# The welfare effects of Mobile Broadband connectivity in Latin America

May 2026

The GSMA is a global organisation unifying the mobile ecosystem to discover, develop and deliver innovation foundational to positive business environments and societal change. Our vision is to unlock the full power of connectivity so that people, industry and society thrive. Representing mobile operators and organisations across the mobile ecosystem and adjacent industries, the GSMA delivers for its members across three broad pillars: Connectivity for Good, Industry Services and Solutions, and Outreach. This activity includes advancing policy, tackling today's biggest societal challenges, underpinning the technology and interoperability that make mobile work, and providing the world's largest platform to convene the mobile ecosystem at the MWC and M360 series of events.

We invite you to find out more at gsma.com

GSMA Intelligence is the definitive source of global mobile operator data, analysis and forecasts, and publisher of authoritative industry reports and research. Our data covers every operator group, network and MVNO in every country worldwide – from Afghanistan to Zimbabwe. It is the most accurate and complete set of industry metrics available, comprising tens of millions of individual data points, updated daily.

GSMA Intelligence is relied on by leading operators, vendors, regulators, financial institutions and third-party industry players, to support strategic decision-making and long-term investment planning. The data is used as an industry reference point and is frequently cited by the media and by the industry itself.

Our team of analysts and experts produce regular thought-leading research reports across a range of industry topics.

www.gsmaintelligence.com

info@gsmaintelligence.com

**Authors**

Pau Castells, GSMA Intelligence
Kalvin Bahia, GSMA Intelligence
Juan Jung, Universidad Pontificia Comillas

# Contents

# Abstract

This study examines the effects of large scale mobile broadband deployments on the socioeconomic outcomes of households in the two largest economies of Latin America: Mexico and Brazil. The analysis draws from detailed georeferenced mobile operator coverage data, alongside municipal-level panel datasets built from local census and household surveys.

The empirical strategy in staggered differences-in-differences methods exploits variations in the timing of network deployment of 3G and 4G mobile broadband networks, as well as the fact that several municipalities remained unserved during the period of analysis.

The results indicate that access to mobile broadband has had substantial socioeconomic effects in both countries, leading to significant increases in household income, spending, and reductions in poverty and unemployment. Interestingly, these gains appear to be more pronounced among low-income and rural municipalities.

This indicates that mobile broadband can constitute a key force in the fight against poverty and for social and economic development.

Keywords: Mobile broadband, Socioeconomic effects, Mexico, Brazil

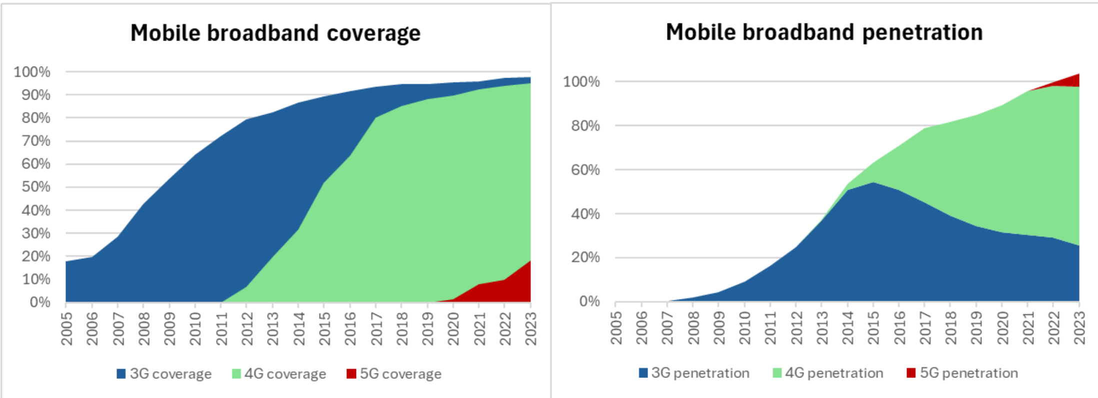
# 1. Introduction

A substantial body of research has examined the socioeconomic effects of internet access across a wide range of outcomes during the past decade. Nevertheless, most empirical studies have concentrated on advanced economies or on cross-country samples. Recent studies have begun to examine emerging economies (e.g., Bahia et al., 2023, 2024 for Tanzania and Nigeria; Yang et al., 2021 for China), yet empirical evidence on the impact of internet access on household and individual welfare remains limited. Moreover, there remain gaps in the literature regarding how the impacts of internet expansion may differ between remote, rural and urban areas (Acris et al., 2025).

In this study, we provide new evidence by examining the impact of mobile broadband availability on socioeconomic outcomes in Latin America. The region has experienced a fast expansion in mobile infrastructure networks, already reaching nearly universal coverage and achieving more than 100% penetration on average. Technological upgrades across technology standards are evident too in the region, as since 2018 the predominant technology for mobile broadband access has been 4G, while 5G networks started to be deployed in 2021 (Figure 1).

**Figure 1. Latin America: mobile broadband coverage and penetration**
Percentage of coverage over total population

Source: GSMA Intelligence




For the purpose of this paper, the analysis focuses on Mexico and Brazil, the two largest markets in Latin America, jointly representing 55% of the population and 50% of mobile internet users in the region. We rely on detailed mobile coverage deployment data and municipal-level data sets built from local sources for both countries covering entirely the period when mobile broadband capable technologies (3G and 4G) were deployed in both countries.

Mobile broadband can facilitate new job opportunities and support the digital transformation of firms, leading to a positive impact on economic activity and a reduction in unemployment rates. However, technological change can also be a source for increased inequalities. Beyond measuring average impacts, our analysis therefore pays special attention to the most vulnerable areas within those countries in order to fully understand the distributional effects of new general-purpose technology.

We test the main possible avenues for the materialization of these economic effects including better access to transfers and through the labor market. Effects are tested with a consistent identification strategy for both Mexican and Brazilian municipalities. This allows us to check the robustness and consistency of the results across two different and completely independent large sets of household data across two different countries in the region. The consistency of results across both countries indicates that the observed effects may be generalizable to other large-scale mobile broadband deployments within the region.

In response to recent debates concerning the limitations of two-way fixed effects (TWFE) approach,[1] this study adopts the differences-in-differences estimation framework developed by Callaway and Sant'Anna (2021), which has been demonstrated to yield unbiased estimates under relatively general conditions. Our results reveal that mobile broadband coverage, particularly through the 4G standard, exerted a substantial and positive influence on socioeconomic indicators on both countries. Notably, these gains are especially relevant among those municipalities facing vulnerable conditions, such as the poor or those located remotely or in rural areas.

This paper advances literature in several important ways. To the best of our knowledge this is the first research to assess the impact of large-scale mobile broadband expansion on socioeconomic indicators at the municipal level in Latin America. In addition, it sheds further light on specific economic mechanisms by looking at the mobile broadband effect over a diverse set of outcomes including transfers and type of spending and occupations affected, with a high degree of confidence in the results down to the depth of data and causal inference methods employed. Moreover, the focus on the less developed and rural municipalities within both countries provides important insights into public policy design, regarding the role of technology for regional cohesion programs.

The remaining of this paper is structured as follows. Section 2 provides a literature review aimed at identifying the specific mechanisms through which socioeconomic effects may materialize following network deployments. Section 3 details the empirical methodology to be used, based on Callaway and Sant'Anna (2021) differences-in-differences estimator. Section 4 presents the databases and the preliminary descriptive evidence regarding recent trends in 3G/4G roll outs and in socioeconomic outcomes. Section 5 presents the econometric results for both countries, both addressing the overall effects and putting the focus on vulnerable territories. Finally, Section 6 ends with some final remarks and conclusions.

[1] The standard TWFE estimator represents a weighted sum of the average treatment effects, where weights can be negative in case of staggered treatment or when treatment effects evolve over time, affecting the estimated regression coefficient (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021).

# 2. Literature review

A large amount of research literature has examined the socioeconomic impact of mobile internet access during the past decade. Early research indeed linked basic mobile telephony to macroeconomic growth. For example, Gruber and Koutroumpis (2011) characterized mobile telecommunications as a *General-Purpose Technology* exhibiting increasing returns due to the presence of network externalities. Much of the early literature was concerned with basic mobile telephony (2G voice and SMS) which had limited data and internet applications. Around 2010, however, focus shifted toward broadband internet access as the new critical technological standards delivered via 3G/4G wireless networks. These standards enable high-speed data transmission opening the door to more transformative applications like e-learning, e-banking, e-health, e-commerce, and the digital transformation of enterprises.

While some authors argue about the potential of the internet to exacerbate social and economic inequality (Afzal et al., 2022), another stream of literature highlights the potential for broad-based development gains (Acris et al., 2025). Already by the mid-2000s, mobile phones were hailed as transformative for low-income communities. Jensen (2007) documented how the introduction of mobile phones in Kerala, India eliminated information asymmetries in fish markets, reducing price dispersion and increasing both consumer and producer welfare. Similarly, Aker (2010) found that when mobile coverage reached grain markets in Niger, price dispersion fell by about 10-16%, translating into better market efficiency. Other studies from across Africa and Asia arrived at similar results: for instance, Muto and Yamano (2009) found Ugandan farmers' market participation increased with mobile coverage, and sales in remote communities increased. These micro-level studies demonstrate how improved market coordination, lower transaction costs, and new income opportunities can benefit certain population segments across emerging countries (Galperin, 2017).

Beyond the impact on economic activity, the literature also suggests the positive effect that mobile networks can have on financial inclusion (Aracil et al., 2025), facilitating transactions and increasing access to payment systems for those with limited access to traditional banking (Galperin et al., 2022). The expansion of mobile banking services should lower transaction costs and increase the frequency and value of remittances received, with particularly strong effects among vulnerable households. In addition, mobile banking can also help governments in the task of delivering cash transfers, reducing both program costs and costs for recipients.

All this micro-level evidence suggests that welfare should increase after the large-scale deployments of these technologies, but it is only more recently that empirical research started to provide broader evidence on how broadband connectivity affects household welfare, jobs, and poverty reduction in developing countries. Recent work by Bahia et al. (2023) in Tanzania finds large positive impacts on household consumption and poverty reduction as a result of 3G mobile internet deployments. Using a differences-in-differences design with panel household survey data, Bahia and colleagues estimate that 3G coverage increases per capita consumption, lifts many households above the poverty line, and raises labor force participation in covered areas. In rural China, where internet use has spread rapidly in recent years, Yang et al. (2021) conclude that mobile internet use has a significant negative impact on multidimensional poverty, and note the effect is heterogeneous across regions. Another study from Bahia et al. (2024), in this case for Nigeria, found that mobile broadband coverage had large and positive impacts on household consumption and poverty reduction, with effects being stronger among poorer households.

We were also able to find some evidence, although limited, regarding Mexico and Brazil. Using cross-sectional household survey data, Mora-Rivera and García-Mora (2021) apply a quasi-experimental propensity score matching approach to compare outcomes for rural Mexican households with and without internet access. They find that internet access has a significant poverty-reducing effect: the incidence of both income poverty and multidimensional poverty is lower among connected rural households, suggesting that connectivity helps families improve their livelihoods. Interestingly, their study finds larger positive effects in Mexico's less developed rural regions. In the Amazonas region of Brazil, mobile broadband spurred major economic gains even in remote regions, driving growth in urbanization, firm creation, and employment. Rural areas benefited most, showing that digital infrastructure can reduce isolation, boost local economies, and narrow regional inequalities (Acris et al., 2025).

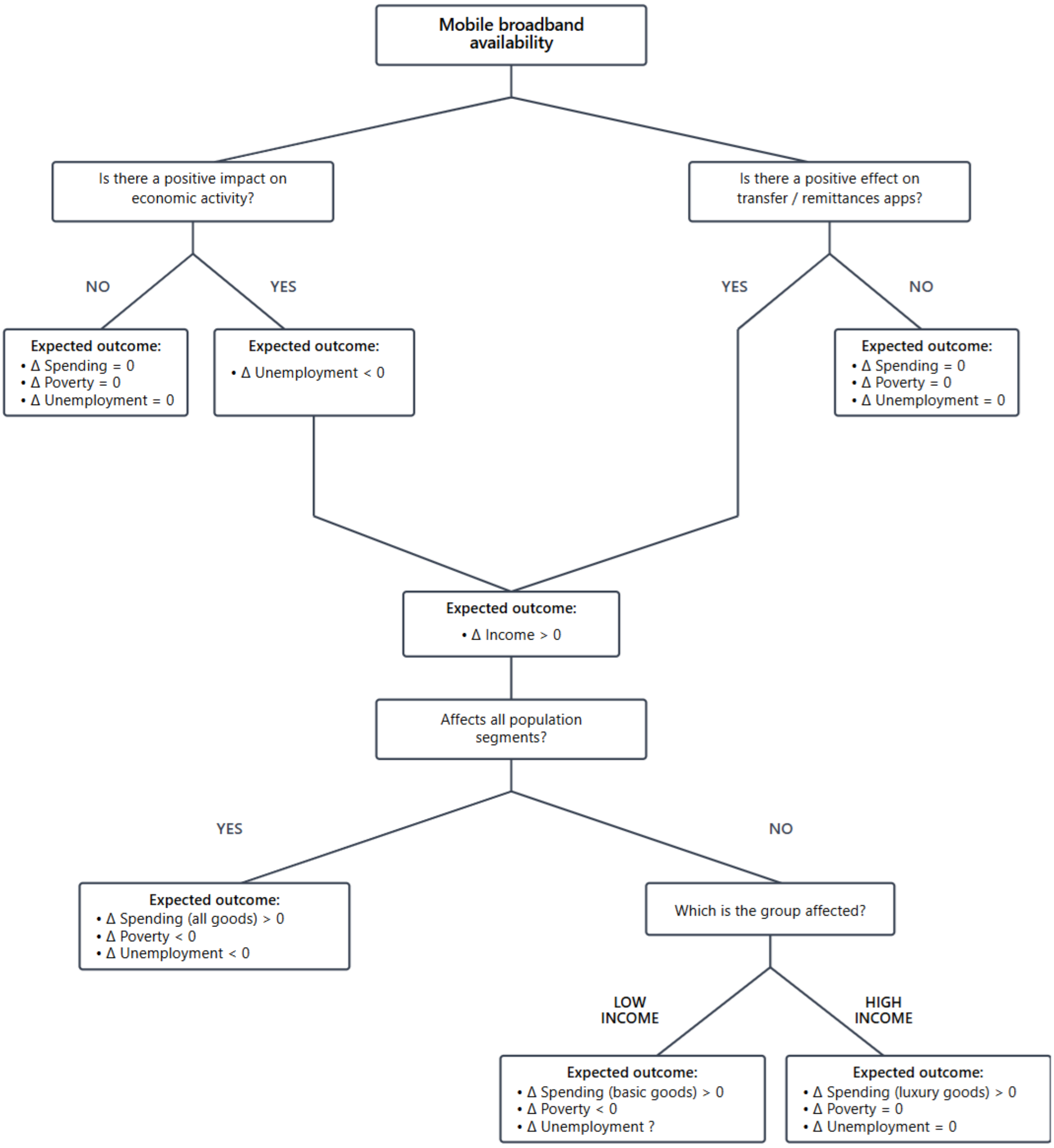
However, the existing studies for both Mexico and Brazil still leave important gaps that require further empirical research to be conducted. In particular, no study for either country or in Latin America more generally has to date provided a full evaluation of the overall and distributional effects of a large-scale deployment of mobile broadband technologies. Mora-Rivera and García-Mora (2021) analysis on Mexico focuses only on poverty, leaving unanswered many questions regarding the effects of connectivity on other welfare indicators such as spending or unemployment. Also, methodologically the research of Mora-Rivera and García-Mora (2021) presents some limitations, as it relies on a cross-section sample (with data from a single year of data, 2016). Aside from not analyzing the full deployment over time the methods employed did not exploit a panel structure, thus being unable to employ modern differences-in-differences estimators. As for the Acris et al. (2025) research conducted for Brazil, it only focuses on the 3G technology effects across Amazonian region, thus not covering 4G deployments nor the overall Brazilian case.

Our contribution covers these gaps and is in fact the first research based on a large-scale roll-out of mobile networks in Latin America that also evaluates its socio-economic impacts with a panel framework using modern causal inference methods.

Figure 2 summarizes the main paths and outcomes identified in the literature, showing how mobile broadband can influence socioeconomic outcomes.

**Figure 2. Diagram of Mobile broadband socioeconomic effects**

Source: GSMA Intelligence




Starting from the top, we can expect a positive impact on economic activity that can translate into higher employment as mobile broadband adoption facilitates new job opportunities and supports digital transformation in firms, particularly in rural and lower-income regions. Mobile broadband can also have a relevant effect on money transfers and remittances. The expansion of mobile money services lowers transaction costs and increases the frequency and value of remittances received, with particularly strong effects among vulnerable households.[2]

2 While technically possible with 2G standard, the expansion of digital financial services (such as mobile money) across both countries mostly took place after 2017, therefore it coincided with the period of rapid expansion of 3G and 4G technologies, according to the World Bank Global Findex database.

Considering that both unemployment reduction and transfers received should conduct to increased income levels, these effects should yield substantial increases in household consumption and thus reduce the share of individuals living in poverty conditions. Recognizing that mobile broadband's impact can vary across population segments, we can expect richer households experiencing gains primarily through luxury consumption, while poorer groups may benefit from expanded access to basic goods, increased resilience, and improved welfare outcomes.

Therefore, the main aim of this research is verifying if these effects took place in the Mexican and Brazilian municipalities as well as identifying which of the sketched paths prevailed.

# 3. Methodology for empirical analysis

The empirical approach is based on the generalization of the difference-in-difference approach to the cases where the treatment is staggered over different periods, as was the case of the 3G and 4G deployments across Mexican and Brazilian municipalities.

The treatment effect is recovered using empirical specifications such as:

$$Log(Outcome) = \alpha_i + \gamma_t + \delta Treatment_{it} + \lambda X_{it} + \varepsilon_{it}$$

Where sub-indices $i$ and $t$ denote municipality and year, respectively. $\alpha_i$ are municipality-level fixed effects, while $\gamma_t$ represent year fixed effects. The treatment variable is either 3G or 4G coverage, which indicates whether the respective technologies are available in the municipality $i$ at year $t$. It is worth noting that the treatment effect derived from our empirical design captures all the impacts enabled by mobile internet, both direct (e.g. those associated with internet users) and indirect ones (stimulates economic activity that even non-internet users benefit from), although it is not possible from this specification alone to separate and identify each of them individually. Finally, $X_{it}$ denotes a vector of covariates aimed to control time-variant heterogeneities.

If all municipalities were treated in the same period, a TWFE estimation of the parameter δ in the previous equation should be an appropriate approximation of the treatment effect of interest. However, this is not the case when treatment is staggered, as in both Mexican and Brazilian cases, or when treatment effects evolve over time (Goodman-Bacon, 2021). As pointed out by several authors, the standard TWFE estimator represents a weighted sum of the average treatment effects, where weights can be negative, affecting the estimated regression coefficient (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021).

Given the limitations of the traditional TWFE estimator, the empirical analysis employs the differences-in-differences approach proposed by Callaway and Sant'Anna (2021), specifically designed to address these shortcomings. We choose to conduct the empirical work using Callaway and Sant'Anna (2021) rather than other similar approaches as this has proven to be the most widely used difference-in-differences estimator since 2021, especially for settings with staggered adoption and treatment effect heterogeneity.

The estimation follows a two-step procedure. First, pairwise 2×2 average treatment effects on the treated (ATTs) are calculated as “group-time average treatment effects” for each treatment cohort (early and late adopters) across post-treatment periods. In each case, the control group comprises municipalities that have not yet received the treatment. Second, these cohort-period specific estimates are aggregated to produce an overall ATT.

An important assumption of differences-in-differences models is that, in the absence of treatment, variations over time in the outcome variable between observations that received the treatment and those without it would have remained constant. This parallel trend assumption is tested through the significance of pre-trends. If we cannot reject the null hypothesis of parallel trends and no anticipation assumptions based on the average pre-trend values, then the estimation can be considered accurate. Therefore, estimates conducted for both Mexico and Brazil also include the analysis of pre-trends to check the validity of the estimations.

All estimations are initially performed for both 3G and 4G treatments on the full available sample of municipalities in the Mexican and Brazilian contexts. After identifying the technology with the most pronounced effects, subsequent analyses focus exclusively on such technology, with subsample estimations targeting more vulnerable groups, as defined by development level and locational attributes. In the former, subsamples are determined according to percentiles of the relevant variable’s distribution, for example income, spending or poverty; in the latter, municipalities are categorized by population density. Regarding location, we classify intermediate-density areas as "Rural" and the lowest-density areas as "Remote".[3] This distinction is relevant, as both countries have complex geographies across forest and mountains that justify the inclusion of a Remote category that goes beyond the traditional rural municipalities present in most other countries.

This approach facilitates a nuanced assessment of heterogeneous impacts across socio-economic and geographic strata. The criteria used for sample stratification differs slightly between Mexico and Brazil, reflecting underlying disparities in data availability. For Brazil, the large number of observations permits a more granular partition, allowing us to isolate the base of the distribution (below the 25th percentile) and to define intermediate groups as those falling between the 25th and 75th percentiles. In contrast, the Mexican data is constrained by a smaller number of municipalities and a shorter time span and requires broader groupings; as such, the sample is divided into terciles (below the 33rd percentile, 33rd–66th percentiles, and above the 66th percentile). Further disaggregation in the Mexican case yields subsamples with insufficient observations for meaningful inference.

3 The thresholds we use to denote a rural municipality, based on percentiles of the population density distribution, are less than 101 persons/km2 for Mexico and 52 persons/km2 for Brazil, being in both cases a much tighter criteria than the one used by OECD of 150 persons/km2 (OECD, 2006). The difference in the thresholds used for both countries is reasonable given that Brazil presents a much larger territory, 8.5 million km2 in contrast to the 2 million km2 of Mexico. In addition, the remote territories will refer in both countries to those areas in more extreme locations, typically due to isolated or complex geographic conditions, identified as those with less than 28 persons/km2 (in Mexico) and less than 11 persons/km2 (in Brazil).

# 4. Descriptive analysis

## 4.1. Household data

The analysis for Mexico leverages detailed historical operator coverage maps[4] and considers two different household databases. First, to estimate the impact of mobile broadband on unemployment and poverty we rely on microdata from the census conducted in 2000, 2010 and 2020 waves, along with the intercensal surveys conducted in 2005 and 2015. On the positive side, the census sample includes all the municipalities and is based on microdata averages from the most extensive sample, thus effectively covering the overall universe of Mexican population. On the negative side, the time-periods are constrained to 5 datapoints (and data availability on the poverty variable is further constrained to only 2010, 2015 and 2020).

The second database for Mexico is built from the microdata of the *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH), that is conducted every two years for approximately 1000 municipalities per wave (out of a total of 2,462). This dataset is used for estimating the impact of mobile broadband on spending and transfers. From it, we built up to 10 biannual periods that allow us to explore longer time-series, although with the limitation of covering less than half of the municipalities.

Variables included in both samples are described in Table 1. The unemployment rate is calculated as unemployed individuals as a share of total active population.[5] In turn, poverty rates are those reported by municipality as the percentage of population in poverty situation, with data available for 2010, 2015 and 2020 only. Turning into the ENIGH sample, the spending outcome variable is defined as total monthly expenditure by person,[6] divided by the poverty line thresholds reported by the *Consejo Nacional de Evaluación de la Política de Desarrollo Social* (CONEVAL). Using spending rather than income as a measure of household economic activity provides empirical advantages, as income tends to be underestimated in survey data due to reporting bias, particularly in economies with high levels of informality.

[4] Data was sourced from GSMA Coverage maps and complemented with additional data provided by Mexican operators.
[5] Considering that the active population was not reported in the 2005 intercensal estimation, for that year the values were inputted through linear interpolation.
[6] The spending figures are reported per household and quarter, but we divided them into 3 to get a monthly measure and by the average of individuals per household to get a metric per person, to be divided by the monthly per person poverty threshold.

## Table 1. Mexico: variable description and descriptive statistics

Source: GSMA Intelligence

| Sample | Variable | Definition | Mean | Std. Dv. |
|---|---|---|---|---|
| Census | Unemployment | Unemployment rate (as a share of total active population) | 0.029 | 0.031 |
| | Poverty | Percentage of population in poverty condition | 0.648 | 0.2130 |
| | Education | Average years of schooling among people aged 15 and over. | 6.635 | 1.750 |
| | Population | Total population | 44,579.350 | 130,455.300 |
| | Indigenous share | People who identify themselves as Indigenous according to their culture (as a share of total population) | 0.279 | 0.359 |
| ENIGH | Spending | Total monthly expenditure by person divided by the poverty line threshold (in both cases measured in Mexican pesos) | 0.704 | 0.685 |
| | Transfers | Cash and in-kind transfers payments received by person (as share of poverty line threshold) | 0.189 | 0.144 |
| | Minimum wage | Quarterly general minimum wage (in Mexican pesos) | 8,372.297 | 3,902.547 |
| | Socioeconomic status | Socioeconomic status scale according to household characteristics, from 1 (low) to 4 (high) | 2.087 | 0.977 |
| | Hours worked | Number of hours worked per week. | 39.443 | 8.235 |
| Coverage data | 3G coverage | Binary indicator that takes value of 1 if the municipality has 3G coverage (0 in other case) | 0.664 | 0.472 |
| | 4G coverage | Binary indicator that takes value of 1 if the municipality has 4G coverage (0 in other case) | 0.419 | 0.493 |
| | 2G coverage (%) | Share of population covered by 2G | 0.618 | 0.389 |
| | 3G coverage (%) | Share of population covered by 3G | 0.478 | 0.418 |

GSMA coverage maps for the treatment variables were complemented with data obtained from Telcel, the main telecommunications operator in Mexico.[7] It is worth noting that the deployment of mobile broadband networks outside of urban areas typically meant the arrival of the internet for a location, as the presence of fixed broadband areas outside of major urban areas was almost non-existent in Mexico when both 3G and 4G started to be rolled out. Our coverage maps for Mexico include continuous coverage levels for 2G, 3G and 4G technology standards by municipality. Some temporal gaps were filled following a conservative approach described in the Appendix. As a result, a series of binary treatments series was built for both 3G and 4G technologies, covering all municipalities across the sample periods. From the census sample we were able to collect data on education (average years of schooling), total population and the share of indigenous people.[8] In turn, in the ENIGH sample these heterogeneities are captured through socioeconomic status, hours worked, and minimum wage.

As for Brazil, the sample is built from different sources, mainly the Relação Anual de Informações Sociais (RAIS)[9] and the Instituto de Pesquisa Econômica Aplicada (IPEA). As in the case of Mexico, the panel is defined at the municipal level. The full list of variables used in the empirical analysis is detailed in Table 2.

[7] We consider a municipality to be covered once the first operator deploys network in it. This approximation is consistent with the use of Telcel data, as this is the market leader and usually the first one in deploying networks across the country.
[8] Linear interpolation was used to input missing values for the case of education and the share of indigenous population.
[9] Initiative from the *Ministério do Trabalho e Emprego*

**Table 2. Brazil: variable description and descriptive statistics**

Source: GSMA Intelligence

| Variable | Definition | Mean | Std. Dv. | Source |
|---|---|---|---|---|
| Income | Average wage divided by the poverty line threshold (in both cases measured in Brazilian reais) | 3.347 | 1.153 | RAIS |
| Transfers | Number of beneficiaries of the Bolsa Familia Program | 2,209.641 | 7,572.338 | IPEA |
| Poverty | Share of population earning less than the minimum wage | 0.127 | 0.137 | RAIS |
| 3G coverage | Binary indicator that takes value of 1 if the municipality has 3G coverage (0 in other case) | 0.465 | 0.499 | Teleco |
| 4G coverage | Binary indicator that takes value of 1 if the municipality has 4G coverage (0 in other case) | 0.169 | 0.375 | Teleco |
| Workers | Number of workers | 11,670.350 | 119,334.000 | RAIS |
| Rural | Share of rural population | 0.357 | 0.219 | IPEA |
| College | Share of workers with college education | 0.136 | 0.092 | RAIS |
| Illiteracy | Illiteracy rate | 0.156 | 0.097 | IPEA |

Due to data availability, outcome variables present some differences with those used in the Mexican analysis. We were not able to measure the impact of unemployment as this variable is not available in a panel structure for the municipality level. In addition, spending is also unavailable, therefore we focus on income levels which are available and are expressed through average wages reported by RAIS. These are measured as a share of the monthly poverty line threshold (defined in Brazil as the equivalent in reais to US$ 6.85/day in purchaser power parity).[10]

Turning into the transfers outcome variable, the nature of this indicator for the Brazilian case is also different to that of the Mexican sample, from two perspectives. First, because it refers to the quantity of individuals receiving transfers (not to the average amount per transfer), and second, because it refers exclusively to government transfers related to the Bolsa Familia program, and not

[10] This is the World Bank defined parameter for poverty, also used as a reference by the *Instituto Brasileiro de Geografia e Estatística* (IBGE) and IPEA.

to other kinds of transfers. The source of the number of beneficiaries of the transfers from Bolsa Familia Program is IPEA.[11] As for the poverty outcome, the indicator again differs from the one used for Mexico, as this is not an official poverty measure (unavailable for municipality-level over the timeframe of the panel), rather than that, it just refers to the share of population earning less than the minimum wage and thus being a proxy of poverty indicator (source: RAIS).

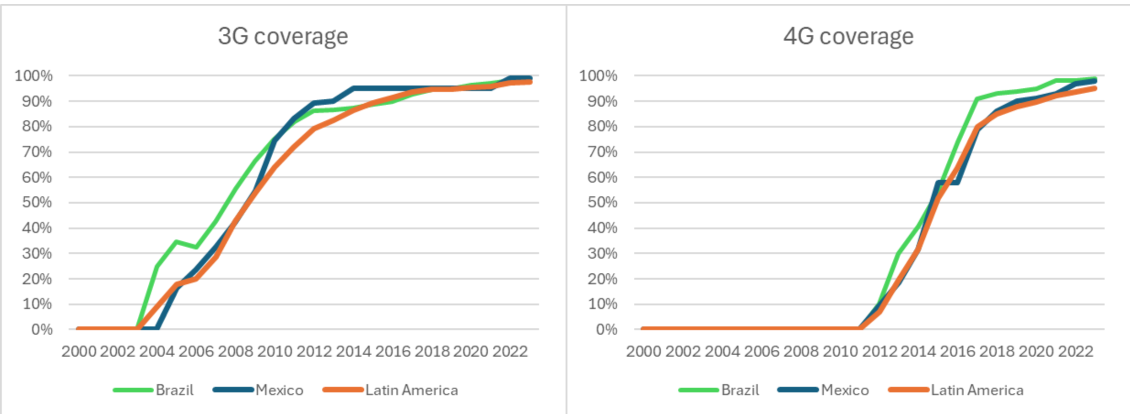
Treatment variables for Brazil are dummy variables taking value of 1 if the respective technology standards are available at the municipal level (3G and 4G), and zero in other case. The source of this data is Teleco, a Brazilian consulting and market intelligence firm. Finally, control variables include the number of workers, the share of workers with college education (in both cases, the source is RAIS), the share of rural population living within each municipality, and the illiteracy rate (from IPEA).[12]

## 4.2. The roll out of 3G and 4G networks in Latin America

In Figure 3 we report on the evolution of national-level coverage for 3G and 4G technologies for both countries, in both cases including the comparison with the Latin American average. Initial 3G deployments were just slightly faster in Brazil than in Mexico and the rest of the region, reaching in 2008 the 50% threshold on the share of covered population (this was achieved in 2009 in Mexico and in Latin America). As for the 4G standard, the initial pace of deployments was similar across both countries and the region's average, starting in 2012 and reaching 50% of the population covered in 2015, although Brazilian deployments were slightly faster, being this the first of the two countries to pass 90% of population covered, two years earlier than in Mexico. Figures 4 and 5 provide further detail for 4G deployments in both Mexico and Brazil.

**Figure 3. Evolution of mobile broadband coverage**

Source: GSMA Intelligence

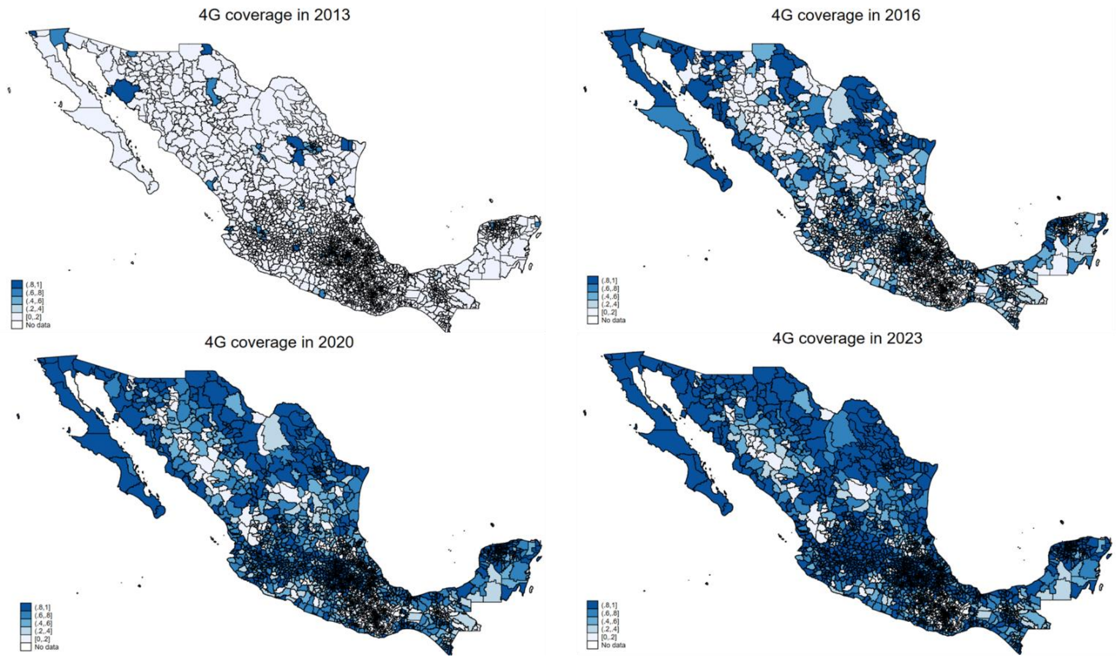



11 As data for 2014 and 2015 is missing, a lineal interpolation to cover those gaps was applied.
12 Linear interpolation was applied to input missing years for the share of rural population and illiteracy rate variables.

There were very few municipalities covered with 4G in Mexico by 2013, as denoted in Figure 4 The bulk of deployments took place between 2016 and 2020. Most of the municipalities were already covered by the technology in 2020.

**Figure 4. Mexico: evolution of 4G coverage**

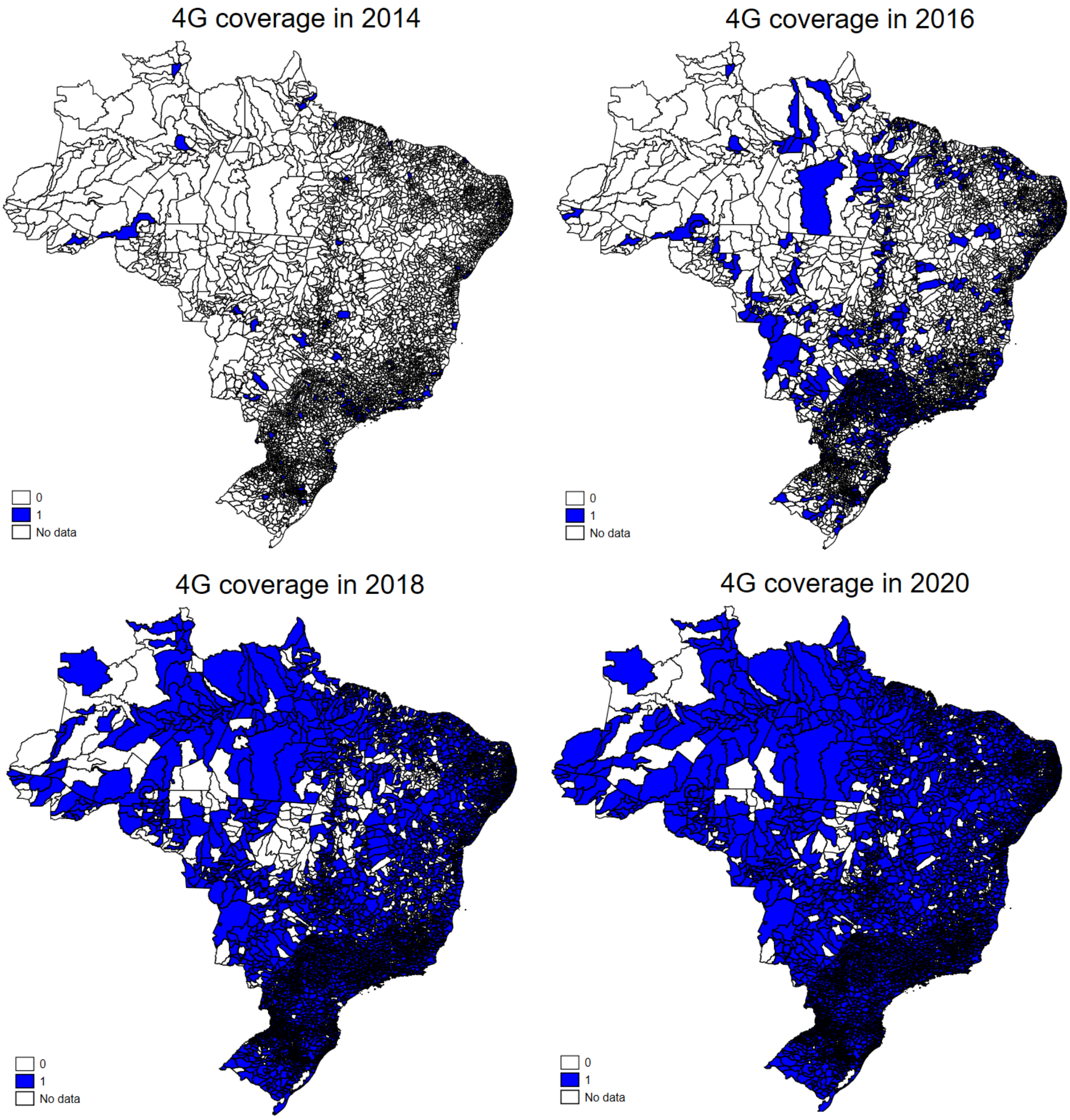
Source: GSMA Coverage Maps




In the case of Brazil (Figure 5) few locations were covered with 4G in 2014 and 2016, while by 2018 most of them had already received deployments. This suggests that the bulk of the municipalities in the country received the 4G coverage between 2016 and 2018. By 2020, 93% of the municipalities were already covered, leaving very few control observations. For this reason, 4G estimations for Brazil are restricted to the period 2009-2019.

**Figure 5. Brazil: evolution of 4G coverage**

Source: Teleco




## 4.3. Trends on main socioeconomic outcomes

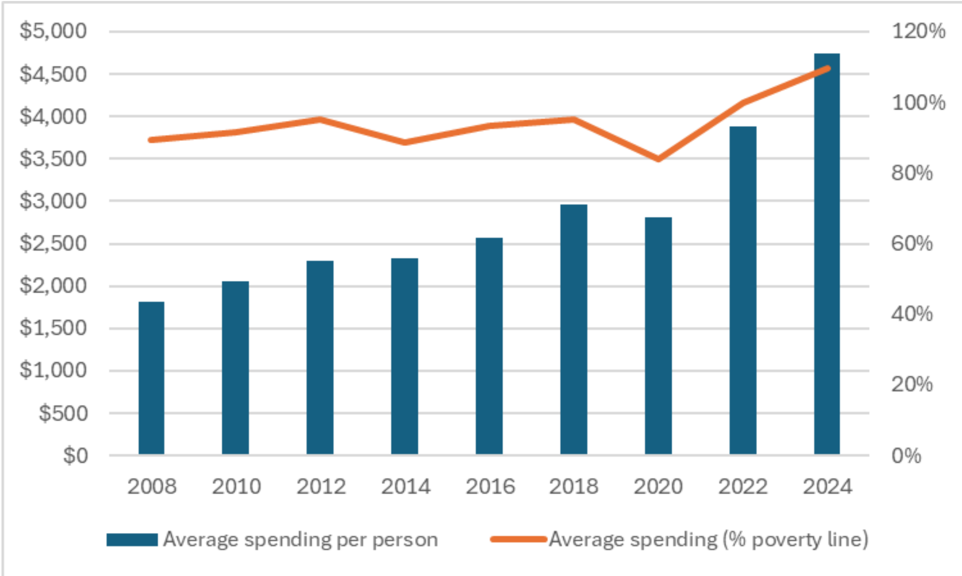
To understand the underlying socio-economic context under which these rollouts occur, we analyzed the main trends on selected socioeconomic outcomes for both Mexico and Brazil. In Figure 6 we report the evolution of spending levels in Mexico since 2008.[13] Results indicate a positive trend on average spending levels, although with a slowdown during 2020 possibly

---

[13] For comparison purposes, the current exchange rate between US dollars (USD) and Mexican pesos (MXN) is approximately 1 USD = 18 MXN.

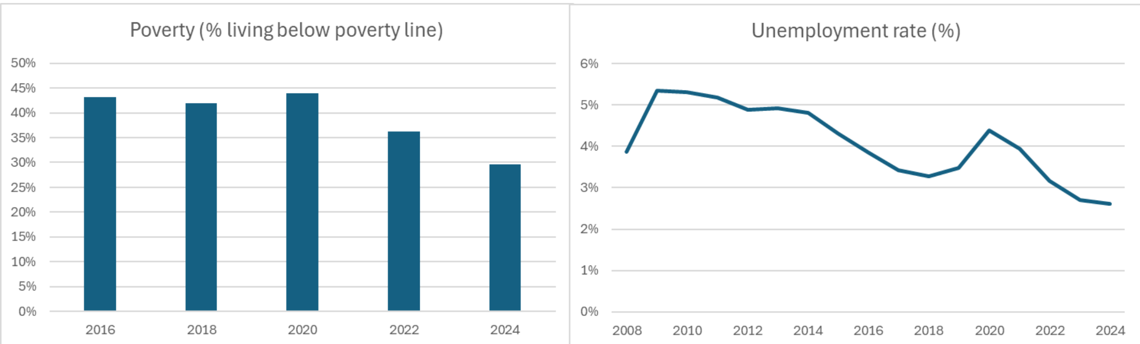
attributable to the COVID-19 crisis. When measured as a share of the poverty line, the positive trend is attenuated, only reaching remarkable growth between 2020 and 2024.

**Figure 6. Mexico: evolution of spending levels**
Mexican pesos
Source: ENIGH survey and CONEVAL




Evolution of poverty and unemployment levels for Mexico is reported in Figure 7. For both indicators evidence suggests a positive trend in reductions, only temporarily interrupted by the 2020 crisis. In addition, from 2020 onwards both poverty and unemployment experienced important reductions. These results point to a gradual improvement in economic conditions that coincided with the expansion of both 3G and 4G networks. Section 5 sheds light into whether this reflects mere correlation or if there are also causal links.

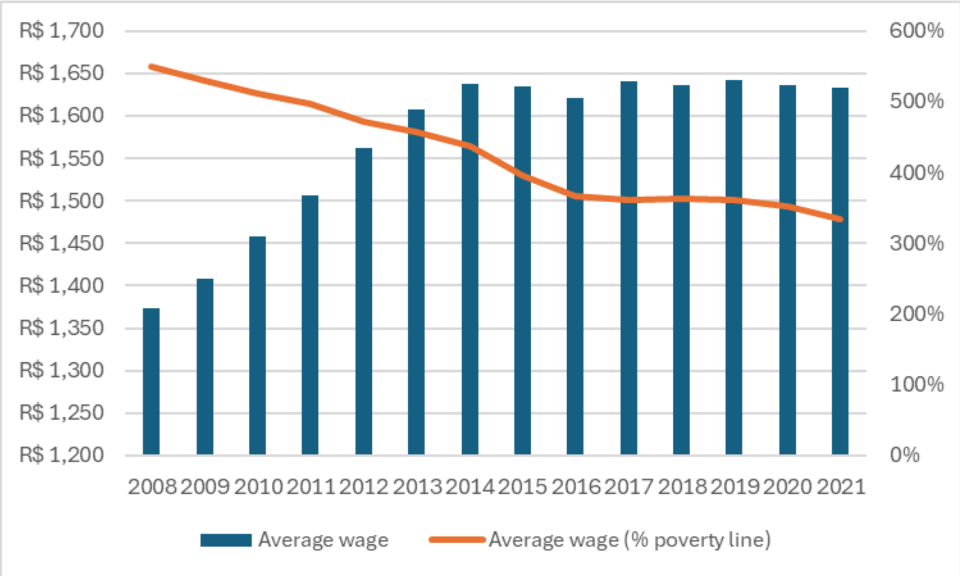
**Figure 7. Mexico: evolution of poverty and unemployment**
Percentage of people
Source: ENIGH survey and World Bank




As for Brazil, results indicate a stagnation for average income levels since 2015, which coincides with the end of the commodity-boom that triggered the fast growth in the previous decade in the country (Figure 8).[14] When measured as the share of the poverty line, there is a negative trend of income up to 2016, although this is largely influenced by the depreciation of the real (as the poverty line is measured as the equivalent in reais to US$ 6.85 dollars/day in purchasing power parity).

**Figure 8. Brazil: evolution of income levels**
Brazilian reais

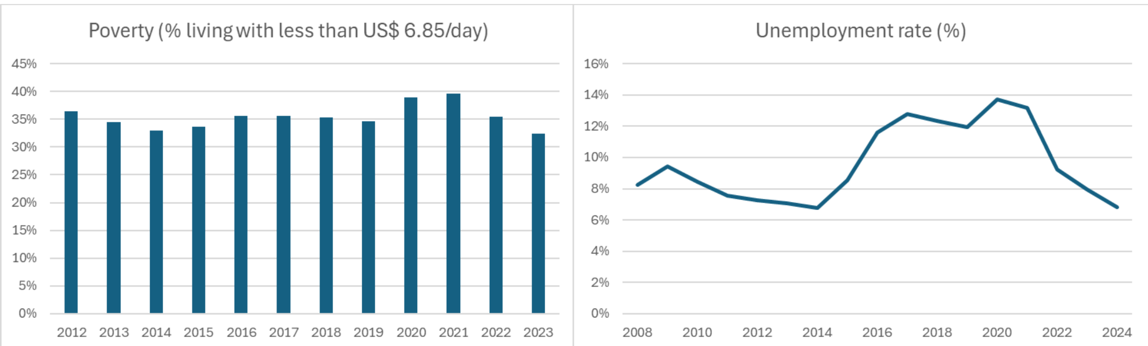
Source: RAIS




Poverty and unemployment levels in Brazil were also affected by the end of the commodity boom and the COVID crises, although decreasing trends were clearly achieved before 2015 and from 2020 onwards. Overall, it can be said that socio-economic outcomes in Brazil did not improve as much as in Mexico over the analyzed period (especially from 2013 onwards), although there are some mild reductions in poverty and unemployment rates observed in Figure 9.

**Figure 9. Brazil: evolution of poverty and unemployment**
Percentage of population

Source: IBGE and World Bank




[14] The current exchange rate between US dollars (USD) and Brazilian reais (BRL) is approximately 1 USD = 5.5 BRL.

# 5. Estimation results

This section presents the empirical results for the differences-in-differences estimations conducted using the approach designed by Callaway and Sant'Anna (2021) for the set of outcome variables in both countries. We start by analyzing the impacts on spending/earnings, followed by the effects on poverty. At the end of this section, we provide additional evidence regarding some of the potential mechanisms behind these effects.

## 5.1. Spending and earnings

We begin analyzing for Mexico the effects of 3G and 4G on spending levels. These estimates were conducted through the ENIGH dataset (Table 3). All estimates include municipal and period fixed effects, and robust standard errors are clustered by municipality. Average pre-trend coefficients are reported, yielding non-significant values in all cases. As shown in Table 3, both 3G and 4G technologies present positive and significant ATTs, although the impact seems to be larger for the latter (the difference between both effects is statistically significant at a 10% level). The ATT for 4G is 17.9%, which is equivalent to increasing monthly spending per person by US$ 29 at the current exchange rates.

**Table 3. Mexico: mobile broadband impact on household spending**

Source: GSMA Intelligence

| Dep. Var: Log (Spending) | Overall | Overall | Spending < Median | Low spenders (<33p) | Mid-spenders (33p-66p) | Rural (density 33p-66p) | Rural + Remote (density<66p) |
|---|---|---|---|---|---|---|---|
| ATT (3G) | 0.139*** | | | | | | |
| | [0.047] | | | | | | |
| ATT (4G) | | 0.179** | 0.528*** | 0.658** | -0.024 | 0.422** | 0.277*** |
| | | [0.078] | [0.154] | [0.315] | [0.170] | [0.169] | [0.141] |
| Average pre-trends | -0.785 | -0.090 | -0.066 | 0.042 | 0.081 | -0.027 | 0.193 |
| | [1.524] | [0.098] | [0.180] | [0.414] | [0.052] | [0.158] | [0.156] |
| Controls | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES |

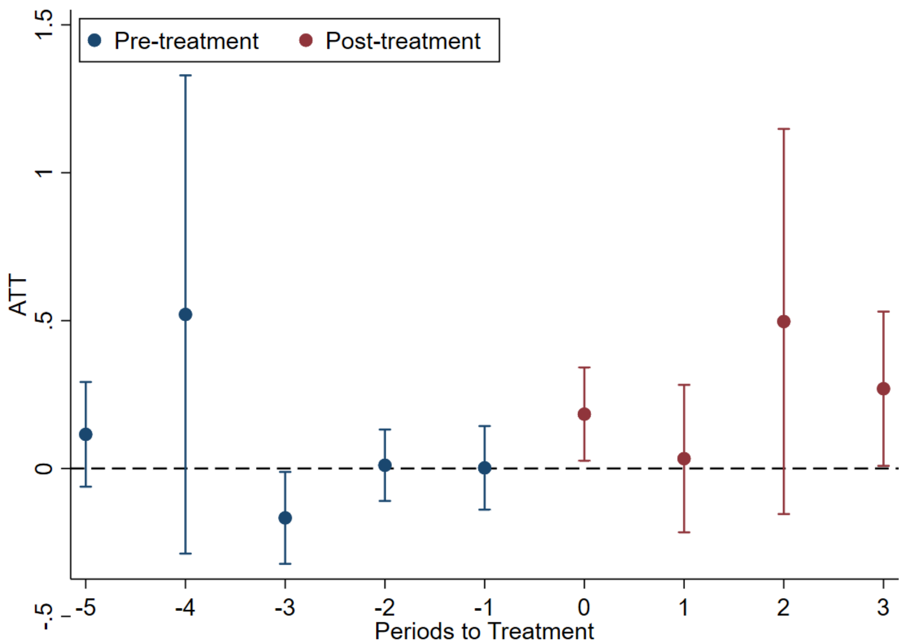
| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Period FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 1,922 | 2,601 | 520 | 232 | 656 | 460 | 968 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 2G coverage (%) and 3G coverage (%) included as controls in 3G and 4G estimates, respectively. All estimates include minimum wage, socioeconomic status and hours worked as controls. Estimations for the Rural and remote sample were conducted without the group treated in the last period as their inclusion as controls overestimated considerably the resulting ATT.

In Figure 10 we plot the overall event study for 4G impacts on spending. Pre-trends behave mostly as expected, not showing significant differences between treated and control groups. Impacts are positive and significant for the first period after treatment.

**Figure 10. Mexico: event study - 4G impact on spending**
Average treatment effects on the treated

Source: GSMA Intelligence




Note: 90% confidence intervals presented. Pre-trends shown up to 5 periods.

When splitting the sample by spending level, the results of Table 3 are clear in pointing that the largest impact was found on the lower spending, poorer municipalities. While the ATT for the lower third of municipalities in spending terms seems impressive (65.8%), it is important to take into account that these locations present very low average spending levels (average of 24.9% of the poverty line). This means that when converted into monetary units, this treatment effect seems modest in absolute terms (equivalent to US$ 40.59 dollars per person/month).

In addition, the effects are concentrated in rural and remote locations, which experience much larger ATTs than the sample average.[15] For example, in rural areas, the effect over spending is quantified as US$ 43 per person/month. When estimating the effect for both rural and remote locations, the ATT is lower than on purely rural ones but still considerably above the overall average of the sample.

Putting together the results presented in Table 3, the evidence points to most benefited municipalities being those belonging to disadvantaged groups, such as lower spenders and rural areas, potentially suggesting that mobile broadband deployments can be a relevant tool for social and territorial development in an emerging region like Latin America.

Focusing on those municipalities where spending levels are the lowest (up to 33 percentiles of the distribution, or 24.9% of the poverty line), we estimate next which is the main source of spending increase, by type of expenditure category as defined by the ENIGH survey (detailed in Table 4).

**Table 4. Mexico: spending categories**

Source: ENIGH

| Group | Description of included goods and services |
|---|---|
| Food | Food, beverages, and tobacco |
| Clothes | Clothing and footwear |
| Housing | Housing, maintenance services, electricity, and fuels |
| Clean | Articles and services for cleaning, household care, domestic appliances and furniture, glassware, domestic utensils, and linens |
| Health | Health care |
| Transport | Transport; acquisition, maintenance, accessories and services for vehicles; communications |
| Education | Education services, educational articles, recreation articles, and other recreation expenses |
| Personal | Personal care, accessories and personal effects, and other miscellaneous expenses |
| Transfers | Expense transfers |

[15] Restrictions in sample size and difficulties in ensuring the parallel trends assumption prevented us to estimate impacts on remote locations only, therefore we group them with the rural ones to create a category of rural and remote locations.

Results by spending category are presented in Table 5. Overall, this evidence suggests that the most favored individuals were those located in disadvantaged territories, with their spending increase focused on basic goods and services. Individuals from the poorer municipalities, which were able to benefit most from a more dynamic economy due to 4G and increase their living standards, concentrated their spending increases in food, housing, cleaning articles, health and personal products. The sum of these spending groups represents 64.30% of the overall household spending, being most of them essential goods and services. Housing and health spending were the items that increased the most.

**Table 5. Mexico: mobile broadband impact on spending**

By type of spending – low-spending municipalities (spending < 33p)

Source: GSMA Intelligence

| Dep. Var: Log(Spending type) | Food | Clothes | Housing | Clean | Health | Transport | Education | Personal | Transfers |
|---|---|---|---|---|---|---|---|---|---|
| ATT (4G) | 0.142** | 0.516 | 0.816*** | 0.303*** | 1.727*** | -0.386 | 0.169 | 0.460** | -1.662 |
| | [0.058] | [0.348] | [0.227] | [0.110] | [0.548] | [0.665] | [0.343] | [0.204] | [1.145] |
| Average pre-trends | 0.074 | 0.315 | 0.089 | 0.031 | 0.308 | -0.286 | 0.410 | 0.187 | -0.825 |
| | [0.314] | [0.388] | [0.272] | [0.211] | [1.477] | [1.190] | [0.737] | [0.365] | [1.526] |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Period FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 344 | 344 | 344 | 344 | 344 | 344 | 339 | 344 | 319 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 2G coverage (%) and 3G coverage (%) included as controls in 3G and 4G estimates, respectively. All estimates include minimum wage, socioeconomic status and hours worked as controls.

Turning into the Brazilian case, Table 6 reports the results for mobile broadband impact on income. ATT is not statistically significant for 3G,[16] while it is significant at a 10% level in the case of 4G,

[16] Unfortunately, the lack of 2G coverage data for municipalities in the Brazilian sample prevented controlling for legacy technology availability in the case of 3G estimates.

with the coefficient suggesting that 4G led to an increase of nearly 1% in income levels (as share of poverty line). This is aligned with the findings of the Mexican case in the sense that 4G yielded a larger economic effect than 3G. On magnitude, the overall effect seems to be modest, equivalent to US$ 6 per person/month based on current exchange rate.[17] The apparent lower effects found in the Brazilian case in comparison with Mexico can be associated with the different dependent variable used. In Brazil, we are using income levels, an indicator that sometimes is underreported in emerging regions such as Latin America. If that is the case, there may be some attenuation bias in the results.

**Table 6. Brazil: mobile broadband impact on income**

Source: GSMA Intelligence

| Dep. Var: Log (Income) | Overall | Overall | Income < Median | Low-income (<25p) | Mid-income (25p-75p) | Rural (density 25p-75p) | Rural + Remote (density<75p) | Rural (>50% pop) |
|---|---|---|---|---|---|---|---|---|
| ATT (3G) | 0.006 | | | | | | | |
| | [0.006] | | | | | | | |
| ATT (4G) | | 0.009* | 0.009* | 0.011* | 0.008 | 0.020** | 0.008* | 0.014** |
| | | [0.005] | [0.005] | [0.007] | [0.007] | [0.008] | [0.004] | [0.006] |
| Average pre-trends | -0.008 | 0.001 | 0.001 | -0.004 | 0.005 | 0.003 | 0.001 | 0.000 |
| | [0.012] | [0.002] | [0.002] | [0.003] | [0.003] | [0.002] | [0.002] | [0.003] |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 65,942 | 60,507 | 30,400 | 15,234 | 30,313 | 30,579 | 45,569 | 16,085 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 3G coverage included as controls in 4G estimates. All estimates include illiteracy rate, log(workers), rural and college as controls.

[17] For Brazil, we quantify these results using the current exchange rate in purchasing power parity as this is the metric used for the poverty line conversion.

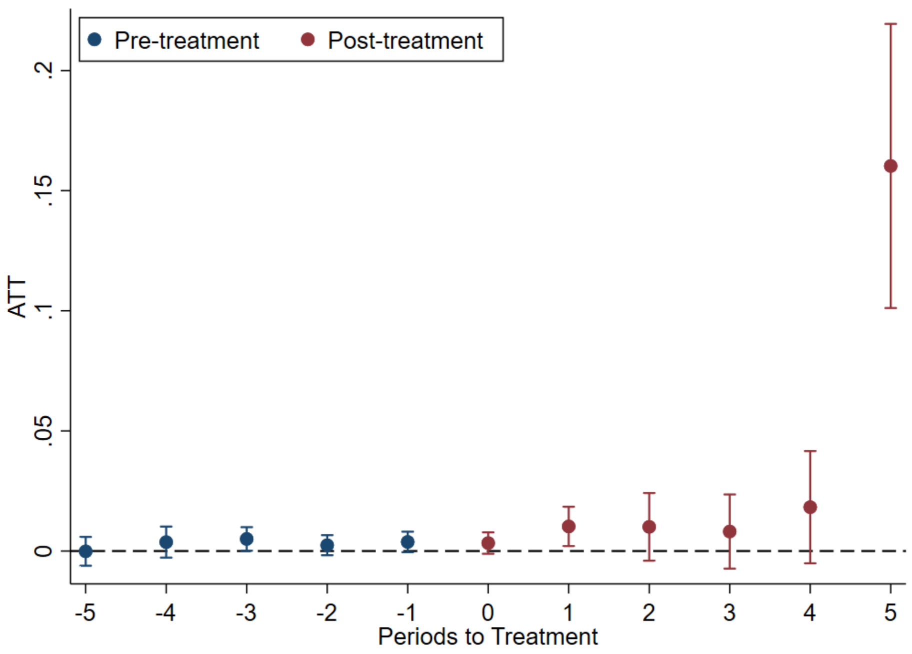
The complete event study for 4G impact on income in Brazil is presented in Figure 11, showing the significant effects of the technology deployment. The effects seem to take place through a number of periods, with large impacts being reached beyond the first post-treatment year.

When splitting the sample by level of income, it seems that the most benefited municipalities are those with income levels below the median, and in particular, the poorer ones (those of the 25 percentiles of the average income distribution), with an ATT of 1.1%. However, due to low-income levels for this group, the gains are still modest, again in line of US$ 6. By location, and consistently with the results for Mexico, the findings indicate that the highest impact was in those municipalities that we identify as rural (with population density ranging from the 25 and 75 percentiles of the sample). For the rural sample, the ATT is equivalent to US$ 13 per person/month. In addition, those municipalities that had more than 50% of the population living in rural areas also experienced a much larger impact than the average effect.

**Figure 11. Brazil: event study - 4G impact on income**

Average treatment effects on the treated

Source: GSMA Intelligence




Note: 90% confidence intervals presented. Pre-trends shown up to 5 periods.

Digging further into the economic sectors more associated with these economic effects, results from Table 7 indicate that wage increases as a result of 4G generated impact took place in the agriculture and manufacturing sectors (increases of 2.3% and 3.6%, respectively), while no significant effects were verified for commerce and services. For the agriculture sector, the ATT is equivalent to US$ 12 per person monthly, while for manufacturing workers the impact is quantified as US$ 24 per person monthly.

**Table 7. Brazil: mobile broadband impact on income by sector**

Source: GSMA Intelligence

| Dep. Var: Log(Income) | Sector of activity | | | |
|---|---|---|---|---|
| | Commerce | Services | Agriculture | Industry |
| ATT (4G) | -0.004 | -0.021 | 0.023*** | 0.036*** |
| | [0.003] | [0.015] | [0.007] | [0.012] |
| Average pre-trends | 0.002 | -0.004 | -0.001 | 0.005 |
| | [0.002] | [0.003] | [0.002] | [0.004] |
| Controls | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Observations | 60,090 | 59,689 | 53,849 | 52,033 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in bracket. All estimates include 3G coverage, illiteracy rate, log(workers), rural and college as controls.

For the poorer municipalities, we report the impact on income by occupation in Table 8. As can be seen, the impact has been significant for this population segment mainly for those individuals conducting mid-level technical tasks, and those related to service occupations. All in all, these results provide some evidence that, broadly, the economic impact was more concentrated on the manufacturing and agriculture sectors, and specifically for the case of poorer municipalities, the impact was mainly associated with workers that carry on mid-level technical and service occupations.

**Table 8. Brazil: mobile broadband impact on income**
By type of occupation – poorer municipalities (income < 25p)
Source: GSMA Intelligence

| Dep. Var: Log(Income) | Type of occupation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Public sector | Science and arts | Mid-level technicians | Administrative | Services | Agriculture | Industry | Repair and maintenance |
| ATT (4G) | 0.025 | 0.007 | 0.033** | -0.012 | 0.010* | 0.012 | 0.007 | -0.004 |
| | [0.016] | [0.015] | [0.016] | [0.008] | [0.006] | [0.011] | [0.011] | [0.020] |
| Average pre-trends | 0.011 | -0.007 | 0.002 | -0.008 | 0.003 | -0.001 | 0.002 | -0.002 |
| | [0.008] | [0.008] | [0.007] | [0.006] | [0.002] | [0.002] | [0.005] | [0.008] |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 14,933 | 15,060 | 14,923 | 15,204 | 15,205 | 12,912 | 15,047 | 11,793 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in bracket. All estimates include 3G coverage, illiteracy rate, log(workers), rural and college as controls.

In sum, the evidence demonstrates that the rollout of advanced mobile broadband technologies generated important socio-economic benefits for both Mexican and Brazilian municipalities, particularly in disadvantaged and rural areas. These locations have been traditionally affected by disadvantages associated with their rural/remote location and low density that downplays the economic effects triggered by urban agglomeration. The results presented in this section suggest that mobile connectivity can open possibilities for these regions to overcome, at least partially, these barriers for economic development. Naturally, public intervention must be key for these locations to address these barriers and in particular to provide a sound framework to stimulate broadband deployment from private operators. Moreover, isolated regions may present some advantages (in terms of lower wages and housing costs) which can be exploited to attract economic activity if good broadband infrastructure is available. On the other hand, remote areas experience a lower impact than the rural ones in most cases, suggesting that in these regions mobile broadband connectivity alone may not be enough, and hence complementary interventions from public authorities may be needed to reduce the barriers faced.

## 5.2. Results for poverty

To analyze the impact of technology on poverty levels, we start with the Mexican case using the census sample (Table 9).[18] When relying on the entire group of municipalities, the overall ATT is not significant for the case of 3G and 4G. However, when splitting the sample, some interesting results arise. There has been a significant poverty reduction (of 1.7%) after 4G deployments among those municipalities that present poverty levels above the median (more than 66.5% of the population in poverty conditions). This is equivalent to a reduction from 82.1% of population living under poverty (current average for this segment) to 80.7%.

**Table 9. Mexico: mobile broadband impact on poverty**

Source: GSMA Intelligence

| Dep. Var: Log (Poverty) | Overall | Overall | Poverty > Median | Poorer (>66p) | Mid-poverty (33p-66p) | Rural (density 33p-66p) | Rural + Remote (density<66p) |
|---|---|---|---|---|---|---|---|
| ATT (3G) | 0.008 | | | | | | |
| | [0.018] | | | | | | |
| ATT (4G) | | -0.030 | -0.017* | -0.004 | -0.026** | -0.035** | -0.003 |
| | | [0.032] | [0.009] | [0.010] | [0.012] | [0.016] | [0.032] |
| Controls | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,096 | 3,902 | 1,588 | 886 | 1,462 | 1,312 | 2,310 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 3G coverage (%) included as control in 4G estimates. All estimates include 2G coverage (%), education and indigenous share as controls.

Digging further, this effect seems to be concentrated on those with mid-poverty levels rather than in the poorer ones, as the ATT reached -2.6% in those municipalities located between the 33 and 66 percentiles of the poverty distribution (share of population living in poor conditions ranging from 55.9% and 76.6%). In these cases, that present an average poverty level of 66.2%, the ATT is equivalent to a reduction to 64.5% in that poverty rate. By location, the effect is even larger for

[18] Unfortunately, for the poverty estimations we were unable to estimate pre-trends, as the sample is restricted to only three periods (2010, 2015 and 2020).

those rural municipalities, as the ATT reaches -3.5% (equivalent to a reduction of current poverty rate from 69.9% to 67.5%). This reduction in poverty rates can be the result of reduced unemployment, and also due to connectivity enabling small businesses and entrepreneurs to access wider markets, boosting sales and growth. In addition, vulnerable households can benefit through access to educational and financial resources, enhancing skills and productivity.

Next, we turn into the analysis of the case of Brazil. In this case, we proxy poverty as the share of population earning less than the minimum wage (Table 10).

**Table 10. Brazil: mobile broadband impact on poverty**

Source: GSMA Intelligence

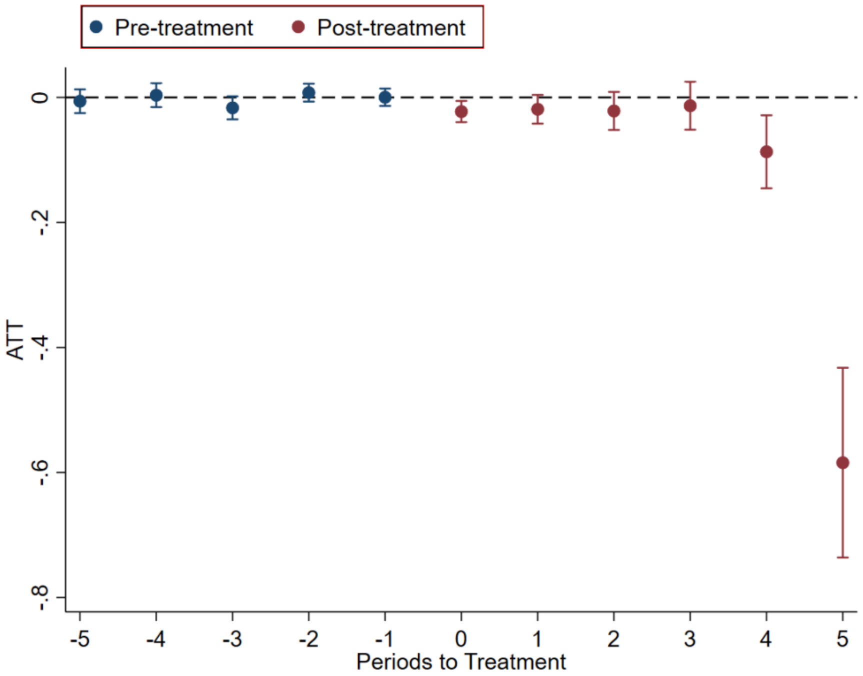
| Dep. Var: Log (Poverty) | Overall | Overall | Poverty > Median | Poorer (>75p) | Mid-poverty (25p-75p) | Rural (density 25p-75p) | Rural + Remote (density<75p) | Rural (>50% pop) |
|---|---|---|---|---|---|---|---|---|
| ATT (3G) | 0.000 | | | | | | | |
| | [0.019] | | | | | | | |
| ATT (4G) | | -0.027** | -0.048** | -0.032 | -0.037** | -0.024 | -0.018 | -0.053** |
| | | [0.012] | [0.021] | [0.039] | [0.018] | [0.019] | [0.013] | [0.024] |
| Average pre-trends | 0.024 | 0.007 | 0.005 | 0.015 | 0.002 | 0.009 | 0.003 | 0.004 |
| | [0.020] | [0.007] | [0.007] | [0.011] | [0.010] | [0.008] | [0.007] | [0.009] |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 65,806 | 60,444 | 30,412 | 15,217 | 30,236 | 30,525 | 45,495 | 16,058 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 3G coverage included as controls in 4G estimates. All estimates include illiteracy rate, log(workers), rural and college as controls.

Results are significant for the case of 4G, suggesting an ATT of -2.7%, thus effectively reducing the share of individuals earning less than the minimum wage. The ATT is equivalent to the share of people earning less than the minimum wage being reduced from the current sample average of 12.7% to 12.4%.

As presented in the event study in Figure 12, the impact of 4G on poverty across Brazilian municipalities takes some time to reach the overall effects, confirming that economic activity requires some adaptability and adjustment process after receiving a technological improvement in order for the full impact to materialize.

**Figure 12. Brazil: event study - 4G impact on poverty**
Average treatment effects on the treated
Source: GSMA Intelligence




Note: 90% confidence intervals presented. Pre-trends shown up to 5 periods.

When splitting the sample, it seems clear that the poverty reduction was concentrated in that half representing the poorer municipalities, although the effect is significant for those in the middle of the poverty distribution, rather than in the poorer ones (similar results as in the Mexican case). Focusing on those municipalities with poverty above the median, the ATT is equivalent to the share of people living with less than the minimum wage being reduced from the current average of 21% to 20%.

Finally, the ATT is not significant in remote and rural areas as defined by population density, although the effect reaches the highest impact in those municipalities were more than half of the population lives under rural conditions, with an important poverty reduction of 5.3%. In these cases, the ATT is equivalent to a reduction from 17% to 16.1% in the share of people earning less than the minimum wage.

## 5.3. Potential mechanisms

In this section, we explore potential mechanisms that can be behind the effects on spending/income and poverty presented above. As explained in the literature review section, these positive economic impacts can be associated with improved access to job opportunities or increased transfers received.[19] Therefore, we explore the treatment effects on both unemployment levels and transfers received by individuals.

Analysis on unemployment levels is done only for Mexico (using the census dataset), as data is not available for Brazil at the municipal level under for multiple time periods. Results are presented in Table 11. Both 3G and 4G present a negative and significant ATT, effectively suggesting that the deployment of both technologies contributed to dynamizing municipal economies, and thus, to reduce unemployment levels. The coefficient of the ATT is larger for the case of 3G, although it is only significantly different than zero at a 10% level, while it is not statistically different than the one reported in the case of 4G, which in turn seems to be more robust as it is significant at 1%.

**Table 11. Mexico: mobile broadband impact on unemployment**

Source: GSMA Intelligence

| Dep. Var: Log (Unemployment) | Overall | Overall | Income < Median | Low-income (<33p) | Rural (density 33p-66p) | Rural + Remote (density<66p) |
|---|---|---|---|---|---|---|
| ATT (3G) | -0.381* | | | | | |
| | [0.220] | | | | | |
| ATT (4G) | | -0.195*** | -0.137** | -0.217* | -0.187* | -0.106 |
| | | [0.068] | [0.070] | [0.127] | [0.113] | [0.115] |
| Average pre-trends | 0.059 | 0.006 | -0.043 | -0.098 | 0.024 | 0.014 |
| | [0.049] | [0.029] | [0.036] | [0.068] | [0.041] | [0.036] |
| Controls | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES |

[19] Another possible mechanism includes greater market transparency enabled by improved access to information, as mobile broadband facilitates price comparison, finding better deals, and reaching broader markets, leading to increased and more efficient consumption.

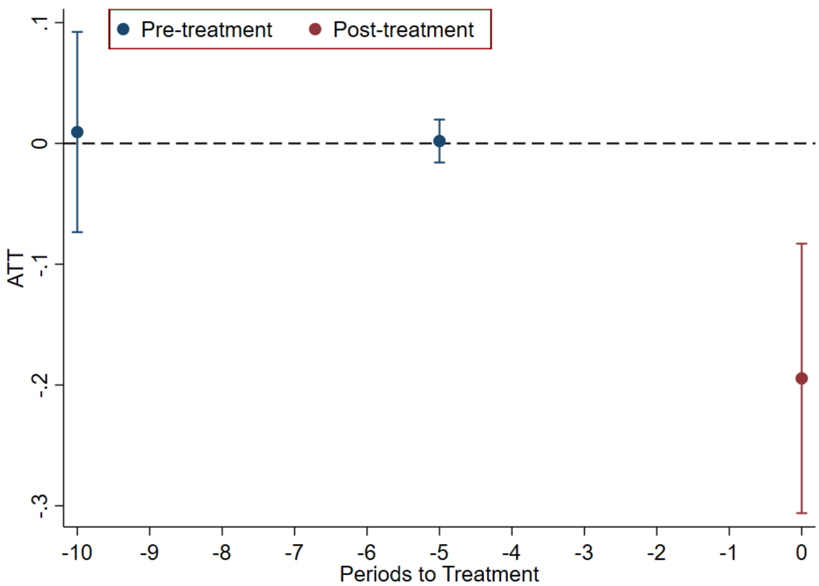
| | | | | | | |
|---|---|---|---|---|---|---|
| Year FE | YES | YES | YES | YES | YES | YES |
| Observations | 6,558 | 7,764 | 3,294 | 1,984 | 2,616 | 4,623 |

*Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 2G coverage (%) and 3G coverage (%) included as controls in 3G and 4G estimates, respectively. All estimates include population and indigenous share as controls.*

Focusing on the ATT from the 4G estimation, this is equivalent to a 2.9% unemployment rate (sample average) being reduced to 2.3% due to the arrival of technology. This result suggests that broadband deployments can dynamize the economy through business-level digital transformation, increasing organizational efficiency, and creating additional employment demand. Moreover, mobile broadband diffusion can enable faster, richer access to job search platforms, employment listings, and online recruitment processes. This greatly reduces search costs and improves matching efficiency between job seekers and employers, helping unemployed individuals find and secure work opportunities more quickly. Also, broadband diffusion is key to support the growth of app-based, gig-economy, and platform work (delivery, ridesharing, freelancing), creating new forms of employment and self-employment outside traditional sectors.

The event study is presented in Figure 13, with the two pre-trends behaving as expected. Unfortunately, the census sample limited time periods prevented us from estimating effects for multiple periods.

**Figure 13. Mexico: event study - 4G impact on unemployment**
Average treatment effects on the treated
Source: GSMA Intelligence




Note: 90% confidence intervals presented

Focusing on 4G and a more granular analysis for more vulnerable municipalities, in the remaining columns of Table 11 we find that unemployment reduction was larger across those municipalities with lowest average income levels (the first 33 percentiles of the sample), indicating that most of the effects seems to be concentrated in these locations, rather than in those with higher incomes. In these locations, the treatment effect is equivalent to a 2.6% unemployment rate being reduced to 2%.

By location, those that we classify as rural municipalities are those that primarily get most of the economic impact. On the other hand, the effect is not significant when we add the purely remote municipalities. In case of rural municipalities, the ATT is equivalent to the average 2.9% unemployment rate being reduced to 2.4%.

Next, we turn into the impact of mobile technology on transfers received. Mobile broadband advances can contribute to making financial services more accessible to all households. This can be explained as mobile broadband enables digital money transfer services (such as mobile money and app-based remittances), which are typically cheaper, faster, and more secure compared to traditional non-digital channels. This reduces transaction costs and increases the frequency and accessibility of transfers for vulnerable households. Also, technology facilitates financial inclusion by bringing unbanked populations into the digital financial ecosystem.

Results for Mexico are presented in Table 12. The ATT is positive and significant for the case of 3G, but negative in the case of 4G. A possibility to explain this negative effect associated with the deployment of 4G technology can be that the unemployment reduction induced by this technology reduced the need of certain population segments to rely on transfers from family or social programs, although further research may have to be conducted to verify this. Focusing on the case of 3G, because is the technology associated with the increase in these transfers, it seems clear that the impact has been concentrated on those territories that usually receive the largest transfer amounts (beyond the 66 percentiles of the sample distribution) and thus being more prone to vulnerable conditions. However, the effects are not evident in rural or remote locations, meaning that urban conditions may still play a role in accessibility to transfers. Overall, we can argue that there is some evidence, albeit a weak one, on the effects of mobile broadband on transfers for the case of Mexico.

**Table 12. Mexico: mobile broadband impact on transfers**

Source: GSMA Intelligence

| Dep. Var: Log (Transfers) | Overall | Overall | Transfers > Median | High transfers (>66p) | Mid-transfers (33p-66p) | Rural (density 33p-66p) | Rural + Remote (density<66p) |
|---|---|---|---|---|---|---|---|
| ATT (3G) | 0.136* | | 0.054 | 0.801*** | -0.034 | 0.131 | 0.126 |
| | [0.071] | | [0.132] | [0.310] | [0.098] | [0.103] | [0.110] |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ATT (4G) | | -0.234** | | | | | |
| | | [0.112] | | | | | |
| Average pre-trends | 0.179 | 0.069 | 0.124 | -0.114 | 0.108 | 0.143 | 0.144 |
| | [1.416] | [0.075] | [0.233] | [0.247] | [0.082] | [0.118] | [1.499] |
| Controls | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES |
| Period FE | YES | YES | YES | YES | YES | YES | YES |
| Observations | 2,210 | 3,211 | 715 | 287 | 703 | 414 | 941 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 2G coverage (%) and 3G coverage (%) included as controls in 3G and 4G estimates, respectively. All estimates include minimum wage, socioeconomic status and hours worked as controls.

Next, we turn into the impact on transfers for Brazil. As explained in section 4, the transfers variable for the Brazilian case refers to the quantity of individuals receiving government transfers related to the Bolsa Familia program. The timeframe of the estimates was restricted to the period 2009-2016, as the program underwent significant changes from 2017 onwards, particularly once the government of Jair Bolsonaro took office, reducing significantly the enrollment of new beneficiaries and thus limiting the reach and coverage of the program. Therefore, the timeframe was truncated to avoid these changes in the program to act as confounding factors.

It is worth noting that the period of analysis is before the migration to digital accounts made by the Bolsa Familia program in 2021.[20] Before that change in the program, the methods to withdraw the funds provided were through two potential cards provided to beneficiaries: the "Tarjeta Bolsa Familia" or through the "Tarjeta Ciudadana". However, despite the absence of digital accounts during that period, the expansion of mobile internet could have played a significant role in increasing the program reach. Mobile broadband may have contributed to increasing awareness about the program, and to improved access to relevant information about eligibility, enrollment procedures, and program benefits. By enhancing the flow of information and reducing administrative barriers to joining the program, technology could have helped increase the number of beneficiaries even prior to digital account integration.

Results, presented in Table 13, show a not significant effect for the case of 3G, but an important impact of 4G, with an ATT of 2.6% and significant at 1% level. By municipality group, results show

20 More information here: https://www.cnnbrasil.com.br/economia/macroeconomia/bolsa-familia-passa-a-ser-pago-em-conta-digital-para-mais-1-9-milhao-de-pessoas/

that the impact was larger in those municipalities that receive more transfers, and thus those being more prone to vulnerable population. By location condition, the impact is verified in both rural and remote and rural areas, although not for those municipalities with more than half of the population living in rural conditions. As in the case of Mexico, the fact that impact for rural and remote areas in Brazil is below that of the overall sample again points to some urban related effects that facilitate the accessibility to these programs.

**Table 13. Brazil: mobile broadband impact on transfers**

Source: GSMA Intelligence

| Dep. Var: Log (Transfers) | Overall | Overall | Transfers > Median | High transfers (>75p) | Mid-transfers (25p-75p) | Rural (density 25p-75p) | Rural + Remote (density<75p) | Rural (>50% pop) |
|---|---|---|---|---|---|---|---|---|
| ATT (3G) | -0.033 | | | | | | | |
| | [0.032] | | | | | | | |
| ATT (4G) | | 0.026*** | 0.039*** | 0.040** | 0.018** | 0.017** | 0.013** | -0.010 |
| | | [0.007] | [0.012] | [0.017] | [0.009] | [0.007] | [0.006] | [0.014] |
| Average pre-trends | -0.003 | -0.002 | -0.005 | -0.010 | -0.001 | 0.003 | 0.001 | -0.008 |
| | [0.005] | [0.004] | [0.005] | [0.007] | [0.007] | [0.005] | [0.004] | [0.005] |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Municipality FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 52,964 | 44,263 | 22,240 | 11,128 | 22,175 | 22,231 | 33,135 | 11,703 |

Note: ***p<1%, **p<5%, *p<10%. Robust standard errors clustered by municipality in brackets. 3G coverage included as controls in 4G estimates. All estimates include illiteracy rate, log(workers), poverty and college as controls.

Overall, we can conclude that while there is some evidence on positive effects of mobile technology on transfers, these are weak and do not allow us to reach firm conclusions. On the other hand, the impact of mobile internet on unemployment seems to be clear and robust (at least for the case of Mexico), therefore suggesting that a more dynamic labor market is the prevailing mechanism through which the socioeconomic effects addressed in sections 5.1 and 5.2 took place.

# 6. Conclusions

Mobile broadband connectivity enables a wide range of applications that can stimulate economic activity and enhance wellbeing. This is especially relevant in contexts such as emerging countries, where an important part of their households lives in vulnerable conditions. Through this study we were able to examine the effects of 3G and 4G broadband networks in Mexico and Brazil, the two largest countries of the Latin American region.

Our findings reveal positive impacts on several fundamental socioeconomic determinants, including income, spending, unemployment and poverty. These gains appear to be even more pronounced among those municipalities facing more vulnerable conditions, such as poor or rural/remotely located ones. Even if a convergence analysis remained out of the scope of this research, our results for both Mexico and Brazil suggest that mobile connectivity might constitute a factor favoring regional cohesion.

For both countries, the results were mostly identified with 4G rather than with 3G deployments. This can be explained as the 4G was rolled out quite closely after 3G in both countries, which limited potential impacts of the later, as soon individuals and business were upgrading to the newer standard. Also, the advances in broadband speed from the 4G may have played its part, as it enabled a more generalized use of internet for business processes and individual uses, in contrast with 3G that provides a basic access to internet.

Taken together, these findings reinforce the case for integrating broadband deployment into broader socioeconomic development in vulnerable areas of emerging economies. The process of closing the digital divide consists of bridging the connectivity gap in locations where the deployments are usually non profitable, such as rural areas or those in which the purchasing power of the individuals is limited. Therefore, public authorities should provide an accurate regulatory and policy framework to facilitate these deployments, for example adopting business-friendly regulations, reducing bureaucracy and administrative process, lowering taxation and improving universal service mechanisms that target these areas. Results presented in this paper fully justify these interventions aimed at vulnerable locations, considering the positive socioeconomic effects that connectivity can generate in these areas.

Nonetheless, the study faced some limitations. First, we were unable to assess the effects of the latest generation of mobile technology standards, 5G, as its deployment remains recent and relevant data is not yet available. Further investigation could also explore potential spatial externalities and spillover effects, as evidence from advanced economies suggests that broadband deployment in one locality can influence outcomes in surrounding areas (e.g., Briglauer et al., 2021). Finally, a deeper examination of the heterogeneity of impacts—and the underlying mechanisms driving these differences—would provide critical guidance for the formulation of rural development policies in emerging economies. Overall, these limitations also provide useful directions for future research in this field.

# 7. References

Acris Melo, A. K., Holanda Alves, P. J., & Matheus de Araujo, J. (2025). Economic development in remote areas: The impact of mobile broadband in the Brazilian Amazon [Working paper]. Federal University of Paraíba (UFPB) & Institute of Applied Economics (IPEA).

Afzal, A., Firdousi, S. F., Waqar, A., & Awais, M. (2022). The influence of internet penetration on poverty and income inequality. *Sage Open*, 12(3), 21582440221116104.

Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, 2(3), 46–59.

Aracil, E., Jung, J., & Melguizo, A. (2025). Leveraging fintech mobile money to expand banks' financial services in developing countries. *Finance Research Letters*, 72, 106280.

Bahia, K., Castells, P., Cruz, G., Masaki, T., Pedrós, X., Pfutze, T., Rodríguez-Castelán, C. & Winkler, H. (2024). The welfare effects of mobile broadband internet: Evidence from Nigeria. *Journal of Development Economics*, 170, 103314.

Bahia, K., Castells, P., Cruz, G., Masaki, T., Rodríguez-Castelán, C., & Sanfelice, V. (2023). Mobile broadband, poverty, and labor outcomes in Tanzania. *The World Bank Economic Review*, 37(2), 235–256.

Briglauer, W., Dürr, N., & Gugler, K. (2021). A retrospective study on the regional benefits and spillover effects of high-speed broadband networks: Evidence from German counties. *International Journal of Industrial Organization*, 74, 102677.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2), 200-230.

Galperin, H., Katz, R., & Valencia, R. (2022). The impact of broadband on poverty reduction in rural Ecuador. *Telematics and Informatics*, 75, 101905.

Galperin, H., & Viecens, M. F. (2017). Connected for development? Theory and evidence about the impact of Internet technologies on poverty alleviation. *Development Policy Review*, 35(3), 315–336.

García-Mora, F., & Mora-Rivera, J. (2021). Internet access and poverty reduction: Evidence from rural and urban Mexico. *Telecommunications Policy,* 45(3), 102076

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of econometrics*, 225(2), 254-277.

Gruber, H., & Koutroumpis, P. (2011). Mobile telecommunications and the impact on economic development. *Economic Policy*, 26(67), 387–426.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *Quarterly Journal of Economics*, 122(3), 879–924.

Muto, M., & Yamano, T. (2009). The impact of mobile phone coverage on market participation: Evidence from Uganda. *Food Policy*, 34(4), 276–283.

OECD (2006). El Nuevo Paradigma Rural. Políticas y Gobernanza. Estudios de política rural de la OCDE

Yang, L., Lu, H., Wang, S., & Li, M. (2021). Mobile internet use and multidimensional poverty: Evidence from a household survey in rural China. *Social Indicators Research*, 158(3), 1065–1086.

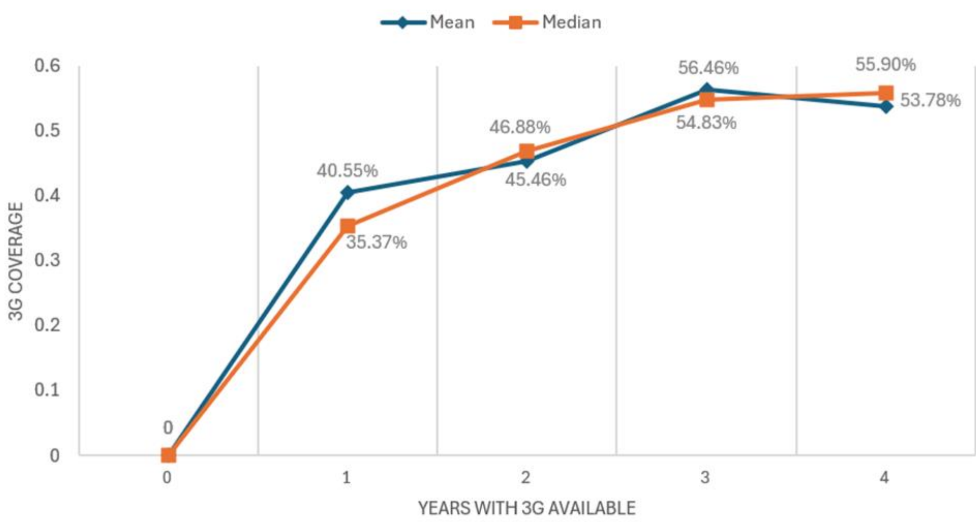
# 8. Appendix: 3G and 4G imputation procedure for Mexican municipalities

The original data of 3G/4G coverage in Mexican municipalities presented missing values for certain years (2015, 2017-2019). Treatment values for 3G and 4G were converted into binary (1/0) depending on coverage reaching a positive value or not. After that, we took a twofold approach to input the missing values.

First, we followed an absorbing assumption, by assuming that if coverage is 0 in period *t*, then it should be 0 in every period *t-n* (for every *n>0*). Similarly, if coverage is 1 in period *t*, then it should be 1 in every period *t+n* (for every *n>0*). Most of missing were filled with that conservative criterion, however some gaps remained.

Therefore, we took a second approach to filling the remaining gaps. In this case, the procedure consisted in mimicking for the uncomplete municipalities the average trajectory of 3G and 4G coverage in those municipalities for which data is available. Starting with 3G, the typical trajectory of deployment consisted of municipalities reaching 35%-40% coverage during the first year, 45%-47% in the second, and so on (Figure A1). Taking the median as a reference, all those municipalities with missing information that reached at least 46.88% of coverage in an observed year are assumed to be into at least the second year of coverage and thus should be inputted a 1 in the 3G coverage binary indicator the previous year if missing (zero in other case). Same procedure was done for the rest of years.

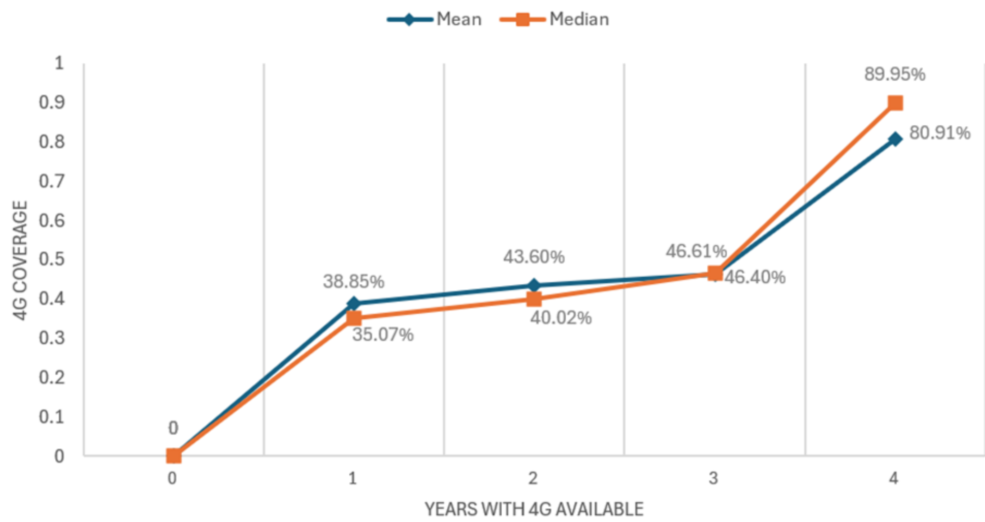
**Figure A1. Typical 3G trajectory in Mexican municipalities**
Percentage of coverage
Source: GSMA Intelligence




Similarly, we took into consideration the typical 4G trajectory to fill missing's in that treatment variable. As can be seen in median value in Figure A2, all municipalities that reached at least

40.02% 4G coverage in an observed year are assumed to have positive coverage the previous year when missing (in other case zero is assumed), and a similar procedure was applied for the remaining years.

**Figure A2. Typical 4G trajectory in Mexican municipalities**
Percentage of coverage
Source: GSMA Intelligence




Finally, when estimating regressions for 4G (3G) treatment we include as control legacy 3G (2G) technology coverage from the continuous estimator. In those cases, missing's from these continuous coverage controls were inputted through linear interpolation.

GSMA Intelligence

gsmaintelligence.com