# MOBILE INTERNET CONNECTIVITY AND HOUSEHOLD WEALTH IN THE PHILIPPINES

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Zhiwu Wei (zw387@cam.ac.uk) is a Leverhulme Trust and Issac Newton Trust Early Career Fellow at the University of Cambridge. Neil Lee (n.d.Lee@lse.ac.uk) is a professor of economic geography at London School of Economics and Political Science. Yohan Iddawela (yiddawela@adb.org) is an economist (data science) at the Economic Research and Development Impact Department, Asian Development Bank.



ASIAN DEVELOPMENT BANK

6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
Tel +63 2 8632 4444; Fax +63 2 8636 2444
www.adb.org



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## ABSTRACT

Mobile internet has become a fundamental component of modern infrastructure. In this paper, we consider the impact of mobile internet connectivity on household wealth in the Philippines. We construct a granular measure of local mobile internet connectivity using comprehensive information on approximately 0.27 million geocoded cell towers, and identify causal impact through a novel instrumental variable based on proximity to submarine cable landing points. Our results suggest that mobile internet connectivity significantly increases household wealth, with effects that persist across education levels and are more pronounced in urban areas compared to rural ones. Combining individual survey datasets with Points-of-Interest data, we investigate mechanisms and demonstrate that improved connectivity stimulates activities in several key economic sectors that create employment opportunities. Additionally, mobile internet connectivity enhances individual educational outcomes and promotes female labor force participation, though predominantly in occasional or seasonal roles.



***Keywords:*** mobile internet, cell tower, wealth inequality, Philippines

***JEL codes:*** F14, J24, J63, L86, O33


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## I Introduction

There has been a rapid increase in the availability and use of the internet in the developing world. As internet use has become increasingly common, the mobile phone has become the dominant mode of access, particularly among the poor. Internet use has had a profound economic impact, and studies in multiple contexts have shown important impacts (Aker and Mbiti, 2010; Forman et al., 2012; Akerman et al., 2015; Bahia et al., 2024). These benefits, however, are unevenly distributed across populations. Studies show that internet access generally has a greater positive impact on high-skilled employment and wages than lower-skilled labor markets (Hjort and Poulsen, 2019).

In this paper, we consider how the availability and quality of mobile internet access affects household wealth in the Philippines, a lower-middle-income country which saw a rapid rollout of mobile internet access in the 2010s, from initially low levels. Between 2010 and 2022 the share of the population using the internet went from 25 to 75 percent, and the number of mobile cellular subscriptions per 100 people went from 88 to 144.[1] The Philippines possesses a unique geography whereby it is comprised of over 7,000 islands. Given this, the cost and complexity of rolling out infrastructure has been an ongoing challenge. As such, fixed broadband internet in the Philippines has historically been expensive and slow. This has led to the vast majority of the population accessing the internet via their phones (Kanehira et al., 2024). Over this period, the Philippines experienced rapid economic growth, largely driven by its expanding service sector. This sector includes business process outsourcing, digital financial services, and e-commerce, all of which depend heavily on reliable internet access.

Since mobile internet coverage is not rolled out randomly, causally identifying its impact on household economic outcomes poses significant empirical challenges. In developing countries, for example, mobile internet usage is often poorly documented due to limited availability of high-quality survey data. Furthermore, failing to account for local socioeconomic conditions that affect both household wealth and cell tower deployment could result in omitted variable bias. Beyond that, another plausible endogeneity concern is reverse causality: while improved mobile internet access may boost household wealth, wealthier communities and metropolitan urban centers, by contrast,

[1] More details on the temporal trends of individual internet usage and mobile cellular subscriptions in the Philippines can be found in the following links: https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=PH and https://data.worldbank.org/indicator/IT.CEL.SETS.P2?locations=PH.

might also wield greater lobbying power to attract public investments in internet infrastructure or draw more commercial investments because of their larger market sizes.

To address these empirical challenges, our identification strategy begins by developing a granular measure of local mobile internet connectivity, proxied by the density of cell towers whose coverage scopes overlap with local communities. This measure is constructed using geospatial big data comprising approximately 0.27 million geocoded cell towers sourced from OpenCelliD—a comprehensive, large-scale database providing precise locations and detailed information on cell towers. To overcome the endogeneity of mobile internet connectivity, we exploit the Philippines' archipelago geography to develop a novel instrumental variable based on local communities' geographical proximity to the nearest submarine cable landing points. The underlying intuition is that shorter distances to landing points reduce construction costs associated with expanding internet infrastructure, thereby influencing geographic patterns of mobile internet connectivity.[2] Indeed, we find evidence that better access to these landing points leads to substantial increases in mobile internet connectivity. Moreover, conditional on province fixed effects, the associations between distance to submarine cable landing points and various local socioeconomic factors—such as population density, nightlight luminosity, and livestock density—are statistically insignificant, supporting the plausibility of the exclusion restriction assumption.

Based on this approach, we first examine the overall impact of mobile internet connectivity on household wealth, using household survey data from the 2017 and 2022 waves of the Demographic and Health Survey (DHS). We find that better access to mobile internet is positively associated with household wealth, as measured by the DHS wealth index, which is constructed using principal component analysis of household asset ownership. Consistent with the relevance assumption of the instrumental variable approach, the first-stage results reveal a significant negative relationship between mobile internet connectivity and distance to the nearest

[2] Identification leveraging gradual rollout of submarine cables has become an important empirical technique. For instance, Hjort and Poulsen (2019) employ a Difference-in-Differences strategy based on proximity to terrestrial cables and the timing of gradual arrival of submarine cables to estimate the causal impact of high-speed internet on employment in Africa. We build on this literature with a focus on mobile internet access coming from proximity to cell towers, rather than fixed broadband, and introduce a new instrumental variable approach that uses distance to submarine cable landing points, rather than timing. While specific landing point locations are influenced by geography, distance of households from landing points is plausibly random and orthogonal to economic conditions, with controlling for province fixed effects, as we demonstrate in Section IV.

submarine cable landing point. Our 2SLS estimates indicate that doubling density of mobile internet cell towers in a neighborhood leads to a 0.04 standard deviation increase in the household wealth index, a magnitude roughly ten times larger than the corresponding OLS estimates. These findings are robust to alternative measures of mobile internet connectivity, including varying the default coverage scopes of cell towers and using a service quality measure incorporating mobile internet download or upload speeds.

We conduct a series of placebo tests and robustness checks to assess key threats to identification, as well as to validate our measurement and estimation strategies. First, using data from the 2003 DHS wave, when some submarine cables and their landing points had already been constructed but cell towers had not yet been deployed, our reduce-form estimates show that distance to landing points is not significantly associated with household wealth, reinforcing the validity of our exclusion restriction that mobile internet connectivity is likely the sole channel through which distance to submarine cable landing points affects household wealth. Second, we apply the plausibly exogenous framework proposed by Conley et al. (2012), directly including the instrumental variable in the second-stage regressions. The results suggest that such violations of the exclusion restriction would have to be substantial to undermine the observed relationship between mobile internet connectivity and household wealth, making such violations unlikely to present a serious concern.

Third, we generate placebo instruments by randomly reassigning the values of our baseline instrument either to other communities within the same survey wave or to communities within the same province (possibly across survey waves). Neither approach yields statistically significant effects or diagnostic statistics consistent with a strong instrument, supporting the interpretation that our results are not driven by chance associations. Importantly, we also find that landing points established prior to 2003 yield a weak instrument; however, this issue is mitigated when we incorporate landing points established through 2017. This finding aligns with expectations and suggests that more recent and advanced internet infrastructure is particularly relevant for the rollout of mobile cell towers. Finally, our results remain robust across a range of additional specifications, including alternative measures of the dependent variable and mobile internet connectivity, as well as different methods for estimating standard errors, such as Conley standard errors to account for spatial correlation (Conley, 1999). We also test for spillover effects by including mobile internet density in neighboring communities and find no evidence of bias.

Information and communication technology (ICT) is often characterized by disparities not only in access but also in the distribution of its benefits across different types of users (e.g., Akerman et al., 2015).[3] We next investigate digital inequality in the benefits of mobile internet connectivity, beginning with its spatial dimension, specifically, the differential impacts of connectivity across urban and rural areas. While including all urban samples introduces weak instrument concerns as politically and economically important areas might receive prioritized cell tower deployment irrespective of their proximity to submarine cable landing points, excluding samples in the largest and most densely populated urban areas, i.e., those above the 90th percentile in population size, yields strong instrument and meaningful results: we find that the effect of mobile internet connectivity is substantially larger in urban areas than in rural ones, by a factor of approximately 3.6. In other words, households in urban areas are likely to experience greater wealth gains from improved access to mobile internet, at least for those in medium-sized cities and towns. As a result, we also cautiously interpret our aforementioned IV estimates for the full sample as local average treatment effects for households residing in rural areas and in urban areas with population sizes below the 90th percentile.

We also examine the heterogeneous effects of mobile internet connectivity across educational attainment groups. Categorizing households by the education level of household heads, we find significantly positive effects among those with the lowest levels of education. This suggests that even basic mobile internet access can create opportunities for economic advancement among households with lower socioeconomic status, in contrast to the substitution argument often emphasized in the literature. However, the estimated benefits of internet access tend to increase with higher levels of educational attainment, although the coefficients become less statistically significant—possibly reflecting a ceiling effect, whereby households with higher socioeconomic status may have already realized most of the gains from internet access.

The findings that households in both rural and urban areas, and across varying educational levels, benefit in terms of wealth from mobile internet connectivity likely reflect the role of mobile internet as a fundamental component of modern infrastructure (Greenstein, 2020), which stimulates broader economic activities and associated employment opportunities, as well as

[3] Akerman et al. (2015) examine the effects of broadband adoption on labor productivity and wages in Norway. They find that broadband access improves labor market outcomes and productivity for skilled workers, as it complements their ability to perform nonroutine abstract tasks, while it adversely affects unskilled workers by substituting their roles in routine tasks.

enhances human capital accumulation through improved access to information and digital technologies for learning and education. We conclude our empirical analysis by examining these underlying mechanisms. Using data on Points of Interest (POI), we show that areas with better mobile internet connectivity tend to have a higher density of POIs associated with key economic sectors, including Business and Professional Services, Dining and Drinking, Retail, and Travel and Transportation. On the supply side of the labor market, we also find it increases female labor force participation in seasonal and occasional work, while reducing participation in year-round employment.[4] Moreover, we find evidence that improved mobile internet connectivity enhances individual educational outcomes. Overall, our results suggest that access to mobile internet is an important tool in increasing wealth, but that it may change the structure of the labor market.

Our paper makes a number of contributions to the literature. First, we focus on household wealth rather than income and employment, which are the focus of most earlier studies (e.g., Forman et al., 2012; Hjort and Poulsen, 2019; Akerman et al., 2015). Second, we examine how the benefits of mobile internet access vary across different skill groups and between urban and rural areas. Third, our identification strategy builds on earlier work, notably Hjort and Poulsen (2019) and Imbruno et al. (2025), by using submarine cables as a source of variation. However, we focus specifically on distance to cable landing points, rather than the timing of rollout, and we are the first to apply this method in an archipelago economy. Finally, we add evidence from Southeast Asia to literature that has mostly focused on the African context (Hjort and Tian, 2025).

The paper is structured as follows. The next section provides background on internet access in the Philippines, possible theoretical mechanisms, with related research. In Section III, we describe data sources and present descriptive statistics on mobile internet connectivity, submarine cable landing points, and household wealth. We subsequently set out our identification strategy and how we deal with the challenges of establishing causality in Section IV. We present our main results and examine the channels through which mobile internet connectivity affects household wealth in Section V. Finally, we conclude and discuss the policy implications of these findings.

[4] Our DHS data for the Philippines lacks data files focused specifically on male respondents, limiting our ability to analyze male employment outcomes. A promising avenue for future research is to systematically investigate whether the wealth-enhancing effects of mobile internet access also operate through its impact on male employment, and to assess potential gender disparities in the economic benefits of digital connectivity.

# II Background

## II.A Internet Access Challenges in the Philippines

As is common in many lower-middle-income countries, internet usage in the Philippines has only recently become widespread. Yet, despite these advances, the quality and affordability of mobile internet in the Philippines lag behind other Southeast Asian countries. A significant driver of this are regulatory barriers, of which there are several.

For instance, the Philippines is one of the only countries in the world that still requires a legislative franchise for the construction and operation of telecommunications networks. This means operators must obtain a franchise through an act of Congress, in addition to obtaining standard regulatory approvals (World Bank, 2020). The effect of this is stymied competition in the telecom sector, which subsequently fails to spur innovation that can drive down the cost of roll out (Kanehira et al., 2024).

However, a major policy shift occurred with the passage of the "Konektadong Pinoy" law, which lapsed into effect in August 2025 (Government of the Philippines, 2025). The law removes the congressional franchise requirement for new players, streamlines licensing procedures, and promotes infrastructure sharing for faster rollout. It also establishes clearer rules on the efficient use of radio frequency spectrum, with the aim of opening the market to greater competition and accelerating connectivity in underserved areas.

Additionally, trenching for underground fibre often accounts for as much as 80 percent of deployment costs, largely because each operator must independently apply for rights-of-way and excavation permits. Without coordination, roads are repeatedly dug up by different firms (World Bank, 2024). Aerial deployment faces similar inefficiencies because electric poles are regulated by energy-sector agencies, whereas telecom infrastructure falls under a separate body (World Bank, 2024). This fragmentation creates unclear pole-attachment rules, bilateral contracting, and variable rental terms; many broadband providers therefore construct their own poles, which increases the cost of extending networks from landing points. Some reforms seek to address these barriers, including the Bayanihan 2 Law (Congress of the Philippines, 2020) and Executive Order No. 32 (Office of the President of the Philippines, 2023). While these measures have simplified certain national-level permits, site acquisition is still delayed by local-government approvals and homeowners' association clearances (World Bank, 2024).

In addition to these regulatory and institutional barriers, geography compounds these issues. The Philippines' geography, consisting of more than 7,000 islands, creates significant cost and coordination challenges for extending digital infrastructure beyond international cable landing stations. Fibre-optic and microwave backhaul must cross bodies of water, traverse rugged terrain, and connect sparsely populated areas. As a result, the capital cost of backbone infrastructure is estimated to be around five times higher than in countries located on a single contiguous landmass (Department of Information and Communications Technology, 2019). In this context, it is inefficient for each mobile network operator to construct its own long-haul transmission network. A shared, open-access fibre backbone, whereby operators lease capacity from a common provider, can reduce duplication, spread fixed costs across users, and allow firms to focus investment on local access infrastructure rather than expensive inter-island connections. However, until the introduction of the national open-access backbone in 2024, most long-haul networks in the Philippines were developed by individual commercial operators, contributing to high costs of roll-out and uneven reach (Department of Information and Communications Technology, 2019).

Taken together, the country's fragmented geography, absence of shared backbone infrastructure until recently, and regulatory complexity have made it significantly more expensive to expand broadband infrastructure inland from submarine cable landing stations.

## II.B Mechanisms: Impact of Mobile Internet Access

The rapid expansion of mobile internet has had complex economic implications in the Philippines. Significantly, the country has experienced substantial growth in the gig economy, accelerated by the pandemic and driven by increased adoption of app-based food delivery services (ADB, 2023). Many firms in the dominant service sector are reliant on access to fast internet. For example, Business Process Outsourcing (BPO) firms depend on real-time digital communication to serve overseas clients, while retail and finance increasingly use online platforms for transactions and customer engagement. Furthermore, mobile internet plays a crucial role in facilitating remittances, which accounted for approximately 9.4 percent of GDP in 2022, allowing recipients to access funds with greater security and ease.[5]

[5] Further details on the temporal trends of remittances received as a percentage of GDP can be found in: https://data.worldbank.org/indicator/BX.TRF.PWKR.DT.GD.ZS?locations=PH.

Access to the internet significantly reduces the cost and effort associated with finding information, leading to enhanced efficiency and increased innovation (Kusumawardhani et al., 2023; Akerman et al., 2022). Better internet connectivity also facilitates trade, as countries with robust telecommunications infrastructure are more likely to engage in greater trade volumes (Herman and Oliver, 2023). Consequently, several mechanisms can be identified through which internet access might positively affect individual earnings within local economies.

The literature highlights various direct and indirect effects of internet access on local economies, each potentially influencing household wealth. First, improved internet access boosts skills development by simplifying information access, thereby increasing labor productivity (Chiplunkar and Goldberg, 2022; Caldarola et al., 2023). Additionally, better connectivity enhances the matching process between workers and suitable employment opportunities, facilitating specialization.

Firms also benefit by adopting new technologies, refining management practices, and gaining improved market insights (Hjort and Tian, 2025). Furthermore, internet access reduces barriers to market entry, enabling both local entrepreneurs and external firms to compete in previously isolated markets, consequently lowering price dispersion. Households and businesses further benefit from greater access to essential online services, such as banking, government services, and retail, which may facilitate easier access to remittances, although increased connectivity also raises the risk of online fraud.

Crucially, these economic impacts typically manifest at the community or local economy level rather than solely benefiting individual households with direct internet access. The effects of mobile internet, in particular, may differ between urban and rural areas since mobile connectivity often substitutes for inadequate physical infrastructure. However, the overall outcome depends significantly on which groups gain internet access; limited connectivity among vulnerable populations could potentially exacerbate existing inequalities. Additionally, improved internet connectivity might concentrate economic activities into hubs, potentially widening spatial disparities (Leamer and Storper, 2001).

## II.C Existing Evidence

Internet connectivity generally has positive economic impacts, driving increased employment, productivity growth, and higher household consumption, especially in developing countries (Hjort and Tian, 2025). Broad evidence indicates improved market efficiency, better access to information, and enhanced welfare outcomes across various contexts (Kaila and Tarp, 2019; Beuermann et al., 2012; Paunov and Rollo, 2015). For example, Aker and Mbiti (2010) shows that mobile phone coverage significantly reduced price dispersion in grain markets in Niger, reflecting improved market integration and efficiency. While experimental studies on information provision have yielded mixed results, recent work tends to suggest positive impacts on productivity (Fabregas et al., 2025).

More specifically, studies focused on Southeast Asia highlight nuanced and varied effects of internet access. In Indonesia, Kusumawardhani et al. (2023) find that internet availability primarily supports job search activities rather than directly increasing employment, particularly benefiting younger individuals. Furthermore, Jung and Rogers (2024) reveal unintended consequences, such as increased deforestation in Uganda, as internet-enabled information access encouraged non-farm workers to enter agriculture.

Identifying the causal impacts of internet connectivity remains methodologically challenging, largely due to the non-random placement of telecommunications infrastructure. Researchers have addressed these challenges through innovative strategies, prominently using submarine cable installations as exogenous shocks. Notably, Hjort and Poulsen (2019), Simione and Li (2021), Goldbeck and Lindlacher (2024), and Mensah and Traore (2023) provide robust evidence from Sub-Saharan Africa showing substantial economic growth, productivity enhancements, and increased foreign direct investment following submarine cable connectivity. These studies emphasize the importance of rigorous identification strategies in accurately capturing the economic effects of improved digital infrastructure.

## III Data and Measurement

Operationalizing our empirical analysis of the relationship between mobile internet connectivity and household wealth necessitates integrating various geospatial data sources. To this end, we combine data on (*i*) georeferenced cell towers across the Philippines; (*ii*) the geographical locations and operational timelines of submarine cable landing points around the islands; and (*iii*) information on households' wealth status, relevant characteristics (e.g., household size and socioeconomic features in surrounding communities), and specifically their precise residential locations to enable alignment with our internet data. This section lays out the primary data sources and explains how we measure the core variables that are used in our analysis. Additional data sources are introduced later when they are used for the first time. [6]

### III.A Cell Towers and Mobile Internet Density

We source mobile internet data from OpenCelliD, a large-scale global open database providing extensive information on cell towers and their locations.[7] The OpenCelliD database records information for each cell tower, including the generation of broadband cellular network technology (radio types: GSM/2G, UMTS/3G, LTE/4G, and NR/5G), the country and region where the cell tower is located, and its geographic coordinates (longitude and latitude). The database also flags whether the geographic coordinates of cell towers are provided directly by telecom companies or derived from user-submitted data, which combines the signal strength received by user's mobile equipment with its positional information.[8] Additionally, the database records the date each cell tower was first added into the database and when it was seen. We restrict our analysis to cell towers located in the Philippines that were first added into the database between 2008 and 2022.[9] As a consequence, we ultimately obtain 265,246 georeferenced cell towers, all with geographic coordinates derived from user-submitted data, and containing three radio types – GSM, UMTS, and LTE. We use the date each cell tower was first added to the database as a proxy for its construction time and we assume no cell towers are decommissioned due to a lack of such information. While we acknowledge the data limitations regarding the locations, construction times, and active durations of cell towers, OpenCelliD, to the best of our knowledge, offers the most accurate and freely available data on cell tower locations in the Philippine context. Nonetheless, as discussed in the next section, our empirical strategy is well-equipped to account for these potential measurement errors.

Using the cell tower data, Figure 1 illustrates the cumulative number of cell towers in the Philippines from 2008 to 2022, categorized by radio types. We observe a rapid roll-out of cell

[6] Details on auxiliary data sources are provided in Appendix A. The Appendix is available at http://dx.doi.org/10.22617/WPS250440-2.
[7] For more details and information on the methodology, visit https://opencellid.org/. The OpenCelliD project is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.
[8] If the geographic coordinates of a cell tower are obtained in the second way, the database also includes the number of (user-submitted) samples or measurements processed to determine the location, as well as a radius indicating the range within which the actual location is likely to fall.
[9] We found only one cell tower in the Philippines that was added to the database before 2008, which is likely to come out as an erroneous entry.

towers across all three radio types between 2012 and 2017. After 2017, the number of GSM and UMTS towers plateaued, while LTE towers continued to grow steadily through 2022. Within this period, GSM remained the dominant radio type in the composition of cell towers. Confirming the aforementioned patterns, Figure 2 shows the spatial distribution of cell towers and the proportion of population covered by mobile internet across provinces with four snapshots taken in 2008, 2012, 2016, and 2020.[10] The results indicate that initial cell tower construction was concentrated in core urban areas, particularly Manila. However, since 2016, cell towers have expanded to cover a wide range of the country, with coverage proportions appearing relatively uniform across provinces. We further analyze the relationship between GDP per capita, population, and new cell tower construction at the provincial and district levels from 2018 to 2022 (see Appendix Table E.1). We find no evidence that GDP per capita or population significantly predicts new cell tower construction, suggesting that by this stage, cell tower deployment was no longer broadly focused on wealthier or more populous areas but was likely aimed at achieving "last-mile" coverage.

The primary independent variable we employ in our analysis is mobile internet density, which captures the extent of households' exposure to mobile internet at the DHS cluster level. This approximates villages in rural areas or streets in the urban, as detailed in Section III.C. We create this measure of internet density by calculating the number of cell towers that overlap with DHS clusters. Figure 4 provides a schematic representation of this approach. Our starting point is DHS clusters, for which we create 10-km buffers around rural clusters and 2-km buffers around urban clusters. his accounts for the intentional displacement of household coordinates to protect privacy and prevent disclosure, as explained below. We then create buffers around each cell tower that was active at the time of the DHS survey. The buffer size reflects the typical coverage radius of each technology: 10 kilometers for GSM, 5 kilometers for UMTS, and 3 kilometers for LTE.

[10]To calculate the proportion of the population covered by mobile internet (namely, coverage share), we overlay annual geospatial population data from WorldPop (2018) with cell tower data. The proportions represent the percentage of the population within a specified radius of cell towers relative to the total population in each province. Using basic engineering guidelines, we define the coverage radius as 10 km for GSM towers, 5 km for UMTS towers, and 3 km for LTE towers. We do not account for factors such as terrain, vegetation, or weather conditions that might affect signal reach. While providing precise estimates of individuals with mobile internet access would be of interest to many readers, it lies beyond the scope of this paper. Instead, these calculations aim solely to illustrate broad patterns. However, as shown in Panel B of Appendix Figure B.1, our coverage share measure is positively associated with the percentage of households with internet access across provinces (data on household internet access is sourced from the IPUMS International census database), providing some supporting evidence for the validity of our measure. Panel A of Appendix Figure B.1 shows the share of the population within the coverage radius of cell towers across the entire country from 2008 to 2020.

These distances are based on standard engineering guidelines and are used to approximate the area each tower could serve.[11] We calculate the number of cell towers for each DHS cluster by counting how many tower buffers overlap with the cluster's buffer.[12] We divide this cell tower count by the population within each DHS cluster to obtain the average, and then take the logarithm of this value to measure mobile internet density in our subsequent analysis.[13]

There are two important caveats regarding our density measure to capture mobile internet exposure. First, as discussed previously, the locations of both the DHS clusters and the cell towers may not be exact. Because of this, our measure of internet density might be subject to measurement error. Second, there is a conceptual issue with how exposure is defined. For instance, a household located near just one cell tower may actually get stronger and more consistent mobile internet than a household that happens to sit at the edge of several towers' coverage areas. So even if a cluster overlaps with multiple towers, this does not always mean better internet access.[14] In Appendix Figure C.1, we first validate our measurement of mobile internet density by examining the relationship between the share of households owning mobile phones (from the DHS surveys in 2017 and 2022) and mobile internet density across DHS clusters. The figure presents bin scatter plots of the share of households owning mobile phones against mobile internet density, using 20 equally sized bins, weighted by population. We find highly positive correlations between our mobile internet density measure and the share of mobile phone ownership. Nonetheless, we provide a more comprehensive discussion of how our identification strategy addresses these empirical concerns in Section IV.

[11]However, our results remain qualitatively and quantitatively similar when using buffer radii ranging from 3 km to 10 km in 1 km increments for all three types of cell towers (see Figure 6).

[12]Appendix Figure 6 presents average cell tower counts per 1,000 people across DHS urban and rural clusters, varying the cell tower buffer radius from 3 km to 10 km in 1 km increments.

[13]To address instances where cell tower counts are zero and thus the logarithm cannot be applied, we substitute these cell tower counts with one. However, our results remain nearly unchanged when using values between 0.1 and 10 in increments of 0.1 (see Appendix Figure K.2). Additionally, our findings are highly robust to other transformations, including the inverse hyperbolic sine transformation, neglog transformation, Johnson transformation, as well as square and cube root transformations (see Appendix Table K.1).

[14]To address this, in Section V.A, we examine mobile internet service quality, drawing on mobile upload and download speed data.

### III.B Submarine Cable Landing Points

Our identification strategy relies on proximity to submarine cable landing points across the Philippines as an instrumental variable. Landing points are coastal sites where submarine internet cables connect to terrestrial networks. These cables enable the transmission of large volumes of data across oceans, linking countries to the global internet infrastructure. At the landing points, data is transferred to land-based systems such as fiber-optic networks, data centers, and mobile networks. We collect data of georeferenced submarine cable landing points from Infrapedia, an open-source database to provide complete and versatile infrastructure map of the Internet.[15] We obtain the geographic coordinates (longitude and latitude) of submarine cable landing points and detailed information about the submarine cables connected to them, including the years these cables became operational. For each landing point, we assign its ready-for-service time based on the earliest operational year among the connected submarine cables. Our primary instrumental variable is the Euclidean distance from a DHS cluster's centroid to the nearest existing submarine cable landing point.[16]

Figure 3 depicts the spatial distribution of of submarine cable landing points across the Philippines, color-coded by their ready-for-service years.[17] We see that the majority of submarine cable landing points were constructed either before 2003 or between 2017 and 2022. We focus on the most recent set of submarine cable landing points, which are expected to provide a stronger instrumental variable (as explained in the robustness check section). To test whether these landing points were placed in wealthier areas, we examine provincial GDP data from 2018 to 2022. Specifically, we analyze whether provinces with higher GDP were more likely to host new landing points during this period. To examine this, we calculate the number of landing points constructed in each province and run a Poisson regression with province and year fixed effects, using robust standard errors. The $p$-value for the coefficient on provincial GDP is 0.763 , suggesting that landing points were not disproportionately located in wealthier provinces. Rather, their locations are more likely determined by proximity to international or national

[15]More details are provided in the link: https://www.infrapedia.com.

[16]To minimize distortion in distance measurements, we perform geocomputation based on the WGS84 UTM Zone 51N projection system.

[17]Appendix Table F.1 lists the specific location name and ready-for-service year for each landing point. Appendix Figure F.1 provides a snapshot of the submarine cable network across the Philippines, taken from the Infrapedia database.

submarine cable networks. Although it is not a sufficient condition for the exogeneity of our instrumental variable, such "quasi-random assignment" lends the first piece of credence to its validity. We discuss and consolidate the instrumental variable' validity in more depth in Section IV, where we provide further evidence and address potential concerns regarding its exogeneity and relevance in our empirical analysis.

### III.C Demographic and Health Survey (DHS)

Our household-level data come from Demographic and Health Survey (DHS), a global large-scale, nationally representative cross-sectional survey that collects detailed information on various demographic, health, and population-related topics. The DHS was conducted approximately every five years across various countries. Within each wave, the DHS provides separate datasets for various components, including households (HR), household members (PR), women's (IR), births (BR), children under five (KR), men's (MR), and couples (CR) files. Notably, for some waves, the DHS also provides geographical information on where households are located, at the cluster level, approximating to villages in rural areas or streets in urban areas, as well as additional geographic characteristics for these clusters, such as rainfall, nightlight luminosity, livestock density, temperature, slope of terrain, and other relevant variables.[18] It is important to note that the DHS data provider employs a random displacement of the GPS coordinates of clusters to ensure respondents' confidentiality. Specifically, for urban clusters, the positional error ranges between 0 and 2 kilometers. For rural clusters, the error ranges from 0 to 5 kilometers, with an additional 1% of rural clusters having their GPS positions displaced by between 0 and 10 kilometers.

In the Philippines, there have been five waves of DHS survey since the start of the 21st century: 2003, 2008, 2013, 2017, and 2022, with each wave interviewing around 30,000 households. In this paper, we use data from the Philippine DHS surveys conducted in 2003, 2017, and 2022. We do not include the 2008 survey because cell tower coverage was still limited at that time, and we exclude the 2013 survey because it does not include geographic information for the clusters. The

[18]The DHS surveys employ a two-stage cluster sampling method, with clusters sparsely distributed across the country. This spatial dispersion helps mitigate potential spillover effects – such as households in neighboring clusters benefiting from nearby mobile internet towers even if their own clusters lack coverage – thereby addressing concerns about violations of the Stable Unit Treatment Value Assumption (SUTVA) that could bias our causal estimates. We directly test for such spillover effects in Appendix Table K.3.

2003 survey, as discussed later, allows us to conduct a placebo test to examine the exclusion restriction assumption, given that cell towers had not yet been deployed at that time. In contrast, the 2017 and 2022 survey waves provide us with the data needed to analyze the medium- to long-term impact of mobile internet connectivity on household wealth accumulation. Our primary dataset is household-level data from the HR file, but we also utilize the household members (PR) and women's (IR) files to test various mechanisms. In the case of the Philippines, we do not have access to the men's (MR) files.

The primary outcome variable of interest is the DHS household wealth index, which has been extensively used in the literature as a proxy for household economic well-being in developing countries where reliable income or expenditure data are often unavailable (e.g., Abagna et al., 2025; von der Goltz and Barnwal, 2019; Lowes and Montero, 2021). It is a quintile-based measure derived from data on a household's ownership of various assets. These assets include consumer items such as televisions and cars, dwelling characteristics such as flooring material, drinking water source, and toilet facilities, as well as other factors related to wealth status. Each selected asset is assigned a weight or factor score, which is generated using principal component analysis (PCA). The final scores are then standardized to follow a standard normal distribution, with a mean of zero and a standard deviation of one. Each household is assigned a standardized score for each asset, based on whether the household owns that asset or not. These individual scores are then summed to obtain a total wealth score for the household. Next, individuals are ranked according to the total wealth score of the household in which they reside. The sample is then divided into five population quintiles, which are used to define wealth categories labeled as: Poorest (1), Poorer (2), Middle (3), Richer (4), and Richest (5). Appendix Table D.1 presents the share of households owning specific items or services, categorized by the household wealth quintiles. Indeed, we find that households with higher wealth status tend to own more durable goods, but less capital goods related to the agricultural sector.

We also source a rich set of household-level characteristics from the DHS survey, including household size, the age, gender, and educational attainment of the household head. In addition, we gather cluster-level features from the DHS geospatial covariate datasets, such as whether the cluster is located in an urban area, population size, population density, nightlight luminosity, rainfall, and daytime land surface temperature. These variables are used in our subsequent analysis. Summary statistics for these variables, along with our primary variables, are reported in Appendix Table G.1.

## IV Empirical Strategy: Instrumental Variable from Submarine Cables

Our parameter of interest is the medium- to long-term impact on household wealth accumulation, stemming from the staggered rollout of cell towers and the resulting variation in mobile internet exposure across localities in the Philippines. Specifically, we examine whether mobile internet connectivity contributes to improving households' wealth status by leveraging exogenous variations in cell tower density driven by the extent of remoteness from the submarine and territorial cable network. In other words, we instrument mobile internet density using the Euclidean distance from the centroid of each DHS cluster to the nearest existing submarine cable landing point. The Philippines is an archipelagic country that depends on a network of submarine and land-based cables to provide internet access. Our instrumental variable is based on the idea that areas farther from cable landing points face higher costs for building internet infrastructure. As a result, these areas tend to have fewer cell towers. We assume that, after conditional on a key set of covariates and focusing on comparisons within a small geographic area, the distance to the nearest landing point is not correlated with other factors that affect household wealth.

Before examining the identification assumption in detail, we first describe our baseline econometric model, which is estimated using two-stage least squares (2SLS):

$$Wealth_{icpt} = \mu_t \ \ \alpha_p \ \ \gamma_0 \cdot Mobile\ \widehat{internet}\ density_{cpt} \ \ X'_{icpt}\Omega_0 \ \ \epsilon_{icpt}, \tag{1}$$

$$Mobile\ internet\ density_{cpt} = \mu_t \ \ \alpha_p \ \ \gamma_1 \cdot Distance_{cpt} \ \ X'_{icpt}\Omega_1 \ \ \varepsilon_{cpt}, \tag{2}$$

where $Wealth_{icpt}$ denotes household wealth status, measured in quintiles of the DHS Household Wealth Index on a scale from 1 (poorest) to 5 (richest), for household $i$, residing in DHS cluster $c$, within province $p$, and interviewed in wave $t$ (2017 or 2022).[19] We standardize the quintile dependent variable for ease of interpretation. Our primary explanatory variable is mobile

[19] As mentioned above, the two waves of the DHS survey correspond to periods following a surge in the number of cell tower rollouts across the Philippines, at least 9 years after the construction of cell towers began in the country (see Figure 1 for details). This timing allows us to study the medium- to long-term impact of mobile internet connectivity on household wealth accumulation.

internet density, $Mobile\ internet\ density_{cpt}$, defined as the log of cell tower counts per 1,000 residents for each DHS cluster. $\gamma_0$ therefore denotes the parameter of our interest. The instrument, $Distance_{cpt}$, denotes the Euclidean distance from the centroid of each DHS cluster to the nearest existing submarine cable landing point.[20]

Our specifications also include fixed effects for the survey wave and province ($\mu_t$ and $\alpha_p$) to capture overall differences in household wealth across the time and regional dimensions. For example, survey wave fixed effects enable comparisons within each wave, thus accounting for the issue that the Wealth Index constructed from a mix of household assets might be statistically inconsistent between waves due to changes in the composition of assets involved. Moreover, the importance of distance in influencing cell tower rollouts may diminish over a broad geographic scale (e.g., mobile internet operators might prioritize distant but economically or politically significant areas despite higher construction costs). By incorporating provincial fixed effects, we narrow the focus to comparisons among DHS clusters within a relatively small geographic scale, where distance is more likely to play a crucial role as a determinant of cell tower construction. Additionally, as we demonstrate below, focusing on a smaller geographic scale increases the likelihood that DHS clusters are balanced across other socio-economic factors that might also affect cell tower deployment.

We control for a rich set of covariates at both the cluster and household levels, denoted as $X'_{icpt}$. Our cluster-level controls include: (*i*) a dummy variable indicating whether DHS clusters are situated in urban areas; (*ii*) population density and nightlight luminosity, which broadly capture local economic development (urbanization and economic activities); (*iii*) rainfall and temperature, reflecting overall climatic conditions that may influence both economic activities and the feasibility of cell tower construction (e.g., lightning strike intensity has been shown to impact mobile phone coverage (Manacorda and Tesei, 2020)); and (*iv*) slope of terrain that could influence the strength and quality of mobile internet signals (e.g., Wang, 2021). At the household level, we control for the number of household members, as well as the age, gender, and educational attainment of the household head, as these factors are likely to directly affect household wealth status.

[20] For the 2017 DHS survey wave, we calculate the distance for DHS clusters based on landing points that were operational in 2017 (i.e., those constructed before 2017), taking out of consideration those that became operational only after that year. For the 2022 DHS survey wave, we include all landing points that were operational by 2022. Our results, however, remain robust when using alternative sets of instruments, such as the distance to landing points established before 2003 (see columns (1) and (2) of Table I.1 for more details).

Importantly, we include mobile phone ownership as a control variable because our dependent variable—constructed using principal component analysis (PCA)—is based on various household asset ownership indicators, including mobile phones. Incorporating mobile phone ownership helps mitigate potential omitted variable bias. $\epsilon_{icpt}$ and $\varepsilon_{cpt}$ represent the error terms, and we cluster standard errors at the DHS cluster level.[21] Throughout the paper, we apply sampling weights in estimations to ensure our samples' representativeness.

The empirical strategy presented above allows us to address a range of endogeneity concerns with respect to identifying the causal effects of mobile internet density on household wealth. First, our approach, conditional on the validity of the instrumental variable, enables us to rule out bias resulting from a variety of omitted variables, such as differences in local economic performance that may determine both household wealth and cell tower density. It also addresses concerns of reverse causality, wherein mobile internet connectivity could enhance household wealth, but conversely, higher household wealth may, in turn, influence the density of cell tower construction in the locality (e.g., residents from wealthier areas lobby government for more mobile internet infrastructure). Furthermore, the strategy accounts for measurement error issues inherent in the data. For instance, as mentioned above, DHS clusters are intentionally displaced to preserve respondents' anonymity, which introduces imprecision in the geographical locations. Similarly, cell tower data, being crowdsourced from a global community of volunteers, may suffer from inaccuracies in the construction timelines and reported locations.[22] Additionally, the method of measuring mobile internet density—using an overlay of cell tower buffers with DHS cluster buffers—presents conceptual challenges, e.g., some clusters may be in close proximity to a limited number of cell towers, while others might overlap with the periphery of multiple cell tower buffers without substantial coverage or connectivity. By employing the instrumental variable approach, we not only mitigate omitted variable bias and reverse causality but also reduce the distortions caused by measurement errors in our data.

[21]Our results remain robust when alternative methods are used to estimate standard errors. For instance, we cluster standard errors at the province-by-wave level or apply Conley standard errors with varying distance cutoffs (Conley, 1999). More details are provided in Appendix Table K.2.

[22]This is particularly true given that we can only use the time when the cell tower was first recorded in the database as a proxy for its construction time. Additionally, the GPS locations of the cell towers are approximated based on the strength of the signal received and the positions of user equipment, although the OpenCellid data provider has processed billions of measurements to estimate the positions of millions of cell towers.

**Instrument Relevance** To examine the validity of our instrumental variable, we begin by testing whether remoteness from submarine cable landing points reduces mobile internet density. Figure 5 presents binned scatterplots illustrating the relationship between the local density of cell towers and the distance to the nearest submarine cable landing points across DHS clusters. In addition to considering all cell towers collectively, we further disaggregate them by radio types—GSM, UMTS, and LTE—and calculate the corresponding measures of mobile internet density for each type. The descriptive results align with our theoretical expectations, showing a negative association between the instrument and mobile internet density, regardless of the cell tower type used for measuring density. In our subsequent estimations, we provide 2SLS regression results including first-stage estimates. Together, these results indicate sufficient instrument relevance.

**Exclusion Restriction** A major identifying assumption of our empirical approach is that the distance to the nearest existing submarine cable landing point influences household wealth solely through its effect on mobile internet density, conditional on a key set of covariates and fixed effects. In the previous sections, we demonstrated that landing points are not preferentially located in wealthier provinces but are instead determined by geographical factors and the need to integrate with the global submarine cable network or internal internet infrastructure. However, this finding does not fully establish the exogeneity of distance to landing points, as this measure may also capture proximity to coastlines, which is therefore closely correlated with local economic development and violate the exclusion restriction assumption. Table 1 investigates the associations between the distance to submarine cable landing points and various local socio-economic factors across DHS clusters. In columns (1) and (2), we examine the relationships with population density and nightlight luminosity using the full set of DHS clusters, whereas columns (3) through (7) focus on livestock density, restricting our focus to rural clusters. Indeed, we find that in the absence of province fixed effects, DHS clusters located farther away from submarine cable landing points tend to exhibit lower population density, dimmer nightlight luminosity, and lower density of livestock such as pigs and chickens. However, these differences across socio-economic dimensions diminish once province fixed effects are included, suggesting that socio-economic factors are more likely to be balanced with respect to distance from submarine cable landing points when comparisons are made within a relatively small geographic scale. Consequently, we include province fixed effects in all subsequent 2SLS estimations.

In our empirical exercises as described below, we perform a range of robustness checks and placebo tests to further evaluate the validity of the exclusion restriction. First, we utilize the DHS survey conducted in 2003 – prior to the rollout of cell towers in the Philippines but after the establishment of an early wave of submarine cable landing points – to assess whether the distance to these landing points predicts household wealth at that time. If distance is found to influence household wealth in 2003, it is plausible that it operates through channels other than mobile internet density, therefore invalidating the exclusion restriction. Additionally, we perform placebo tests by randomly assigning the baseline instrument values to other DHS clusters within the same survey wave or within the same province. A valid instrument should reveal that these placebo instruments exhibit weak instrument characteristics and lack significant association with household wealth status. We also employ the plausibly exogenous framework proposed by Conley et al. (2012), allowing our instrumental variable to exert direct effects on the main outcomes of interest. This method enables us to assess the sensitivity of our findings to varying degrees of instrument invalidity. We provide detailed discussions of these robustness checks and the associated results in the following sections.

## V Empirical Results

### V.A Impacts on Household Wealth

Our empirical analysis begins by estimating our baseline specification, as defined in Equation (1) and Equation (2), leveraging the distance to the nearest existing submarine cable landing point as an instrument for mobile internet density, while controlling for survey wave fixed effects and province fixed effects. As a benchmark, we report simple OLS results to illustrate the endogenous correlational relationship between mobile internet density and the household wealth index constructed based on asset ownership. Both the OLS and 2SLS results are presented in Table 2.

We find a positive and statistically significant association between mobile internet density and the standardized household wealth index, a finding that holds across all specifications as we sequentially introduce controls for locality (column (1)) and household characteristics (column (2)), and mobile phone ownership which we include to address concerns that our results may be skewed by access to mobile devices, rather than access to mobile internet infrastructure like cell towers (column (3)). While the coefficient estimates for mobile internet density reduce slightly in magnitude, they all remain positive and significant at the 1 percent level.

Next, we present the instrumental variable estimates in columns (4) to (6). Panel A shows that the second-stage results suggest a positive causal effect of mobile internet density on household wealth. This finding is consistent across all three models, which control for locality-level and household-level confounders, including mobile phone ownership. Consistent with our theoretical expectations, we can see a significantly negative relationship from the first-stage results in Panel B: as the distance from a submarine cable landing point increases, mobile internet density declines. Furthermore, the first-stage Kleibergen-Paap Wald rk F statistics all exceed the standard threshold of 10, and the Anderson-Rubin tests reject the null hypothesis. Together, these results indicate that our instrument is a strong predictor of local cell tower density.

One can also see that our 2SLS estimates are notably larger than the OLS estimates (approximately tenfold). In the fully specified model, doubling the number of cell towers per 1,000 people within neighborhoods is associated with a 0.04 ($\approx\ 0.145\ \times\ log2$) standard deviation increase in the household wealth index. This implies that the OLS approach underestimates the role of mobile internet density in improving household wealth status. Beyond the influence of omitted variables, measurement errors (and thus attenuation bias), and reverse causality, as discussed earlier, the larger 2SLS estimates may reflect local average treatment effects (LATE) specific to areas where the construction of cell towers is primarily determined by ease of access to the cable network, a point we will elaborate on in the next section.

A natural concern regarding our measurement of mobile internet density is whether coverage, based on prescribed buffers around cell towers (i.e., proximity of users to mobile towers) and the average count of locally built cell towers, effectively captures mobile internet connectivity or the quality of internet service available. We examine this issue through two approaches. First, we acknowledge that distance-based measures of mobile internet access may not capture connectivity consistently across different localities due to factors such as geographical topography, climate, and other local conditions. For instance, flat areas farther from cell towers than mountainous regions may still experience better mobile internet access (it is important to note that our inclusion of terrain slope as a control variable could partially account for this issue). Consequently, we vary the coverage radius for our measure of mobile internet density and re-estimate our IV equations in Figure 6.

Our results are shown on the left side of the figure. They display the coefficient estimates for mobile internet density and their 95 percent confidence intervals, using the benchmark radii. These are based on three models that include different sets of controls, as shown in Table 2. Next, we recalculate mobile internet density using different cell tower radii, shown on the horizontal axis. The baseline estimates are marked with dashed lines for comparison. The figure shows that the results remain stable, even when all cell towers are assumed to cover areas up to 10 kilometers. This suggests that the specific choice of cell tower radius has little effect on the main findings.

As a second check to account for differences in internet service quality, we supplement our analysis with mobile internet performance data. Specifically, we use upload and download speed data from Ookla®, accessed through the Development Data Partnership. The data is available quarterly from 2019 to 2024 at a resolution of approximately 610 square meters. It is collected each time the Speedtest® application is used on a mobile device. Its measurements have been filtered to only include GPS-quality location accuracy. In doing so, we first generate buffers around DHS clusters with radii of 10 kilometers for rural clusters and 2 kilometers for urban clusters, overlaying these buffers with mobile internet speed shapefiles from Ookla® to calculate the annual average speed within each buffer (see more details in Appendix A). We then construct a mobile internet quality measure by multiplying the local average number of cell towers (per 1,000 people) by the mobile internet speed, before applying a logarithmic transformation. Subsequently, we perform the IV estimations as described above, using the Euclidean distance from the DHS cluster's centroid to the nearest existing submarine cable landing point to instrument for mobile internet quality.[23]

Table 3 presents the associated results, with the measure of mobile internet quality constructed from download speed in columns (1) to (3) and from upload speed in columns (4) to (6). Across all permutations, we find that an increase in mobile internet quality, whether measured by upload or download speeds, leads to a rise in overall household wealth. Within diagnosis checks, the first-stage results continue to show significantly negative associations between our instrument and mobile internet quality. The F-statistics remain above 10, and the AR tests are statistically significant at the 1 percent level, suggesting that our instrument is not weak for mobile internet

[23]Note that the regressions are conducted only on the sample from the 2022 wave of the DHS survey, as the Ookla® data available to us aligns exclusively with this period.

quality. Taken together, the results indicate that the density of mobile internet cell towers measured in our analysis positively impacts household wealth conditions, with the effect primarily driven by mobile internet connectivity and service quality.

**Robustness Checks** We now turn to evaluating the robustness of our empirical strategy, probing the validity of distance to submarine cable landing points as an instrument for mobile internet density. As demonstrated below, our findings are robust to a range of placebo tests and to variations in several salient dimensions of our measurements and estimation approaches.

First, we provide plausible empirical evidence on exclusion restriction that mobile internet access is the only channel through which distance to submarine cable landing point impacts household wealth, conditional on a crucial set of control variables. To this end, we conduct reduced-form estimations by regressing the standardized household wealth index on distance to submarine cable landing point, using DHS data from the combined 2017 and 2022 waves and more importantly, using DHS data from the 2003 wave, a period when submarine cables existed but mobile cell towers had not yet been rolled out in the Philippines.

Appendix Table H.1 presents the results, with columns (1) and (2) showing the reduced-form relationship between distance to submarine cable landing point and household wealth in 2003 as a placebo test (note that mobile phone ownership is not controlled for, as this variable was unavailable in that wave), and columns (3)–(5) reporting the relationship for the 2017 and 2022 waves. Conditional on province fixed effects, and local and household characteristics, one can see the expected negative and statistically significant relationship between household wealth and distance from submarine cable landing point in the post-rollout period; however, while there is a negative association before the rollout, it was not statistically significant at the conventional level. The absence of a significant relationship between household wealth and distance from submarine cable landing point before the rollout of mobile cell towers, but its emergence after the rollout, suggests that mobile internet access is likely the sole channel through which the distance influences household wealth.

Second, we further examine the assumption of instrument exogeneity by following the plausibly exogenous framework proposed by Conley et al. (2012). The main idea of this approach is to allow our instrumental variable to have direct effects on the main outcomes of interest; specifically, the instrumental variable is involved in the second-stage regression with a coefficient $\delta$. If the exclusion restriction assumption holds, $\delta$ would be equal to zero with perfect instrument exogeneity. By contrast, various values of $\delta$ imply violation of the exclusion restriction assumption. The magnitude of $\delta$ therefore allows us to assess how robust our findings are to different degrees of instrumental invalidity. In Appendix Figure J.1, we find that our estimated relationship between mobile internet density and household wealth remains robust even with substantial violations of the exclusion restriction assumption. We discuss the application of this plausibly exogenous framework with empirical findings in more depth in Appendix J.

Third, we employ several alternative instrument variables, with results reported in Appendix Table I.1. As opposed to our baseline instrumental variable, which captures the distance to the nearest *existing* submarine cable landing point at the time of the survey, columns (1) and (2) use alternative sets of landing points to construct the instrument. Column (1) utilizes only landing points established before 2003, while column (2) relies on those constructed before 2017 (recall that in our baseline estimations on the DHS survey in wave 2022, we should also consider landing points established between 2017 and 2022). As the table shows, we find that constructing our instrument using landing points established before 2003 leads to a weak instrument (F-statistics = 6.13), but this issue is mitigated when including landing points established until 2017. Indeed, landing points established before 2003 may not provide a valid instrument due to their outdated relevance for mobile cell towers.[24] This corroborates our explanation underlying the instrument that proximity to more advanced internet infrastructure, specifically submarine cables, is positively associated with the current distribution of mobile internet access.

Columns (3) and (4) test placebo instruments: column (3) randomly assigns the baseline instrument values to other clusters within the same survey wave, while column (4) assigns these values randomly to clusters within the same province (possibly across the survey waves). Our results show that the placebo instruments indeed fail to identify the effects of mobile internet density on household wealth, with insignificant first-stage effects and the associated IV diagnostics indicating instrument weakness. This analysis suggests that our previous IV estimates are not merely arising by chance.

We further assess the robustness of our results by varying the measurement of our outcome of interest, key explanatory variable, and the estimation approach for standard errors. Our findings

[24]But it is not due to a limited number of landing points, which could otherwise make distance less important, as areas would roughly share a common distance from a small number of cell towers. In fact, landing points established before 2003 account for 47% of all points considered (see Figure 1 and Appendix Table F.1).

remain consistent and are not meaningfully affected across all these robustness checks. We use the original dependent variable of the household wealth index, measured in quintiles on a scale of 1 (poorest) to 5 (richest), without any standardization, in Appendix Figure K.1. Our results remain qualitatively unchanged when using the original categorical outcome instead of the standardized one. Results from varying the logarithmic transformation for mobile internet density—where, for clusters without cell towers (zero counts), we replace zero values with incremental small numbers ranging from 0.1 to 10 in steps of 0.1—are reported in Appendix Figure K.2. Relative to the baseline specification, the coefficient estimates and 95 percent confidence intervals on mobile internet density are largely unchanged in both magnitude and sign.

Additionally, in Appendix Table K.1, we apply various transformations to our measurement of mobile internet density, including the inverse hyperbolic sine transformation, a neglog transformation, a Johnson transformation, as well as square root and cube root transformations. These transformations have minimal impact on our core findings. Appendix Table K.2 applies different approaches to estimating standard errors. Specifically, we cluster standard errors at the province-by-wave level and implement Conley standard errors (Conley, 1999), with distance cutoffs set at 50 km, 100 km, 150 km, and 200 km, respectively, to account for potential spatial correlation in the data. Across all these specifications, our core coefficient estimates remain statistically significant at conventional levels. A final potential concern is spillover effects – specifically, that households in neighboring clusters may benefit from nearby mobile internet coverage despite the absence of local cell towers. Although the DHS sampling procedure ensures that clusters are sparsely distributed, we formally test for such spillovers by including mobile internet density in the nearest neighboring clusters as additional controls in our 2SLS regressions. The results, as reported in Appendix Table K.3, show no evidence that mobile internet density in the first, second, or third nearest clusters has any significant effect on local household wealth, whereas the coefficients on local mobile internet density remain statistically significant and quantitatively similar.

## V.B Unequal Benefits of Mobile Internet Access

Inequality remains a persistent challenge in developing countries, often exacerbated by uneven access to technology. Moreover, even in situations where access to technology is equitable, the resulting benefits can vary significantly among different social groups due to differential technology usage behavior (e.g., using internet for e-commerce vs. addiction to video games).[25] The Philippines, an archipelago with significant regional and geographical disparities, offers a case study for examining how internet access can influence wealth distribution.

We begin our analysis of digital inequality by examining the impacts of mobile internet connectivity across urban and rural areas. To capture potential differential effects on household wealth, we split our sample into urban and rural households, allowing mobile internet connectivity to have distinct impacts depending on the area of residence. Comparing columns (1) and (2) in Table 4, we observe significantly positive effects of mobile internet density on the standardized household wealth index in rural clusters, while the effects in urban areas are positive, with a coefficient estimate approximately 2.6 times larger in magnitude than that for rural areas, but statistically insignificant. Columns (3) and (4) focus on urban clusters using an alternative definition of urbanization. Column (3) restricts the sample to households located in Barangays (local administrative units at the third level in the Philippines) classified as cities by the Global Human Settlement Layer (GHSL) project. Column (4) expands the sample to include households in Barangays classified as dense towns by the GHSL project. The results indicate that changing the urban definitions does not yield significant effects for urban households. Indeed, the Kleibergen-Paap Wald rk F statistics and AR tests suggest that the 2SLS estimates for urban households might suffer from a weak instrument.

It is important to note that the weak instrument issue for urban clusters is expected, as telecom companies often prioritize densely populated, politically or economically important cities, regardless of their distances from submarine cable landing points. To further assess where our previously estimated LATEs apply, we focus on areas beyond the rural regions where we have found robust estimates with a strong instrument. Continuing with Table 4, our analysis proceeds by focusing on households located in urban clusters while excluding those in Barangays with large population sizes, using data from the GHSL project. Specifically, we progressively exclude

[25] The impact of internet access on inequality has been the subject of extensive and nuanced debate. For example, one perspective suggests that the internet and modern Information and Communication Technologies (ICTs) have the potential to reduce inequality by spreading economic activities and expanding job opportunities across geographic boundaries (Friedman, 2007). This can lead to a more equitable distribution of employment opportunities. However, an opposing viewpoint argues that the advent of the internet has led to “skill-biased technological change”, favoring individuals with higher levels of education and skills (Akerman et al., 2015), therefore, resulting in an increase in income inequality. Empirical evidence on the effects of internet access on inequality remains limited, particularly in the context of developing countries.

Barangays whose population size exceeds the 95th percentile in column (5), the 90th percentile in column (6), the 85th percentile in column (7), and the 80th percentile in column (8).

One can see that excluding urban households in Barangays above the 95th percentile in population size does not change the significance level of the coefficient estimates, compared to the sample that includes all urban households. However, the estimates start to become statistically significant when excluding those above the 90th and 85th percentiles. Notably, once households in Barangays above the 90th percentile are excluded from regressions, the 2SLS estimates no longer suffer from a weak instrument, with an F-statistic of 10.53 and an AR p-value of less than 0.05. In this case, the estimated coefficient reaches 0.254, significant at the 10 percent level, and is 3.6 times larger than the estimate for the rural sample. Given these results, we cautiously conclude that: (*i*) our previously estimated LATEs apply to rural areas and urban areas in Barangays with population sizes below the 90th percentile; and (*ii*) households in urban areas are likely to experience greater wealth gains from access to mobile internet, at least for those in medium-sized cities and towns.

We next examine the differential effects of mobile internet access on household wealth across three educational attainment groups. Specifically, we test the hypothesis that mobile internet access is more likely to result in higher wealth gains for better-educated households, as they may have a better grasp of internet technology for productive use or access to more suitable online job opportunities. Using the educational attainment of household heads, we categorize our sample into three groups: households where the head has less than a primary education, households where the head has a secondary education, and households where the head has education beyond the secondary level. From results presented in Appendix Table L.1, we find that the impact of internet access is the most significant for households with the lowest level of education (column (1)). This suggests that even basic internet access may open up opportunities for economic improvement, potentially through providing access to information, online services, or commerce.

The relationship for households with secondary level education is significant at the 10 percent level (column (2)), whereas it loses significance for households with education higher than secondary (column (3)). However, when we employ the measure of mobile internet quality, the coefficient estimates for households with education beyond the secondary level become statistically significant, though only at the 10 percent level (see Appendix Table L.2). Across all specifications, we observe increasing effects of mobile internet access on household wealth with higher educational attainment. However, given the lower statistical significance on coefficient estimates for better-educated households, we interpret these results as potentially indicating a ceiling effect—households in developing countries with higher education levels may already be maximizing the benefits of internet access, and further improvements in mobile internet density may not significantly enhance their economic outcomes. It may also suggest that these households are reliant on more expensive fixed-line broadband for internet access, making mobile internet density less critical for wealth generation.

Taken on its own, these findings suggest that, while, on the whole, citizens benefit from improved mobile internet access, the returns of improved access to the mobile internet varies by location and educational attainment. Understanding these dynamics is important for informing policies that can bridge the digital divide and promote inclusive economic growth.

### V.C Mechanisms: New firms, the labour market, and education

As shown above, there are a number of potential channels through which mobile internet connectivity might improve household wealth in the medium to long run. In this section, we assess two key pathways through which this effect may operate: (*i*) stimulated local economic activities driven by mobile internet as a fundamental infrastructure, which in turn creates more employment opportunities; and (*ii*) improved educational attainment facilitated by better access to information and digital technologies for learning and teaching.

Mobile internet access arguably plays a fundamental role in a majority of economic activities. It can foster entrepreneurship by providing a platform for building businesses, a distribution channel for reaching customers, and a cost-effective alternative to selling products or services without the need for physical space. To examine whether local economic activities respond differently to mobile internet density, we utilize data on Points of Interest (POIs) in key economic sectors from Foursquare OS Places.[26]

We extract POIs related to Arts and Entertainment, Business and Professional Services, Dining and Drinking, Retail, and Travel and Transportation. We measure economic activities within each

[26] Foursquare OS Places is an open database that provides detailed information on 100 million places worldwide, including restaurants, retail stores, landmarks, and other POIs. In the Philippines alone, approximately 0.80 million geocoded places have been recorded since 2009. These POIs are categorized into 1,245 classifications across six levels and we focus on the first level in our analysis.

DHS cluster from a pool of the 2017 and 2022 waves, using POI density, defined as the number of POIs per 1,000 people.[27]

With POI density as the outcome variable, we conduct our IV estimations, controlling for wave fixed effects, province fixed effects, and cluster characteristics as in our household-level analysis. We present the estimates in Table 5, with different columns focusing on different types of POIs. To mitigate weak instrument issues in large urban areas as discussed above, Panel A excludes clusters located in Barangays with population sizes exceeding the 99th percentile, while Panel B further excludes urban clusters located in Barangays with population sizes exceeding the 80th percentile. From results in both panels, one can see that the density of POIs in the sectors of Business and Professional Services, Dining and Drinking, Retail, and Travel and Transportation differentially increase in localities with higher mobile internet density. However, we find no evidence of a positive impact on the sector of Arts and Entertainment. This suggests that mobile internet access indeed boosts crucial economic activities that could provide more job opportunities and, in turn, improve household wealth.

Subsequently, we analyze the supply side of the labor market, evaluating the impact of mobile internet connectivity on individual employment status. We examine employment outcomes using the "Individual Record" (IR) datasets of DHS survey, which primarily focus on women in households (we restrict the sample to women aged 18 and above). We first estimate our baseline 2SLS model for female respondents, using binary indicators as dependent variables to capture different employment statuses: whether the female is employed during the seven days preceding the survey interview or at any point in the past 12 months. As shown in columns (1) and (2) of Table 6, we find that females are more likely to be employed—either recently or during the 12 months prior to the interview—in areas with higher levels of mobile internet connectivity. Columns (3) to (5) focus on employed women and examine how mobile internet connectivity influences their mode of employment, using binary dependent variables indicating whether the respondent was employed year-round, seasonally, or occasionally. Interestingly, the results show a negative association between mobile internet connectivity and year-round employment among women, while seasonal

[27]For DHS clusters in 2017, POIs considered were those with entry dates before 2017 and not marked as closed in the database, while for clusters in 2022, POIs were those recorded before 2022 and had not been closed by then. It is important to note that the date a POI entered the database does not necessarily reflect its actual opening date, just as the recorded close date may not precisely indicate when the POI ceased operations. While the ideal approach would be to include only active POIs, data limitations prevent us from doing so.

and occasional employment are positively associated. This pattern suggests that mobile internet may enable more flexible work arrangements for female workers.

Given that only 50 percent of women are currently employed in the Philippines, these findings underscore the need for targeted interventions—such as digital literacy programs, childcare support, and skill-building initiatives—to help women fully capitalize on the economic opportunities enabled by internet access. The Philippine DHS survey does not include “MR” files focused on male respondents, limiting our ability to analyze male employment outcomes. A promising avenue for future research is to systematically examine whether the wealth-enhancing effects of mobile internet access also operate through its impact on male employment, and to assess gender disparities in the economic benefits of digital connectivity. Men may be better positioned to capitalize on internet-enabled economic opportunities, possibly due to existing gender disparities in the labor market, digital skills, or sectoral employment patterns.

We now consider educational outcomes, utilizing the “Personal Record” (PR) datasets, which provide individual-level information on household members (the sample is restricted to individuals aged 18 and above). The 2SLS estimates are reported in columns (6) and (7) of Table 6, respectively. Our outcome variables of interest are a binary indicator for attaining at least secondary education (column (6)), and the number of years of educational attainment (column (7)). The results indicate that higher mobile internet density significantly increases the probability of attaining secondary education and the total years of schooling, suggesting that improved internet access could perhaps facilitate better educational outcomes by providing access to online learning resources, educational materials, and information on schooling opportunities. This implies that mobile internet may play a role in reducing long-term human capital inequalities, especially in rural or underserved areas.

## VI Conclusion

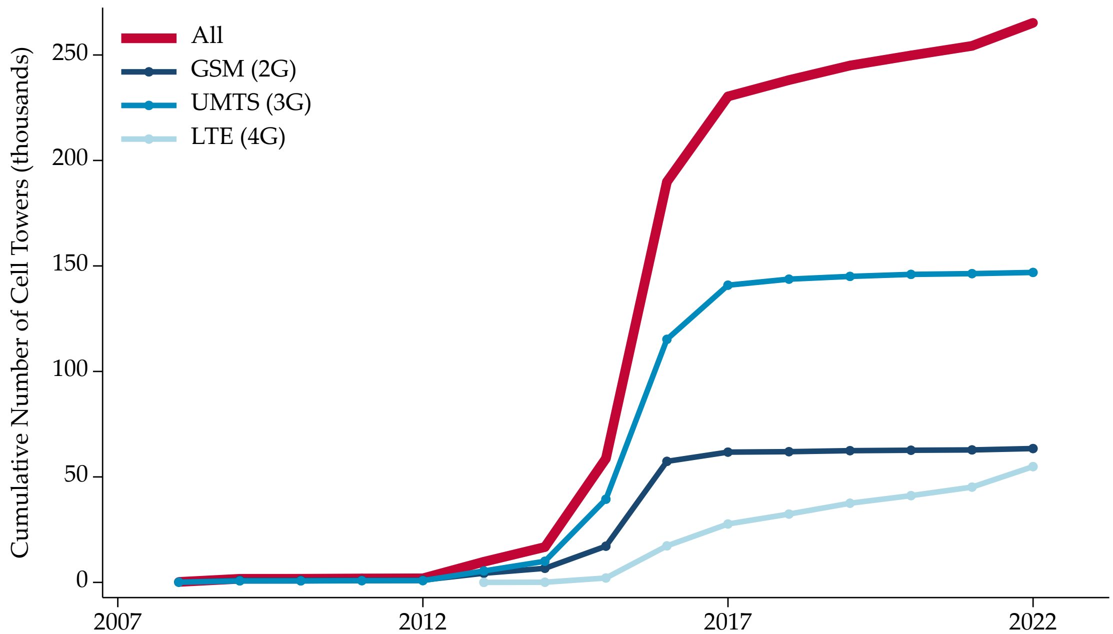
The growing use and importance of internet access has had profound economic impacts across the world. This paper has considered the impact of growing mobile internet access on household wealth in the Philippines. We use the staggered rollout of cell towers and an instrumental variable based on distance to the nearest submarine cable landing point for causal identification. Our results show that mobile internet connectivity leads to higher household wealth. Our estimates represent local average treatment effects that exclude the most densely populated urban areas where the instrument is relatively weak in strength. Within this sample, all groups appear to benefit from mobile internet connectivity, with more pronounced effects observed in urban areas compared to rural ones. We also find positive effects across varying levels of educational attainment, with the magnitude of the effects increasing as education levels rise, although the estimates are less statistically significant for higher education groups. Overall, our findings show that mobile internet helps raise household wealth and that the gains are broadly shared.

We test mechanisms that these benefits of mobile internet connectivity likely operate through its role as a fundamental component of modern infrastructure, and find that it stimulates economic activities in crucial sectors which could generate employment opportunities. On the other hand, our results indicate that mobile internet connectivity increases female labor force participation in occasional and seasonal employment, while reducing engagement in year-round jobs. It also appears to enhance human capital accumulation through improved access to information and digital learning tools. Together, our findings underscore the multifaceted value of digital connectivity in promoting inclusive economic development, and contribute to ongoing debates about the distributional impact of mobile internet access (e.g., Hjort and Tian, 2025). They highlight that there are important payoffs from investments in digital infrastructure but that, while important, these investments are not enough. Complementary investments such as digital skills training and improved access to mobile devices will help ensure benefits are more widely and equitably shared.

The Philippines provides a useful setting for our identification strategy; however, caution is warranted in generalizing the results beyond this context. As an archipelagic country, internet access may play a more important role in connectivity and economic activity compared to more geographically contiguous countries, which makes it well-suited for our approach. Moreover, the Philippines' service-oriented economy and its considerable reliance on remittances may shape the relationship between mobile internet access and household wealth in ways that differ from other settings. In addition, our findings reflect the rollout of a specific technology during a specific time period, and these effects may not persist as technologies and usage patterns evolve. Nonetheless, our results provide strong evidence that improved and more widespread mobile internet access can contribute to increased household wealth. And a promising direction for future research would be to test the external validity of our findings by applying a similar empirical strategy in other developing countries.

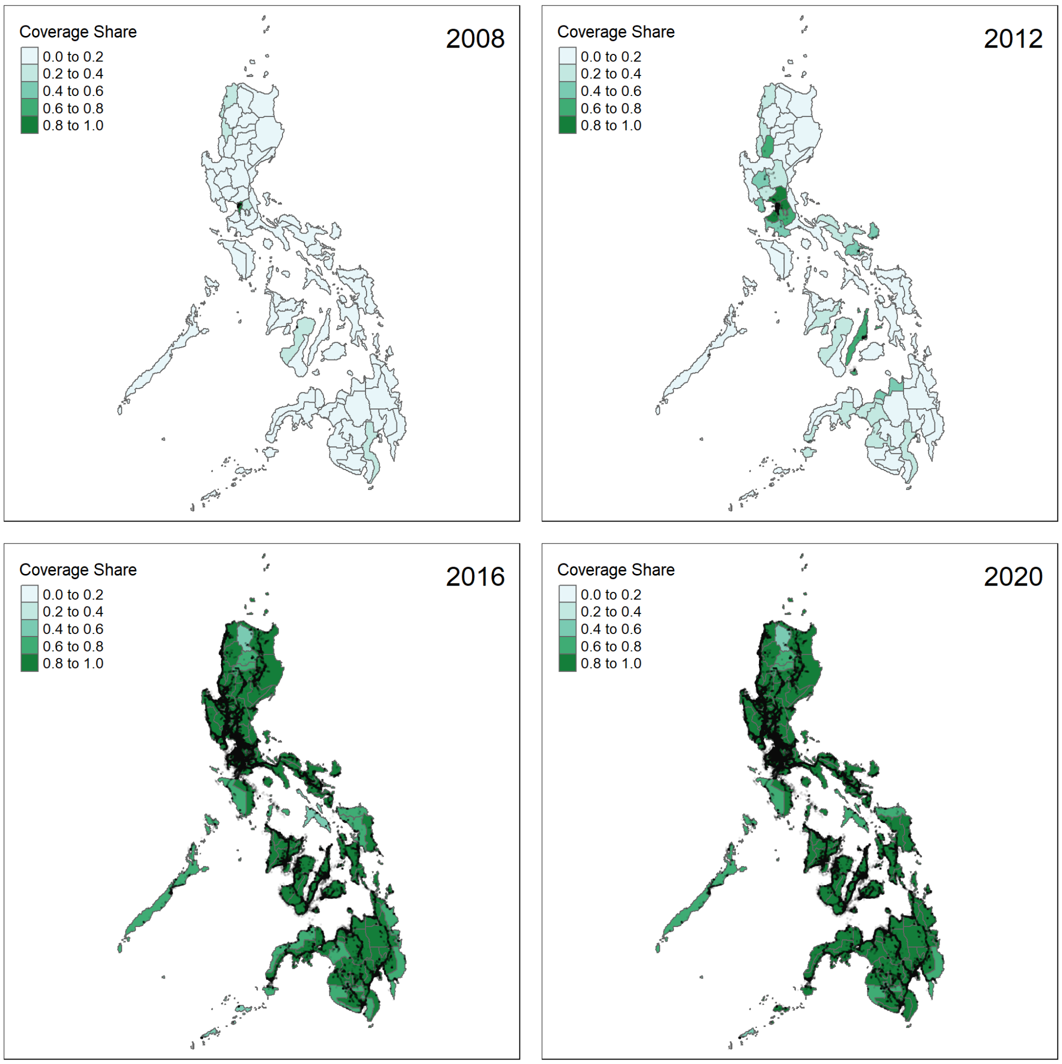
## FIGURES AND TABLES

Figure 1: Cumulative Number of Cell Towers in the Philippines Over Time, 2008-2022



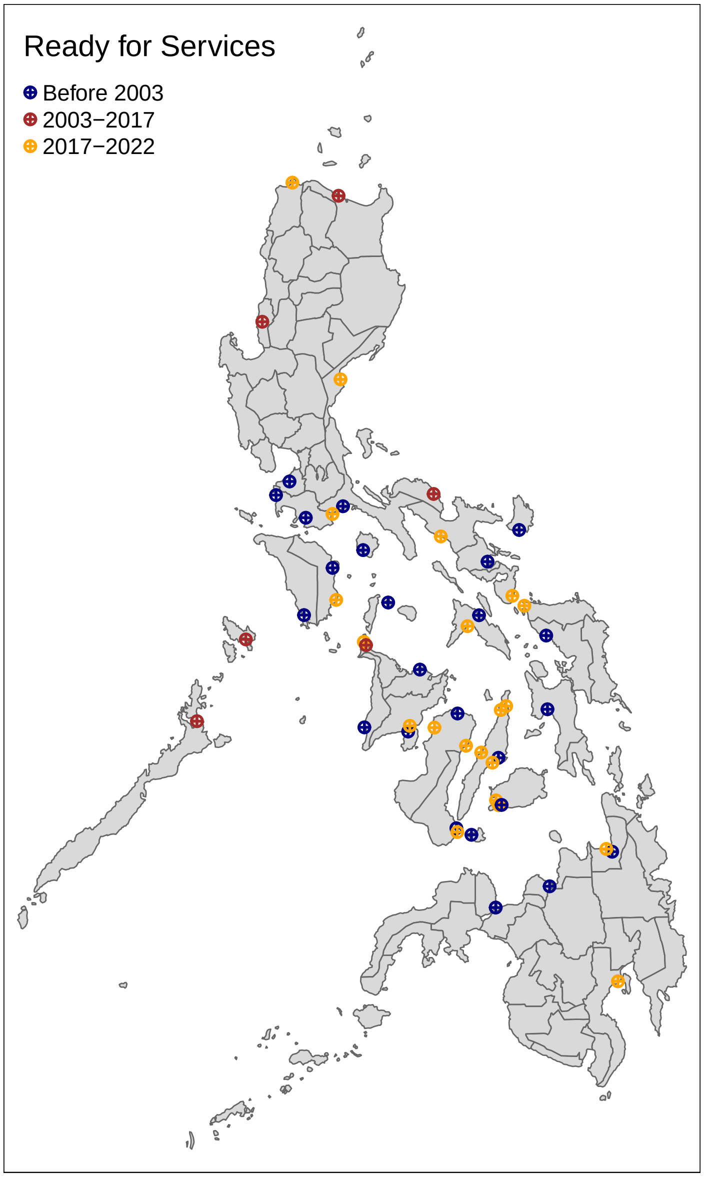

Notes: This figure shows the cumulative number of cell towers in the Philippines from 2008 to 2022, categorized by radio types: GSM (2G), UMTS (3G), and LTE (4G). Our data includes a total of 265,246 georeferenced cell towers, sourced from the OpenCelliD database.
Source: Authors' calculations.

Figure 2: Mobile Internet Coverage Across the Philippines



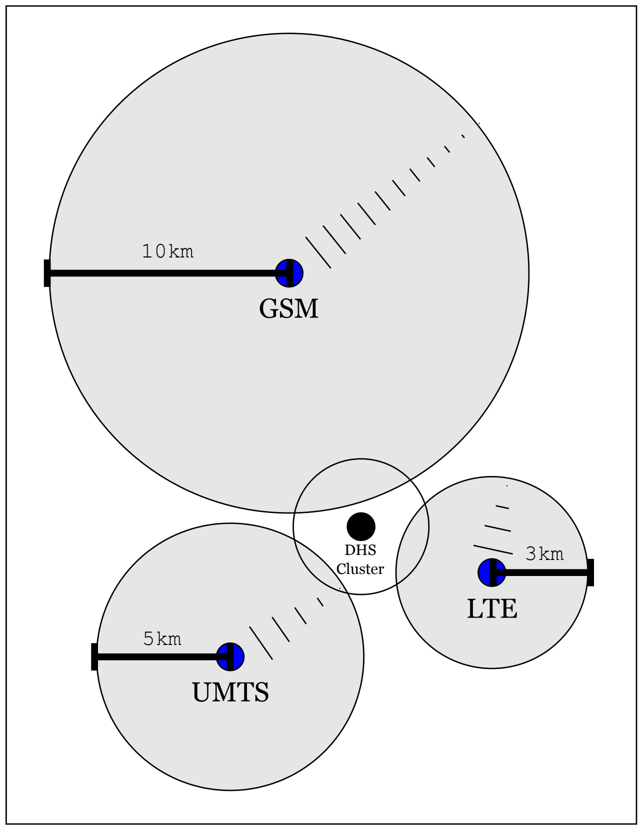

Notes: This figure illustrates the spatial distribution of cell towers (represented by black dots) and the proportion of population covered by mobile internet across provinces in the Philippines. To calculate coverage shares, we overlay annual geospatial population data from WorldPop (2018) with cell tower data. Coverage shares represent the percentage of population within a certain radius of cell towers relative to the total population in each province. We define the coverage radius as 10 km for GSM towers, 5 km for UMTS, and 3 km for LTE.
Source: Authors' calculations.

Figure 3: Landing Points of Submarine Cables Across the Philippines



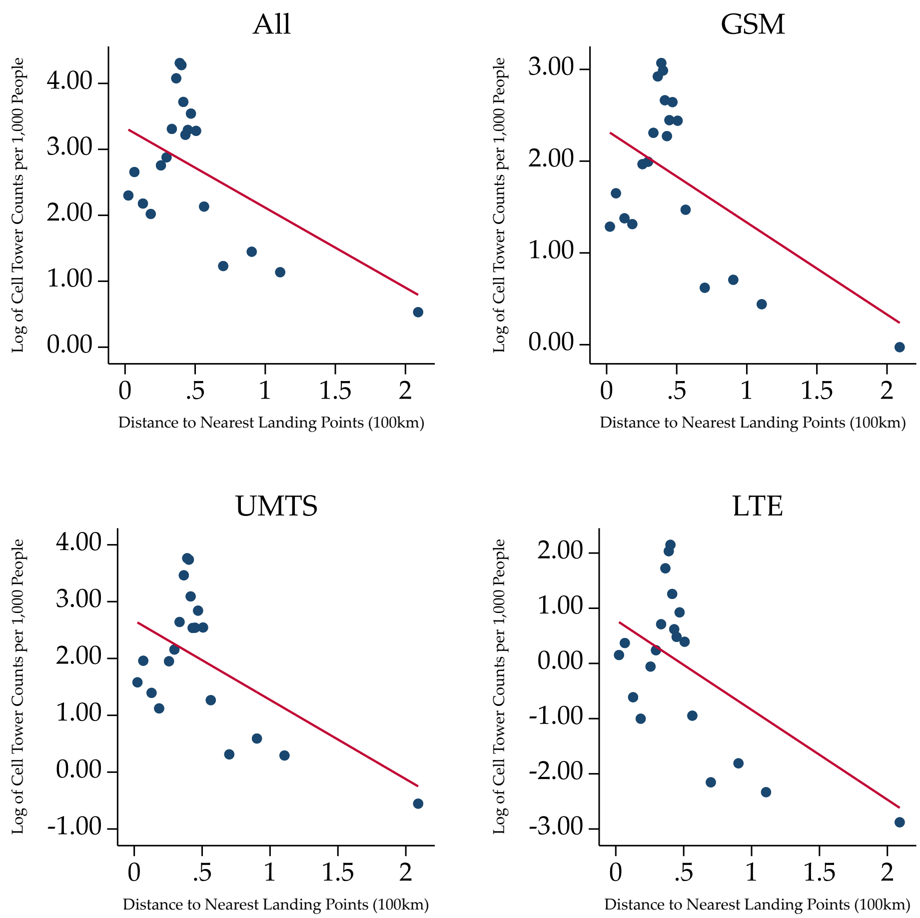

Notes: This figure illustrates the spatial distribution of submarine cable landing points across the Philippines, color-coded by the year they became operational. Blue points represent landing points that were ready for services before 2003, red points for those operational between 2003 and 2017, and orange points for those that became active between 2017 to 2022.

Figure 4: Schematic of Mobile Internet Density Measurement



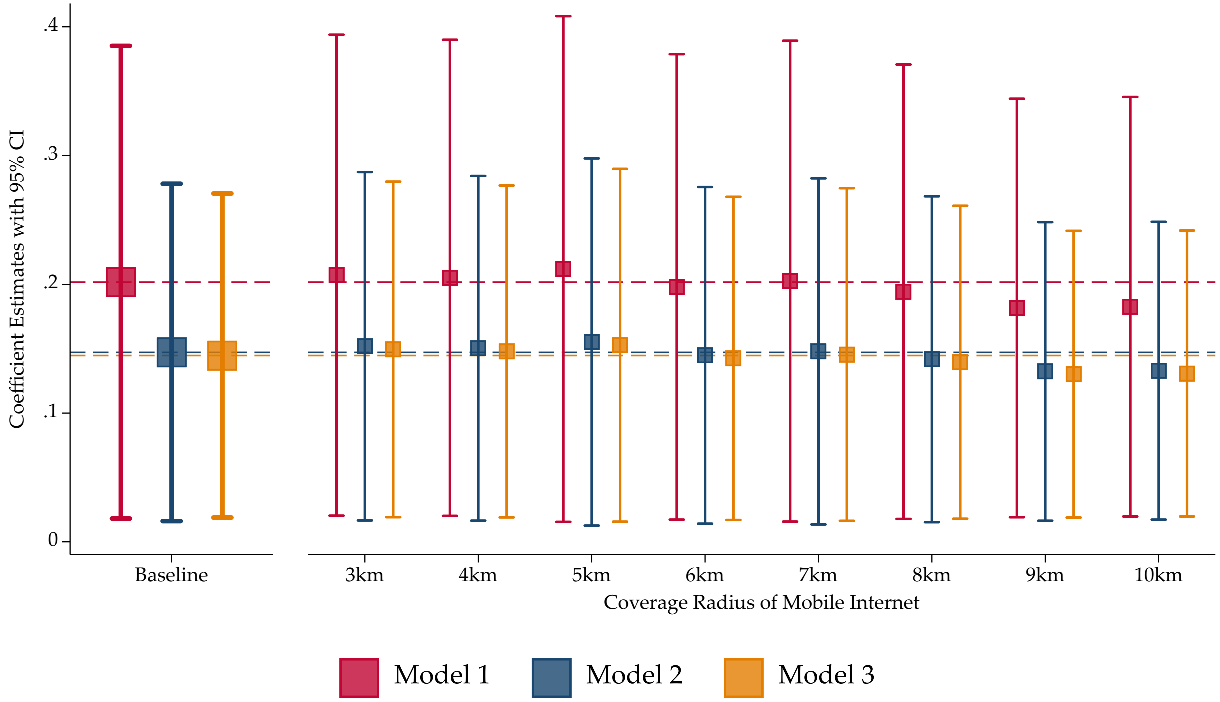

Notes: This figure provides a schematic representation of how we measure mobile internet density, defined as the log of cell tower counts per 1,000 people across DHS clusters. To calculate the number of cell towers covering these clusters, we generate buffers around the clusters (with a 10 km radius for rural clusters and a 2 km radius for urban clusters) and around the cell towers (with radii of 10 km for GSM, 5 km for UMTS, and 3 km for LTE). The cell tower count is determined by the towers whose buffers intersect with the cluster buffer. We generate buffers around the clusters because their original locations are intentionally displaced to protect privacy and prevent disclosure.
Source: Authors' calculations.

Figure 5: Mobile Internet Density and Distance to Nearest Landing Point




Notes: This figure presents the relationship between mobile internet density and the distance to the nearest existing submarine cable landing points across DHS clusters. Mobile internet density is measured as the log of cell tower counts per 1,000 people (to address instances where cell tower counts are zero, we substitute these values with one). To determine the number of cell towers covering DHS clusters, we create buffers around clusters (with a radius of 10 km for rural clusters and 2 km for urban clusters) and buffers around cell towers (with radii of 10 km for GSM, 5 km for UMTS, and 3 km for LTE). The cell tower count is based on towers whose buffers intersect with the clusters' buffers. The figure shows bin scatter plots of mobile internet density against the distance to the nearest landing point of submarine cables, using 20 equally-sized bins, weighted by population. We also break down cell towers by their radio types—GSM, UMTS, and LTE—and calculate the corresponding measurement of mobile internet density across clusters.
Source: Authors' calculations.

Figure 6: Mobile Internet Density and Household Wealth, Varying Coverage Radius




Notes: This figure plots the coefficient estimates for the impact of mobile internet density on household wealth. The dependent variable is household wealth status, standardized from quintiles on a scale of 1 (poorest) to 5 (richest). The primary explanatory variable, mobile internet density, is measured as the log of cell tower counts per 1,000 people within each DHS cluster; for clusters with zero cell towers, we replace zero values with one to enable logarithmic transformation. For all specifications, we instrument mobile internet density using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. The baseline results are replicated from columns (4), (5), and (6) of Table 2, where the coverage radius is set at 10 km for GSM towers, 5 km for UMTS, and 3 km for LTE. To test the robustness of the results, we uniformly vary the coverage radius for all cell tower types from 3 km to 10 km and replicate the same 2SLS regression specifications. Model 1 controls for factors at the cluster level (an urban dummy, population density, nightlight luminosity, rainfall, temperature, and slope of terrain); Model 2 adds household-level controls, including the number of household members, the age, gender, and educational attainment of the household head, while Model 3 further controls for household mobile phone ownership. All specifications incorporate fixed effects for survey wave and province to capture temporal and regional variations. Standard errors are clustered at the DHS cluster level, and sampling weights are applied to maintain representativeness. The figure also presents the associated 95% confidence intervals. Baseline levels are marked by grey lines for reference.
Source: Authors' calculations.

Table 1: Exogeneity of Distance to Nearest Landing Point

| | Pop. Density | Nightlight | Livestock Density: Cattle | Goat | Pig | Sheep | Chicken |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | **PANEL A: No Province FE** | | | | | | |
| Distance | -16.382*** | -6.206*** | -0.702 | -0.161 | -32.605*** | 0.026 | -302.846** |
| | (6.086) | (1.126) | (0.982) | (2.159) | (7.939) | (0.045) | (136.668) |
| | **PANEL B: Province FE** | | | | | | |
| Distance | 3.857 | -0.780 | -0.906 | 0.283 | 1.536 | 0.030 | 102.449 |
| | (7.445) | (0.767) | (0.790) | (1.244) | (4.841) | (0.028) | (139.287) |
| Mean DV | 117.14 | 13.66 | 15.59 | 26.43 | 98.97 | 0.24 | 1179.16 |
| Observations | 3184 | 3184 | 1824 | 1824 | 1824 | 1824 | 1824 |
| Number of cluster | 245 | 245 | 233 | 233 | 233 | 233 | 233 |

Notes: This table presents OLS regression results at the cluster level, using data from the 2003, 2017, and 2022 DHS geospatial covariate datasets. The dependent variables are population density (thousands per $km^2$ ) in column (1), nightlight luminosity (0-63) in column (2), and specific livestock densities (heads per $km^2$) from columns (3) to (7). The primary explanatory variable is the Euclidean distance of DHS clusters to the nearest existing submarine cable landing point. We use the full sample of both urban and rural clusters to analyze population density and nightlight luminosity, while focusing exclusively on rural clusters for the analysis of livestock density. Panel A presents results without province fixed effects, while Panel B further includes them. All specifications incorporate survey wave fixed effects to account for temporal variations. Standard errors are clustered at the province-by-wave level, and population weights are applied. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

Table 2: The Effect of Mobile Internet Density on Household Wealth

| | Standardized Household Wealth Quintile | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | 2SLS | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | | **PANEL A: Second-Stage Results** | | |
| Mobile internet density | 0.023*** | 0.019*** | 0.016*** | 0.202** | 0.147** | 0.145** |
| | (0.009) | (0.006) | (0.006) | (0.094) | (0.067) | (0.064) |
| Kleibergen-Paap Wald rk F statistic | | | | 21.02 | 20.77 | 20.74 |
| AR Test *p*-value | | | | 0.01 | 0.01 | 0.01 |
| Observations | 53648 | 53648 | 53648 | 53648 | 53648 | 53648 |
| Number of cluster | 2308 | 2308 | 2308 | 2308 | 2308 | 2308 |
| | | | | **PANEL B: First-Stage Results** | | |
| Distance | | | | -0.607*** | -0.603*** | -0.603*** |
| | | | | (0.132) | (0.132) | (0.132) |
| Wave FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Household Controls | No | Yes | Yes | No | Yes | Yes |
| Mobile Phone Ownership | No | No | Yes | No | No | Yes |

Notes: This table presents the results of OLS and 2SLS regressions at the household level, based on data from the 2017 and 2022 DHS surveys, corresponding to periods of cell tower rollouts across the Philippines. The dependent variable is household wealth status, standardized from quintiles on a scale of 1 (poorest) to 5 (richest). The primary explanatory variable, mobile internet density, is measured as the log of cell tower counts per 1,000 people within each DHS cluster; for clusters with zero cell towers, we replace zero values with one to enable logarithmic transformation. For 2SLS specifications, we instrument mobile internet density using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. The table includes Kleibergen-Paap Wald rk F statistics and Anderson-Rubin (AR) test *p*-values to evaluate the strength and relevance of our instrumental variable. For 2SLS regressions, we report both first-stage and second-stage results with Panel A and B. In columns (1) and (4), household wealth quintile is regressed on mobile internet density, controlling for factors at the cluster level (an urban dummy, population density, nightlight luminosity, rainfall, temperature, and slope of terrain). Columns (2) and (5) add household-level controls, including the number of household members, the age, gender, and educational attainment of the household head, while columns (3) and (6) further control for household mobile phone ownership. All specifications incorporate fixed effects for survey wave and province to capture temporal and regional variations. Standard errors are clustered at the DHS cluster level, and sampling weights are applied to maintain representativeness. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

Table 3: The Effect of Mobile Internet Quality on Household Wealth, 2SLS

| | Download Speed | | | Upload Speed | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **PANEL A: Second-Stage Results** | | | | | |
| Mobile internet quality | 0.208** | 0.149*** | 0.143*** | 0.261** | 0.187** | 0.180** |
| | (0.086) | (0.057) | (0.053) | (0.119) | (0.079) | (0.075) |
| Kleibergen-Paap Wald rk F statistic | 16.33 | 16.08 | 16.06 | 11.24 | 11.03 | 11.02 |
| AR Test *p*-value | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 |
| Observations | 26722 | 26722 | 26722 | 26722 | 26722 | 26722 |
| Number of cluster | 1099 | 1099 | 1099 | 1099 | 1099 | 1099 |
| | **PANEL B: First-Stage Results** | | | | | |
| Distance | -0.782*** | -0.774*** | -0.774*** | -0.621*** | -0.615*** | -0.614*** |
| | (0.193) | (0.193) | (0.193) | (0.185) | (0.185) | (0.185) |
| Wave FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Household Controls | No | Yes | Yes | No | Yes | Yes |
| Mobile Phone Ownership | No | No | Yes | No | No | Yes |

Notes: This table presents the results of 2SLS regressions at the household level, utilizing data from the 2022 DHS survey, which aligns with the period covered by the Ookla Speedtest database for mobile internet speed. Panel A reports the first-stage results and Panel B the second-stage results. The dependent variable of the 2SLS regressions is household wealth status, which is standardized from quintiles on a scale of 1 (poorest) to 5 (richest). The endogenous variable is mobile internet quality, measured by the log of cell tower counts per 1,000 people multiplied by mobile internet speed (in mbps). Zero cell counts are replaced with one. The mobile internet quality measure is constructed based on download speed in columns (1) to (3), and upload speed in columns (4) to (6). The speed data are obtained from the Ookla Speedtest database. To assess mobile internet quality around DHS clusters, we create buffers around clusters, with radii of 10 km for rural clusters and 2 km for urban clusters, overlaying these with Ookla's mobile internet speed raster data to calculate the average speed within each buffer. Across all 2SLS specifications, mobile internet quality is instrumented using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. The table includes Kleibergen-Paap Wald rk F statistics and Anderson-Rubin (AR) test *p*-values to evaluate the strength and relevance of our instrumental variable. Columns (1) and (4) includes controls for factors at the cluster level (an urban dummy, population density, nightlight luminosity, rainfall, temperature, and slope of terrain). Columns (2) and (5) add household-level controls, including the number of household members, the age, gender, and educational attainment of the household head, while columns (3) and (6) further control for household mobile phone ownership. All specifications include province fixed effects to account for regional differences. Standard errors are clustered at the DHS cluster level, and sampling weights are applied to ensure the representativeness of results. This analysis is limited to 2022, the only year in which DHS and Ookla data overlap. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

Table 4: Effects of Mobile Internet Density Across Urban and Rural Areas

| | Rural | Urban | Alternative DEGURBA: City | Alternative DEGURBA: City and Dense Town | Exclude Large Barangays: <=95 | Exclude Large Barangays: <=90 | Exclude Large Barangays: <=85 | Exclude Large Barangays: <=80 |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | **PANEL A: Second-Stage Results** | | | | | | | |
| Mobile internet density | 0.071** | 0.185 | 0.443 | 0.338 | 0.162 | 0.254* | 0.182** | 0.154* |
| | (0.030) | (0.174) | (0.335) | (0.220) | (0.184) | (0.146) | (0.085) | (0.081) |
| Kleibergen-Paap Wald rk F statistic | 33.46 | 6.68 | 3.33 | 4.59 | 6.13 | 10.53 | 12.57 | 18.60 |
| AR Test *p*-value | 0.02 | 0.25 | 0.02 | 0.03 | 0.34 | 0.03 | 0.02 | 0.05 |
| Observations | 35154 | 18494 | 14773 | 20498 | 14134 | 10732 | 8069 | 5975 |
| Number of cluster | 1459 | 849 | 697 | 934 | 641 | 478 | 356 | 264 |
| | **PANEL B: First-Stage Results** | | | | | | | |
| Distance | -0.882*** | -0.538*** | -0.591* | -0.487** | -0.533** | -0.687*** | -1.047*** | -1.331*** |
| | (0.152) | (0.208) | (0.324) | (0.227) | (0.215) | (0.212) | (0.295) | (0.309) |
| Wave FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mobile Phone Ownership | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table presents the results of 2SLS regressions at the household level, based on data from the 2017 and 2022 DHS surveys, corresponding to periods of cell tower rollouts across the Philippines. The dependent variable is household wealth status, standardized from quintiles on a scale of 1 (poorest) to 5 (richest). The primary explanatory variable, mobile internet density, is measured as the log of cell tower counts per 1,000 people within each DHS cluster; for clusters with zero cell towers, we replace zero values with one to enable logarithmic transformation. Across all specifications, we instrument mobile internet density using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. The table includes Kleibergen-Paap Wald rk F statistics and Anderson-Rubin (AR) test p-values to evaluate the strength and relevance of our instrumental variable. We report both first-stage and second-stage results with Panel A and B. Columns (1) and (2) restrict the sample to households located in rural and urban clusters, respectively. Columns (3) and (4) focus on urban clusters but using alternative definition of degree of urbanization. Column (3) limits the sample to households located in Barangays (local administrative units at the third level in the Philippines) that are classified as cities according to the Global Human Settlement Layer (GHSL) project. Column (4) expands the sample by including households located in Barangays that are classified as dense towns by the GHSL project. Columns (5) to (8) focus on households located in urban clusters but exclude those in Barangays with large population sizes (data come from the GHSL project) – specifically, excluding Barangays whose population size exceeds the 95th percentile in column (5), 90th percentile in column (6), 85th percentile in column (7), and 80th percentile in column (8). All regressions include controls for cluster-level factors, including population density, nightlight luminosity, rainfall, temperature, slope of terrain, as well as household-level characteristics like the number of household members, the age, gender, and educational attainment of the household head, as well as household mobile phone ownership. Fixed effects for survey wave and province are incorporated to account for temporal and regional variations. Standard errors are clustered at the DHS cluster level, and sampling weights are applied to ensure representativeness. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

Table 5: Potential Transmission Channels: Economic Sectors

| | Arts and Entertainment | Business and Professional Services | Dining and Drinking | Retail | Travel and Transportation |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | **PANEL A1: Second-Stage Results, Exclude Clusters above 99th Percentile** | | | | |
| Mobile internet density | 0.145 | 0.693*** | 0.758*** | 0.608*** | 0.749*** |
| | (0.149) | (0.218) | (0.206) | (0.195) | (0.234) |
| Kleibergen-Paap Wald rk F statistic | 11.21 | 11.21 | 11.21 | 11.21 | 11.21 |
| AR Test *p*-value | 0.39 | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 2037 | 2037 | 2037 | 2037 | 2037 |
| Number of cluster | 88 | 88 | 88 | 88 | 88 |
| | **PANEL A2: First-Stage Results, Exclude Clusters above 99th Percentile** | | | | |
| Distance | -0.806*** | -0.806*** | -0.806*** | -0.806*** | -0.806*** |
| | (0.241) | (0.241) | (0.241) | (0.241) | (0.241) |
| | **PANEL B1: Second-Stage Results, Exclude Urban Clusters above 80th Percentile** | | | | |
| Mobile internet density | 0.070 | 0.557*** | 0.685*** | 0.503*** | 0.633*** |
| | (0.188) | (0.188) | (0.184) | (0.163) | (0.179) |
| Kleibergen-Paap Wald rk F statistic | 29.87 | 29.87 | 29.87 | 29.87 | 29.87 |
| AR Test *p*-value | 0.72 | 0.02 | 0.01 | 0.02 | 0.01 |
| Observations | 1586 | 1586 | 1586 | 1586 | 1586 |
| Number of cluster | 86 | 86 | 86 | 86 | 86 |
| | **PANEL B2: First-Stage Results, Exclude Urban Clusters above 80th Percentile** | | | | |
| Distance | -0.855*** | -0.855*** | -0.855*** | -0.855*** | -0.855*** |
| | (0.156) | (0.156) | (0.156) | (0.156) | (0.156) |
| Wave FE | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes |
| Cluster Controls | Yes | Yes | Yes | Yes | Yes |

Notes: This table presents the results of 2SLS regressions at the cluster level using data in 2017 and 2022, coinciding with periods of cell tower rollouts in the Philippines. The dependent variables are densities of Points of Interest (POI), categorized into Arts and Entertainment, Business and Professional Services, Dining and Drinking, Retail, and Travel and Transportation, measured as the logarithm of the number of POIs per 1,000 people. For clusters with zero POIs, values are replaced with one to enable logarithmic transformation. The primary explanatory variable across all regressions, mobile internet density, is measured as the log of cell tower counts per 1,000 people within each DHS cluster; for clusters with zero cell towers, we replace zero values with one to enable logarithmic transformation. Across all 2SLS specifications, we instrument mobile internet density using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. To assess the strength and relevance of the instrumental variable, Kleibergen-Paap Wald rk F statistics and Anderson-Rubin (AR) test *p*-values are reported. Panel A excludes clusters located in Barangays with population sizes exceeding the 99th percentile. Panel B excludes urban clusters located in Barangays with population sizes exceeding the 80th percentile. Population data are sourced from the GHSL project. All regressions include controls for cluster-level factors, including an urban dummy, population density, nightlight luminosity, rainfall, temperature, and slope of terrain. Fixed effects for survey wave and province are incorporated to account for temporal and regional variations. Standard errors are clustered at the province level. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

Table 6: Potential Transmission Channels: Employment and Education

| | Employment | | | | | Educational Attainment | |
|---|---|---|---|---|---|---|---|
| | All Female | | Employed Female | | | Household Member | |
| | Currently Employed | Employed in Past Year | All Year | Seasonal | Occasional | >=Secondary | Education Year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | **PANEL A: Second-Stage Results** | | | | | | |
| Mobile internet density | 0.052** | 0.049* | -0.067** | 0.048* | 0.018* | 0.045* | 0.626* |
| | (0.025) | (0.026) | (0.032) | (0.029) | (0.010) | (0.027) | (0.335) |
| Mean DV | 0.50 | 0.59 | 0.71 | 0.24 | 0.05 | 0.76 | 10.57 |
| Kleibergen-Paap Wald rk F statistic | 21.31 | 21.31 | 24.94 | 24.94 | 24.94 | 22.80 | 22.80 |
| AR Test *p*-value | 0.02 | 0.03 | 0.01 | 0.05 | 0.05 | 0.07 | 0.03 |
| Observations | 42642 | 42642 | 24704 | 24704 | 24704 | 146309 | 146309 |
| Number of cluster | 2307 | 2307 | 2306 | 2306 | 2306 | 2308 | 2308 |
| | **PANEL B: First-Stage Results** | | | | | | |
| Distance | -0.610*** | -0.610*** | -0.663*** | -0.663*** | -0.663*** | -0.631*** | -0.631*** |
| | (0.132) | (0.132) | (0.133) | (0.133) | (0.133) | (0.132) | (0.132) |
| Dataset | IR | IR | IR | IR | IR | PR | PR |
| Wave FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Personal Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Household Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: This table presents the results of 2SLS regressions at the individual level using data from the 2017 and 2022 DHS surveys, coinciding with periods of cell tower rollouts in the Philippines. Columns (1) through (5) investigate employment outcomes using the "Individual Record" (IR) datasets, which primarily focus on women in households. The sample is restricted to women aged 18 and above. Columns (1) and (2) examine women's employment status, using binary dependent variables indicating whether a woman was employed during the seven days preceding the survey or at any point in the past 12 months. Columns (3) to (5) focus on women who were employed at any point in the past 12 months, using binary dependent variables that indicate whether the respondent was employed year-round, seasonally, or occasionally. Columns (6) and (7) explore the impact on educational attainment, utilizing the "Personal Record" (PR) datasets, which provide individual-level information on household members. The sample is restricted to individuals aged 18 and above. The dependent variable in column (6) is a binary indicator for attaining at least secondary education, while in column (7), it is the number of years of educational attainment. The primary explanatory variable across all regressions, mobile internet density, is measured as the log of cell tower counts per 1,000 people within each DHS cluster; for clusters with zero cell towers, we replace zero values with one to enable logarithmic transformation. Across all 2SLS specifications, we instrument mobile internet density using the Euclidean distance from the cluster's centroid to the nearest existing submarine cable landing point. To assess the strength and relevance of the instrumental variable, Kleibergen-Paap Wald rk F statistics and Anderson-Rubin (AR) test *p*-values are reported. The table also provides the mean values of the dependent variables for context. All regressions include controls for cluster-level factors—such as an urban dummy, population density, nightlight luminosity, rainfall, temperature, and terrain slope—as well as household-level characteristics (e.g., number of household members, and the age, gender, and educational attainment of the household head) and individual-level characteristics, including age, gender, and marital status. Fixed effects for survey wave and province are incorporated to account for temporal and regional variations. Standard errors are clustered at the DHS cluster level, and sampling weights are applied to ensure representativeness. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Authors' calculations.

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## Mobile Internet Connectivity and Household Wealth in the Philippines

This paper analyzes the impact of mobile internet connectivity on household wealth in the Philippines using comprehensive information on 0.27 million geocoded cell towers, and identifies causal impact through a novel instrumental variable based on proximity to submarine cable landing points. The results suggest that mobile internet connectivity significantly increases household wealth, with effects that persist across education levels and are more pronounced in urban areas than in rural ones. The analysis also finds that improved connectivity stimulates activities in several key economic sectors that create employment opportunities. Further, it enhances educational outcomes and promotes female labor force participation.

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**ASIAN DEVELOPMENT BANK**
6 ADB Avenue, Mandaluyong City
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