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The impact of internet access on COVID-19 spread in Indonesia

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THE IMPACT OF INTERNET ACCESS ON COVID-19 SPREAD IN INDONESIA

Johannes S. Kunz, Carol Propper, and Trong-Anh Trinh

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ABSTRACT

The coronavirus disease (COVID-19) pandemic has highlighted the crucial role of Internet access in pandemic prevention and response. Internet access has facilitated the rapid dissemination of vital information, provided telemedicine services, and enabled remote work and education. This study uses a wide range of data sources to investigate the geographic variation of Internet access proxied by 3G mobile broadband during the COVID-19 pandemic in Indonesia. We employ several approaches to account for potential confounding factors, including using lightning strikes as an instrumental variable, to confirm the significant role that the Internet played in the spread of COVID-19 cases. Our findings suggest that increasing Internet access could positively impact pandemic prevention and response efforts, particularly in regions with limited connectivity. Therefore, improving Internet infrastructure in developing countries may be crucial in preventing future pandemics.

Keywords: health emergencies, Internet access, information, COVID-19 spread

JEL codes: I12, I15, I31, O18, L96, H41

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1 Introduction

The emergence of the coronavirus disease (COVID-19) in December 2019 and its rapid spread into a global pandemic has profoundly impacted societies worldwide, causing widespread anxiety and concern among the public. The need to control the spread of the virus has necessitated strict measures such as nationwide quarantines and increased sanitation protocols, leading to social and economic disruption in various sectors (Brodeur, Gray, Islam, and Bhuiyan 2021). In addition, fear and panic have fueled prejudice and discrimination against certain groups (Lu et al. 2021). At the same time, remote working and teaching have become the norm for many, necessitating a major shift in working and educational practices (Bloom, Davis, and Zhestkova 2021). The pandemic has also significantly impacted mental health, with the isolation and anxiety caused by the pandemic becoming a major concern (Brodeur et al. 2021, Butterworth et al. 2022). Moreover, the pandemic has exposed deep-seated poverty and health disparities within many societies, highlighting the urgent need to address these issues (Ahmed et al. 2020). As disease outbreaks are not likely to disappear in the near future, it is crucial to understand preparedness strategies that can reduce the impact of future diseases.

The COVID-19 pandemic has brought the importance of Internet access into sharper focus. Prior research suggests that Internet access may play a crucial role in health emergencies (Barrero, Bloom, and Davis 2021; Alipour, Fadinger, and Schymik 2021; Barrero et al. 2021; Whitelaw et al. 2020). With the rapid spread of the virus, there was an urgent need for the quick and effective dissemination of information to the public. The Internet has enabled the rapid sharing of updates on the virus through websites, social media, and messaging platforms. Additionally, the Internet has provided health authorities

a platform to communicate directly with the public, sharing guidance on preventive measures such as wearing masks, washing hands, and social distancing. Telemedicine has emerged as a vital tool in the fight against COVID-19, allowing healthcare professionals to provide virtual consultations, monitor patients remotely, and reduce the risk of exposure to the virus in healthcare facilities. However, the impact of Internet access on pandemic prevention may be partially positive, as it can also facilitate the spread of misinformation. For example, false claims about the effectiveness of certain treatments or the safety of vaccines have been widely circulated online, hampering efforts to contain and mitigate the disease (Cinelli et al. 2020, Bursztyn et al. 2020). Therefore, the overall effect of Internet access on pandemic prevention is an empirical question that requires further investigation.

In developing countries where the health care system is often underdeveloped, Internet access is crucial in reducing the spread of COVID-19. The World Bank reports that only 19.1% of the population in low-income countries has access to the Internet, compared to 87.7% in high-income countries (Kelly and Rossotto 2011). This limited access to the Internet exacerbates the challenges faced by the health systems in these countries, making it difficult to manage the pandemic effectively. Access to the Internet is essential for healthcare delivery, disease surveillance, and public health interventions. It allows people to access reliable information about the virus, preventive measures, and telemedicine services that reduce the burden on overworked health systems.

Additionally, Internet access enables people to work from home, reducing the need for physical contact and minimizing the risk of spreading the virus. Therefore, higher access to the Internet is likely associated with a reduction in COVID-19 transmission in

developing countries. Figure 1 plots the relationship between country-level average mobile Internet speed and the number of COVID-19 cases for several economies in Asia and the Pacific countries, suggesting that stronger Internet connections are associated with lower COVID-19 transmission rates and, consequently, deaths.

This study provides empirical evidence of the role of Internet access during the COVID-19 pandemic by exploiting subnational data on mobile broadband, and COVID-19 spread in Indonesia. Indonesia became the epicenter of the pandemic in Southeast Asia, with the highest number of confirmed cases and deaths in the region by the end of 2022 (Figure 1 and Appendix A.6). Several factors contributed to the severity of the situation, including limited testing and tracing capacity, inadequate healthcare infrastructure, and public skepticism towards the government's pandemic response measures. Moreover, the variation in Internet access across regions and provinces posed a challenge in Indonesia, with implications for education, healthcare, and economic opportunities. Although some areas had higher levels of Internet access, particularly in urban areas and on the islands of Java and Bali, other areas, particularly rural and remote ones, had limited Internet access due to inadequate infrastructure and resources. This limited access could exacerbate the risk of infection in those regions, especially during the COVID-19 pandemic, where access to government information about the disease became increasingly crucial. Figure 2 shows that areas with higher Internet access are associated with lower disease transmission rates, providing further evidence of the importance of Internet access in controlling the spread of COVID-19 in Indonesia and other developing economies.

Our empirical strategy builds on the variation in 3G mobile broadband access across districts in Indonesia in 2019. While the pre-COVID period is less likely to be related to the spread of diseases, concerns remain about the correlation between Internet access and other factors that could influence the spread of the disease. Therefore, we adopt an instrumental variable approach to address this issue, using the incidence of lightning strikes as an instrument (Guriev, Melnikov, and Zhuravskaya 2021; Manacorda and Tesei 2020; Do, Gomez-Parra, and Rijkers 2023). Our strategy assumes that areas with higher incidences of lightning display slower adoption of mobile phone technology. At the same time, it is reasonable to assume that lightning strikes are uncorrelated with the spread of COVID-19. However, this assumption may not hold unconditionally as lightning strikes could be correlated with geographical and climatic variables or the availability of infrastructures or services that might have an independent effect on COVID-19 outcomes. Thus, we control for a wide range of potential determinants of COVID-19, such as demographic factors and health infrastructure, to isolate the effect of 3G access on the spread of the disease.

We find that access to 3G Internet plays a vital role in reducing the transmission rate of COVID-19 in Indonesia. Our study shows that the number of COVID-19 cases is approximately 25% lower in areas where 3G Internet access is available. Our findings hold even when we control for other factors that could affect the virus's spread and consider the potential endogeneity of Internet access. One possible explanation for this result is that Internet access provides individuals with easy access to accurate information about the virus, such as how to prevent infection, where to get tested, and what to do if they become ill. This information can help people make informed decisions about their

behavior, leading to reduced transmission rates. Furthermore, we found that the effect of Internet access on reducing COVID-19 transmission is consistent across different data points during the COVID-19 period and across various waves of the pandemic. This suggests that access to information is essential in mitigating the effects of COVID-19 and that policies to promote Internet access could be an effective tool in controlling the spread of the virus.

Our study builds upon the extensive literature examining the crucial role of information dissemination in enhancing health awareness and facilitating positive outcomes in low- and middle-income countries. The transformative potential of accessible, timely, and relevant information has been highlighted, with evidence suggesting its ability to empower communities and individuals to make informed decisions regarding their health and well-being (Dupas 2011, Jalan and Somanathan 2008, Aker and Mbiti 2010). Previous studies have pinpointed several factors that contribute to an effective pandemic response. For instance, providing information on preventive measures has been demonstrated to overcome barriers to prevention among impoverished households in Africa, particularly in combatting malaria (Cohen and Dupas 2010). Contrarily, it has been found that empowering women and girls or improving education does not necessarily boost preventive behavior (Duflo, Dupas, and Kremer 2015; Behrman 2015). In the context of COVID-19, Chang et al. (2022) and Bargain and Aminjonov (2020) reported that countries with higher levels of political trust and social cohesion were more successful in executing effective pandemic response measures. Similarly, Mendolia, Stavrunova, and Yerokhin (2021) showed a strong correlation between government information about the pandemic's spread and human mobility, which subsequently aids in curbing the spread.

These studies collectively suggest that effective communication and transparency are pivotal in preventing and mitigating the spread of infectious diseases, such as COVID-19. Despite the underlying mechanism of these measures, often Internet access, our study is the first to assess the direct impact of Internet access on the spread of COVID-19 in low-resource settings.

By focusing on access to the Internet, we also contribute to the broader literature on the role of the Internet in improving health outcomes. A growing body of literature has begun to focus on the health implications of the Internet, which has been shown to increase the demand for healthcare services (Suziedelyte 2012, Amaral-Garcia et al. 2022), improve self-reported health status (Lam, Jivraj, and Scholes 2020; Hunsaker, Hargittai, and Micheli 2021), and affect psychological well-being (Golin 2022, McDool et al. 2020). In the context of developing countries, access to the Internet can lead to better health outcomes, particularly in low-income and rural areas. For example, Chen and Liu (2022) found that increased Internet access reduces the incidence of being overweight in the People's Republic of China (PRC) as it allows people to engage in more health-related activities, such as searching for health information and communicating with healthcare providers. Together, these studies suggest that access to the Internet can play a crucial role in improving health outcomes, particularly during the pandemic.

2 Data

We start by describing the various data sources we employed; more information on the variables and their sources can be found in Appendix Table B.1.

2.1 Main Data

COVID-19 Data

To conduct our analysis, we utilized the COVID-19 data provided by the Indonesian COVID-19 Task Force, which was established by the President of the Republic of Indonesia in March 2020 to manage, control, monitor, create, and implement strategic policies for the acceleration of the national COVID-19 response. The dataset includes a comprehensive range of measures at the local level, such as the weekly number of COVID-19 cases, incidence rate per 100,000 population, number of COVID-19 deaths among confirmed cases, and mortality rate per 100,000 population. In addition, we aggregated the weekly data at the regency level, covering the period from 1 March 2020 to 18 February 2023, and encompassing 514 second-level administrative divisions comprising 416 regencies and 98 cities located in 38 provinces of Indonesia.

In Figure A.1, we plot the aggregated number of cases at the national level using data from both the Government of Indonesia and Johns Hopkins University (Dong et al. 2022). Overall, both sources demonstrate a similar trend in the emergence of COVID-19 in Indonesia, particularly during the early stages of the pandemic. However, the local data used in our analysis excludes unidentified areas; therefore, the reported figures are lower than the national trend. Nonetheless, we conduct several robustness tests to ensure that this issue does not compromise the validity of our findings.

Internet Data

For our study, we utilized digital maps of global mobile network coverage provided by Collins Bartholomew's Mobile Coverage Explorer. The data contained information about signal coverage at a 1x1-kilometer grid level. The network operators worldwide submitted

this data to the Mobile Communications Association (GSMA), representing the interests of mobile network operators. First, we determine if a particular 1x1-kilometer grid had a 2G, 3G, or 4G signal. The spatial signal exposure distribution is then calculated as the average of all the 1x1 indicators (whether there was a signal) belonging to a regency.

In our analysis, we concentrate on the coverage of the 3G network. The adoption of 3G technology marks a significant milestone in the evolution of mobile communication, enabling users to access and interact with online content, including social media, in a much more efficient manner. The more basic 2G networks are limited to voice calls, SMS text messaging, and multimedia messages (MMS). The measure of Internet access adopted for our analysis is anchored in previous studies (Guriev, Melnikov, and Zhuravskaya 2021; Manacorda and Tesei 2020; Do, Gomez-Parra, and Rijkers 2023). We compute the proportion of areas within each regency with network access by evaluating the grid cells corresponding to that regency. This information is then aggregated to generate a composite picture of network access for the entire regency. It is worth noting that this approach does not provide a direct measure of Internet usage. Instead, it provides a measure of potential access. To augment our understanding of Internet quality within the regencies, we also consider 4G network coverage. 4G, as a technologically advanced successor to 3G, provides enhanced data speeds, reduced latency, and expanded network capacity, encouraging and facilitating more intensive Internet usage. This dual focus on accessibility and quality allows us to provide a nuanced analysis of Internet coverage in the context of our study.

Geographic Distributions and Unconditional Associations

Figure 3 presents the fluctuations in COVID-19 transmission rates alongside the extent of Internet coverage across diverse regencies in Indonesia. This visualization facilitates our understanding of the intricate relationship between these two variables in a pandemic scenario. The figure reveals substantial variations in COVID-19 transmission rates and Internet coverage across different areas. For instance, populated regions of the country, such as Jakarta and Surabaya, report significantly higher infection rates than their less-populated, rural counterparts, as evidenced by the number of confirmed cases and deaths. Interestingly, a similar trend is observed in mobile broadband coverage, where urbanized regencies demonstrate higher mobile broadband coverage. Notably, access to 3G is widespread in highly developed regions such as Sumatra and Java, while Internet coverage in the Eastern areas such as Maluku and Papua is relatively low. While the figure indicates substantial variations in COVID-19 transmission rates and Internet coverage across regions, it is worth noting that various other factors, such as access to healthcare facilities, living conditions, and public health measures, can confound this relationship. For example, a more educated local population will likely have better Internet access but is also expected to comply with instructions.

2.2 Covariates Data

Demographic Data

To account for such demographic characteristics, we aggregate data at the regency level from multiple sources. First, we draw on our COVID-19 database, which provides information on population density and gender ratio at the regency level. Second, we

supplement this data with several key indicators from the 2010 Indonesian population census conducted by Statistics Indonesia in May and June 2010, which surveyed 237.6 million people. Specifically, we include the proportion of the population aged 65 and older, the proportion of individuals without any formal education, the proportion of individuals with graduate degrees, the average household size, and the proportion of the population living in rural areas. Furthermore, we follow Bazzi et al. (2019) and Alesina and La Ferrara (2005) to calculate the ethnic fractionalization and polarization at the regency level.¹

To consider the characteristics of the workforce in the pre-COVID-19 period, we utilize data from the National Labor Force Survey (SAKERNAS) conducted by the National Statistic Board in 2019. SAKERNAS is a survey designed specifically to gather employment data, providing insights into the general state of employment and employment structure changes in Indonesia over time, and is representative at the province level (Suryadarma, Suryahadi, Sumarto 2007). To measure employment, we focus on several indicators, including the proportion of workers who have a long-travel commute (more than 1 hour) as well as those who use public transportation. Additionally, we construct an index to assess the ability to work from home (also known as telework ability) by sector, following recent literature (Dingel and Neiman 2020, Asian Development Bank 2021).

Health Data

The health data utilized in our analysis are derived from Open Street Map (OSM), an open-source, collaboratively constructed global mapping project that provides detailed

¹ The fractionalization and polarization indices are calculated using the following formulas: $fractionalization = 1 - \sum_{j=1}^J \pi_j^2$ and $polarization = 4 \sum_{j=1}^J \pi_j^2 (1 - p_j)$, where p_j is the share of the ethnic group j .

geographic data. The OSM data for Indonesia are instrumental in quantifying the number of healthcare facilities across various geographic locations, specifically clinics, and hospitals. Clinics are defined as health facilities where outpatient medical care is provided, often by general practitioners or specialists for family or internal medicine. Conversely, hospitals are more extensive facilities that provide a broader range of services, including inpatient care, specialized surgeries, and emergency services. This dataset offers a comprehensive spatial distribution of healthcare infrastructures across the nation, thus enabling the identification of potential disparities in the provision of health services. In conjunction with the OSM data, we also incorporate local healthcare spending data at the regency (or city) level, available from 2017 to 2021.

Economic Indicators

To estimate local economic activity in Indonesian districts, we utilize satellite nightlight data from the Visible Infrared Imaging Radiometer Suite (VIIRS) administered by the National Oceanic and Atmospheric Administration (NOAA). This methodology has gained popularity in economic research as a reliable proxy for growth outcomes (Hodler and Raschky 2014; Henderson, Storeygard, and Weil 2012) and was found to be superior to other economic variables in some circumstances (Martinez 2022).² We calculate the nightlight density for all Indonesian districts by aggregating satellite images from daily grids to yearly data.³

² In the context of Indonesia, Gibson et al. (2021) find a positive relationship between district-level VIIRS data and gross domestic product (GDP).

³ Atmospheric conditions may impact the ability of satellite sensors to capture night lights. We follow the Copernicus program's recommendation to exclude results from pixels with above 10% cloud fraction by performing cloud masking to address this. For more details: *Copernicus*. 2020. "Flawed Estimates of the Effects of Lockdown Measures on Air Quality Derived from Satellite Observations." March 26. <https://atmosphere.copernicus.eu/flawed-estimates-effects-lockdown-measures-air-quality-derived-satellite-observations?q=flawed-estimates-effects-lockdown-measures-air-quality-satellite-observations>.

We add the recently made available sub-national human development index compiled for Indonesia in 2019 on the regency level, capturing economic status, human well-being, and flourishing more broadly.⁴

Weather Data

We obtain weather data from ERA5, which is the fifth generation of reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). Using reanalysis data has several benefits for our study. Firstly, weather stations' spatial and temporal coverage is often limited in many developing countries. In contrast, reanalysis data covers a larger geographical area and is available over a more extended period. Secondly, reanalysis data may resolve issues related to weather data, such as endogeneity concerns associated with weather stations placement and variations in the quality and quantity of data collection, as noted in previous studies (Auffhammer et al. 2013, Donaldson and Storeygard 2016). ERA5 incorporates information from various sources, including ground stations, satellites, weather balloons, and climate models, to provide weather data from 1979 onwards. The data has a high spatial resolution of 31 kilometers (km) and has been standardized to a regular latitude-longitude grid of 0.25 degrees. For this study, we use the yearly temperature (measured in Celsius) and precipitation (measured in millimeters) data, which we aggregate at the regency level for Indonesia using the inverse-distance weighting approach (Deschenes and Greenstone 2011).

As an instrument for Internet coverage, we employ data on lightning strikes sourced from the World Wide Lightning Location Network (WWLLN) dataset (Kaplan and Lau

⁴ The sub-national indexes are still relatively rare. An alternative approach for other contexts, a recent machine learning approach using satellite data, have been proposed (Sherman et al. 2023).

2021). This dataset provides detailed grid-level data of lightning strikes, with a precision of $0.5^\circ \times 0.5^\circ$ per grid. We then aggregate these data from the grid level up to the regency level for Indonesia. Our measure of lightning strike is the mean stroke power in megawatts (MW), aggregated at the yearly basis. This measure provides a unique perspective on the intensity and energy of lightning activity, which we hypothesize to be a relevant proxy for assessing Internet coverage in the region.

3 Empirical Model

We aim to investigate the effects of Internet access, proxied by pre-pandemic (t_0) 3G availability ($G3access_{r,t_0}$), on reducing COVID-19 cases and deaths at the regency level r in Indonesia. We adopt the methodology proposed by Kunz and Propper (2022) to assess the over-time association between COVID-19 outcomes and pre-pandemic access to the Internet, such that

$$E(y_{r,t}|X) = \exp(\alpha_t + \tau_t G3access_{r,t_0} + x'_{r,t_0} \beta_t + \delta_{p,t}) \quad (1)$$

where $y_{r,t}$ is the cumulative cases (or deaths) in regency (or city) r in month t , adjusted by 10,000 population. We control for a set of covariates (x'_{r,t_0}), all measured on the regency level and before the pandemic's start. These include demographic factors, health facilities, economic activities, and weather conditions. Additionally, we include province fixed effects (δ_p) to control for unobservable factors affecting our outcomes at the province level (the main level of local policymaking). We employ robust standard errors to account for potential heteroskedasticity when estimating repeated cross-sections and clustered at the regency level when estimating pooled models.

In our primary analysis, we concentrate on the last date in our dataset (i.e., 18 February 2023) and execute a single cross-sectional regression. However, we also estimate Equation (1) for each month separately to illustrate the time trends in the association between Internet access and COVID-19 outcomes. We utilize a Poisson regression model as our primary specification, acknowledging the heavily skewed nature of the cases (Figure A.2). To ensure the robustness of our findings, we evaluate alternative model specifications, including log-transformed OLS and negative binomial regressions. We ultimately choose the Poisson model owing to its beneficial properties, such as being part of the linear, exponential family, demonstrating robustness to misspecification, not necessitating ad-hoc transformation, and avoiding issues related to incidental parameter prediction (Silva and Tenreyro 2006 discuss this in detail).

Like any other infrastructure, the expansion of mobile network coverage is likely influenced by endogenous factors. For example, providers of network services tend to prioritize areas with high economic activity and potential demand. However, this trend may be linked to other factors that may, in turn, determine the spread of the pandemic. As a result, simple conditional associations between mobile phone penetration and COVID-19 spread might not correspond to the causal impact. To address this issue, we estimate the following first stage of the Poisson-IV model to mitigate the issue of endogeneity:

$$G3access_{r,t_0} = \beta + \gamma_1 f(Lightning_{r,t_0}) + \gamma_2 temperature_{r,t_0} + \gamma_3 precipitation_{r,t_0} + x'_{r,t_0} \beta + \delta_p + \epsilon_{r,t_0} \quad (2)$$

where the instrumental variable, $Lightning_r$, is measured by the average lightning stroke power at the rency level. Our empirical strategy is thus in line with a recent study using the Poisson-IV estimator (Graff Zivin et al. 2023).

We now discuss the validity of the instrument employed in our analysis. A good instrumental variable should satisfy several conditions, including exogeneity, relevance, and exclusion. Regarding the exogeneity condition, lightning strikes are a natural phenomenon that occurs independently of COVID-19 spread, making them an exogenous factor in relation to our outcome of interest. Additionally, it is important to note that we measure lightning strikes during the pre-pandemic period, further ensuring the exogeneity of our instrument.

In terms of the relevance condition, our instrument is strongly correlated with Internet access, as supported by previous studies (Andersen et al. 2012; Guriev, Melnikov, and Zhuravskaya 2021; Manacorda and Tesei 2020; Do, Gomez-Parra, and Rijkers 2023). Specifically, lightning strikes can cause significant damage to digital infrastructure, leading to higher costs associated with digital technology diffusion. This correlation is particularly relevant in areas with a higher frequency of lightning strikes, where challenges in setting up and maintaining Internet infrastructure may arise. Furthermore, it is worth noting that this IV is ideally suited to our context, as to countries around the equator, as much of the IV's variation is from this region (Figure B.1).

However, there is the possibility of lightning strikes affecting other infrastructure that could indirectly influence the spread of COVID-19 during the pandemic. While the exclusion condition is not directly testable, we have taken measures to control for potential confounding factors, such as weather conditions, humidity, the number of cell

towers, and economic activities in our models. These additional controls help to mitigate the potential indirect effects of lightning strikes on COVID-19 spread by capturing other relevant factors that could mediate this relationship.

Finally, we modify Equation (1) by including interaction terms between Internet access and a range of factors to examine the heterogeneous effects of Internet access on COVID-19 transmission.

$$E(y_{r,t}|X) = \exp(\alpha_t + \tau_t G3access_{r,t_0} + \tau_t^x G3access_{r,t_0} \times 1[x \geq med_x]) + x'_{r,t_0} \beta_t + \delta_{p,t} \quad (3)$$

In this equation, $1[x \geq med_x]$ represents an indicator for whether variable x is larger or equal to the median. We concentrate on the primary hypothesis concerning how Internet access might affect the spread of COVID-19 at the regency level. For the heterogeneity analysis, we employ both the Poisson regression as in Equation (1) and the analogous Poisson-IV regressions, using $f(Lightning_{r,t_0}) \times 1[x \geq med_x]$ as an additional instrument. We focus on variables deemed important in the literature cited here, such as education level, living areas, health facilities, economic activities, and labor force characteristics.

4 Results

Main Findings

Table 1 presents results from Equation (1) for increasing sets of covariates, providing a comprehensive analysis of the role of Internet access in reducing COVID-19 transmission. In column 1, the unadjusted association is large, negative, and statistically highly significant. This finding suggests that Internet access, proxied by 3G availability, is

indeed associated with a reduction in COVID-19 cases at the regency level in Indonesia. However, the association slightly reduces when including province-level fixed effects, which account for policy-making differences (column 2).

Subsequently, we add covariates likely to affect the spread of COVID-19. In doing so, we aim to control for potential confounding factors and isolate the specific effect of Internet access on pandemic outcomes. Columns 3 to 7 results demonstrate that the association between Internet access and COVID-19 transmission remains robust even when accounting for various demographic, healthcare, economic, ethnic, and labor force characteristics. The most substantial drop in the association occurs when including demographic variables, after which the association remains relatively stable. The pseudo R^2 increases considerably, particularly when the analysis employs fixed effects and demographic variables.

A few of these variables contain missing values, which reduces the sample size. To address this issue, we include these variables either by imputing zeros along with indicators for missing values (column 8) or using the multiple imputation method proposed by Rubin (1996) with 99 random draws (column 9). Both approaches yield nearly identical results, confirming the robustness of our findings. Our preferred model is column 8, and we will focus on this specification in the remainder of the text. By accounting for missing data in our analysis, we ensure a more comprehensive assessment of the relationship between Internet access and COVID-19 transmission, further enhancing the validity and generalizability of our conclusions.

In terms of interpretation, we demonstrate that having access to 3G Internet is associated with a substantial reduction in COVID-19 cases by approximately 25% using

our preferred estimation in column 7 of Table 1. The magnitude of the effect is noteworthy, particularly in the context of a developing country such as Indonesia, where resources for public health interventions may be limited. Furthermore, the magnitude of the effect observed in our study is particularly relevant compared to the effectiveness of other non-pharmaceutical interventions (NPIs) in reducing COVID-19 transmission. While the impact of specific NPIs varies across studies, the 25% reduction associated with Internet access is comparable to, or even greater than, the effects reported for some widely implemented measures such as social distancing, mask-wearing, and travel restrictions (VoPham et al. 2020, Leech et al. 2022, Kwok et al. 2021). For example, VoPham et al. (2020) show that higher social distancing was associated with a 29% reduction in COVID-19 incidence.

These results have important policy implications, especially for developing countries that face challenges in containing the spread of infectious diseases like COVID-19. Our findings suggest that improving Internet access can reduce disease transmission, as it facilitates better dissemination of health-related information, enables remote work and education, and promotes telemedicine services, which collectively reduce the need for physical interaction and help limit the spread of the virus.

Figure 4 supports our main findings by consistently demonstrating the effects of Internet access on COVID-19 transmission throughout the pandemic. Furthermore, the stability of these effects over time suggests that factors such as vaccine distribution and potential data inconsistencies at the pandemic's beginning are unlikely to significantly influence the observed relationship between Internet access and COVID-19 outcomes.

Notably, the stable estimates over time indicate that the benefits of Internet access in mitigating the spread of the virus have persisted throughout the various stages of the pandemic. This consistency reinforces the importance of digital connectivity as a crucial factor in public health strategies, both during the initial response to an outbreak and in ongoing efforts to control and manage the spread of infectious diseases. As the pandemic evolves and new challenges arise, such as new variants and changes in public health guidelines, the persistent effects of Internet access on reducing COVID-19 transmission underscore its enduring significance in supporting effective public health interventions.

Robustness

Table 2 demonstrates that the effects presented in our main analysis are highly robust to various specifications and alternative approaches. These include Log-OLS (column 2), Negative Binomial regression (column 3), alternative measures of 3G access (imputed versus not imputed) (columns 4 and 5), not using population weights (column 6), and imputing the outcomes for areas that did not report any cases (columns 7 and 8).⁵ Our preferred specification is arguably the most conservative among these approaches. Using the log-transformed OLS approach is similar in terms of the marginal effect. The robustness of our findings across various specifications and alternative methods strengthens our confidence in the highly stable association between Internet access and the spread of COVID-19.

Speed or Access

Table 3 presents the results for different Internet speeds, including 2G, 3G, and 4G. In the context of the pandemic, these differences in capabilities and data speeds may have

⁵ Columns 7 and 8 differ as for some, we observe province and population. For the remainder, we impute population in column 8.

significant implications for the effectiveness of various non-pharmaceutical interventions, such as remote work, online learning, and the dissemination of public health information. While 2G primarily supports basic services such as SMS and voice calls, 3G enables mobile Internet access, and 4G offers improved data speeds and enhanced mobile Internet experiences. Access to higher-speed Internet, such as 3G and 4G, allows individuals and communities to better adapt to the challenges posed by the pandemic and adhere to public health guidelines while maintaining social and economic activities. Our preferred measure, 3G, exhibits the most substantial relationship with the pandemic experience. When we include all three types of Internet access simultaneously, 2G loses its significance, dropping close to zero, and appears less relevant regarding its impact on COVID-19 transmission. Conversely, 4G demonstrates a similar effect to our main measure, 3G, although its association with the pandemic experience is again weaker.

Another aspect worth considering is the potential non-linear effect of Internet access on COVID-19 transmission. This may be important because the relationship between Internet access and COVID-19 outcomes could be characterized by diminishing returns or threshold effects, where the impact of increased Internet access on transmission rates plateaus or even reverses beyond a certain point. For instance, very high levels of Internet access could exacerbate the spread of misinformation or contribute to complacency in following public health guidelines, ultimately leading to adverse effects on COVID-19 transmission. However, our analysis does not find clear evidence of non-linear effects (Table A.1). Including a second-order polynomial term does not reveal a non-linear relationship. This may be due to data limitations, given that we only have 454 observations and considerable covariance among the variables. When we use an

indicator variable instead of the continuous 0-to-1 variable, the results suggest that higher Internet exposure is more beneficial in reducing COVID-19 transmission. However, the marginal effect remains similar (25%), consistent with the overall association observed in our main analysis.

Placebo

To further validate our main specification, we examine an alternative measure that we have access to, health care spending at the regency level, available from 2017 to 2021. Figure 5 presents this as an alternative outcome, specified analogously to our main model, with the exception that we drop the log health care spending from the set of covariates but include all other variables (as confirmed in Table 1, this measure has minimal impact on our main specification). Our analysis demonstrates that conditional on the extensive set of controls, there is no significant difference between high and low Internet exposure regions in per-population healthcare spending.

This placebo test provides further evidence supporting the validity of our main findings, as the lack of association between Internet access suggests that, conditional on the extensive sets of controls, the areas are broadly similar.

5 Results Using Instrumental Variables

Addressing the potential endogeneity of Internet access is crucial to our analysis. Specifically, we are concerned about the possibility that the level of Internet access in a regency may be correlated with unobservable characteristics that also influence COVID-19 transmission. For instance, regions with high Internet access might be more urbanized, have better healthcare infrastructure, or exhibit different social behaviors, all of which can

independently affect the spread of the virus. If these factors are not adequately controlled for, our estimates of the effect of Internet access on COVID-19 transmission could be biased.

To mitigate this concern, we implement an instrumental variable (IV) approach using the frequency of lightning strikes preceding the pandemic (December 2019)—contemporaneously to our measure of mobile phone coverage—as an instrument. The logic behind this choice is that lightning strikes can disrupt Internet connections, thereby serving as a source of exogenous variation in Internet access (Guriev, Melnikov, and Zhuravskaya 2021; Manacorda and Tesei 2020). It is important to note, however, that for the validity of our IV approach, we must control for general weather conditions, as these could be correlated with both lightning frequency and COVID-19 outcomes.⁶

Table 4 presents the results of our IV analysis. Column 1 differs from our main results due to the inclusion of weather controls such as temperature and rainfall. While we do not expect these factors to influence COVID-19 cases directly, they are essential for the validity of our IV approach. In line with this expectation, the main coefficient of interest (the effect of Internet access) is almost indistinguishable from our original estimates (Table 1). Finally, column 2 presents the reduced form regression results, showing a significant positive association between lightning strikes and COVID-19 cases, confirming our instrument's relevance.

Column 3 presents the second-stage regression results in Panel A and the corresponding first-stage results in Panel B. First, we find a strong and negative relationship between lightning strikes and Internet access (Panel B). The Cragg-Donald

⁶ Noted above we employ the Poisson-IV estimator as described in detail by Graff Zivin et al. (2023). Still, we also confirm that our results are robust to using log-transformed linear two-stage least squares (2SLS).

Wald F statistic is 70.386, which is well above the common rule-of-thumb threshold of 10, suggesting that our instrument is not weakly identified.⁷ In the second-stage of the IV model, we continue to observe the effect of Internet access on COVID-19 transmission increases when instrumented by lightning strikes, although the standard error also grows as expected in an IV approach. This similarity implies that, if anything, our Poisson estimates provide a lower bound for the impact of Internet access on the spread of COVID-19.

Magnitude

The implied magnitude of the effects is, therefore, between 25% and 50% reduction in local COVID-19 spread. Aggregating this across areas, accounting for the unequal distribution of people across regencies, implies a standard deviation increase in Internet exposure, a nationwide reduction by 1.2 and 2.5 million cases, essentially bringing Indonesia closer to its peer countries, Japan, the Philippines, and Thailand (Figure 1).

Some or Full Exposure

Next, we ask whether some Internet in the region, bringing essential information to the community or wide-spread mobile coverage, is generating more considerable case incident reductions. In other words, we assess where the average marginal effect is the largest in the distribution. To this end, we calculate the marginal effect and average across percentiles of the Internet exposure, both for the Poisson and Poisson-IV results.

Figure 6 presents the implied effects. Two observations are noteworthy. First, despite being slightly larger in the distribution's lower parts, the overall benefit of mobile exposure is relatively stable. Second, note that the bottom four percentiles are clustered together

⁷ Similarly, the Anderson-Rubin Wald test yields a statistic of 12.28 (p-value of 0.0005), which further supports the credibility of our instrument and indicates a low likelihood of weak identification.

as they have 0, showing the substantial unequal distribution of mobile access exposure. Comparing the raw and the IV results confirms a similar pattern across the exposure distribution.

Heterogeneity

Our analysis thus far has established a robust and consistent relationship between Internet access and reducing COVID-19 transmission. Next, we ask whether some areas benefit more from mobile exposure. Finally, we assess the differential effects of Internet access on COVID-19 transmission across various dimensions, including the educational level of the population, demographic factors such as household size, the nature of living areas, the presence of health facilities, economic activities (proxied by nightlight), human development index, ethnic fractionalization and polarization, and labor force characteristics. Figure 7 depicts the coefficient estimates of the interactions (Tables A.3 and A.4 for coefficient estimates).

Two findings emerge as particularly notable. First, our analysis unveils a noteworthy distinction: the effects of Internet access on COVID-19 transmission appear less beneficial in rural areas or those with a higher concentration of agricultural activities. Specifically, an increase in 3G Internet access is associated with a more extensive spread of the disease in these areas compared to their urban counterparts. Several factors might explain this counterintuitive finding. Rural areas often need help with lower-quality Internet connections, limiting the efficiency and effectiveness of digital solutions in mitigating COVID-19 transmission. The predominance of agricultural activities might make remote work less feasible, as many agrarian tasks require physical presence. Moreover, these

regions might also be more prone to digital illiteracy, leading to less effective use of Internet resources.

The second notable finding pertains to the differential effects observed in areas with varying telework capabilities. Regions with a higher proportion of the population able to work from home demonstrate stronger evidence of 3G access playing a role in reducing the transmission of the virus. During the pandemic, the capacity for telework has been crucial in containing the spread of COVID-19. Working from home mitigates the need for commuting and in-person interactions, thereby lowering the risk of virus transmission. Furthermore, telework-compatible jobs often necessitate a higher level of digital literacy, which may also foster greater awareness and adherence to public health guidelines disseminated through digital channels. Given that the trend towards telework shows no signs of diminishing, even in a post-pandemic context (Aksoy et al. 2022), our findings suggest that policies promoting telework and improving digital skills could constitute a vital component of strategies to combat COVID-19 and future pandemics, particularly in regions with significant telework potential.

6 Conclusion

We assessed the relationship between Internet coverage and COVID-19 transmission, specifically within the context of Indonesia. Utilizing a unique dataset at the subnational level, we ascertain that access to 3G broadband Internet plays a pivotal role in reducing the transmission rate by approximately 25%. This underscores the significant role that technology, particularly digital connectivity, plays in mitigating the impact of the pandemic. Our results remain robust across diverse specifications and identification strategies,

notably including lightning strikes as an exogenous shock to Internet quality. The stable effects observed over time emphasize the enduring relevance of digital connectivity in public health strategies. It also accentuates the potential long-term benefits of prioritizing investments in digital infrastructure to enhance the resilience of communities to infectious disease outbreaks and other public health crises.

Our study contributes to the existing literature on the effects of digital technology on health outcomes, particularly within the context of developing countries. Here, detailed data during the pandemic is often scarce. We also shed light on the potential mechanisms underlying the observed relationship, such as using telemedicine to promote health and prevent the spread of the virus.

From a policy perspective, our findings provide insights for preventing and managing future pandemics. Policymakers should reassess the investments in digital infrastructure and literacy programs to ensure equitable access to technology, promoting public health in emergencies. Our analysis does come with certain limitations that should be acknowledged. First, there might be bias due to the challenges of defining 3G coverage boundaries, which could introduce attenuation bias in our estimates. Future research could utilize more accurate and granular data on Internet coverage to refine these estimates. Additionally, the exploration of how digital connectivity impacts mobility behaviors could provide a more nuanced understanding of how Internet access influences the spread of diseases like COVID-19, particularly if more detailed subnational data becomes available. Second, the reporting of COVID-19 cases might be correlated with pre-pandemic Internet quality, suggesting that our estimates provide a lower bound for the actual effect of Internet access on COVID-19 transmission. Despite these limitations,

our findings underscore the potential role of digital infrastructure in public health responses to pandemics and other health crises.

In conclusion, our study underscores the vital role of technology in tackling the COVID-19 pandemic and advancing public health in the digital age. The importance of digital connectivity in today's world cannot be overstated, and our research calls for a renewed focus on this essential facet of modern life in future public health strategies.

TABLES AND FIGURES

Table 1: Associations between G3 Internet Exposure and COVID-19 Cases: Late Pandemic Stage

Dependent variables: Cumulative cases by 10T population, 18 Feb 2023									
	Adding covariates							Imputation	
	Raw	+Prov. FE	+Demo- graphics	+Health facilities	+Econ. status	+Ethnic comp.	+Labor force	Set 0	via: Multiple
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Internet exposure	-1.495 (0.222)	-1.125 (0.417)	-0.651 (0.323)	-0.606 (0.315)	-0.611 (0.285)	-0.690 (0.290)	-0.787 (0.313)	-0.630 (0.255)	-0.630 (0.255)
Semi-elasticity (1sd)	-0.32	-0.28	-0.20	-0.19	-0.19	-0.21	-0.23	-0.20	
<i>N</i>	454	454	454	345	323	321	321	454	454
Mean dep.	0.50	0.50	0.50	0.40	0.42	0.42	0.42	0.50	0.50
SD dep.	1.45	1.45	1.45	0.87	0.89	0.89	0.89	1.45	1.45
<i>pR</i> ²	0.05	0.41	0.51	0.37	0.38	0.38	0.38	0.53	
Province FE		✓	✓	✓	✓	✓	✓	✓	✓
Demographics			✓	✓	✓	✓	✓	✓	✓
Health facilities				✓	✓	✓	✓	✓	✓
Economic status					✓	✓	✓	✓	✓
Ethnic composition						✓	✓	✓	✓
Labor force							✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects, GSMA = Mobile Communications Association, SD = standard deviation.

Notes: This table presents coefficients estimates from equation (1), of regressions of cumulative COVID-19 cases per 10,000 population on the regency level (18 February 2023) and increasing various sets of covariates all measure before the pandemic begins, for a description of the covariates (Table B.1). At the bottom, we present pR^2 pseudo (ml) R^2 , the mean and standard deviation of the outcome variable, and the semi-elasticity for 1 sd change in internet exposure, that is $(\exp(\tau) - 1) * sd(\text{Internet exposure})$. Column (1) depicts the raw association, Column (2) adds province (38) fixed effects, three demographic variables (population density, population, male-female ratio, the share of the population aged 65 and older, the share of people without any education, the share of people with graduate degrees, log household size, rural area), (4) adds health infrastructure measures (number of clinics, number of hospitals, and log of health care spending), (5) adds economic indicators (second order polynomial of nightlight, sub-national human development index - score), (6) ethnicity (ethnic diversity, and polarization), and (7) labor force variables (share of workers able to telework, the share of workers with a long distance (>1hour) commute, and that use public transportation, and the share working in agriculture). The final two columns replace missing values in covariates with 0 and an indicator for missing values (8), and (9) implements the multiple imputation approach by Rubin (1996). All regressions are weighted by population and use robust standard errors.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table 2: Testing Additional Robustness

Dependent variables: Cumulative cases by 10T population, 18 Feb 2023								
	Base	Log-cases OLS	Neg. Bin.	Alt. 3G measure		Without weights	Missing Outcomes	Impute All
	(1)	(2)	(3)	Plain	Imputed	(6)	(7)	(8)
Internet exposure (3G)	-0.630 (0.255)	-0.365 (0.200)	-0.630 (0.255)			-1.005 (0.226)	-0.627 (0.255)	-0.627 (0.255)
Internet exposure (3G- MCE)				-1.090 (0.491)				
Internet exposure (3G-MCE)-imputed					-1.126 (0.496)			
Semi-elasticity (1sd)	-0.20	-0.13	-0.20	-0.13	-0.13	-0.26	-0.20	-0.19
<i>N</i>	454	454	454	365	454	454	465	510
Mean dep.	0.50	0.50	0.50	0.60	0.50	0.50	0.49	0.45
SD dep.	1.45	1.45	1.45	1.60	1.45	1.45	1.43	1.37
pR^2	0.53		0.46	0.54	0.53	0.57	0.53	
Province FEs	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓	✓	✓	✓	✓
Economic status	✓	✓	✓	✓	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓	✓	✓	✓	✓
Labor force	✓	✓	✓	✓	✓	✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects, GSMA = Mobile Communications Association, OLS = ordinary least squares, SD = standard deviation.

Notes: Table 1 column (8) presents the main model, see notes therein, represented in column (1). Column (2) presents an OLS regression on the logged outcome measure—the marginal effect is adjusted via $\exp(\tau) - 1$. Column (3) alternatively presents a negative binominal model, (4) uses the alternative exposure measure and (Mobile Coverage Explore - MCE) is sourced directly from the network operators and thus incurs gaps in coverage, which we impute with 0 and add missing indicator in (5). Column (6) drops the population-weighting and (7) and (8) impute areas with missing observation in the outcome (all variables, respectively) with 0.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table 3: Association between Different Internet Speeds and Potential Non-Linear Effects

Dependent variables: Cumulative cases by 10T population 18 Feb 2023				
	Base	2G	4G	Jointly
	(1)	(2)	(3)	(4)
Internet exposure (3G)	-0.630 (0.255)			-0.530 (0.319)
Internet exposure (2G)		-0.366 (0.294)		0.104 (0.296)
Internet exposure (4G)			-0.472 (0.202)	-0.372 (0.200)
Semi-elasticity (1sd)	-0.20	-0.09	-0.13	
[1em] <i>N</i>	454	454	436	436
Mean dep.	0.50	0.50	0.52	0.52
SD dep.	1.45	1.45	1.47	1.47
pR^2	0.53	0.53	0.53	0.54
Province FEs	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓
Economic status	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓
Labor force	✓	✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects, GSMA = Mobile Communications Association, SD = standard deviation.

Notes: The Table presents coefficients analogous to Table 1-Column (8)—represented in Column (1). Column (2) replaces our main measure with 2G exposure, and (3) with 4G, Column (4) estimates the model jointly.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of February 18th, 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table 4: IV Results

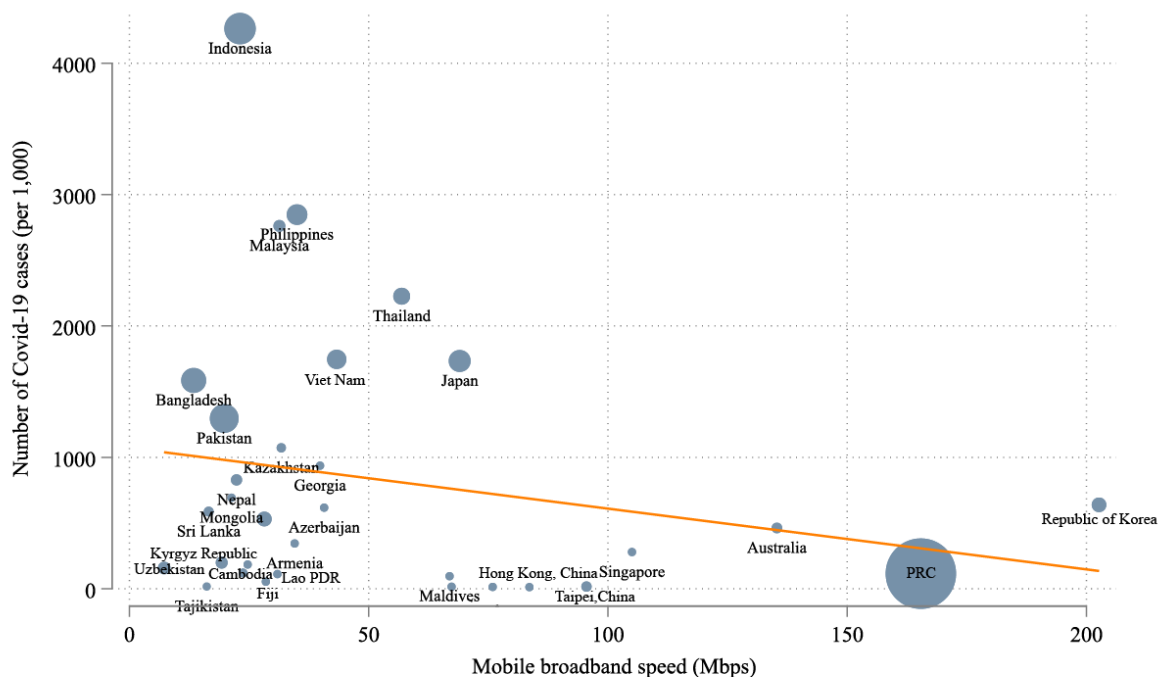
Dependent variables: Cumulative cases by 10T population, 18 Feb 2023			
	Main	Reduced form	IV 5 km rad. dec 2019
	(1)	(2)	(3)
<i>Panel A. Cases</i>			
Internet exposure (3G)	-0.660 (0.257)		-1.440 (0.394)
Lightning strike frequency (5 km)		7.919 (2.429)	
Semi-elasticity (1sd)	-0.20		-0.32
<i>Panel B. First stage</i>			
Lightning (5 km, Dec 2019)			-4.050 (0.518)
<i>N</i>	454	454	454
Difference per million for 1sd increase	-1.66		-2.50
Fstat			61.05
Province FEs	✓	✓	✓
Demographics	✓	✓	✓
Health facilities	✓	✓	✓
Economic status	✓	✓	✓
Ethnic composition	✓	✓	✓
Labor force	✓	✓	✓
Weather controls	✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects, GSMA = Mobile Communications Association, km = kilometer, SD = standard deviation.

Notes: The Table presents coefficients estimates from equation (1) using IV-Poisson with control function (2). Column (1) adjusts Table 1 Column (8) by adding weather covariates. Column (2) shows the reduced form of lightning strikes in the 5 km radius in December 2019, contemporaneously with the 3G mobile exposure. The bottom of the Table predicts the difference in cases for one std. Deviation in internet exposure and the F-statistic of the first stage.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure 1: Mobile Broadband Speed and COVID-19 Cases, Asia and the Pacific

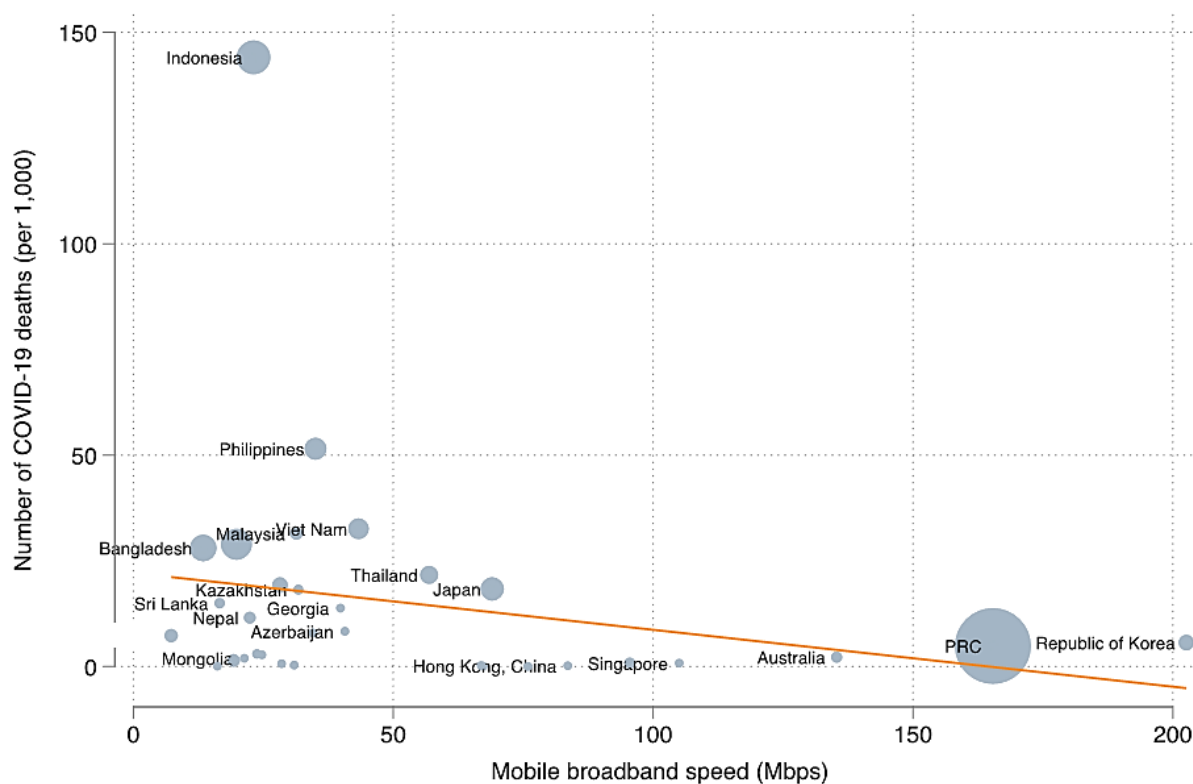


COVID-19 = coronavirus disease, Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.

Notes: COVID-19 data were measured as of 1 January 2023, and adjusted for population. Mobile broadband speed (in Mbps) was measured in 2020.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile broadband speed at country-level from <https://worldpopulationreview.com/country-rankings/internet-speeds-by-country>

Figure 2: Mobile Broadband Access and COVID-19 cases, Indonesia

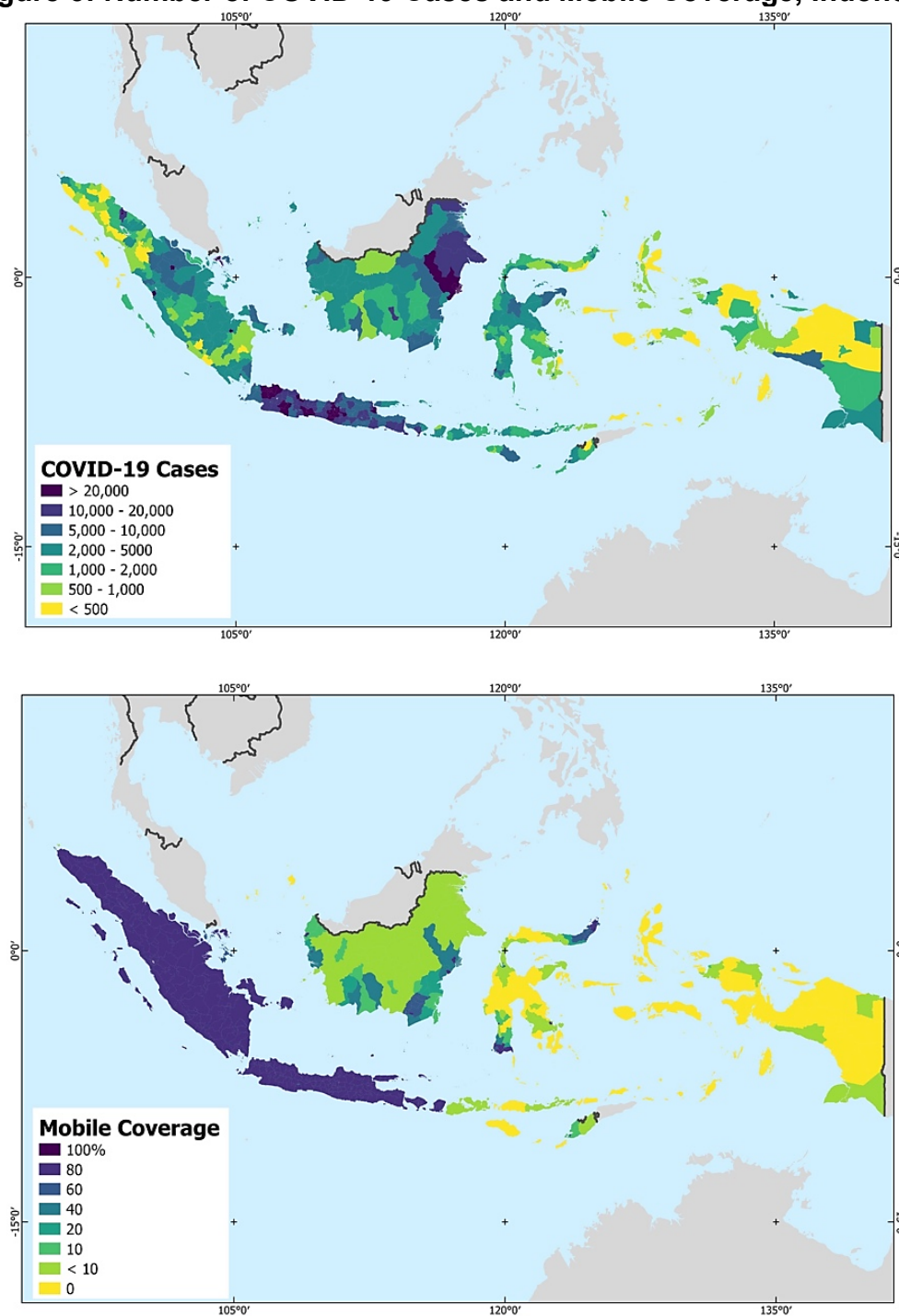


COVID-19 = coronavirus disease, PRC = People's Republic of China.

Notes: COVID-19 data were measured as of February 18th, 2023, and adjusted for population. Mobile broadband speed (3G access) was measured in 2019.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile broadband speed from <https://worldpopulationreview.com/>.

Figure 3: Number of COVID-19 Cases and Mobile Coverage, Indonesia



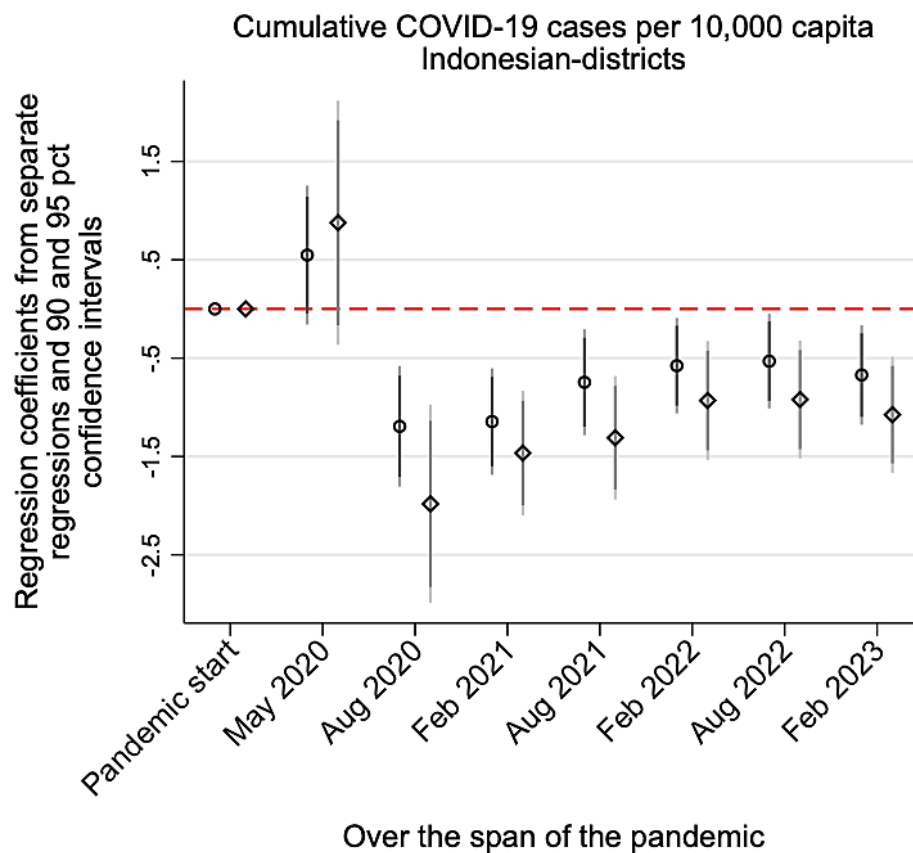
COVID-19 = coronavirus disease, GSMA = Mobile Communications Association.

Notes: This figure shows cumulative COVID-19 cases on 18 February 2023 (top) and 3G mobile network exposure (bottom) across regencies in Indonesia.

The boundaries, colors, denominations, and any other information shown on this map do not imply, on the part of the Asian Development Bank, any judgment on the legal status of any territory, or any other endorsement or acceptance of such boundaries, colors, denominations, or information.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile internet data from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure 4: Association between Number of COVID-19 Cases and Deaths, and Mobile Coverage, Indonesia throughout Pandemic

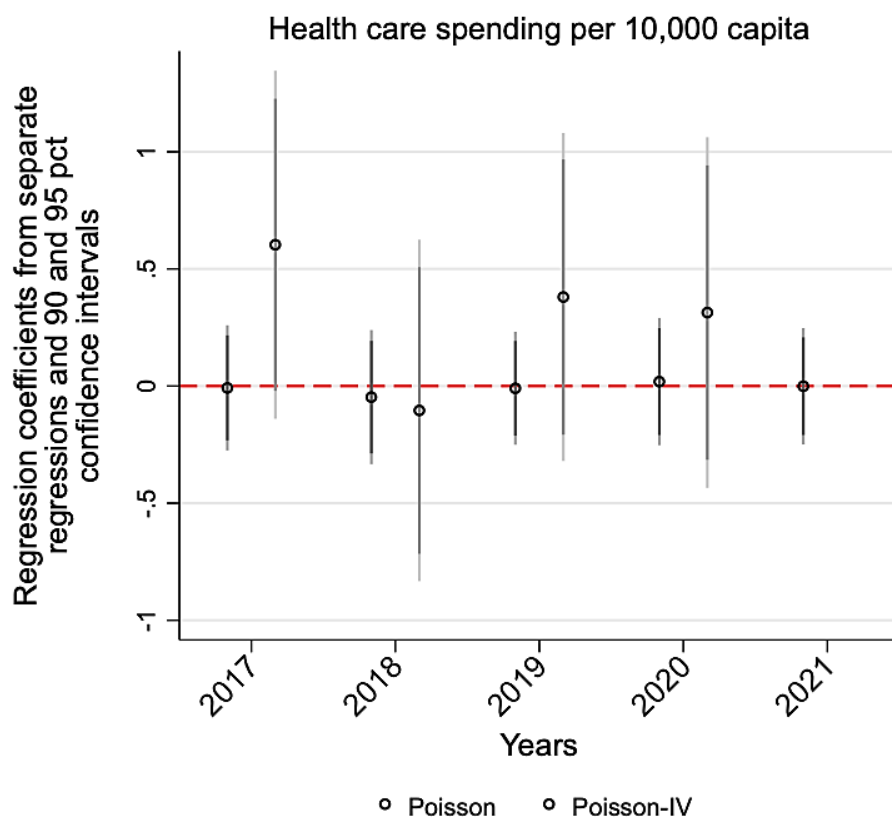


COVID-19 = coronavirus disease, GSMA = Mobile Communications Association.

Notes: The figure presents regression coefficients of regressions (90-dark and 95-light level confidence intervals) presented in Table 1 (see notes therein) column 8, separately for various dates throughout the pandemic covering various waves of new COVID-19 variants. Round markers depict cases and squares depict deaths.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure 5: Placebo Test—Local Health Care Spending by 10,000 Population

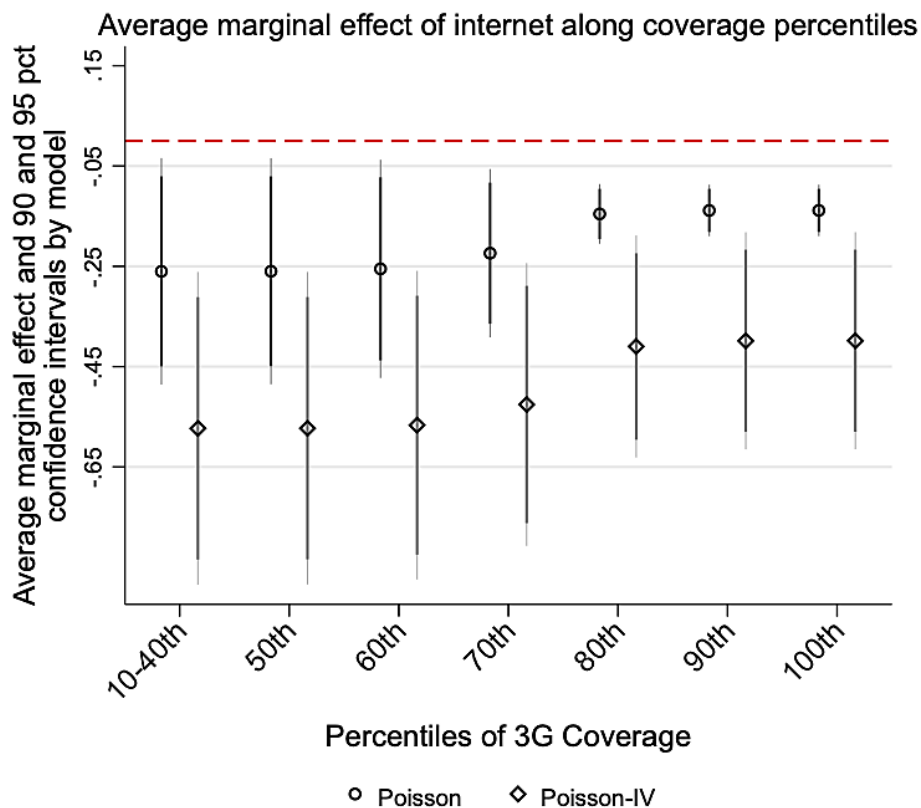


GSMA = Mobile Communications Association.

Notes: This figure presents analogous regressions to Table 1 Column (8) using as outcome regional health care spending across years before and during the pandemic. Spending is accordingly dropped from the set of controls.

Sources: Health care spending data, adjusted for population over the years. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure 6: Average Marginal Effect by Model

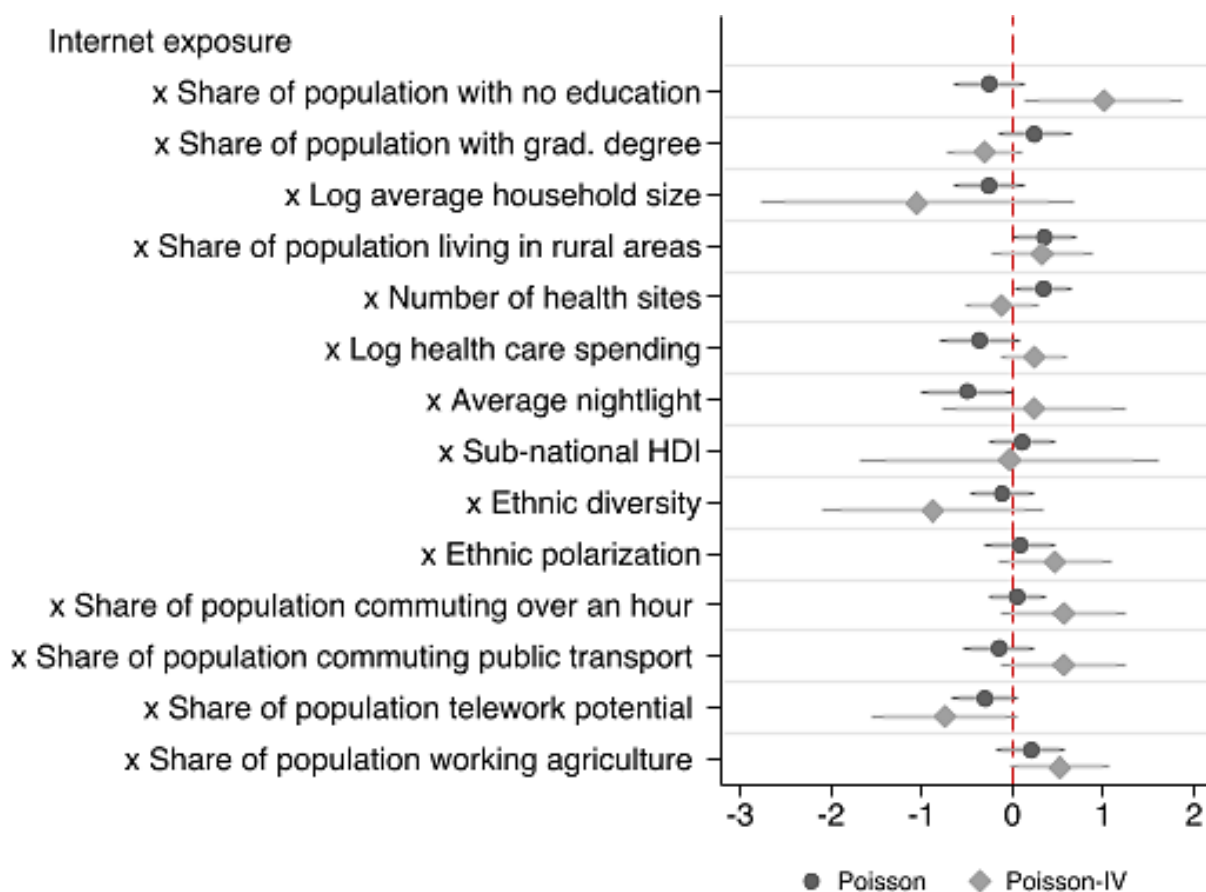


COVID-19 = coronavirus disease, GSMA = Mobile Communications Association.

Notes: The figure shows the average marginal effects (and standard errors based on the delta method) over the percentiles of the mobile access exposure. The first four percentiles (10%–40%) are all in the first group, as they have no mobile access. Circles correspond to Table 4 Column (1) and squares to Column (3).

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure 7: Heterogeneity



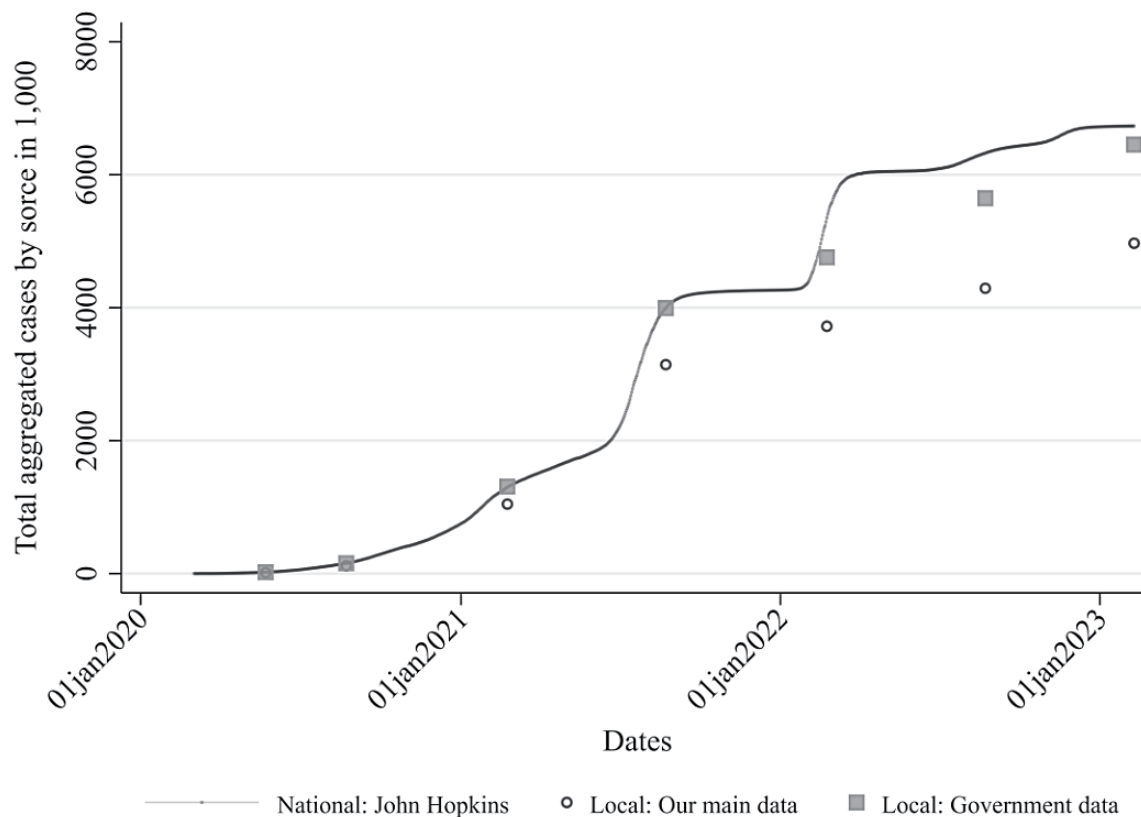
COVID-19 = coronavirus disease, GSMA = Mobile Communications Association, HDI = Human Development Index.

Notes: This figure shows the interaction coefficients τ^x from equation (3). Circles correspond to Table 4 Column (1) and squares to Column (3). Tables A.3 and A.4 have the coefficient estimates.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Appendix: Additional Figures and Tables

Figure A.1: Comparison of Data Sources—Cases throughout the Pandemic

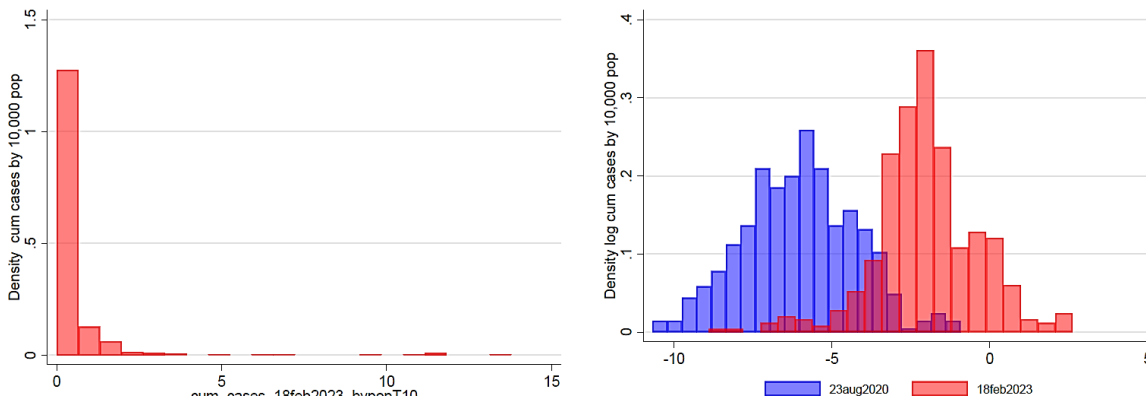


COVID-19 = coronavirus disease, GSMA = Mobile Communications Association.

Notes: Figure compares the aggregated local data available (circles), not all cases can be associated with a region, i.e., cruise ships, tourists, etc., including these (squares), and finally, the national data aggregated by John Hopkins.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force. National data come from John Hopkins cross-national COVID-19 file.

Figure A.2: Skewed Cases on Last Day, and Logged Values Beginning and End

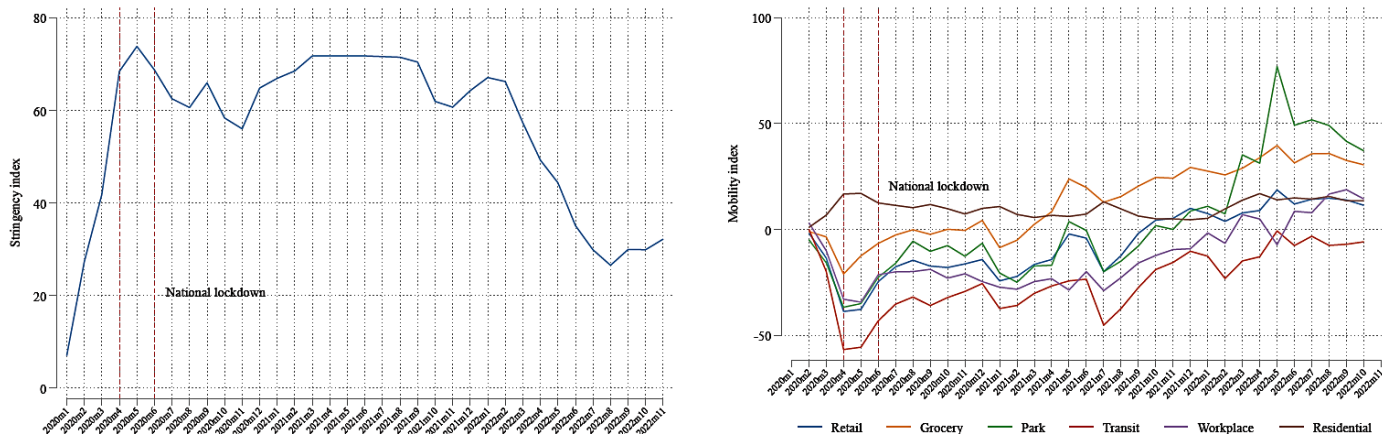


COVID-19 = coronavirus disease.

Notes: Right figure shows the raw distribution of our outcome variable for the last date available at data extraction. The left figure depicts the log-transformed outcome at the beginning of the pandemic (23 Aug 2020) and the late stage (18 Feb 2023)– our main outcome.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force.

Figure A.3: Stringency Index and Google Mobility

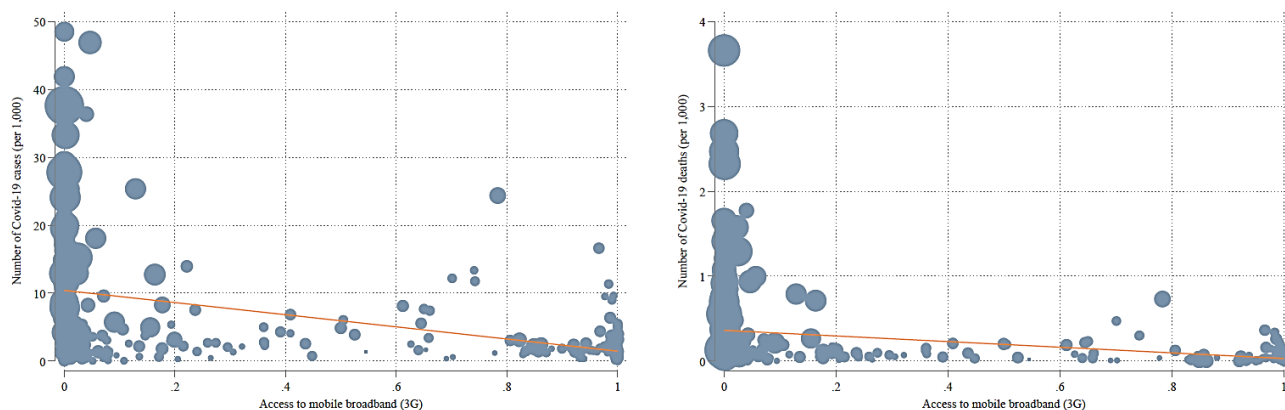


COVID-19 = coronavirus disease.

Notes: Data from the Oxford COVID-19 Government Response Tracker. Data from COVID-19 Community Mobility Reports.

Source: Data available at <https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker>

Figure A.4: COVID-19 Cases, Deaths and 3G Access (Alternative Data)

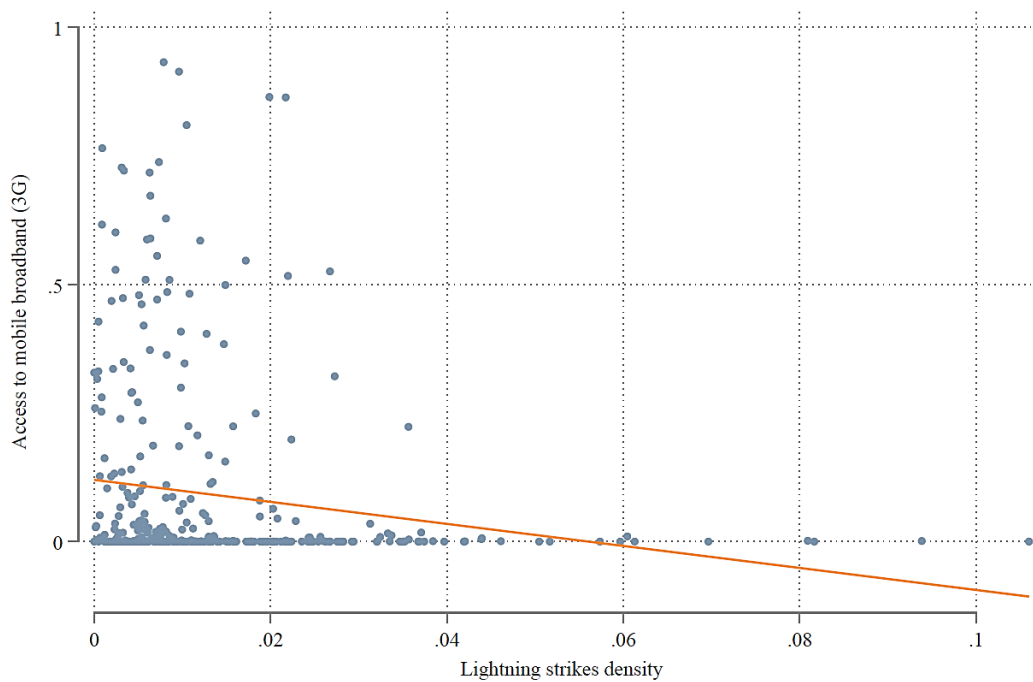


COVID-19 = coronavirus disease.

Notes: Data is adjusted by population.

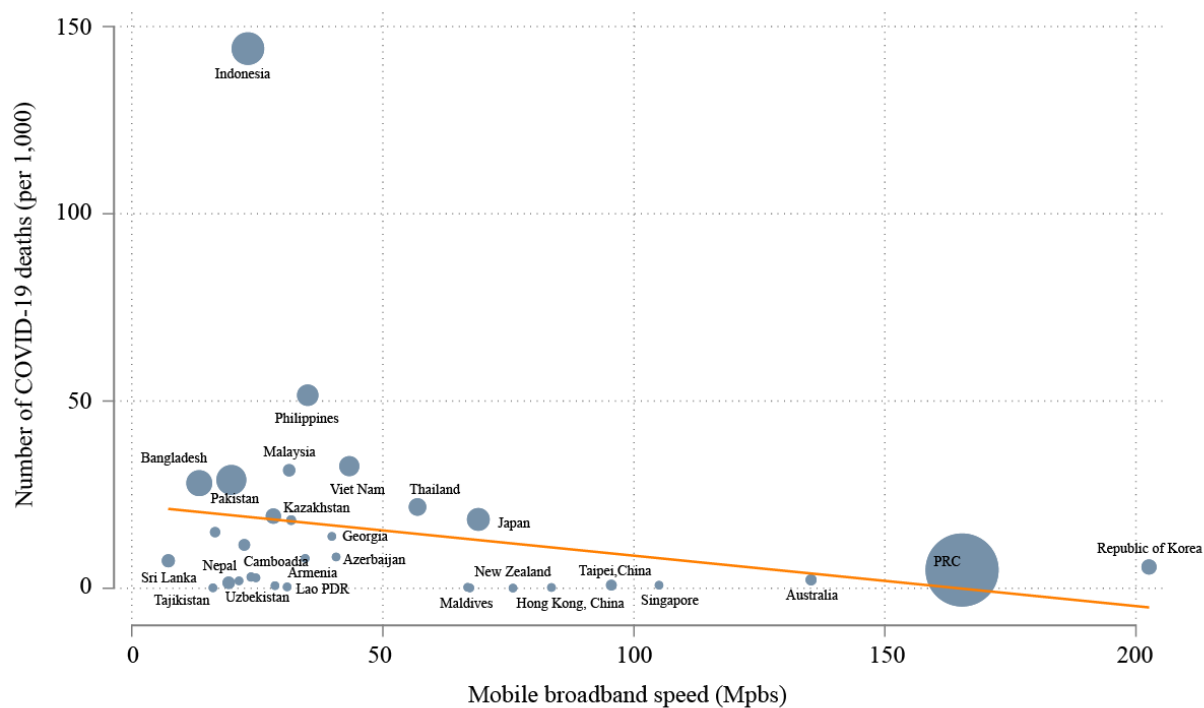
Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure A.5: Lightning Strikes and 3G Internet



Source: Lightning strike data is from the World Wide Lightning Location Network (WWLLN).

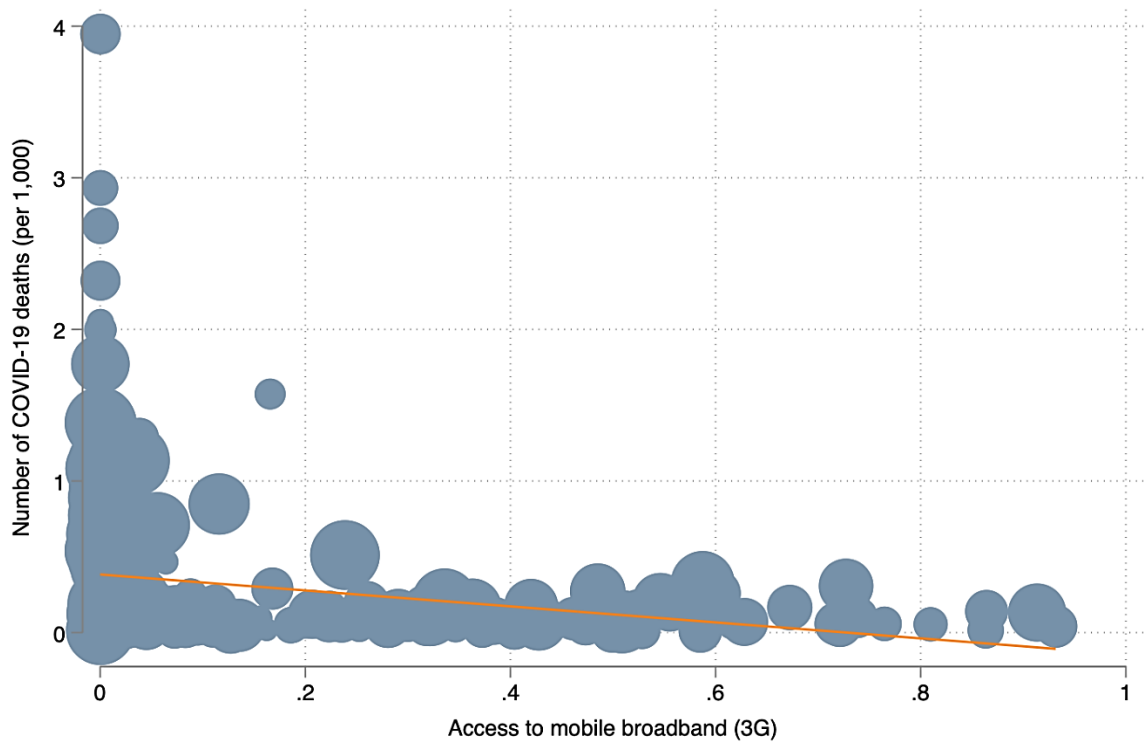
Figure A.6: Mobile Broadband Speed and COVID-19 Deaths, Asia and the Pacific



COVID-19 = coronavirus disease, Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China.

Notes: COVID-19 data were measured as of 1 January 2023, and adjusted for population. Mobile broadband speed (in Mbps) was measured in 2020.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile broadband speed from <https://worldpopulationreview.com/>.

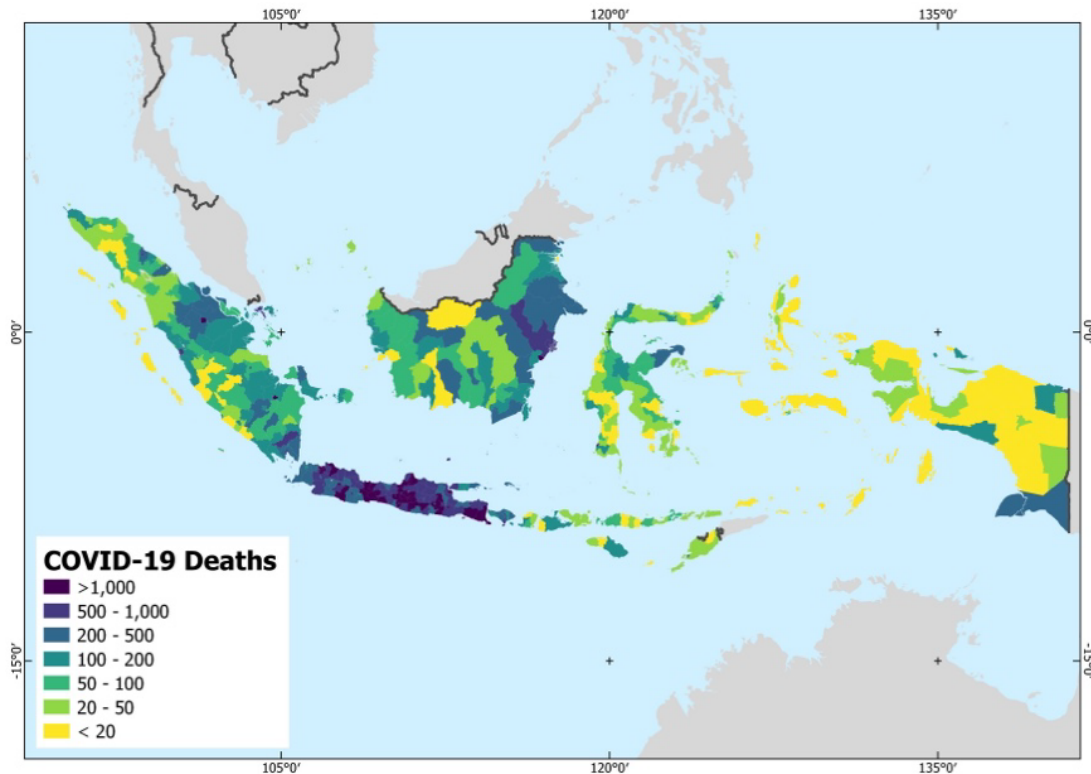
Figure A.7: Mobile Broadband Access and COVID-19 Deaths, Indonesia

COVID-19 = coronavirus disease.

Notes: COVID-19 data were measured as of 18 February 2023, and adjusted for population. Mobile broadband speed (3G access) was measured in 2019.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile internet data from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure A.8: Number of COVID-19 Deaths, Indonesia

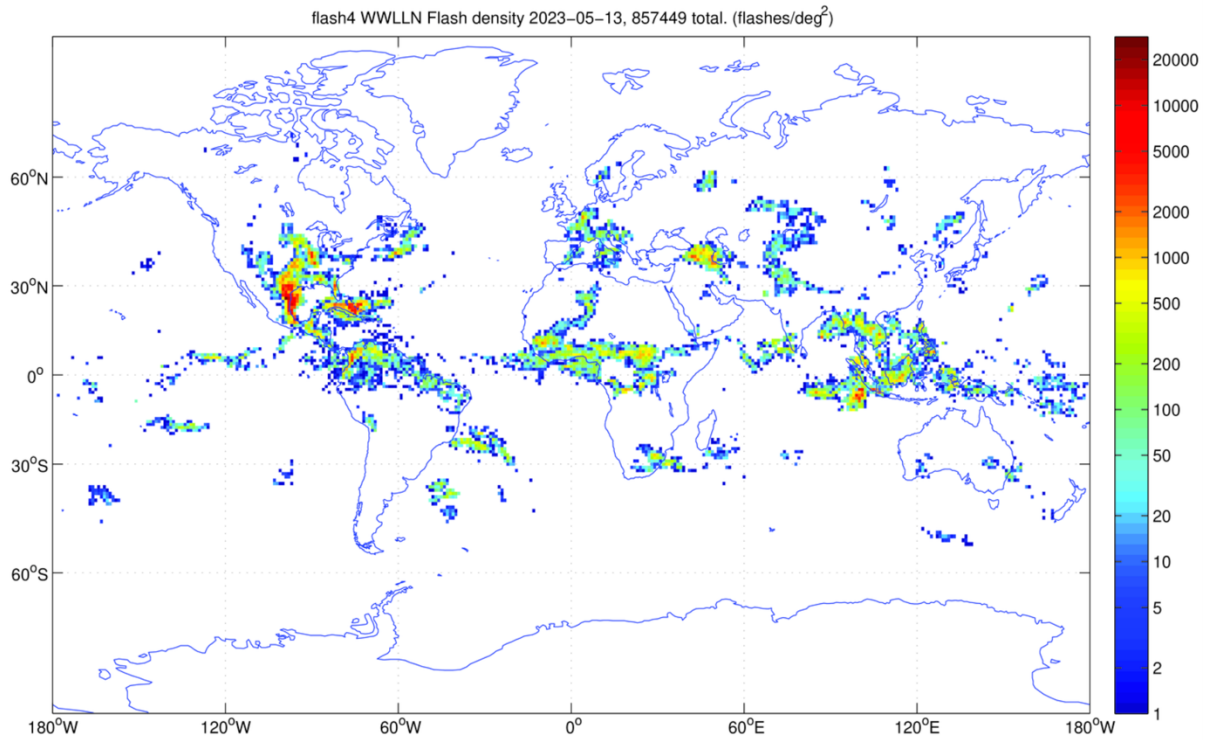


COVID-19 = coronavirus disease.

Notes: COVID-19 data come from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023.

The boundaries, colors, denominations, and any other information shown on this map do not imply, on the part of the Asian Development Bank, any judgment on the legal status of any territory, or any other endorsement or acceptance of such boundaries, colors, denominations, or information.

Sources: COVID-19 data from the Indonesian COVID-19 Task Force. Mobile internet data from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Figure B.1: Example of Worldwide Lightning Strikes

Note: The boundaries, colors, denominations, and any other information shown on this map do not imply, on the part of the Asian Development Bank, any judgment on the legal status of any territory, or any other endorsement or acceptance of such boundaries, colors, denominations, or information.

Source: World Wide Lightning Location Network. <https://wwlln.net/>.

Table A.1: Association between Different Internet Speeds and Potential Non-linear Effects

Dependent variables: Cumulative cases by 10T population, 18 Feb 2023						
	Replicated from main text				Polynomial	Indicator
	Base	2G	4G	Jointly		
	(1)	(2)	(3)	(4)	(5)	(6)
Internet exposure (3G)	-0.630 (0.255)			-0.530 (0.319)	-1.138 (0.712)	
Internet exposure (2G)		-0.366 (0.294)		0.104 (0.296)		
Internet exposure (4G)			-0.472 (0.202)	-0.372 (0.200)		
Internet exposure ² (3G)					0.508 (0.580)	
1[Internet exposure > p75] (3G)						-0.252 (0.159)
<i>N</i>	454	454	436	436	454	454
<i>pR</i> ²	0.53	0.53	0.53	0.54	0.53	0.53
Mean dep.	0.50	0.50	0.52	0.52	0.50	0.50
SD dep.	1.45	1.45	1.47	1.47	1.45	1.45
Marginal effect	-0.24	-0.14	-0.18		-0.43	
Province FEs	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓	✓	✓
Economic status	✓	✓	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓	✓	✓
Labor force	✓	✓	✓	✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects.

Notes: See Table 3's notes.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table A.2: Role of Internet over Different Pandemic Stages

Dependent variables: Cumulative cases by 10T population, different pandemic stages						
	23 Aug 2020	23 Feb 2021	23 Aug 2021	23 Feb 2022	23 Aug 2022	18 Feb 2023
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A. Cases</i>						
Internet exposure	-1.160 (0.303)	-1.093 (0.274)	-0.705 (0.271)	-0.536 (0.247)	-0.493 (0.245)	-0.630 (0.255)
<i>N</i>	442	453	453	401	402	454
<i>pR</i> ²	0.07	0.42	0.77	0.91	0.94	0.94
Mean dep.	0.01	0.10	0.32	0.42	0.48	0.50
SD dep.	0.04	0.29	0.80	1.19	1.41	1.45
<i>Panel B. Deaths</i>						
Internet exposure	-2.133 (0.466)	-1.387 (0.321)	-1.216 (0.316)	-0.851 (0.300)	-0.843 (0.299)	-0.987 (0.296)
<i>N</i>	294	397	408	375	376	417
<i>pR</i> ²	0.01	0.02	0.04	0.04	0.04	0.05
Mean dep.	0.00	0.00	0.01	0.01	0.01	0.01
SD dep.	0.00	0.01	0.02	0.02	0.02	0.03
Province FEs	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓	✓	✓
Economic status	✓	✓	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓	✓	✓
Labor force	✓	✓	✓	✓	✓	✓

COVID-19 = coronavirus disease, FE = Fixed effects, GSMA = Mobile Communications Association, km = kilometer, SD = standard deviation.

Notes: See Table 3's notes.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table A.3: Heterogeneity: Poisson

Dependent variables: Cumulative cases by 10T population, 18 Feb 2023														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Internet exposure	-0.518 (0.284)	-0.710 (0.301)	-0.509 (0.251)	-0.842 (0.268)	-0.750 (0.248)	-0.420 (0.308)	-0.203 (0.270)	-0.743 (0.289)	-0.565 (0.256)	-0.754 (0.260)	-0.675 (0.267)	-0.552 (0.286)	-0.446 (0.297)	-0.761 (0.271)
× Share of population with no education	-0.256 (0.198)													
× Share of population with grad. degree		0.243 (0.207)												
× Log average household size			-0.264 (0.197)											
× Share of population living in rural areas				0.352 (0.180)										
× Number of health sites					0.343 (0.161)									
× Log health care spending						-0.367 (0.222)								
× Average nightlight							-0.499 (0.261)							
× Sub-national HDI								0.104 (0.190)						
× Ethnic diversity									-0.113 (0.184)					
× Ethnic polarization										0.086 (0.195)				
× Share of population commuting over an hour											0.047 (0.161)			
× Share of population commuting public transport												-0.143 (0.199)		
× Share of population telework potential													-0.300 (0.183)	
× Share of population working agriculture														0.203 (0.195)
Province FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Economic status	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor force	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

FE = Fixed effects, HDI = Human Development Index.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table A.4: Heterogeneity: Poisson IV

Dependent variables: Cumulative cases by 10T population, 18 Feb 2023														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Internet exposure	-2.371 (0.596)	-1.190 (0.468)	-0.627 (0.715)	-1.631 (0.412)	-1.472 (0.398)	-1.648 (0.439)	-1.460 (0.376)	-1.406 (0.695)	-0.924 (0.517)	-1.728 (0.485)	-2.133 (0.625)	-1.921 (0.585)	-0.876 (0.516)	-1.723 (0.486)
× Share of population with no education	1.006 (0.441)													
× Share of population with grad. degree		-0.308 (0.207)												
× Log average household size			-1.052 (0.882)											
× Share of population living in rural areas				0.326 (0.280)										
× Number of health sites					-0.121 (0.205)									
× Log health care spending						0.242 (0.189)								
× Average nightlight							0.238 (0.513)							
× Sub-national HDI								-0.034 (0.834)						
× Ethnic diversity									-0.879 (0.617)					
× Ethnic polarization										0.464 (0.315)				
× Share of population commuting over an hour											0.565 (0.352)			
× Share of population commuting public transport												0.561 (0.351)		
× Share of population telework potential													-0.740 (0.408)	
× Share of population working agriculture														0.520 (0.282)
Province FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Health facilities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Economic status	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ethnic composition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Labor force	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

FE = Fixed effects, HDI = Human Development Index.

Sources: COVID-19 data, adjusted for population, was sourced from the Indonesian COVID-19 Task Force, using measurements taken as of 18 February 2023. Mobile internet data was obtained from Collins Bartholomew's GSMA Mobile Coverage Explorer database.

Table B.1: Variable Overview

Variable	N	Mean	SD	Description	Source
Cumulative cases 18 Feb 2023	454	10942.60	31381.30	Total number of cases at the regency level as of 18 Feb 2023	Indonesian COVID-19 Task Force
Cumulative deaths 18 Feb 2023	417	305.66	504.09	Total number of deaths at the regency level as of 18 Feb 2023	Indonesian COVID-19 Task Force
Mobile 3g OCI	500	0.37	0.45	Share of areas at the regency level having access to 3G as of December 2019 (OpenCellID)	Collins Bartholomew's Mobile Coverage Explorer
Mobile 3g MCE	499	62.93	44.91	Share of areas at the regency level having access to 3G as of December 2019 (Mobile Coverage Explorer)	Collins Bartholomew's Mobile Coverage Explorer
Mobile 4g OCI	482	0.76	0.36	Share of areas at the regency level having access to 4G as of December 2019 (OpenCellID)	Collins Bartholomew's Mobile Coverage Explorer
Mobile 2g OCI	500	0.52	0.34	Share of areas at the regency level having access to 2G as of December 2019 (OpenCellID)	Collins Bartholomew's Mobile Coverage Explorer
Population density	465	0.89	2.43	Population density at the regency level	Indonesian COVID-19 Task Force
Population	465	2.85	2.14	Total population at the regency level	Indonesian COVID-19 Task Force
Population over 65	510	0.08	0.03	Share of population with a university degree or higher at the regency level	2010 Indonesian population census
Population with no education	510	0.19	0.11	Share of population with a university degree or higher at the regency level	2010 Indonesian population census
Population with high education	510	0.09	0.05	Share of population with a university degree or higher at the regency level	2010 Indonesian population census
Household size	510	4.16	0.46	Average household size at the regency level	2010 Indonesian population census
Rural areas	510	0.60	0.31	Share of population living in rural areas	2010 Indonesian population census
Number of clinics	363	14.00	42.60	Number of clinics in 2019 at the regency level	Open Street Map (OSM)
Number of hospitals	363	8.00	14.03	Number of hospitals in 2019 at the regency level	Open Street Map (OSM)
Health spending	484	27.01	18.76	Amount of (realized) health spending in 2019 at the regency level	Open Street Map (OSM)

Continued on the next page

Variable	N	Mean	SD	Description	Source
Nighttime light	500	2.14	5.07	Average nighttime (Visible Infrared Imaging Radiometer Suite - VIIRS) as of December 2019	National Oceanic and Atmospheric Administration (NOAA)
Human development index	465	2.97	1.42	Human development index at the regency level in 2019 (quintiles)	Badan Pusat Statistik
Ethnic fractionalization	510	0.46	0.31	Probability that two randomly selected people in a regency belong to different ethnic groups	2010 Indonesian population census
Ethnic polarization	510	0.45	0.25	Probability that a group of individuals in a regency is divided into different ethnic groups	2010 Indonesian population census
Long-distance work	510	0.05	0.03	Share of population traveling ≥ 1 hour to work at the regency level	National Labor Force Survey 2019
Public transport work	510	0.06	0.05	Share of population using public transport to work at the regency level	National Labor Force Survey 2019
Teleworkability	510	0.22	0.05	Teleworkability by industry at the regency level	National Labor Force Survey 2019
Agriculture share	510	0.38	0.22	Share of population working in agriculture	National Labor Force Survey 2019
Temperature	500	25.80	1.92	Average monthly temperature as of December 2019 (Celsius degree)	ERA5 reanalysis data
Rainfall	500	0.21	0.08	Average monthly precipitation as of December 2019 (millimeters)	ERA5 reanalysis data
Lightning strike	500	0.01	0.01	Average lightning stroke power as of December 2019 (5-minute resolution)	World Wide Lightning Location Network

COVID-19 = coronavirus disease, MCE = Mobile Coverage Explorer, OCI = OpenCellID.
Source: Authors' compilation.

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The Impact of Internet Access on COVID-19 Spread in Indonesia

This study examines the impacts of 3G internet connectivity on COVID-19 case rates across districts in Indonesia. By analyzing geographical variations in mobile internet access and employing lightning strikes as an instrumental variable, the study establishes a causal link between improved internet connectivity and reduced transmission of COVID-19. The findings suggest that investments in digital infrastructure might be a crucial and effective tool in pandemic prevention and response.

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