases from July 14 – August 11. In Model 1a, a 1 percentage point increase in BIA is associated with a decrease of 3.86 weekly new cases per 100 thousand county residents ($p < 0.001$). Throughout the entire 4-week period, the effect size reflects a decrease of 15.44 total cases per 100,000 residents for every 1 percentage point increase in BIA. After controlling for sociodemographic characteristics and state fixed-effects in Model 1b and including the mask index as a mediating variable in Model 1c, the effect size of BIA on COVID-19 incidence in this early period decreases somewhat (Model 1b: −3.457, $p < 0.001$; Model 1c: −3.519, $p < 0.001$).

Models 2a through 2c show COVID-19 incidence from July 14 – September 8. In Model 2a, a 1 percentage point increase in BIA is associated with 3.14 fewer COVID-19 weekly cases per 100 thousand residents ($p < 0.001$), or 25.12 fewer total COVID-19 cases per capita across the whole period. Upon controlling for sociodemographic characteristics and state fixed-effects in Model 2b and accounting for mediation from the mask index in Model 2c, the effect size of BIA on COVID-19 cases decreases to −2.23 ($p < 0.001$) in both models. Model 2c reflects a decrease of 17.84 COVID-19 cases per capita in the whole 8-week period for every 1 percentage point increase in BIA.

Finally, Models 3a through 3c show COVID-19 incidence in the July 14 – October 6 period. In Model 3a, a 1 percentage point increase in BIA is associated with 2.94 fewer weekly COVID-19 cases per 100 thousand residents ($p < 0.001$), or 35.28 fewer total COVID-19 cases during this 12-week period. Upon controlling for sociodemographic characteristics and state-fixed effects in Model 3b, a 1 percentage point increase in BIA is associated with 1.51 fewer weekly COVID-19 cases per 100 thousand residents ($p < 0.001$), net other variables. The effect size of BIA on COVID-19 incidence in this period remains similar upon controlling for masking in Model 3c (BIA: −1.469, $p < 0.001$). Model 3c predicts 17.64 fewer total COVID-19 cases per 100 thousand residents for each 1 percentage point increase in BIA across the full 12-week period.

Fig. 1 visualizes the findings of Table 3, Models 1c, 2c, and 3c. Across all three periods, counties with higher BIA were predicted to have lower COVID-19 incidence rates, all else equal. The figure also visualizes that the association between BIA and COVID-19 incidence becomes weaker over time, as the difference between counties with some of the lowest and highest values of BIA shrinks in successive periods. For example, counties at the 90th percentile of household BIA were predicted to have a COVID-19 incidence rate that was 33.71% lower than that of counties at the 10th percentile from July 14 – August 11, 2020. However, in the July 14 – October 6, 2020, counties at the 90th percentile of BIA were predicted to have only a 19.25% lower incidence rate than counties at the 10th percentile of BIA.

In sum, across all three periods, there is support for Hypothesis 2 that household BIA is associated with a lower incidence rate of COVID-19 infection. That said, this association attenuates in longer periods. In addition, the effect of BIA on COVID-19 cases does not appear to be substantively mediated by masking in a county. This suggests that other mechanisms mediate the association between BIA and COVID-19 cases more than information about masking.

5.4. Internet access and COVID-19 mortality

Table 4 demonstrates support for Hypothesis 3 that BIA is associated with a decrease in COVID-19 morbidity across all periods. Models 1a through 1c depict COVID-19 weekly COVID-19 mortality per 100 thousand residents reported between July 14 and August 11, 2020 (See Supplemental Table S3 for the full table.). In Model 1a, a 1 percentage point increase in BIA is associated with 0.12 fewer weekly deaths per 100 thousand residents ($p < 0.001$) across this four-week period, or 0.48 fewer deaths per capita across the entire period. The effect size decreases somewhat after controlling for sociodemographic characteristics in Model 1b (−0.0885, $p < 0.001$). After including masking as a possible mediator in Model 1c, the effect size remains similar, with a 1 percentage point increase in BIA being associated with 0.09 fewer weekly deaths per 100 thousand residents ($p < 0.001$), or 0.36 fewer total deaths per 100 thousand residents across the whole period, net other variables.

Models 2a through 2c show the results of models of COVID-19 mortality by BIA from July 14 – September 8, 2020. In Model 2a, a 1 percentage point increase in BIA is associated with 0.12 fewer weekly deaths per 100 thousand residents ($p < 0.001$), or 0.96 total deaths per capita in the period. Controlling for sociodemographic variables and state fixed-effects in Model 2b attenuates the association to −0.09 ($p < 0.001$). Including masking in the Model 2c leaves the effect size almost unchanged, where a 1 percentage point increase in BIA is associated with 0.09 fewer weekly deaths per 100 thousand residents ($p < 0.001$), or 0.72 fewer total deaths per 100 thousand residents, in both models, net of other variables.

Models 3a through 3c show the results of models of COVID-19 mortality from July 14 – October 6, 2020, on BIA. In Model 3a, a 1

Table 2
County mask use regressed on internet access.

	Model 1	Model 2	Model 3	Model 4
% Broadband [a]	0.523***	0.552***	0.114***	0.0855***
	(0.0202)	(0.0190)	(0.0289)	(0.0238)
Lagged cases and deaths [b]	NO	**YES**	**YES**	**YES**
Sociodemographic controls [c]	NO	NO	**YES**	**YES**
State fixed-effects	NO	NO	NO	**YES**
Constant	40.37***	34.57***	76.55***	72.94***
	(1.675)	(1.599)	(5.068)	(4.131)
R^2	0.179	0.284	0.620	0.798

N = 3074 counties. *p < 0.05, **p < 0.01, ***p < 0.001; Standard errors in parentheses.

[a] : Broadband internet access measured among households.

[b] : Cases and deaths per 100K residents on July 14, 2020, the last day of the masking survey.

[c] : Sociodemographic controls include % NH Black, % NH American Indian/Alaska Native, % Hispanic, aged 65+, female, uninsured, poverty rate, educational attainment (bachelor's degree or higher), Trump votership, social capital, and county metropolitan status.

Table 3
Association between new COVID-19 cases per capita 4-, 8-, and 12-weeks after July 14, 2020, and internet access.

	July 14 – August 11, 2020 [a]			July 14 – September 8, 2020 [a]			July 14 – October 6, 2020 [a]		
	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
% Broadband [b]	−3.857***	−3.457***	−3.519***	−3.137***	−2.227***	−2.234***	−2.936***	−1.510***	−1.469***
	(0.282)	(0.361)	(0.361)	(0.203)	(0.274)	(0.275)	(0.166)	(0.227)	(0.227)
Mask index			0.725**			0.0796			−0.482**
			(0.276)			(0.210)			(0.173)
Lagged cases and deaths [c]	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
Sociodemographic controls [d]	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
State fixed-effects	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
Constant	452.7***	301.9***	249.1***	372.7***	288.2***	282.4***	349.3***	276.5***	311.6***
	(23.39)	(62.54)	(65.64)	(16.82)	(47.54)	(49.95)	(13.72)	(39.25)	(41.19)
R^2	0.0574	0.728	0.728	0.0722	0.700	0.700	0.0929	0.700	0.701

N = 3074 counties, weighted by population; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Standard errors in parentheses
[a] Effect sizes adjust for the number of weeks in the respective period to facilitate comparisons between periods. Effect sizes are divided by 4 in models 1a-1c, 8 in models 2a-2c, and 12 in models 3a-3c.
[b] Broadband internet access measured among households.
[c] Cases and deaths per 100K residents on July 14, 2020, the last day of the masking survey.
[d] Sociodemographic controls include % NH Black, % NH American Indian/Alaska Native, % Hispanic, aged 65+, female, uninsured, poverty rate, educational attainment (bachelor's degree or higher), Trump votership, social capital, and county metropolitan status.

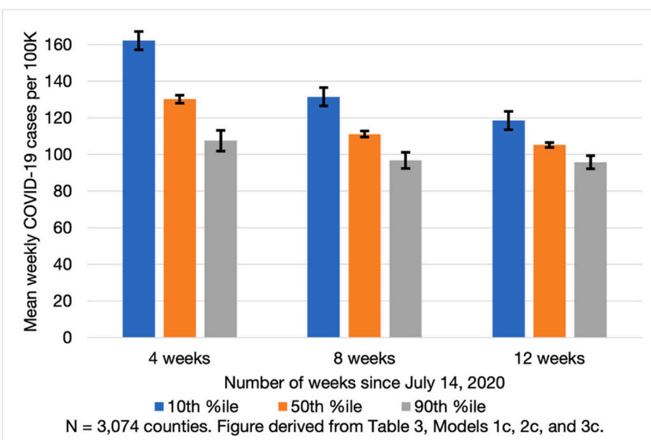

Fig. 1. Predicted margins of BIA on average weekly new COVID-19 cases per capita.

percentage point increase in BIA is associated with 0.12 fewer weekly deaths per 100 thousand residents ($p < 0.001$), or 1.44 fewer total deaths per 100 thousand residents across the full period. After accounting for sociodemographic characteristics and state fixed-effects in Model 3b, the effect size lessens slightly to −0.09 ($p < 0.001$). After masking is included in the model, a 1 percentage point increase in BIA is associated with 0.09 weekly fewer deaths per 100 thousand residents ($p < 0.001$), or 1.08 total fewer deaths per 100 thousand residents across the whole period, net other variables.

Fig. 2 illustrates the strong negative association between county-level BIA and COVID-19 mortality across all three periods. The predicted margins depicted in this figure are estimated from Table 4, Models 1c, 2c, and 3c, and all other independent variables are held at their means. Across all three periods, counties with higher BIA were predicted to have lower COVID-19 mortality than counties with lower BIA. Additionally, unlike the models for cases, the difference in COVID-19 mortality between the highest- and lowest-BIA counties increases slightly as the time horizon grows. In the four-week period, counties at the 90th percentile of BIA were predicted to have 47.56% fewer COVID-19 deaths per capita than counties at the 10th percentile of BIA. In comparison, in the 12-week period, counties at the 90th percentile of BIA were predicted to have 52.71% lower COVID-19 mortality than

Table 4
Association between new COVID-19 deaths per capita 4-, 8-, and 12-weeks after July 14, 2020, and internet access.

	July 14 – August 11, 2020 [a]			July 14 – September 8, 2020 [a]			July 14 – October 6, 2020 [a]		
	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
% Broadband[b]	−0.116***	−0.0885***	−0.0904***	−0.120***	−0.0890***	−0.0898***	−0.118***	−0.0908***	−0.0905***
	(0.00690)	(0.0110)	(0.0110)	(0.00593)	(0.00949)	(0.00950)	(0.00503)	(0.00841)	(0.00843)
Mask index			0.0221**			0.00899			−0.00305
			(0.00838)			(0.00725)			(0.00643)
Lagged cases and deaths[c]	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
Sociodemographic controls[d]	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
State fixed-effects	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
Constant	11.83***	2.865	1.254	11.97***	2.225	1.569	11.70***	3.256*	3.478*
	(0.572)	(1.901)	(1.995)	(0.491)	(1.644)	(1.727)	(0.417)	(1.458)	(1.532)
R^2	0.0846	0.591	0.592	0.117	0.601	0.601	0.152	0.581	0.581

N = 3074 counties, weighted by population; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Standard errors in parentheses.
[a] Effect sizes adjust for the number of weeks in the respective period to facilitate comparisons between periods. Effect sizes are divided by 4 in models 1a-1c, 8 in models 2a-2c, and 12 in models 3a-3c.
[b] Broadband internet access measured among households.
[c] Cases and deaths per 100K residents on July 14, 2020, the last day of the masking survey.
[d] Sociodemographic controls include % NH Black, % NH American Indian/Alaska Native, % Hispanic, aged 65+, female, uninsured, poverty rate, educational attainment (bachelor's degree or higher), Trump votership, social capital, and county metropolitan status.

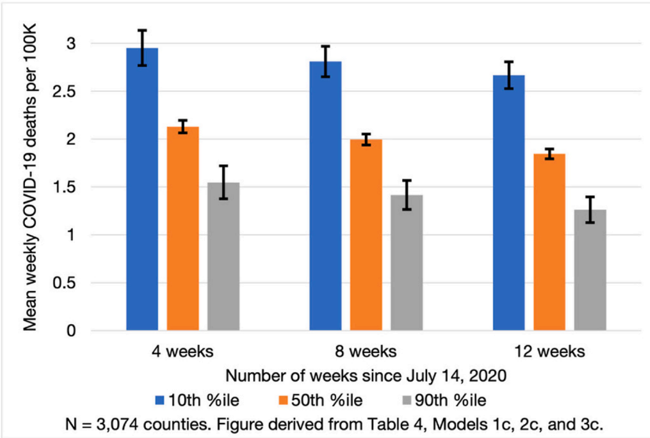

Fig. 2. Predicted margins of BIA on average weekly new COVID-19 deaths per capita.

counties at the 10th percentile of BIA.

In sum, there is support for Hypothesis 3 across all three periods that BIA is associated with lower COVID-19 mortality in counties. Unlike models for Hypothesis 2, these associations get slightly stronger across longer periods. Similarly to COVID-19 cases, there does not appear to be evidence that these associations are substantively mediated by masking, suggesting that other mechanisms besides information about masking may mediate the association between BIA and mortality.

6. Discussion/conclusion

This study adds to the growing literature on the social processes underpinning the COVID-19 pandemic by investigating how internet access shaped its spread in the summer and fall of 2020. Though effective communication has long been important to public health, the pandemic demonstrated that the timely communication of accurate, up-to-date health information is critical. The internet played a significant role in aiding public health communication strategies, but these impacts may not have been felt in parts of the country where internet access is more limited. Thus, this paper hypothesized that internet access would improve COVID-19 health behaviors and subsequently decrease the burden of COVID-19 cases and deaths.

This study finds support for all three hypotheses, suggesting that household BIA was associated with modest increases in masking and strong decreases in COVID-19 incidence and mortality in summer and early fall 2020. Importantly, while there is a statistically significant association between internet access and masking net of controls, the effect size for this relationship is not substantively meaningful. What is more, masking does not meaningfully mediate any association between internet access and incidence and mortality. This suggests that individuals may have used the internet in other ways to prevent COVID-19 infection and mortality.

The three overlapping periods of interest to this study provide additional insight into how the momentum of the pandemic shifted in light of conditions in July 2020. Focusing on Models 1c, 2c, and 3c of Table 3, the association between BIA and weekly new COVID-19 cases grew weaker as the periods expanded, suggesting that the internet may have contributed less value as a resource to protect against COVID-19 cases across a longer period. Though outside the scope of the current study, this may be explained by the changing dynamics of the pandemic that were occurring in the transition from summer to fall 2020 (Smith & Allen, 2022). The equivalent models in Table 4 show that the association of BIA on weekly COVID-19 deaths is strong and stable across all three periods. Combined with findings about COVID-19 incidence, this suggests that individuals with internet access may have used the internet in ways that promoted recovery from COVID-19 infection, though this study cannot test that claim directly.

This study leaves several stones unturned for future research. First, masking is only one of many public health measures that may benefit from information diffusion via the internet. Some researchers have found that higher BIA is associated with higher COVID-19 vaccination rates (Li, 2022; Michaels et al., 2021), but other preventative measures like staying at home have received less attention. Second, future researchers should integrate studies of internet use with internet access. While this paper suggests that studying the effect of the internet on pandemic health outcomes is incomplete when focusing solely on internet use, it is not accurate to argue that internet use is unimportant. Instead, reading these two constructs in consort with each other would likely yield critical results for scholars and practitioners. Third, research on internet access in the context of the COVID-19 pandemic should encourage researchers to investigate the potential effects of internet access on other health conditions before, during, and after the pandemic. With unequal internet access across the U.S., segments of the population with ample internet access may be able to get health-related information with greater ease than those without. Fourth, future research should consider the role that internet access plays in health in a global context. While about 20% of U.S. adults lack internet access, more than one-third of the global population remains disconnected, and most of the world's internet non-users are in developing countries (International Telecommunication Union, 2021; Pew Research Center, 2024). The effects of internet access (and a lack thereof) may be especially pronounced in parts of the world where more people remain offline.

This study is not without its limitations, many of which center around the nature of the data. Data on COVID-19 incidence and mortality are replete with quality concerns stemming from unequal access to testing and mischaracterization of death certificates (Boyle, 2021; Mullachery et al., 2022). COVID-19 incidence and mortality data most likely an undercount of true trends, leading to more conservative findings in this study, especially regarding trends in COVID-19 incidence. Individuals without internet access may also be expected to have been less likely to get tested for COVID-19, leading to the estimates of COVID-19 incidence in low internet access counties being biased downward. Additionally, findings may be subject to ecological fallacy such that the county-level findings described here do not reflect individual patterns (Piantadosi et al., 1988). While more granular data at the individual- or census-tract level would be preferred, the county-level is the smallest geographic area where data are publicly available and comprehensive on most of the variables of interest in this study. Finally, demographic data used in this study are time constant and measured using the 2015–2019 ACS. In particular, BIA is a static measure and does not capture any changes in internet access across the pandemic. Several programs came online to provide internet access to low-income families for educational purposes as schools transitioned to remote education. What's more, quasi-experimental research from Canada found that the implementation of free internet access to low-income families reduced the incidence of COVID-19 (Goetz, 2022).

Despite these limitations, this study contributes to a growing understanding of the social dynamics of the COVID-19 pandemic by considering how BIA was associated with preventative behavior and infection and mortality rates in the early pandemic in the U.S. The results of the study offer support for enhancing public health communications strategies to engage with residents of low-internet access areas to effectively spread public health communications. To fully illuminate the effect of the internet on COVID-19, further research must shine a light on the complexities of the internet, including more targeted analysis of internet access and expanding research into internet use.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

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Appendix A. Supplementary Materials

Supplementary materials for this article can be found online at https://doi.org/10.1016/j.ssmph.2025.101747.

Data availability

Data will be made available on request.

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