High-Speed Mobile Internet, Firms, and Labour Market Outcomes: Evidence from Ecuador*

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November 20, 2024

Abstract

Do firms benefit from high-speed internet if it comes through mobile connections ? Combining panel data on the universe of formal firms in Ecuador alongside information on the introduction of 4G in Ecuadorian cantons, I estimate the effects of high-speed mobile internet on employment and wages in firms. To deal with endogeneity arising from the non-random placement of internet infrastructure, I simulate a hypothetical 4G rollout based solely on cost considerations linked to geography, and use it as an instrument. Following the introduction of 4G, employment increases by 7.1% for micro firms in sectors that are the less intensive in the use of digital technologies, with younger workers and men experiencing the largest gains. Wages per worker rise by 3% for micro firms in high digital intensity sectors, and only impact men. I provide suggestive evidence that the effects on employment come from a response at the extensive margin (new users of internet) while effects on wage come instead from a response at the intensive margin (change in internet use by existing users). Overall, high-speed mobile internet positively impacts firm, but firm size and sector matter. Facilitating access to high-speed mobile internet can be important to help micro firms, but might not be effective for larger firms.

Keywords: High-speed internet, 4G mobile internet, micro firms, employment, wage, Ecuador

JEL classification: O12, O33, J23, J31

*I would like to thank participants at the 58th Annual Meetings of the Canadian Economics Association and at CIREQ Lunch Seminars in McGill for their valuable comments. A special note of gratitude to my thesis supervisors, Matthieu Chemin and Sonia Laszlo.

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Internet access is widely recognized as a key element for economic development – contributing for instance to economic growth (e.g., Czernich et al., 2011) or poverty reduction (Bahia et al., 2024; Masaki et al., 2020) – and a high-quality service can be essential to fully unlock its potential. In particular, previous evidence indicates that the availability of high-speed fixed internet positively impacts firms. Hjort and Poulsen (2019), most notably, found that the arrival of fast fixed internet in Africa led to positive effects on employment, which are explained by increased firm entry, productivity, and exports.[1] However, fixed internet tends to be the the main source of internet access for larger firms, whereas smaller firms are more likely to rely on mobile internet, especially in low- and middle-income countries (LMICs) where they play a critical role in job creation and economic development. For instance, in Africa, where smaller firms and self-employment account for nearly 85% of total employment (International Labour Organization, 2019), 77% of large firms primarily access internet through a fixed connection, but only 33% of micro firms do so.[2] Instead, 60% of micro firms (and about 10% of large firms) use mobile internet as their main form of connectivity[3] (Broadband Commission for Sustainable Development, 2023). Therefore, to better understand the role of high-quality internet on firms, it is essential to also look at the impact of high-speed *mobile* internet. Yet, despite substantial investments in mobile network infrastructure that made high-speed mobile internet widely available, it has remained empirically challenging to identify its causal effects because internet infrastructure is usually introduced first in places with higher potential demand, leading to selection bias and reverse causality. Furthermore, it is not clear ex-ante that high-speed mobile internet would also positively benefit firms. Internet tends to exhibit decreasing returns at higher-speed – and even negative consequences – if firms lack capabilities (such as skills) to leverage it (e.g. Briglauer et al., 2024), an issue that can be especially stringent for smaller firms.

In this paper, I use the rollout of the fourth-generation (4G) mobile internet network in Ecuador to provide new evidence on the impact of high-quality internet on firms, focusing on the number of workers employed by firms and the average wage they pay to workers. I address the identification challenge by devising a simple strategy that simulates when 4G would have arrived in Ecuador's cantons[4] if its deployment had prioritized cost minimization, disregarding any demand-side considerations. While the year of initial 4G deployment in an Ecuadorian canton is correlated with demand factors in the actual rollout, this correlation is absent in the simulated rollout. Thus, the simulation creates a source of plausible exogenous temporal and spatial variation in 4G deployment that I use as an instrument to induce quasi-random variation in the

[1] Goldbeck and Lindlacher (2021) also found positive effects on employment and productivity in Africa after the introduction of *low-speed* fixed internet, which suggests that higher speed led to further gains.
[2] Micro firms are defined as firms employing 1 to 4 persons, while large firms correspond to firms with more than 100 employees.
[3] In both cases, the remaining 10% reported public wifi as their main form of connectivity.
[4] Ecuador is divided into provinces (first administrative level), which are further subdivided into cantons (second level) and parishes (third level).

actual rollout.

This empirical strategy takes advantage of the fact that 4G availability is contingent upon the installation of cell towers, the cost of which is impacted by two geographically-related factors: the slope and frequency of lightning strikes of the local terrain. Intuitively, installing a tower on flatter terrain is less expensive and requires fewer towers to cover the same area, while protecting and maintaining towers in areas with frequent lightning strikes incurs higher costs (Manacorda and Tesei, 2020). In practice, I do the simulation as follows. First, each canton is ranked based on its average terrain slope and frequency of lightning strikes, with flatter terrain and fewer lightning strikes receiving higher rankings. Then, for each year, the number of new cantons where 4G can be deployed is set, and the highest-ranked cantons without 4G yet – e.g. the cantons with the lowest deployment costs – receive 4G until this number is reached. This annual maximum is determined by the actual number of cantons that received 4G for the first time in that specific year and corresponds to assuming a national budget constraint (exogenously determined) that limits the number of cantons where 4G can be deployed.

The rollout of 4G in Ecuador offers an ideal context to study this question. Firstly, 4G was the first technology to consistently deliver high-speed mobile internet – defined as a connection with a bandwidth of 25 megabits per seconds (Mbps) (Briglauer et al., 2024) – at a large scale. By significantly improving data speed and reliability compared to previous mobile technologies, 4G should enable firms to increase efficiency by reducing the time needed to perform online and digital tasks and facilitating access to and use of new data-intensive activities and applications, potentially increasing workers and firm productivity or facilitating technology adoption and market access. Furthermore, I present suggestive evidence that the introduction of 4G did increase significantly the speed experienced by Ecuadorian users, and that users did adopt 4G. Secondly, the variation in geographical characteristics of Ecuador allows for an effective application of the empirical strategy. Not only do the average slope and frequency of lightning strikes per square kilometer in each canton vary significantly across the country, they also capture distinct geographic patterns that do not fully align together or with population distribution, providing useful variation to simulate the rollout.

Furthermore, I am able to use firm level data that includes information on employment and wage along with the date when high-speed mobile internet became available to the firm by combining information from two administrative datasets. The first dataset is a panel of the universe of formal firms in Ecuador – including micro firms – and includes information on employment, wage bill and sales, as well as the sector of the firm at the ISIC 4-digit level (4th revision). The second dataset has a historical time series on the number of 4G cell towers per canton in Ecuador. Crucially, the first dataset also contains the location of the firm at the canton level. Thus, I can approximate the availability of 4G for each firm by observing when the first 4G cell tower was installed in the canton where a firm is located.

I find that high-speed mobile internet contributes to increased growth in employment and wage per worker in firms, albeit not for every firms. More specifically, I find that only micro firms benefit, while larger firms see no effects, and the level of digitalization of the sectors in which the micro firm operates also matters. Micro firms in sectors that are the less intensive in the use of digital technologies that see an increase in employment – by 7.1% – while it is the micro firms in sectors that are more intensive in the use of digital technologies that see an increase in wage per worker – by 3%. Furthermore, I also find that these employment effects are stronger for younger workers and men, while the effects on wage only impact men.

I do not find a statistically significant change in sales, productivity, or entry/exit, which are usual mechanisms found in the literature to explain the effects of internet. Instead, when combined with information on internet use by type of firms right before the deployment of 4G, my results suggest that effects on employment come from a response at the extensive margin – i.e. new users of internet – while the effects on wage come instead from a response at the intensive margin – i.e. change in internet use by existing users. I show that just before the introduction of 4G, few micro firms in low digital intensity sectors were using the internet. In contrast, a large proportion of micro firms in high digital intensity sectors were utilizing it, although only a small number were investing in information and communication technologies (ICT). Meanwhile, more than 90% of small, medium, and large firms were already using fixed internet, and the majority of them were investing in ICT. Considering that 4G reduces the cost of internet adoption, saves time, and provides access to new services, the response of firms that were not using the internet before the introduction of 4G (micro firms in low internet digital sectors) to hire more younger workers – who presumably possess the skills to use internet effectively – is consistent with a shift toward internet utilization (extensive margin effect). Conversely, the fact that firms using the internet in a basic manner (micro firms in high digital intensity sectors) respond instead by increasing wages for their workers – presumably those most engaged with internet – is coherent with an expansion in their internet use (intensive margin effect). This is further supported by the lack of a statistically significant response to the introduction of 4G from firms that were already using the internet effectively (small, medium, and large firms), aligning with the view that their high access and usage were already sufficient enough that high-speed mobile internet did not significantly change these dimensions for them.

This paper contributes to a growing literature estimating the economic impacts of internet in developing countries, recently reviewed by Hjort and Tian (2024). In particular, earlier studies finds that access to internet increases productivity (Abreha et al., 2021; Hjort and Poulsen, 2019), labour-force participation and employment rates (Bahia et al., 2024; Chiplunkar and Goldberg, 2022; Goldbeck and Lindlacher, 2021) or wages (Poliquin, 2020). However, these papers either study lower-speed mobile internet technologies (2G or 3G), or investigate fixed internet instead of mobile internet. A few studies do look at high-speed mobile internet (4G), but they do not examine labour market outcomes. Agarwal et al. (2024) use 4G to looks at the impact of information dissemination on agriculture outcomes in India, while Alves (2024) leverages the rollout of 4G in Brazil to evaluate the impact of internet on the banking industry. Furthermore, the impacts on firms were not clear ex-ante. For example, as noted, mobile internet tends to be the main type of internet connection for the smallest firms only. Consequently, benefits might be limited for larger firms. However, the literature shows that users capabilities (such as skills) are important to leverage the potential benefits of accessing internet. Without these capabilities, internet access can even have negative consequences, such as pushing firms out of the market (Cambini and Sabatino, 2023). Thus, my main contribution is to provide empirical evidence on the effects of high-speed mobile internet on firm employment and wage in LMICs countries. More generally, the paper provides a deeper understanding of the interaction between firm characteristics – size, sector, and initial use of internet – and the impact of internet.

My estimation strategy is related to Lipscomb et al. (2013), who developed a model to simulate the placement of hydropower dams and electrical transmission lines in Brazil based only on geographic cost factors that affect suitability – namely water flow and river gradient. They use this hypothetical electricity network as an instrument to estimate the impact of electrification on different local development dimensions. They find that electrification increase the UN Human Development Index computed for each county, and the average housing values. I adapt a simplified version of this approach to a different type of infrastructure – cell towers – and demonstrate its effectiveness in this context.

This paper also contributes to the policy discussion on how to close the digital divide between countries and within countries (World Bank, 2024). My results show an important policy implication when future broadband strategies are considered: if the goal of policymakers is to help micro firms, facilitating access to high-speed mobile internet is important. However, if the goal is to help larger firms, improving mobile internet infrastructure might not be effective.

The remainder of the paper proceeds as follow: Section 1 provides some background, while Section 2 describes the conceptual framework. Section 3 describes the data and Section 4 details the methodology. Finally, Section 5 presents the results, Section 6 discusses potential mechanisms, and Section 7 concludes.

1 Background

Typically, people access internet via either fixed-line connections or mobile connections.[5] Fixed line connections include technologies such as Digital Subscriber Line (DSL) or, more recently, the optical fiber, while mobile connections feature, in particular, the third, fourth and fifth generation (3, 4, and 5G). However,

[5]There is also a third, marginal way (although it is seeing increased interest and development): satellites

due to different factors such as high fixed costs associated with deploying fixed internet connections and low willingness to pay (e.g. Goldbeck and Lindlacher, 2021), LMICs tend to have low(er) penetration rates for fixed-connections. Instead, people use mobile internet as their principal mean to access internet.

Like other LMICs, the main way people access internet in Ecuador is through mobile internet. Using data from the International Telecommunication Union, Figures 1a and 1b show the number of subscriptions per 100 inhabitants for both mobile and fixed internet connections in Ecuador and across different world regions. First, the patterns of subscription for both type of connections in Ecuador resemble those of the world average and middle-income countries – although, contrary to trends in those regions, the number of mobile broadband subscriptions in Ecuador appears to have stagnated since 2018. Second, the number of mobile subscriptions is significantly higher compared to fixed-line ones, and grow at a faster rate.[6]

One way to access the internet through a mobile connection is by using 4G technology. In Ecuador, 4G was first commercially launched in 2013 in the country's two main cities, Quito and Guayaquil. It was subsequently deployed in the rest of the country starting in 2015.[7] Media reports indicate that the most populated areas were targeted first (e.g. El Comercio, 2015a), especially in zones with commercial and touristic activity (e.g. El Comercio, 2015b). This resulted in a rapid and steady increase in the share of the population covered by 4G, going from 10% in 2013 to 49.6% in 2015, and 93.9% in 2022 (International Telecommunication Union).

Furthermore, 4G mobile internet became the mainstream mobile technology used by people, both in absolute and relative numbers. On the one hand, 4G has been adopted by a majority of the population: the number of people with an active mobile internet line enabling a 4G connection increased from 310 at the beginning of 2014 to 949,723 at the end of 2015 and 10,365,254 in December 2022, representing 57% of the Ecuadorian population[8] (ARCOTEL, 2023). On the other hand, it has also become the predominant technology among mobile internet users. Figure 2, which displays the monthly share of active mobile internet line per technology between 2012 and 2022, shows that the proportion of users utilizing 4G increased steadily from 2015 onwards, ultimately comprising around 60% of the total.

Finally, when 4G was deployed in the country, Ecuador already had a large 3G coverage: in 2012, 87.5% of the population was already covered by the 3G mobile network. Thus, any results can be attributed to an upgrade in availability from 3G to 4G.

[6] This would remain true even if we were to take into account the fact that fixed-line connections typically represent the number of connections per household, as there is usually only one subscription per household.

[7] Before the deployment of 4G, the mobile market in Ecuador was de facto a duopoly. Thus, in order to foster competition, the government only allowed a telecommunication state company to provide 4G until 2015, after when it allowed the two private companies to provide 4G as well (Lee et al., 2020).

[8] The total population of Ecuador was 17,989,912 in December 2022.

2 Conceptual framework

2.1 The effects of internet

The empirical and theoretical literature suggests that internet access can influence both the supply of a firm and the demand it faces. On the supply side, it can enhance both labour productivity – directly, via human capital development or via better firm-worker matching – and firm productivity, via its impact on total factor productivity (TFP). Additionally, it can facilitate technology adoption and, more generally, alter the firm's input mix at both intensive and extensive margins, leading to an increase in the firm's supply (Hjort and Tian, 2024). On the demand side, internet access can increase the market demand of a firm by increasing the size of its market – via reduction in information frictions or internet's overall impact on gross domestic product (GDP) – as well as opening up access to new markets, through avenues such as online sales or exports. However, demand can also be reduced due to heightened competitive pressure (Hjort and Tian, 2024; Cambini and Sabatino, 2023; Hjort and Poulsen, 2019).

The magnitude of these effects is impacted by a firm's ability to adopt and effectively utilize the technology (Cambini and Sabatino, 2023; Brambilla, 2018). If a firm does not adopt internet,[9] it may still face a reduced demand due to the increased competitive pressure, resulting in lower output and profits. Similarly, a firm that adopts internet but lacks the capacity to (fully) leverage it may only be able to extract benefits from expanded market size and access or enhanced productivity that are too small to compensate the decreased demand from a stronger competition, leading to a decline in output and profits (albeit to a lesser degree). On the other hand, firms that adopt internet and are able to effectively exploit it are likely to see large gains in demand and cost reduction, outweighing the negative effects of competition and resulting in higher output and profits. Moreover, some of the firms facing decreased profits may choose to exit the market altogether, while the possibility of increased profits may drive new firms capable of exploiting internet to enter the market.

Consequently, internet access can impact firms' labour demand and wage-setting decision. The number of workers employed by a firm will increase if the output effect is positive and labour is either a complement to internet or a substitute which effect is dominated by the output effect. Conversely, employment in the firm may decrease if the output effect is negative and labour is a substitute for internet, or if internet is a complement to labour but its effect is weaker than the output effect. In some cases, the overall level of employment at the firm could remain stable but hide shifts in the composition of the workforce, where an increase in the employment of workers who can benefit from, and effectively use, internet the most (due to

[9] There is a (fixed) cost to the adoption of internet technology (installation, workers adaptation, hiring or firing). Consequently, only firms that expect the benefits from adoption to be higher than the cost will choose to adopt (Brambilla, 2018).

their skills, or the tasks in their jobs) is offset by a reduction in workers who cannot. Although the effects on firm employment are ex-ante ambiguous, the literature generally finds positive impacts. Regarding wages, higher labour productivity should lead to the increase of wages paid by the firm – especially for workers that can exploit internet – as could an increase in profits. Indeed, if profits rise – through higher revenues from increased sales or cost reductions driven by improved productivity – firms may redistribute some of the gains to workers via rent-sharing (Brambilla, 2018). Finally, a change in the average wage per worker paid by the firm could arise from a shift in the composition of its workforce, if the workers who are replaced were being paid lower salaries.

2.2 The impact of 4G mobile internet

4G mobile technology improves data speed at which mobile users can access internet. In particular, Briglauer et al. (2024) find in their literature review on the impact of high-speed broadband on socio-economic outcomes that 4G technology averages a download speed of 15 to 20 Mbps,[10] representing a meaningful increase compared to 3G, which offered speeds of only 3 to 8 Mbps. This advancement in data speed has two primary effects for firms. First, it enables them to save time by visibly reducing the duration needed to access internet and download documents. For instance, the United States Federal Communications Commission found that the average download time for a webpage decreased from 6 seconds at 5 Mbps to less than 2 seconds at 25 Mbps and to just 1 second at 100 Mbps.[11] Secondly, they can access and use with sufficient quality and in a timely manner new, data-intensive activities and applications – provided they have the required ability and needs. This includes, for example, cloud storage or the use of high-quality videos – which opens up the possibility to increase digital presence via social medias, or to use videoconferencing, teleworking or working on the road.

Additionally, at a similar quality, 4G is typically less costly for its users in terms of acquisition and usage compared to other options to access internet (World Bank, 2024). Thus, with a lower cost of adoption – and potential higher benefits –, firms that had yet to adopt internet might decide to make the switch.

Overall, by potentially increasing workers and firm productivity, or facilitating technology adoption and market access, 4G availability should lead to higher wages per worker and an increase in labour demand, as outlined in Section 2.1. However, an additional factor could potentially play a role in the impact of 4G mobile internet: the presence of fixed broadband. For applications requiring low(er) data intensity, mobile and fixed internet can be substitutes, but as the data-intensity requirement increase, mobile internet might

[10] This can go up to an average of 100 Mbps for the most advanced 4G technology versions.

[11] Note that these tests were conducted with fixed internet connections. Exact improvements may vary for mobile connections.

no longer be able to provide the same services and quality (Greenstein, 2020).[12] Consequently, firms that are already using fixed internet may not experience significant additional benefits from adopting 4G – unless they obtain superior speeds from it, or benefits that cannot be provided by a fixed internet connection, such as access on the road.

3 Data

3.1 Economic outcomes

Data on firm outcomes comes from the *Registro Estadístico de Empresas* (REEM), a yearly panel compiled by Ecuador's National Institute of Statistics (INEC) using administrative records.[13] The dataset covers the universe of formal firms in Ecuador and provides information on sales, employment, and wages. It also includes details on firm location at the canton level and industry classification at the ISIC 4 digits level (Rev.4).

For the analysis, I keep the data covering the period 2012-2022, the years that INEC identifies as comparable.[14] Additionally, I classify firms by size and the intensity of digital technology use within their sector. For firm size, I follow the categorization used in the dataset – micro, small, medium A, medium B, or large, based on annual sales or, if unavailable, the number of employees. The only adjustment I make is combining the medium A and B categories into a single medium group (see Table A1 for exact thresholds). To classify firms by internet intensity sectors, I adopt the global taxonomy from Calvino et al. (2018). The authors ranked each 2-digit sector (ISIC Rev. 4 classification) across seven dimensions related to ICT use and then averaged these rankings into a single value. Sectors in the first quartile of the resulting distribution are classified as low internet intensity, while those in the second, third, and fourth quartiles are classified as medium-low, medium-high, and high internet intensity sectors, respectively. Finally, employment is measured as the number of equivalent jobs, defined as the total number of positions in a firm and weighted by the number of months worked. For example, if a firm has one person working in one position for 12 months and concurrently in another position for 6 months, that would be counted as 1.5 employees.

Table A3 in the appendix presents descriptive statistics for the full sample. Two potential issues arise: missing observations and outliers. First, while there are 10,007,067 observations in total,[15] there are only

[12] In particular, unless the fixed connection is using fiber wiring only, Briglauer et al. (2024) point out that 4G can offer capacity and efficiency comparable to fixed internet.

[13] More specifically, it includes firms that filed a declaration with the National Tax Institute (SRI), as well as firms that registered employees to the Social Security Institute (IESS).

[14] The registry began in 2012. Data for earlier years was reconstructed for certain variables, but the availability of information varied.

[15] Representing 2,562,921 different firms.

5,187,067 observations for employment and wage per worker. This discrepancy is due to firms under a special tax regime, the *Régimen Impositivo Simplificado Ecuatoriano* (Ecuadorian Simplified Tax Regime, RISE), whose participation is voluntary and was established in 2008 to combat informality and create a tax culture. Under this regime, firms that meet specific conditions – in particular, having a yearly gross income of $60,000 or less and not operating in the restricted activities – are not required to file income tax and Valued-Added (VAT) returns[16] or maintain accounting records. Only 10% of the firms under this regime have reported the number of employees and wages, whereas 95% of the other firms reported these outcomes (see Table A2, Panel A). Consequently, I exclude observations from the sample for which the taxpayer classification was RISE.[17] Secondly, some values appear surprising. For instance, the maximum wage per worker reported is $1,603,815.75, while the minimum is $0. Consequently, I trim the bottom and top 1% of the data for the employment and wage per workers variables.

The descriptive statistics for the final sample are reported in Table 1. On average, a firm has 3.29 paid positions (hereafter "employment at the firm") with an annual wage of $5,143 per worker. In terms of heterogeneity, the majority of observations come from micro-sized firms (84%), while the distribution across internet intensity sectors is more balanced, ranging from 14% in medium-low internet intensity sectors to 32% in both low and medium-high internet intensity sectors.

3.2 4G availability

For 4G availability, I use data from the administrative records of Ecuador's telecommunications regulatory body (ARCOTEL). This dataset includes a historical monthly time series of 4G cell tower counts reported by each telecommunications operator for each parish, starting from October 2015. Prior to this date, the data is only reported at the provincial level.

I define a canton as having 4G when it has at least one 4G cell tower. To match the availability of firm data, I use data covering the period 2012-2022. To obtain yearly data at the canton level (2015 onwards),

[16] It is replaced by a monthly fee.

[17] In 2022, the regime was replaced by the *Régimen Simplificado para Emprendedores y Negocios Populares* (Simplified Regime for Entrepreneurs and Popular Businesses, RIMPE), which distinguishes between two groups: "popular businesses" with yearly gross incomes of $20,000 or less, and "entrepreneurs" (natural or legal persons) with yearly gross incomes up to $300,000. Popular businesses are not required to file VAT returns and pay a flat fee that ranges from $0 to $60, depending on their income bracket. In contrast, entrepreneurs must make biannual VAT declarations and pay taxes at a marginal rate of 1% to 2%, based on their annual gross income.

As in previous years, 90% of firms not classified under RIMPE in 2022 reported employment and wages. Meanwhile, the reporting rates for RIMPE firms is higher but remained low at 30%. However, RIMPE firms now account for about 70% of the sample (up from around 50% for RISE firms in previous years). Thus, instead of excluding them altogether, I further categorize RIMPE observations into three groups: new firms (no observations in prior years), previously RISE firms (last observation classified as RISE), and not previously RISE firms (last observations not classified as RISE). The decomposition of missing data for these groups is shown in Panel B of Table A2. New and previously RISE firms exhibit missing data rates consistent with RISE in prior years (93.17% and 85.66%, respectively), while not previously RISE firms have missing data rates that are closer to those of non-RISE firms (30.76%). Consequently, I exclude new and previously RISE firms from the sample while retaining not previously RISE firms. This results in a final sample of 573,731 firms for 2022 and aligns with the sample size of non-RISE firms from the previous year (2021), which was 502,446.

I retain the number of 4G towers reported in December of each year and aggregate the tower counts across all parishes within a canton. For the years 2012, 2013, and 2014, I deduce the numbers from the rollout: as the 4G network was initially deployed in the cities of Quito and Guayaquil in 2013 and expanded nationwide starting in 2015 only, I assume that no canton had 4G cell towers in 2012 and that only Quito and Guayaquil had towers in 2013 and 2014. Figure 3 shows the resulting rollout per year and per canton.

3.3 Other characteristics

I supplement these two datasets with demographic, economic, and geographic information at the canton level from various sources. Specifically, I use data based on the 2010 census from the Ecuadorian Institute of National Statistics (INEC) to obtain population figures and to calculate population density as well as the shares of the population under 25, over 60, and living in urban areas for each canton. I also use data on National Accounts at the canton level from the Central Bank of Ecuador to obtain information on GDP and compute the share of agriculture in the canton's Gross Value Added. Additionally, I use data in the form of fine grid cells, computing canton-level values by taking the mean of the grid-cell values that the canton geographically covers. Specifically, I use 100m square grid cells containing information on elevation above sea level, slope of the terrain, and distance to the nearest main road generated by WorldPop (WorldPop, 2018a,b),[18] while I utilize the mean annual lightning flash rate density[19] per 10-kilometer-sided square grid cell[20] from the NASA Global Hydrology Resource Center DAAC (Albrecht, R., S. Goodman, D. Buechler, R. Blakeslee, and H. Christian, 2016). Finally, I use data on tourist attractions provided by the Ministry of Tourism, which includes attractions from a national perspective and provide their geographic locations.

4 Methodology

To estimate the effects of high-speed mobile internet on economic outcomes, I leverage the staggered rollout of 4G cell towers in Ecuador in the following model :

$$y_{i,t} = \beta_1 + \beta_2 * Treated_{i,t} + \beta_3 * X'_{i,t} + \alpha_i + \alpha_{p,t} + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is outcome y for a firm i in year t, $treated_{i,t}$ is a dummy variable equal to 1 if firm i in year t is in a canton where 4G has been deployed,[21] $X'_{i,t}$ is a set of control variables (details in Section 4.2), α_i is firm

[18] The distance to the nearest main road is computed as the distance of the grid-cell center to the closest main road.

[19] Note that this reflects the yearly average over the observation period (from January 1, 1998, to December 31, 2013), rather than year-to-year variations. Nevertheless, lightning flash rate density is consistent over time (Manacorda and Tesei, 2020).

[20] More exactly, per square with side of 0.1 degrees, which is around 10 km at the equator.

[21] Given the data, I cannot directly observe whether a firm uses 4G mobile internet. Therefore, to determine treatment status at time t, I assume a firm is treated if 4G has been deployed in the canton where it is located, i.e. there has been at least one

fixed-effects, $\alpha_{p,t}$ are province-year fixed-effects, $\varepsilon_{i,t}$ is the error term, and β_2 is the coefficient of interest. Standard errors are clustered at the canton level.

By including firm fixed-effects, which capture unobserved differences across units that remain constant over time, and province-year fixed-effects, which control for yearly shocks common to all units within the same province, the model compares within-unit variation among units in the same province. This comparison is based on the identifying assumption that, in the absence of 4G deployment, treated firms would have experienced changes in outcomes similar to those of non-treated firms within the same province. Therefore, β_2 captures the average effect of having 4G on outcome y across firms within the same province, averaged across all provinces.

However, it is unlikely that the rollout of 4G across cantons was conducted randomly. On the contrary, operators tend to prioritize areas where they can maximize profits, typically those with the highest concentration of potential customers.[22] This scenario, suggested by anecdotical evidence in Section 1, is supported by the results in Table A4, which shows canton characteristics by the year of 4G deployment. The later a canton received 4G, the smaller its population and population density, as well as, unsurprisingly, its number of firms, total employment, and GDP. Thus, even in the absence of 4G, firms in treated cantons may have been on different trends compared to non-treated firms.

To correct for the endogeneity in tower deployment, which would bias results if the model is estimated using Ordinary Least Square (OLS), I use an instrumental variable (IV) approach that exploit geographical features of the canton and their impact on internet infrastructure rollout.

4.1 Empirical strategy: simulated rollout

The approach uses two geographic factors, local slope and the frequency of lightning strikes, to simulate a deployment of 4G towers solely based on cost considerations, independent of demand factors.

The rollout and placement of 4G towers are influenced by demand-side factors such as population (which are likely endogenous, as noted earlier), but they also depend on supply-side considerations. In particular, these considerations include terrain variability and lightning strikes frequency. For instance, Gupta et al. (2020) showed that local terrain ruggedness is a strong predictor of whether a tower was actually constructed at the initial site identified for its placement in India's Shared Mobile Infrastructure Program (SMIP),[23] while Ofcom (2019) found that, in the United Kingdom, a higher standard deviation in local elevation (above sea

4G cell tower in the canton.

[22]In particular, the construction of cell towers and the expansion of the network involve significant fixed costs that must be incurred upfront, and this can enable them to recoup these initial capital investments.

[23]The Shared Mobile Infrastructure Program was an Indian government program that aimed to extend mobile phone coverage to identified uncovered areas by subsidizing telecom operators to construct and maintain towers. The program identified 7,871 potential sites for the new towers, resulting in the construction of 7,353 towers (Gupta et al., 2020).

level) is associated with a lower probability of full 3G and 4G coverage. Additionally, Chiplunkar and Goldberg (2022) found that areas with a number of lightning strikes below the median experience faster growth in 3G coverage compared to regions with above-median lightning activity.

To proxy terrain variability, I use terrain slope in my study. The rationale is that flatter areas are more likely to receive towers because they offer easier access and simpler installation, leading to lower costs for tower construction. Figure 4a shows the average slope for each canton. The (longitudinal) center of the country, where the Andes mountains are located, experiences a significant slope on average, while the eastern region and part of the western region, which encompass the Amazon rainforest and a broad coastal plain, respectively, are relatively flat. For lightning strikes, I use the average number of flashes per square kilometer. Intuitively, areas with a higher frequency of lightning strikes are less likely to receive towers due to the increased risk of power surges, which can damage equipment and necessitate mitigation or replacement, leading to higher costs (Chiplunkar and Goldberg, 2022; Mensah, 2021). The average number of lightning strikes for each canton of Ecuador is shown in Figure 4b. The highest number of annual lightning strikes occurs in the eastern region, with more than 10 strikes per square kilometer each year. In contrast, the Galapagos Islands, the southern region, and the cantons along the Pacific coast experience far fewer strikes, averaging less than 1 strike per square kilometer annually. Interestingly, while both geographic features exhibit significant variation in intensity across the country, they appear to capture different patterns. For instance, the south experiences few to no lightning strikes but has steep terrain, whereas the east features a relatively flat terrain and a high number of strikes. Meanwhile, there seems to be no clear correlation in the western region. This suggests that these characteristics can provide useful variation to simulate the rollout.

I conduct the simulation as follows. First, I create a ranking of the cantons, which corresponds to the order of priority for 4G deployment. More specifically, I rank the cantons based on their average level of steepness, where a lower average results in a higher rank. This means, for instance, that the canton with the lowest average steepness is ranked first, while the canton with the highest steepness is ranked last. Similarly, each canton is ranked by its frequency of lightning strikes, from the canton with the fewest strikes (ranked first) to the canton with the most strikes (ranked last). I then calculate a weighted average of these two ranks to obtain a final rank,[24] where a higher final rank indicates a lower overall cost of tower installation – based on the two geographic factors – and, thus, a higher priority for 4G deployment. I use a weight of 0.75 for the steepness rank and 0.25 for the lightning strikes rank, as these values ensure a sufficiently strong first stage while minimizing the correlation between the predicted first year of 4G deployment and demand-side factors (see Section 4.2).

Next, I determine how many cantons can receive 4G for the first time each year. This approach assumes

[24]Any ties is resolved by using elevation, with the canton having the lower elevation receiving the better rank.

a national budget constraint that limits the number of cantons that can be connected each year, preventing all (remaining) cantons from receiving 4G simultaneously in any year. For simplicity, I define this number as the actual number of cantons that received their first 4G cell tower during that year.[25]

Finally, I determine which cantons receive 4G in each year. To achieve this, I allocate 4G to the highest-ranked cantons that have not yet been connected – e.g. the remaining cantons with the lowest deployment costs – until the annual maximum is reached. Figure 5 shows the predicted deployment of 4G. A comparison with the actual rollout depicted in Figure 3 reveals changes in the timing of deployment, further highlighting that the actual rollout was influenced, at least partly, by demand-side factors. For instance, the canton of Quito – Ecuador's capital city and by far the second most populated canton in the country – gets connected in 2020 instead of 2013, given its high average steepness (between 30% and 45%) and medium number of lightning strikes (between 4 and 6 per year). Likewise, the two cantons that receive 4G towers first (in 2013) are rural areas characterized by nearly flat slopes and a very low frequency of lightning strike (between 0.4 and 1 per square kilometer per year), when in reality, these cantons received their first 4G tower in 2018 and 2019.[26] Overall, the average change in the year of deployment is two years, with changes ranging from none (0 years) to a maximum of seven years. Additionally, five of the six cantons that were not yet connected by 2022 in the actual rollout become connected in the simulated rollout, while it is the opposite for five other cantons.[27]

4.2 Empirical specification

I implement this IV approach within a fixed-effects two-stage least square (2SLS) regression framework. In the second stage, I estimate equation 1, where the variable $treated_{i,t}$ is instrumented from the following first stage:

$$treated_{i,t} = \delta_1 + \delta_2 * Z_{i,t} + \delta_3 * X'_{i,t} + \alpha_i + \alpha_{p,t} + \eta_{i,t} \tag{2}$$

$treated_{i,t}$ is a dummy variable equal to 1 if firm i in year t is in a canton where 4G has been deployed, $Z_{i,t}$ is a dummy variable equal to 1 if the firm i is in a canton predicted to have 4G in year t by the simulated rollout, $X'_{i,t}$ is a set of control variables (details below), α_i is firm fixed-effects, $\alpha_{p,t}$ are province-year fixed-effects and $\eta_{i,t}$ is the error term. Standard errors are clustered at the canton level.

This IV approach is valid if the following two assumptions are satisfied. First, the predicted year of 4G arrival needs to be strongly correlated with the actual year of deployment. Intuitively, this condition

[25] That is, 2 cantons in 2013, 33 cantons in 2015, etc. See Figure 3 for the numbers for each year.

[26] Respectively, the canton of Huaquillas in the province of El Oro (population of around 50,000) and the canton of Lomas de Sargetillo in the province of Guayas (population around 20,000).

[27] The sixth actual unconnected canton remains unconnected in the simulation.

is satisfied because the simulated rollout is based on factors that are also predictors of the actual rollout. Furthermore, Table 2 reports the first-stage regression results. The point estimate in column (1) indicates a strong correlation between the simulated and actual availability of 4G: a canton predicted to have 4G in a given year is 25 percentage points more likely to actually have 4G that year compared to a canton not predicted to have 4G, a result statistically significant at the 1% level. Below the point estimate, I report the F-statistic from the Sanderson-Windmeijer multivariate F-test of excluded instruments. It shows that we can reject that the instrument is weak. Column (2) repeats the same exercise, this time including controls (see below). The conclusions remain unchanged.

Second, the instrument must satisfy the exclusion restriction, meaning that the simulated rollout should be affecting firm outcomes solely through its influence on the actual rollout, not directly or through other channels. One concern is that the ranking used to predict 4G deployment may also capture the suitability for other outcomes correlated with labour market outcomes, namely population, agricultural activity, and road connectivity. For instance, more people may be settled in areas that are flatter on average and experience fewer lightning strikes. Similarly, flatter areas tend to be more suitable for agriculture and road construction. As a result, the simulated rollout could be prioritizing the placement of towers in regions that are more populated, more agricultural, and/or have better road connectivity. Another concern is that, since the instrument is based on factors impacting the actual rollout, it may be correlated with outcomes associated with better mobile internet coverage that could also independently affect labour market outcomes. In particular, this includes population density, the proportion of people living in urban areas in the canton, affluence (proxied by GDP per capita) and the share of young and elderly individuals in the population (Ofcom, 2019), as well as the number of tourism sites – as noted in Section 1.

To build confidence in the validity of the instrument, I test whether these elements are predictors of the simulated year of first 4G tower deployment. Column (1) of Table 3 indicates that the local population in 2010 and the mean distance to main roads do not statistically predict the year of first 4G deployment. However, a higher share of agriculture in gross added value of the canton is associated with an earlier deployment year. Furthermore, population density and the proportion of people living in urban areas in the canton are negatively correlated with the year of predicted deployment, while the share of young and elderly individuals in the population and the number of tourism sites are associated with a later year of deployment. However, once we control for the geographical supply-side factors used for the instrument, all these demand-based outcomes become statistically insignificant (while the average slope and the frequency of lightning strikes are, unsurprisingly, strong predictors of the year of 4G deployment).

Furthermore, in columns (3) and (4), I run the same regressions as in columns (1) and (2), but with the year of actual deployment as the dependent variable. Notably, when all outcomes are considered together (column 4), several are associated with an earlier (population, share of urban population) or later (share of agriculture in gross added value, share of young and elderly individuals in the population) year of 4G deployment. This suggests that the lack of statistical significance found in column (2) for the simulated rollout can indeed be attributed to the instrument, supporting the identification assumption – at least when conditioning on these outcomes.

Overall, the instrument appears to satisfy the two conditions for validity, although that may not hold unconditionally. Therefore, in the empirical analysis, I will also control for these variables.

5 Results

5.1 4G deployment, mobile internet speed, and usage

Before analyzing the effects of high-speed mobile internet on firm labour market outcomes, I document the following elements to support, first, that the deployment of 4G increased the mobile internet speeds experienced by users, and second, that firms utilize 4G mobile phone internet.[28]

First, cantons where 4G has been deployed experience a substantial increase in the speed of mobile internet that is not observed in cantons without 4G. Using data from Ookla,[29] Figure 6 shows the evolution of average download speeds experienced by individuals in Ecuador's cantons, based on the year each canton first received a 4G cell tower.[30] In early 2019, users in cantons where 4G was deployed in 2019, 2020, 2021, 2022, or never deployed, were experiencing similar average download speeds, at around 5 Mbps. However, by the end of 2022, users in cantons where 4G had been deployed were experiencing speeds five times faster than those in cantons without 4G (25 Mbps vs. 5 Mbps). Furthermore, while the average download speed in early 2019 was about three times higher in cantons with 4G than in cantons where 4G would be deployed between 2019 and 2022, by the end of 2022, these speeds had become nearly equivalent. These changes align with the timing of 4G deployment. In 2019, only users in cantons where 4G was deployed during that year experienced a significant increase in download speed (from about 5 Mbps to around 15 Mbps, reaching speeds comparable to those of users in cantons with earlier deployment), while speeds in other cantons remained at around 5 Mbps. A similar pattern occurred in 2020, 2021 and 2022: users in cantons that received 4G for the first time that year saw an increase in average download speed, while those in cantons without 4G saw no improvement. By the end of 2022, users in cantons without 4G were still experiencing an average

[28] In my data, I do not have the internet speed a firm experience and whether it uses mobile internet. As such, I use data from other sources.

[29] Ookla operates the platform *Speedtest*, where users can test the quality of their device's internet connection through performance metrics like download and upload speeds. Using geographic coordinates collected with the tests, Ookla aggregated the results quarterly into square grid cells, each measuring approximately 610.8 meters per side at the equator. Note that these measurements are not derived from standardized tests and are performed by users on a voluntary basis.

[30] Data is only available from the first quarter of 2019 onwards.

download speed of around 5 Mbps.[31]

As a placebo test, I conduct a similar analysis using Ookla's data for fixed broadband internet. The results are shown in Figure A1. While the average download speed experienced by users increases over the years, it does so at a comparable rate and in the same proportions across all cantons, regardless of when the canton received its first 4G cell tower. These patterns provide reassurance that the changes observed in Figure 6 are indeed attributable to the introduction of 4G towers. Additionally, they also help to temper concerns that fixed internet speed, rather than 4G, could be influencing the results, as the broadband speed experienced by users do not appear to be widely different among cantons nor correlated with the year of 4G deployment.

Secondly, as shown in Section 1, 4G became the mainstream mobile technology for individuals. Thus, it is reasonable to assume that firms would be using 4G too. This is especially true for micro firms, where the business's internet connection is often the same as the personal connection (Broadband Commission for Sustainable Development, 2023).

5.2 Employment and wage per worker

I now turn to analyzing the effects of high-speed mobile internet on employment and wage per worker in firms. First, Table 4 presents the results for the complete final sample, from which mixed results emerge, depending on the specification.

Focusing on employment, column (1) reports the coefficient associated with the OLS estimation of equation 1, controlling for firm and province-year fixed effects – i.e., the two-way fixed effects estimator (TWFE). The estimated coefficient indicates that 4G deployment is associated with a small employment increase of approximately 1%. Addressing potential endogeneity bias, column (2) shows the results from estimating equation 1 with the IV approach, where the timing of 4G availability is instrumented by the simulated rollout based on geographical characteristics – i.e., the second stage of the 2SLS estimator. The estimated coefficient remains statistically significant and increases to 3.5%, suggesting that endogeneity likely biased the results downward. However, when controls are included in the IV approach (column 3), the coefficient decreases and loses statistical significance.

The pattern for wages is somewhat different. The TWFE estimates in column (4) are also statistically significant and indicate a 0.6% increase in wage per worker following the introduction of 4G mobile internet. However, in the IV approach, this result remains statistically significant only when controls are included (column 6). In that specification, the coefficient indicates that the 4G rollout led to a 1.2% increase in wages per worker, which is higher than the TWFE estimate. This suggests again that a simple comparison of

[31] Note that the number of observations per quarter per canton varies and can be quite low, which may result in noisier values.

treated versus untreated firms, even with fixed effects, likely underestimates the true impact of high-speed mobile internet.

5.3 Heterogeneity by firm characteristics

5.3.1 Firm size

Next, I explore potential heterogeneity in the effects by examining different subsamples. I start by examining subsamples based on firm size in Table 5. Indeed, in larger firms, workers tend to utilize ICT more and to earn a wage premium (De Vera and Garcia-Brazales, 2022). Consequently, not only have larger firms a greater potential to benefit from 4G, they also are more likely to possess the capacities to leverage internet effectively. Thus, we would expect the magnitude of the effects to be greater for larger firms.

However, contrary to expectations, larger firms do not exhibit greater benefits following the introduction of 4G. In fact, there are no statistically significant changes in employment or wage per worker for small, medium, and large firms, regardless of whether controls are included (columns 2, 3, 5, and 6). Instead, it is micro firms that experience positive effects, increasing the average wage they pay their workers by 1.6% (column 6).

Moreover, the results in Table 5 further illustrate the importance of controlling for endogeneity bias. For both employment and wage per worker, the IV estimates differ significantly from those of the TWFE estimator, with all coefficients – except for employment in micro firms – being positive and statistically significant in the latter specification.

5.3.2 Sectoral digital intensity

Table 6 reports the results when the subsamples are based on firm sectors instead. Indeed, in sectors with higher internet usage intensity, workers tend to have a greater ICT task intensity (Calvino et al., 2018). For the same reasons as with larger firms, we would thus expect firms in these sectors to experience a stronger positive impact from the deployment of 4G.

Here, the results on wage per worker are in line with expectations: in the preferred specification that employs the IV approach with controls (column 6), the estimated coefficients are larger for firms in sectors with higher digital intensity, indicating stronger positive effects where anticipated. Specifically, firms in medium-high digital intensity sectors experience a 1.1% increase in wage per worker when using the IV approach (column 5), a finding robust to the inclusion of controls (column 6). For firms in high digital intensity sectors, the coefficients are even larger, although they are only almost statistically significant. In contrast, the results for low and medium-low digital intensity sectors are smaller and statistically insignificant.

These results remain unchanged with the addition of controls.

Conversely, the results for employment are more surprising. Following the introduction of 4G, only firms in *low* digital intensity sectors increase their workforce, hiring 8.2% more employees when using the regular IV approach (column 2), and a slightly lower 7.4% when controls are added (column 3). Similar to the findings for wage per worker, the results remain unchanged with the inclusion of controls.

Additionally, while all but one coefficient from the TWFE specification are statistically significant (columns 1 and 4), most are not robust to the IV approach (columns 2 and 5). For those that do, we again observe a downward bias: coefficients from the TWFE specification are smaller than those from the IV approach, regardless of whether controls are included.

5.3.3 Interaction between firm size and sectoral digital intensity

Finally, I further decompose the results by examining subsamples based on the interaction between firm size and sectoral digital intensity. This enables me to delve deeper to see if additional heterogeneities are driving the results. Moreover, the outcomes are more ambiguous ex-ante: while we might expect large firms in highly digital intensive industries to benefit the most, the effects on smaller firms in high digital sectors and on larger firms in low digital sectors remain uncertain. Table 7 presents the results for micro firms.[32]

First, the employment gains in low digital intensity sectors are driven by micro firms. For these firms, employment increases by 7.8% without controls and 7.1% with controls in the IV approach (columns 2 and 3), both statistically significant at the 10% level. In contrast, results for small, medium, and large firms are insignificant. Second, wage increases per worker is also driven by micro firms. In medium-high and high digital intensity sectors, micro firms experience increases of 1.5% and 3%, respectively (column 5), both significant at the 10% level, with results unchanged by the inclusion of controls (column 6). For small, medium and large firms, all results are again statistically insignificant.

Overall, the introduction of high-speed mobile internet appears to primarily impact micro firms. Furthermore, depending on the micro firm's sector, the impact is different. In low digital intensity sectors, micro firms increased employment without raising wages, while in sectors where the use of digital technologies is more intensive, they increased wages but did not increase their workforce.

[32] Tables reporting the results for small, medium, and large firms are available upon request.

6 Mechanisms

6.1 Sales, productivity, entry and exit

To understand why high-speed mobile internet impacts employment and wages per worker for certain micro firms, I first examine how total sales, productivity, and entry and exit change after the introduction of 4G. As outlined in the conceptual framework in Section 2, 4G has the potential to increase demand, thus affecting total sales and in turn impacting labour demand, while it can also affect productivity, eventually affecting wages per worker. Additionally, 4G may drive the entry of new, different firms (such as less labour-intensive firms) and/or the exit of existing firms (e.g., those unable to leverage internet capabilities), which could further alter the average levels of employment and wages per worker in firms. Table 8 reports the coefficients for these potential mechanisms. Since the dataset lacks information on capital stock, I cannot compute total factor productivity and focus on labour productivity instead. Moreover, the dataset only includes information on firms that are considered "active", i.e. that have made declarations to government agencies. As a result, my variables on entry and exit reflect whether a firm is economically active or inactive instead of entry and exit per se. This is interesting because it enables the capture of movements in and out of the formal sector as well – although it cannot distinguish between these transitions and pure entry or exit –, which is particularly relevant for micro firms, as informality exceeds 50% in Ecuador.

In contrast to several studies that have found these channels to contribute to changes in employment or wages (e.g. Hjort and Poulsen, 2019), the results from the IV specifications suggest that 4G did not affect sales, productivity, or entry and exit. Therefore, different mechanisms are likely at play.[33]

6.2 The role of initial internet connection

Following the conceptual framework in Section 2, a firm's ability to effectively use the technology and the presence of fixed broadband may also play important roles in shaping the impact of 4G mobile internet. However, unlike the channels explored in the previous subsection, I cannot directly test these two potential mechanisms with the available data. Instead, I rely on variables from the dataset and external information to approximate them. On the one hand, I use workers' age and sex as proxies for internet skills. Internet use – particularly for newer technologies and developments – is typically associated with younger people. Furthermore, due to differences in factors such as digital access, job types, education, or social norms, internet skills may vary by sex, with men generally having more developed skills (World Bank, 2016). On the other hand, I rely on data from the *Encuesta Exhaustiva* survey to obtain information on internet usage in

[33]The lack of effects on sales and labour productivity could also be attributed to measurement error. Indeed, many observations with data on employment and wages lack corresponding information on total sales. For instance, the number of observations for total sales decreases by 40% to 50%, depending on the digital intensity sector subsample.

firms. This survey, conducted in 2011 and focused on ICT use, is nationally representative and, importantly, includes micro firms. Although it does not capture the evolution of internet usage, it provides a snapshot just before the introduction of 4G. I obtain three sets of findings that lead to a potential, albeit suggestive, explanation for the findings in Section 5.

First, the changes in employment are more pronounced for younger workers and men. Table 9 reports the estimates for employment changes decomposed by workers' sex and age in micro firms, depending on the digital intensity of their respective sectors. Consistent with the results in Section 5, only micro firms in low digital intensity sectors experience an increase in employment under the IV specifications. Furthermore, the largest increase is observed among younger workers: under the IV specification with controls (column 3), employment rises by 4.7% for workers aged 18 to 29. In contrast, the increases for the 30-44 age group is 4.1%. For older age categories, these numbers drop to 1.7% or 1.9% depending on the IV specification, and are significant for 65 and plus only, at the 10% level. Interestingly, employment increases for both men and women, but the increase is more substantial for men (approximately 6% compared to 3%).

Second, increases in wage per worker are driven solely by men. As shown in Table 10, which reports the impact of 4G deployment on wage per worker by sex in micro firms,[34] wages only rise for micro firms in medium-high and high digital intensity sectors under the IV specifications, in line with the findings in Section 5. Moreover, the increase is larger in the high digital intensity sector category (e.g., column 9 vs. column 12) and only affect men. Changes for women are not statistically significant.

Third, initial internet usage prior to the introduction of 4G correlates positively and strongly with both firm size and the digital intensity of the firm's sector. Table 11 presents the results of the *Encuesta Exhaustiva* survey broken down by firm size. More than 90% of small, medium and large firms were already using fixed internet (columns 3, 4 and 5), while this number was at 15% only for micro firms (column 1). Among micro firms that did not qualify for RISE status[35] – providing a more representative sample of the micro firms in my dataset, as is confirmed by the values on employment and wage – the percentage rises to 44%, although it remains significantly lower than that of larger firms (column 2). I further decompose the results by sector for micro firms that did not qualify for RISE status in Table 12. The data shows that the proportion of internet usage among these firms declined strongly with lower digital intensity in their sector, ranging from 77% for the firms in high digital intensity sectors (column 4) – close to the rates of small and large firms – to just 25% for those in low digital intensity sectors (column 1). A similar pattern is observed for investment in ICT: it exceeds 50% for small, medium, and large firms (columns 3, 4 and 5 in Table 11), while it stands at

[34] Unfortunately, the information per age category is not available in the dataset

[35] The dataset does not indicate whether a firm was under the RISE tax regime (see Section 3 for details on RISE). To approximate this, I use the primary qualification criterion to be eligible for RISE: annual sales below 60,000 USD. Therefore, I consider that a firm does not qualify for RISE if it reported sales above 60,000 USD in the survey.

38.99% for micro firms (that did not qualify for RISE status) in high digital intensity sectors and decreases even further in sectors with lower digital usage, reaching 14.22% for micro firms in low digital intensity sectors (columns 4 to 1 in Table 12, respectively).

Based on these results, and in light of the conceptual framework in Section 2, the employment effects in micro firms from low digital intensity sectors are consistent with a response to 4G introduction at the extensive margin. Given their low internet usage before 4G was introduced, these firms correspond to the non-adopter category outlined in the framework. With 4G lowering the cost of internet access, they become adopters of internet and, as a result, hire more workers with the skills to use it. In contrast, the effects on wage per worker in micro firms from medium-high and high digital intensity sectors are more coherent with a response at the intensive margin. For these firms, the combination of (relatively) high internet usage and low share of investment in ICT categorizes them into the group of basic internet adopters. As such, they already have workers who can use internet and do not need to hire more. Instead, the time savings, lower price, and new services enabled by 4G allow them to expand their internet usage. Consequently, they increase the wages of workers who have the most capabilities in, or potential to benefit from, using internet. Finally, high proportions of internet use and ICT investment position small, medium, and large firms within the category defined as adopters capable of effectively utilizing internet. Therefore, for these firms, 4G does not fundamentally alter their access to internet or what they can accomplish with it, and they do not respond to its introduction in terms of employment or wages.

7 Conclusion

In this paper, I provide new evidence on the impact of high-speed mobile internet on firm labour demand and wage-setting. To address the endogeneity issue of 4G non-random placement, I simulate the rollout of 4G based on cost considerations only and use this as an instrument in a two-stage least square framework. I first show suggestive evidence that the introduction of 4G increased mobile internet speed experienced by users, and that they do use 4G. I find that high-speed mobile internet increases employment, but only for micro firms in internet intensive sectors. I also find that wage per worker increases after the introduction of high-speed mobile internet, but only in micro firms in sectors that are more intensive in the use of digital technologies. Furthermore, I also find that these employment effects are stronger for younger workers and men, while the effects on wage only impact men. Combined with information on internet use by type of firms right before the deployment of 4G, these results suggest that effects on employment come from a response at the extensive margin (new users of internet) while effects on wage come instead from a response at the intensive margin (change in internet use by existing users).

Given that I do not find significant effects on sales, entry and exit, worker productivity, or workforce composition (in firms where wages increase), further research is needed to better understand the underlying mechanisms explaining the results I found. In particular, Viollaz (2018) has shown that internet adoption by Peruvian micro and small firms resulted in the implementation of organizational changes – including management and ICT practices. These changes could lead to increased profits that may, in turn, be shared with workers through a rent-sharing mechanism. Therefore, an interesting avenue for the wage effects would be to explore whether high-speed mobile internet leads to improvement in organizational practices. Another possibility is the role of local economic structure, and whether high-speed mobile internet impacts it. For example, Ridhwan (2021) found that a higher specialization is associated with higher wages, while Amodio et al. (2022) and Fafchamps and El Hamine (2017) found that higher concentration is associated with lower wages. An interesting question would be to explore whether high-speed mobile internet led to the geographical or sectoral reallocation of economic activity in Ecuador.

By positively impacting firms, high-speed mobile internet has the potential to be used as a solution to narrow the digital gap in terms of internet quality (World Bank, 2024). However, due to the heterogenous effects across firms and workers based on their characteristics, additional measures may be required, depending on the specific policy objectives.

References

Abreha, K., Choi, J., Kassa, W., Kim, H. J., and Kugler, M. (2021). *Mobile Access Expansion and Price Information Diffusion: Firm Performance after Ethiopia's Transition to 3G in 2008*. The World Bank.

Agarwal, S., Desai, M., Ghosh, P., and Vats, N. (2024). Bridging the information gap: Sowing the seeds of productivity with high-speed 4g internet. *Available at SSRN 4805486*.

Albrecht, R., S. Goodman, D. Buechler, R. Blakeslee, and H. Christian (2016). LIS 0.1 Degree Very High Resolution Gridded Lightning Climatology Data Collection. Data sets available online [https://ghrc.nsstc.nasa.gov/pub/lis/climatology/LIS/] from the NASA Global Hydrology Resource Center DAAC, Huntsville, Alabama, U.S.A. doi: http://dx.doi.org/10.5067/LIS/LIS/DATA306.

Alves, F. (2024). *The impact of information and communication technologies on banks, credit, and savings: an examination of Brazil.* Bank for International Settlements, Monetary and Economic Department.

Amodio, F., Medina, P., and Morlacco, M. (2022). Labor market power, self-employment, and development.

ARCOTEL (2023). Active lines per technology (Lineas activas por tecnologia). Retrieved from https://www.arcotel.gob.ec/lineas-activas/.

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

Brambilla, I. (2018). Digital technology adoption and jobs: A model of firm heterogeneity. *World Bank Policy Research Working Paper*, (8326).

Briglauer, W., Krämer, J., and Palan, N. (2024). Socioeconomic benefits of high-speed broadband availability and service adoption: A survey. *Telecommunications Policy*, page 102808.

Broadband Commission for Sustainable Development (2023). Making digital connectivity work for msmes.

Calvino, F., Criscuolo, C., Marcolin, L., and Squicciarini, M. (2018). A taxonomy of digital intensive sectors.

Cambini, C. and Sabatino, L. (2023). Digital highways and firm turnover. *Journal of Economics & Management Strategy*.

Chiplunkar, G. and Goldberg, P. K. (2022). The employment effects of mobile internet in developing countries. Technical report, National Bureau of Economic Research.

Czernich, N., Falck, O., Kretschmer, T., and Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal*, 121(552):505–532.

De Vera, M. and Garcia-Brazales, J. (2022). Firm size and the task content of jobs: Evidence from 47 countries. *Available at SSRN 3965077*.

El Comercio (2015a). Movistar expande su red 4g. Retrieved from https://www.elcomercio.com/guaifai/movistar-red-4g-cuenca-telefonica.html (accessed July 2024).

El Comercio (2015b). Operadora privada despliega red 4g en zonas turÃstica y comercial de quito. Retrieved from https://www.elcomercio.com/actualidad/negocios/ecuador-cobertura4g-movistar-internet-telefonia.html (accessed July 2024).

Fafchamps, M. and El Hamine, S. (2017). Firm productivity, wages, and agglomeration externalities. *Research in Economics*, 71(2):291–305.

Goldbeck, M. and Lindlacher, V. (2021). Digital infrastructure and local economic growth: Early internet in sub-saharan africa.

Greenstein, S. (2020). The basic economics of internet infrastructure. *Journal of Economic Perspectives*, 34(2):192–214.

Gupta, A., Ponticelli, J., and Tesei, A. (2020). Information, technology adoption and productivity: The role of mobile phones in agriculture. *NBER Working paper*, (w27192).

Hjort, J. and Poulsen, J. (2019). The arrival of fast internet and employment in africa. *American Economic Review*, 109(3):1032–1079.

Hjort, J. and Tian, L. (2024). *The economic impact of internet connectivity in developing countries*. INSEAD Working paper.

International Labour Organization (2019). *Small Matters: Global evidence on the contribution to employment by the self-employed, micro-enterprises and SMEs*.

International Telecommunication Union. Digital Development Dashboard. Retrieved from https://www.itu.int/en/ITU-D/Statistics/Dashboards/Pages/Digital-Development.aspx (accessed July 2024).

Lee, J. H., Yim, D.-M., Song, M., Ahn, H., Jung, H., Lee, S. W., Park, J., and Kim, H. (2020). Consultation on policy for spectrum allocation and efficient use in ecuador. KISDI Consulting Group.

Lipscomb, M., Mobarak, A. M., and Barham, T. (2013). Development effects of electrification: Evidence from the topographic placement of hydropower plants in brazil. *American Economic Journal: Applied Economics*, 5(2):200–231.

Manacorda, M. and Tesei, A. (2020). Liberation technology: Mobile phones and political mobilization in africa. *Econometrica*, 88(2):533–567.

Masaki, T., Ochoa, R., and Rodríguez-Castelán, C. (2020). Broadband internet and household welfare in senegal.

Mensah, J. T. (2021). Mobile phones and local economic development: a global evidence. *Available at SSRN 3811765*.

Ofcom (2019). Economic geography 2019 - an analysis of the determinants of mobile and fixed coverage in the uk.

Ookla. Speedtest by ookla global fixed and mobile network performance maps. Retrieved from https://registry.opendata.aws/speedtest-global-performance/ (accessed July 2024).

Poliquin, C. W. (2020). The wage and inequality impacts of broadband internet. *University of California. Retrieved August*, 19:2021.

Ridhwan, M. M. (2021). Spatial wage differentials and agglomeration externalities: Evidence from indonesian microdata. *Economic Analysis and Policy*, 71:573–591.

Viollaz, M. (2018). Ict adoption in micro and small firms: Can internet access improve labor productivity?

World Bank (2016). *World Development Report 2016: Digital dividends*. World Bank Publications.

World Bank (2024). *Digital Progress and Trends Report 2023*.

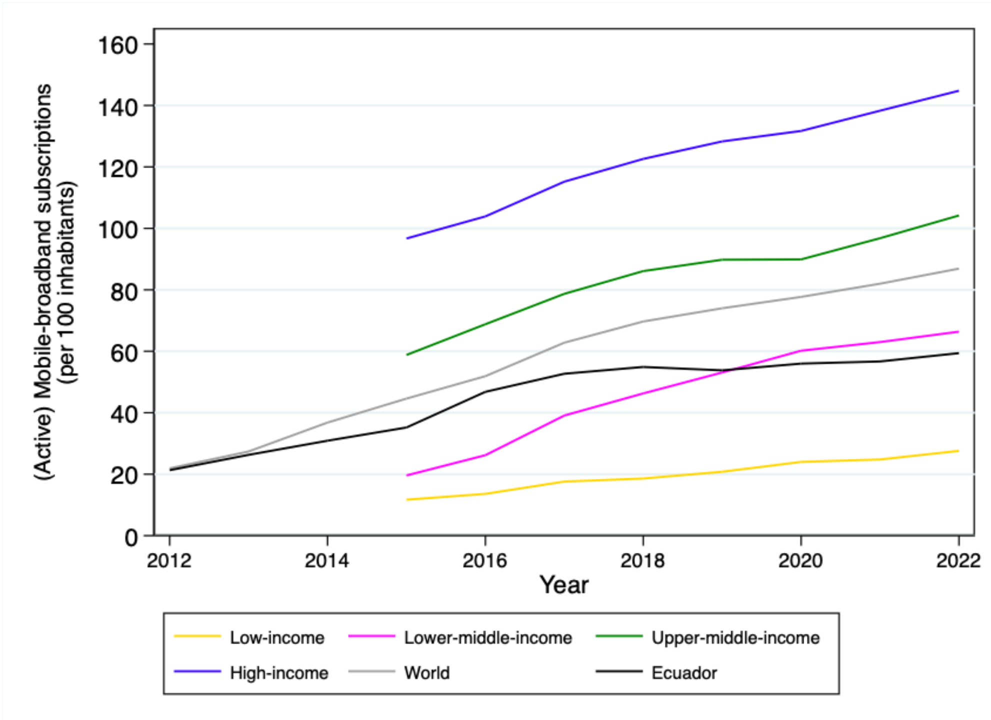
WorldPop (2018a). Global High Resolution Population Denominators Project. Retrieved from https://dx.doi.org/10.5258/SOTON/WP00660.

WorldPop (2018b). Global High Resolution Population Denominators Project. Retrieved from https://dx.doi.org/10.5258/SOTON/WP00644.

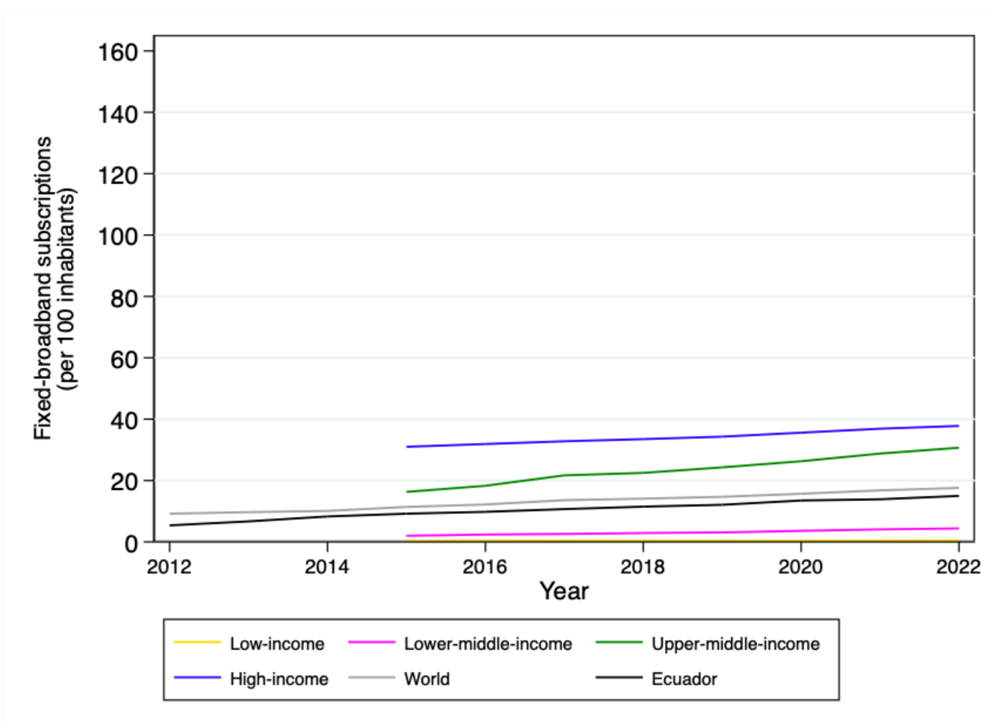
Figures and tables

Figure 1: Number of internet subscriptions by world regions and Ecuador

(a) Active mobile broadband subscriptions

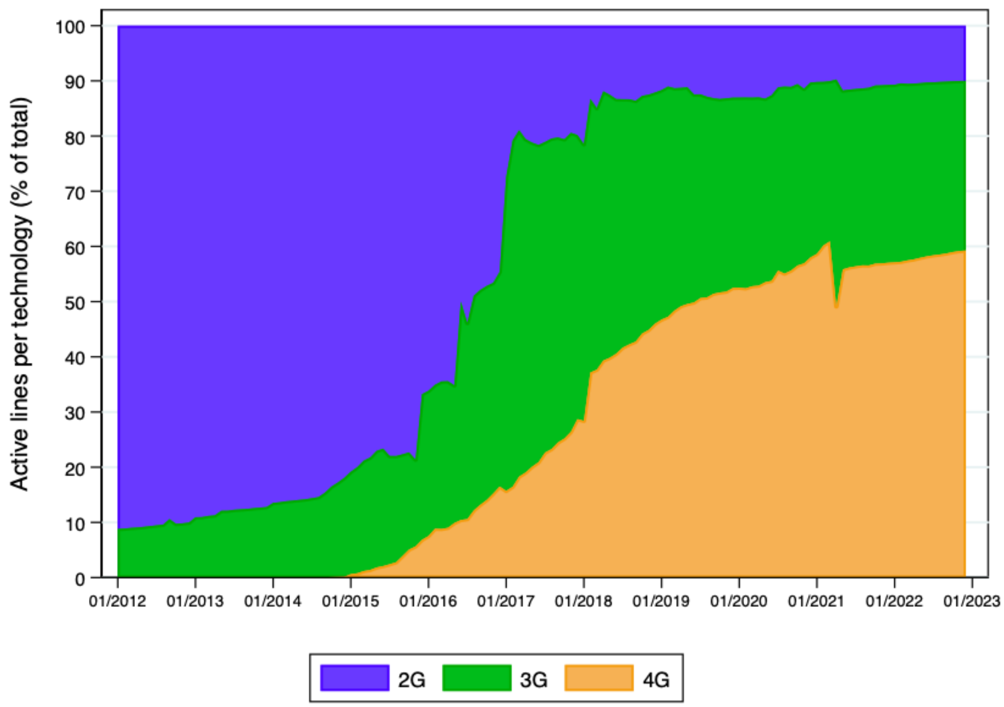


(b) Fixed broadband subscriptions



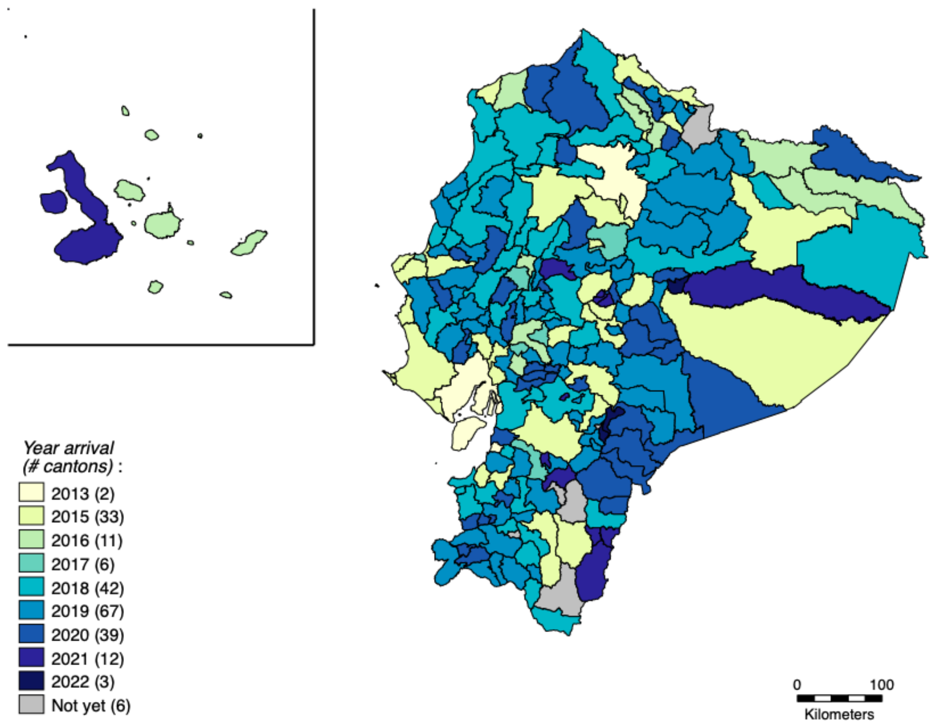
Source: data from the International Telecommunication Union.

Figure 2: Share of active mobile internet line per technology



Source: data from ARCOTEL.

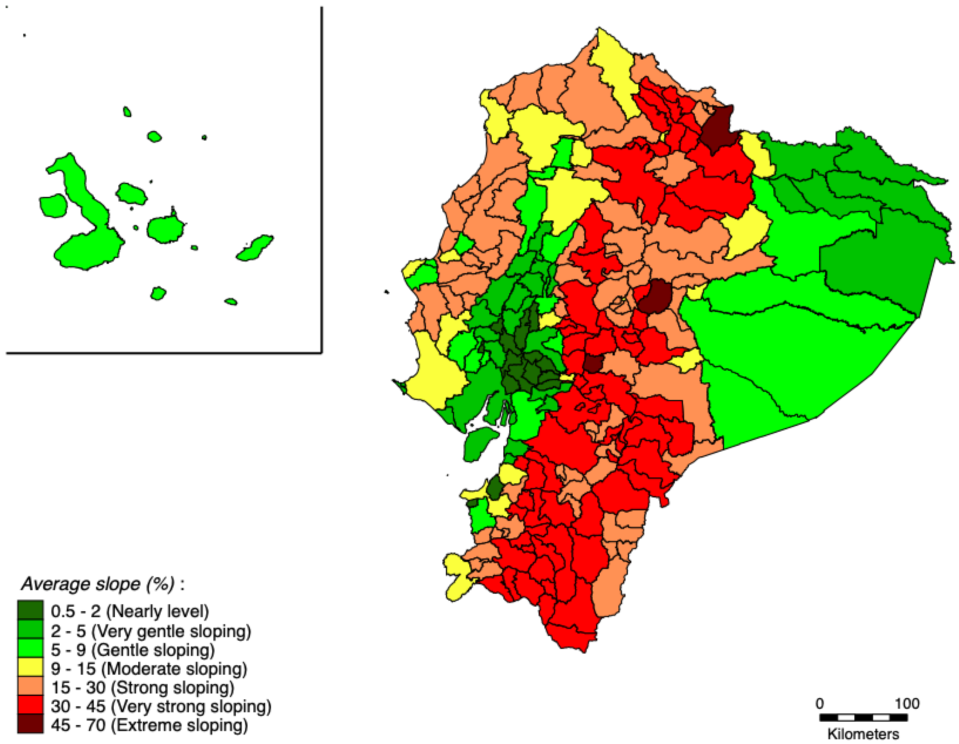
Figure 3: Arrival of 4G per canton per year



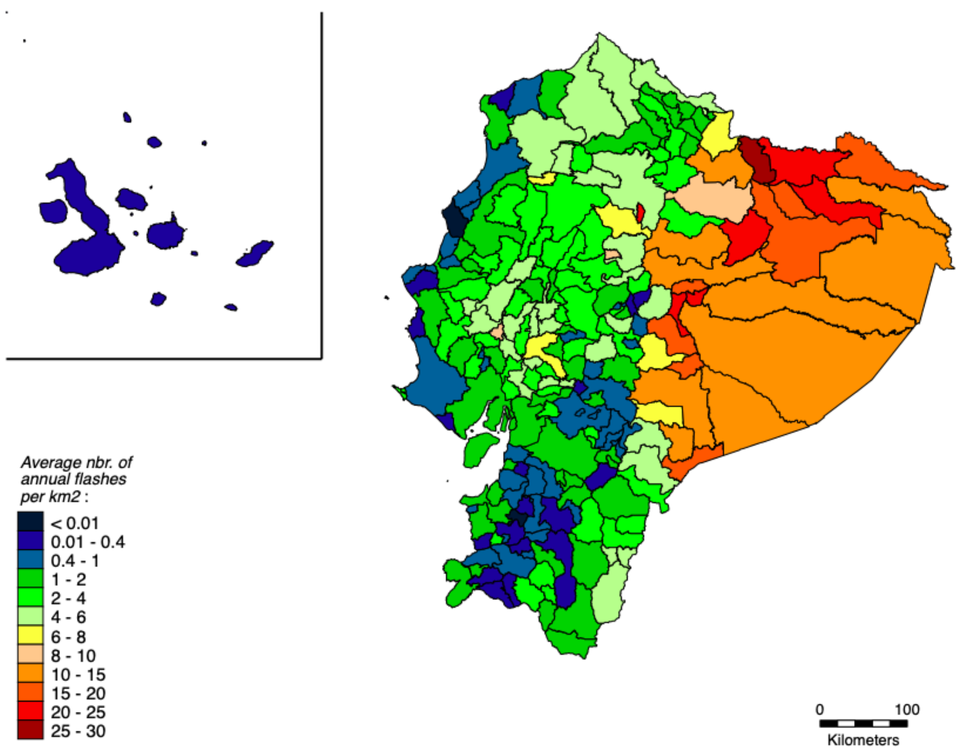
Notes: 4G is considered to have arrived in a canton when the first 4G cell tower is reported in it. See Section 3.2 for details. *Source*: data from ARCOTEL.

Figure 4: Map of the characteristics for the instrument

(a) Slope

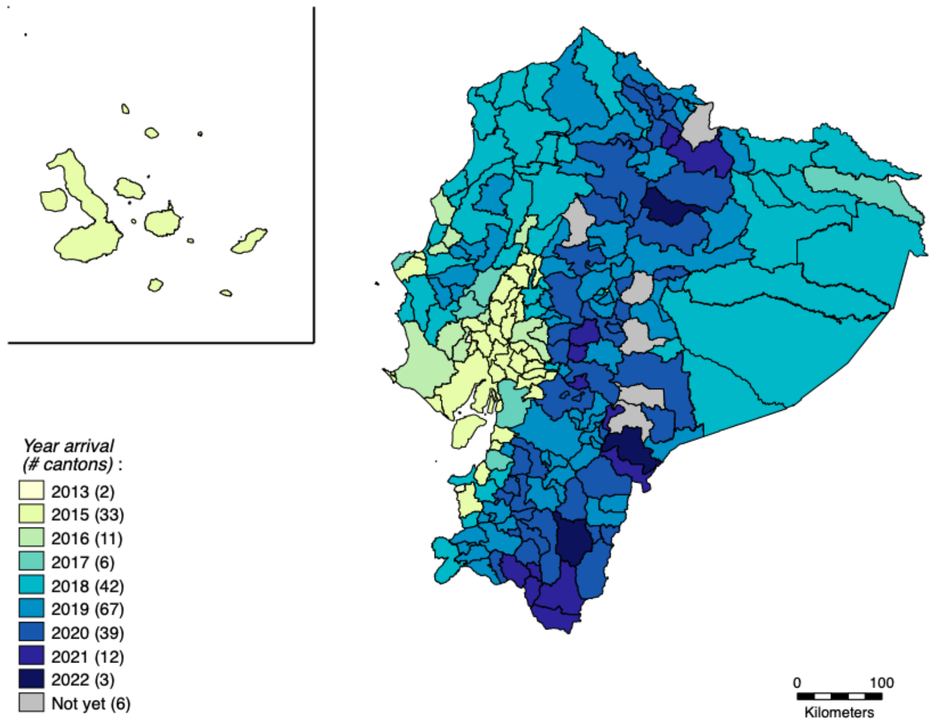


(b) Lightning strikes



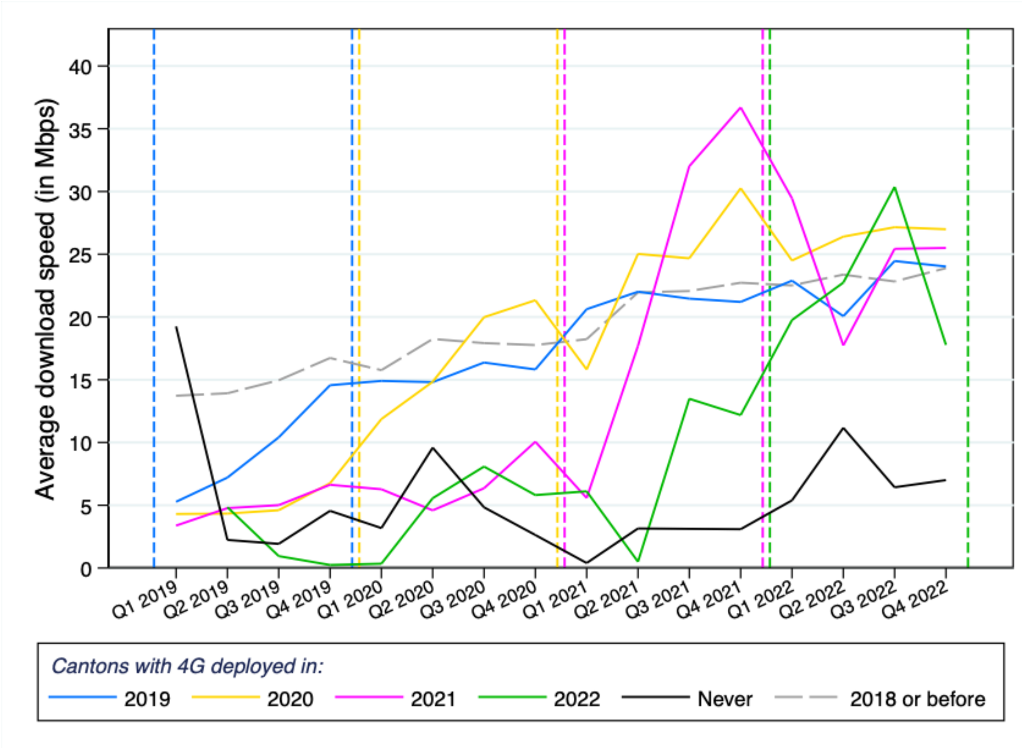
Notes: Each canton average is obtained by taking the mean of the 100 x 100m grid-cell values for slope and 10 x 10 kms grid-cell values for the number of lightning strikes per kilometer square that the canton geographically covers. See Section 3.3 for details. *Source*: data from WorldPop.

Figure 5: Simulated rollout of 4G



Notes: Year of 4G arrival is based on the simulated rollout. See Section 4.1 for details.

Figure 6: Average download speed evolution for mobile internet



Source: data from Ookla.

Table 1: Descriptive statistics - Firm level (final sample)

Variable	Number obs. (1)	Mean (2)	Sd. dev. (3)	Min (4)	Max (5)
Economic variables					
Total employment	4,671,347	3.29	(6.83)	0.08	77.08
Wage per worker (US dollars)	4,624,172	5,143.91	(2,026.99)	1,497.18	16,938.86
Firm size (dummies):					
Micro	5,102,907	0.84	(0.37)	0.00	1.00
Small	5,102,907	0.13	(0.34)	0.00	1.00
Medium	5,102,907	0.02	(0.15)	0.00	1.00
Large	5,102,907	0.01	(0.09)	0.00	1.00
Internet intensity sector (dummies):					
Low	5,102,907	0.32	(0.46)	0.00	1.00
Medium-low	5,102,907	0.14	(0.34)	0.00	1.00
Medium-high	5,102,907	0.32	(0.47)	0.00	1.00
High	5,102,907	0.22	(0.42)	0.00	1.00

Notes: Values cover the years 2012-2022. Details and sources for the outcomes are provided in Section 3.1.

Table 2: First stage regression results (canton level)

	treated	
	(1)	(2)
Simulated treated	0.252***	0.230***
	(0.064)	(0.063)
SW F-statistic	15.56	13.49
Adjusted R-squared	0.746	0.769
Fixed effects	Yes	Yes
Controls	No	Yes
Number of observations	2431	2431

Notes: The dependent variable is a dummy variable equal to 1 if 4G is deployed in the canton in a given year, and 0 otherwise. The independent variable is a dummy variable equal to 1 if 4G would be deployed in the canton based on the simulated rollout in a given year, and 0 otherwise. The regression sample consists of all cantons, and covers the years 2012-2022. Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. *SW F-statistic* is the value of the F-statistic from the Sanderson and Windmeijer (2016) multivariate F-test of excluded instruments for the validity of the instruments. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Predictors of the year of 4G deployment in cantons

	Simulated year first treated		Actual year first treated	
	(1)	(2)	(3)	(4)
Population (2010, in millions)	0.263	-0.035	-0.840***	-0.791***
	(0.398)	(0.099)	(0.113)	(0.102)
Share of agriculture in GAV	-0.033***	0.005	0.031***	0.026***
	(0.009)	(0.003)	(0.007)	(0.009)
Mean distance to a main road	-0.077	-0.008	0.001	-0.010
	(0.051)	(0.016)	(0.025)	(0.024)
Population density (2010, in hundreds)	-0.074*	-0.008	-0.012	-0.022
	(0.037)	(0.009)	(0.015)	(0.016)
GDP per capita (in millions)	12.529	1.820	-2.565	-1.780
	(15.442)	(2.877)	(8.032)	(6.801)
Population share 25 years old or less	0.207**	0.002	0.183***	0.215***
	(0.089)	(0.028)	(0.049)	(0.051)
Population share 60 years old or more	0.369***	-0.050	0.230***	0.301***
	(0.117)	(0.031)	(0.076)	(0.083)
Population share urban	-0.030**	-0.006	-0.014*	-0.017*
	(0.013)	(0.004)	(0.007)	(0.009)
Number of tourism sites	0.201***	0.009	-0.010	0.018
	(0.065)	(0.019)	(0.013)	(0.024)
Average slope		0.282***		-0.043*
		(0.015)		(0.024)
Average number of lightning strikes		0.115***		-0.009
		(0.019)		(0.025)
r2	0.570	0.932	0.812	0.818
Number of observations	221	221	221	221

Notes: The dependent variable is the simulated year the canton received 4G in columns (1) and (2), and the actual year the canton received 4G in columns (3) and (4). The regression sample consists of all cantons. Standard errors are clustered at the canton level and reported in parentheses. See Section 3.3 for more details on the different outcomes. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects on employment and wages

	Log of total employment			Log of wage per worker		
	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
treated	0.009**	0.035*	0.016	0.006***	0.009	0.012*
	(0.004)	(0.020)	(0.016)	(0.001)	(0.006)	(0.006)
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes
Nbr. of observations	4,554,293	4,554,293	4,554,293	4,507,225	4,507,225	4,507,225

Notes: Columns (1) and (4) report the OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5) and (6) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is the total employment in firms for columns (1), (2) and (3), and the wage per worker in columns (4), (5) and (6). The regression sample consists of all firms from the final sample (see Section 3.1 for details). Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Effects on employment and wages by firm size

	Log of total employment			Log of wage per worker		
	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Micro firms						
treated	0.003	0.032	0.015	0.004***	0.010	0.016**
	(0.003)	(0.022)	(0.017)	(0.001)	(0.007)	(0.008)
Nbr. of observations	3,856,224	3,856,224	3,856,224	3,791,122	3,791,122	3,791,122
Panel B: Small firms						
treated	0.020***	0.040	0.012	0.013***	-0.001	-0.007
	(0.007)	(0.032)	(0.028)	(0.002)	(0.007)	(0.008)
Nbr. of observations	583,935	583,935	583,935	575,311	575,311	575,311
Panel C: Medium firms						
treated	0.044***	0.050	0.009	0.024***	-0.001	-0.012
	(0.014)	(0.065)	(0.068)	(0.005)	(0.019)	(0.021)
Nbr. of observations	98,645	98,645	98,645	110,307	110,307	110,307
Panel D: Large firms						
treated	0.081**	0.338	0.329	0.017**	-0.018	-0.035
	(0.035)	(0.212)	(0.214)	(0.007)	(0.028)	(0.035)
Nbr. of observations	15,460	15,460	15,460	30,485	30,485	30,485
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes: Columns (1) and (4) report the OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5) and (6) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is the total employment in firms for columns (1), (2) and (3), and the wage per worker in columns (4), (5) and (6). The regression sample are consists of the micro firms (Panel A), small firms (Panel B), medium firms (Panel C), and large firms (Panel D) from the final sample (see Section 3.1 for details). Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Effects on employment and wages by digital intensity sector

	Log of total employment			Log of wage per worker		
	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low digital intensity						
treated	0.019***	0.082**	0.074**	0.006***	0.007	0.006
	(0.004)	(0.036)	(0.035)	(0.001)	(0.008)	(0.009)
Nbr. of observations	1,440,127	1,440,127	1,440,127	1,425,505	1,425,505	1,425,505
Panel B: Medium-low digital intensity						
treated	0.002	-0.007	-0.035	0.004*	0.000	0.010
	(0.008)	(0.028)	(0.026)	(0.002)	(0.012)	(0.011)
Nbr. of observations	643,159	643,159	643,159	645,020	645,020	645,020
Panel C: Medium-high digital intensity						
treated	0.007**	0.010	-0.011	0.004***	0.011*	0.012*
	(0.004)	(0.014)	(0.014)	(0.001)	(0.007)	(0.007)
Nbr. of observations	1,469,510	1,469,510	1,469,510	1,457,275	1,457,275	1,457,275
Panel D: High digital intensity						
treated	0.017***	0.040	0.030	0.007***	0.021	0.018
	(0.004)	(0.029)	(0.028)	(0.002)	(0.013)	(0.013)
Nbr. of observations	1,001,497	1,001,497	1,001,497	979,425	979,425	979,425
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes: Columns (1) and (4) report the OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5) and (6) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is the total employment in firms for columns (1), (2) and (3), and the wage per worker in columns (4), (5) and (6). The regression sample consists of the firms in low digital intensity sectors (Panel A), medium-low digital intensity sectors (Panel B), medium-high digital intensity sectors (Panel C), and high digital intensity sectors (Panel D) from the final sample (see Section 3.1 for details). Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effects on employment and wages for micro firms

	Log of total employment			Log of wage per worker		
	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Micro X Low digital intensity						
treated	0.014***	0.078*	0.071*	0.004***	0.008	0.008
	(0.003)	(0.041)	(0.037)	(0.001)	(0.009)	(0.010)
Nbr. of observations	1,259,471	1,259,471	1,259,471	1,237,511	1,237,511	1,237,511
Panel B: Micro X Medium-low digital intensity						
treated	-0.005	-0.010	-0.040*	0.002	-0.002	0.008
	(0.007)	(0.025)	(0.022)	(0.002)	(0.012)	(0.011)
Nbr. of observations	554,487	554,487	554,487	547,817	547,817	547,817
Panel C: Micro X Medium-high digital intensity						
treated	0.003	0.004	-0.012	0.001	0.015*	0.017*
	(0.003)	(0.016)	(0.017)	(0.001)	(0.009)	(0.010)
Nbr. of observations	1,146,953	1,146,953	1,146,953	1,131,680	1,131,680	1,131,680
Panel D: Micro X High digital intensity						
treated	0.010**	0.028	0.020	0.005**	0.030*	0.030*
	(0.004)	(0.028)	(0.028)	(0.002)	(0.016)	(0.017)
Nbr. of observations	895,313	895,313	895,313	874,114	874,114	874,114
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes

Notes: Columns (1) and (4) report the OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5) and (6) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is the total employment in firms for columns (1), (2) and (3), and the wage per worker in columns (4), (5) and (6). The regression sample consists of the micro firms from the final sample that are in low digital intensity sectors (Panel A), medium-low digital intensity sectors (Panel B), medium-high digital intensity sectors (Panel C) and high digital intensity sectors (Panel D). See section 3.1 for details. Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Effects on demand, productivity, and firm dynamics

	Log of sales			Log of sales per worker			Becomes active			Becomes inactive		
	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Micro X Low digital intensity												
treated	0.112***	0.034	-0.100	0.087***	0.059	-0.100	-0.017***	0.011	0.022	0.001	-0.026	-0.025
	(0.033)	(0.202)	(0.248)	(0.029)	(0.189)	(0.251)	(0.006)	(0.020)	(0.020)	(0.003)	(0.016)	(0.017)
Nbr. of observations	719,212	719,212	719,212	634,994	634,994	634,994	1,257,818	1,257,818	1,257,818	1,191,235	1,191,235	1,191,235
Panel B: Micro X Medium-low digital intensity												
treated	-0.011	-0.561	-0.738	0.008	-0.323	-0.447	0.011**	-0.001	-0.014	-0.011***	-0.004	0.003
	(0.045)	(0.512)	(0.667)	(0.035)	(0.425)	(0.554)	(0.004)	(0.014)	(0.015)	(0.004)	(0.014)	(0.013)
Nbr. of observations	250,432	250,432	250,432	226,319	226,319	226,319	528,027	528,027	528,027	512,168	512,168	512,168
Panel C: Micro X Medium-high digital intensity												
treated	0.115***	-0.335	-0.453	0.086**	-0.370	-0.515	-0.005	0.015	0.017	0.002	0.006	0.008
	(0.035)	(0.319)	(0.388)	(0.034)	(0.281)	(0.353)	(0.006)	(0.017)	(0.017)	(0.002)	(0.013)	(0.014)
Nbr. of observations	667,572	667,572	667,572	586,564	586,564	586,564	1,147,738	1,147,738	1,147,738	1,062,962	1,062,962	1,062,962
Panel D: Micro X High digital intensity												
treated	0.013	-0.239	-0.521	0.038	-0.521	-0.744	-0.025***	-0.047	-0.050	0.005	0.020	0.025
	(0.047)	(0.539)	(0.485)	(0.041)	(0.377)	(0.470)	(0.008)	(0.043)	(0.045)	(0.004)	(0.030)	(0.033)
Nbr. of observations	554,815	554,815	554,815	474,274	474,274	474,274	911,084	911,084	911,084	840,368	840,368	840,368
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Columns (1), (4), (7) and (10) report OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5), (6), (8), (9), (11) and (12) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is total sales of the firm in columns (1), (2) and (3), and total sales per worker in columns (4), (5) and (6). In columns (7), (8) and (9), it is a dummy equal to 1 if the firm became economically active (i.e. it started to make a declaration to government agencies) and 0 otherwise, and in columns (10), (11) and (12), it is a dummy equal to 1 if the firm became economically inactive (i.e. it stopped making declaration to government agencies). The regression sample consists of the micro firms from the final sample that are in low digital intensity sectors (Panel A), medium-low digital intensity sectors (Panel B), medium-high digital intensity sectors (Panel C) and high digital intensity sectors (Panel D). See section 3.1 for details. Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Employment in micro firms by worker characteristics

	Low			Medium-low			Medium-high			High		
	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Men												
treated	0.012***	0.065*	0.061*	-0.006	0.028	0.011	0.000	-0.004	-0.015	0.006*	0.036	0.033
	(0.003)	(0.033)	(0.032)	(0.005)	(0.027)	(0.025)	(0.003)	(0.013)	(0.015)	(0.003)	(0.028)	(0.030)
Panel B: Women												
treated	0.008***	0.035*	0.028*	0.002	-0.027	-0.049**	0.003	0.004	-0.007	0.006**	0.002	-0.004
	(0.002)	(0.020)	(0.015)	(0.006)	(0.023)	(0.020)	(0.002)	(0.013)	(0.014)	(0.003)	(0.021)	(0.021)
Panel C: Age group 15-17												
treated	0.000	-0.000	-0.000	0.000	-0.001	-0.001	0.000	-0.000	-0.001	0.000	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Panel D: Age group 18-29												
treated	0.009***	0.047*	0.045*	0.010***	-0.013	-0.012	0.006**	-0.012	-0.018	0.004	0.001	-0.003
	(0.002)	(0.025)	(0.025)	(0.003)	(0.016)	(0.012)	(0.003)	(0.016)	(0.017)	(0.003)	(0.021)	(0.021)
Panel E: Age group 30-44												
treated	0.007***	0.048	0.041*	0.006***	-0.000	-0.003	0.002	0.017	0.008	0.004	0.030	0.022
	(0.002)	(0.030)	(0.024)	(0.002)	(0.012)	(0.012)	(0.003)	(0.012)	(0.014)	(0.004)	(0.024)	(0.023)
Panel F: Age group 45-64												
treated	0.007***	0.017	0.017	0.004	0.020	0.021	0.002	0.016	0.010	0.003	0.022	0.025
	(0.003)	(0.014)	(0.015)	(0.002)	(0.014)	(0.013)	(0.003)	(0.015)	(0.015)	(0.003)	(0.020)	(0.023)
Panel G: Age group 65 plus												
treated	0.002*	0.019*	0.017*	-0.004***	-0.003	-0.003	0.001	-0.002	-0.003	0.004***	0.009	0.006
	(0.001)	(0.011)	(0.010)	(0.001)	(0.006)	(0.006)	(0.001)	(0.007)	(0.006)	(0.001)	(0.010)	(0.011)
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Nbr. of observations	1,259,471	1,259,471	1,259,471	554,487	554,487	554,487	1,146,953	1,146,953	1,146,953	895,313	895,313	895,313

Notes: Columns (1), (4), (7) and (10) report OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), while columns (2), (3), (5), (6), (8), (9), (11) and (12) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is employment in micro firms in low digital intensity sectors (columns 1-3), medium-low digital intensity sectors (columns 4-6), medium-high digital intensity sectors in (columns 7-9), and high digital intensity sectors (columns 10-12). The regression sample consists of the workers in micro firms from the final sample (see Section 3.1 for details) who are male (Panel A), female (Panel B), aged 15 to 17 (Panel C), aged 18 to 29 (Panel D), aged 30 to 44 (Panel E), aged 45 to 64 (Panel F), and aged 65 or older (Panel G). For instance, the coefficient in Panel A, column (1), is the estimate of effects on employment for male workers in micro firms that are in low digital intensity sectors. Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: Wage per worker in micro firms by worker characteristics

	Low			Medium-low			Medium-high			High		
	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV	TWFE	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Men												
treated	0.007***	0.016	0.016	0.002	0.002	0.017	-0.001	0.027**	0.029**	0.006**	0.046**	0.043*
	(0.001)	(0.013)	(0.013)	(0.002)	(0.013)	(0.015)	(0.002)	(0.013)	(0.013)	(0.003)	(0.023)	(0.024)
Panel B: Women												
treated	0.007**	-0.006	-0.006	0.003	-0.006	0.001	0.003	0.015	0.016	-0.001	0.005	0.003
	(0.003)	(0.018)	(0.020)	(0.003)	(0.013)	(0.012)	(0.002)	(0.017)	(0.017)	(0.004)	(0.031)	(0.032)
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Nbr. of observations	1,015,981	1,015,981	1,015,981	318,704	318,704	318,704	772,722	772,722	772,722	568,175	568,175	568,175

Notes: Columns (1), (4), (7) and (10) report OLS estimates of equation 1 (i.e., the Two-Way Fixed-Effects estimator), and columns (2), (3), (5), (6), (8), (9), (11) and (12) reports 2SLS estimates of equation 1. The dependent variable is log(X+1), where X is wage per worker in micro firms in low digital intensity sectors (columns 1-3), medium-low digital intensity sectors (columns 4-6), medium-high digital intensity sectors in (columns 7-9), and high digital intensity sectors (columns 10-12). The regression sample consists of the workers in micro firms from the final sample (see Section 3.1 for details) who are male (Panel A), and female (Panel B). For instance, the coefficient in Panel A, column (1), is the estimate of effects on wage per worker for male workers in micro firms that are in low digital intensity sectors. Fixed-effects include firm fixed-effects and province-year fixed-effects. Controls include the interaction between a linear time trend and the following canton characteristics: total population in 2010, share of agriculture in Gross Added Value in 2012, mean distance to roads, population density in 2010, GDP per capita in 2012, share of the population aged 25 or less in 2010, share of population aged 60 or more in 2010, share of urban population in 2010, the number of tourism sites, average slope, and the number of lightning strikes per kilometre square. Standard errors are clustered at the canton level and reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11: Internet usage in firms (2011)

	Micro (all) (1)	Micro (>60000) (2)	Small (3)	Medium (4)	Large (5)
Number of employees	2.08	4.19	23.05	49.70	286.96
Wage per worker	2,647.21	4,094.86	5,908.45	9,480.49	14,173.57
Use internet (%)	15.41	44.01	91.01	98.17	99.33
Use fixed internet (%)	13.92	39.90	84.65	91.81	93.41
Use mobile internet (%)	1.44	3.82	7.69	10.29	16.44
Invest in ICT (%)	10.78	24.43	51.64	59.32	67.78
Observations	22919	2540	3319	1931	1350

Notes: Data come from the Encuesta Exhaustiva survey, a nationally representative survey conducted in 2011 and focused on Technology of Information and Communication use. The survey does not distinguish between RISE and non-RISE firms (see Section 3.1 for details). To align the sample of micro firms in the survey more closely with that of the study, I approximate this distinction by applying the main RISE eligibility criterion: a gross income of less than 60,000 USD. Consequently, all micro firms which reported a total income of 60,000 USD or more are classified as non-RISE. Columns (1), (2), (3), (4), and (5) report, for the number of employees and wage per worker, the mean values for micro firms, micro firms with a total income of 60,000 USD or more (non-RISE micro firms), small firms, medium firms, and large firms, respectively. For the other outcomes, they reports the share of the firms that do the outcome. *ICT* stands for Information and Communication Technologies.

Table 12: Internet usage in micro firms (2011)

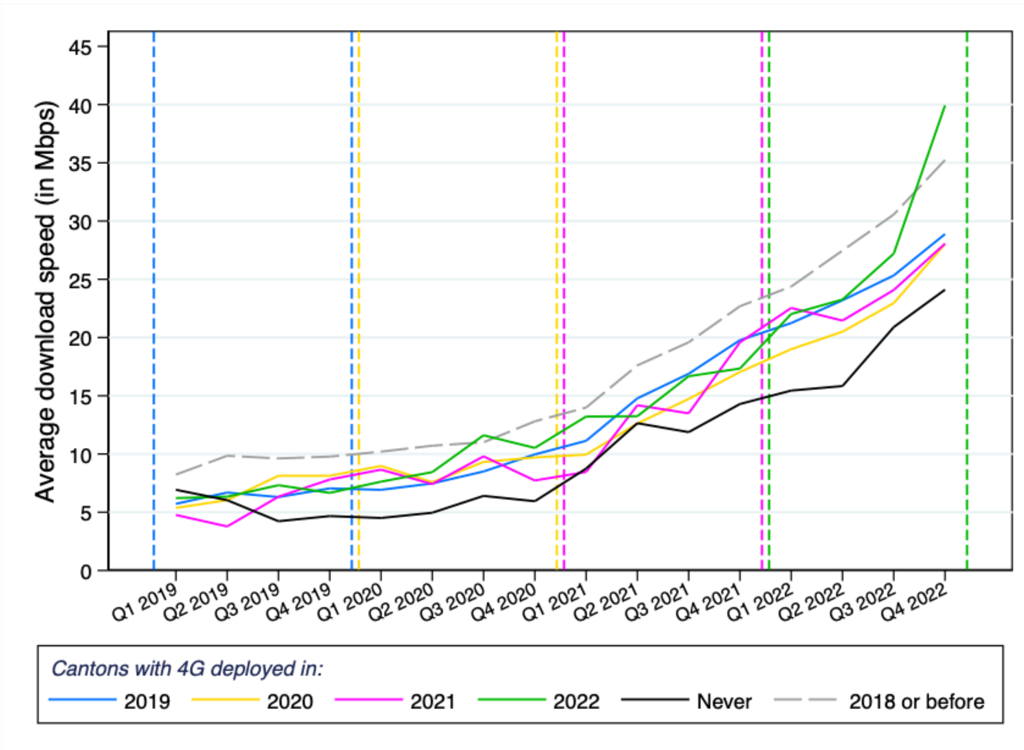
	Low (1)	Medium-low (2)	Medium-high (3)	High (4)
Number of employees	4.69	5.30	3.74	5.22
Wage per worker	4,375.53	3,314.46	3,936.49	5,712.39
Use internet (%)	26.41	51.26	44.71	77.70
Use fixed internet (%)	23.79	46.70	40.34	72.33
Use mobile internet (%)	2.92	4.78	3.64	6.66
Invest in ICT (%)	14.22	29.49	25.22	38.99
Observations	472	276	1621	171

Notes: Data come from the Encuesta Exhaustiva survey, a nationally representative survey conducted in 2011 and focused on Technology of Information and Communication use. The survey does not distinguish between RISE and non-RISE firms (see Section 3.1 for details). To align the sample of micro firms in the survey more closely with that of the study, I approximate this distinction by applying the main RISE eligibility criterion: a gross income of less than 60,000 USD. Consequently, all micro firms which reported a total income of 60,000 USD or more are classified as non-RISE. The sample comprises the micro firms which reported a total income of 60,000 USD or more (non-RISE micro firms). Columns (1), (2), (3), and (4), report, for the number of employees and wage per worker, the mean values for micro firms in low, medium-low, medium-high, and high digital intensity sectors, respectively. For the other outcomes, they reports the share of the firms that do the outcome. *ICT* stands for Information and Communication Technologies.

APPENDIX

A Additional figures

Figure A1: Average download speed evolution for fixed internet



Source: data from Ookla.

B Additional tables

Table A1: Criteria for firm size classification

Size	Total sales (in USD)	Number of employees
Micro	$\leq$ 100,000	$\leq$ 9
Small	100,001 to 1,000,000	10 to 49
Medium	1,000,001 to 5,000,000	50 to 199
Small	$\geq$ 5,000,000	$\geq$ 200

Notes: Criteria used to classify firms by size, following the categorization done by INEC. The determining criteria is total sales and, if unavailable, the number of employees.

Table A2: Observations with the variable employment missing

	Total (1)	Missing (% total) (2)	Not missing (% total) (3)
Panel A: Years 2012-2021			
RISE	4,238,287	3,831,829 (90.41)	406,458 (9.59)
Not RISE	4,529,176	261,567 (5.78)	4,267,609 (94.22)
Panel B: Year 2022			
RIMPE	983,370	701,604 (71.35)	281,766 (28.65)
RIMPE - New	*445,090*	*414,711 (93.17)*	*30,379 (6.83)*
RIMPE - Previously RISE	*220,992*	*189,292 (85.66)*	*31,700 (14.34)*
RIMPE - Not previously RISE	*317,288*	*97,601 (30.76)*	*219,687 (69.24)*
Not RIMPE	256,443	25,209 (9.83)	231,234 (90.17)

Notes: Number of firms, by tax-regime status, for which the variable employment is missing or not. Panel A covers the years 2012-2021 and Panel B cover year 2022, in which there was a change in tax regimes. See Section 3.1 for details.

Table A3: Descriptive statistics (full sample)

Variable	Number obs. (1)	Min (2)	P1 (3)	P25 (4)	P50 (5)	Mean (6)	P75 (7)	P99 (8)	Max (9)
Economic variables									
Total employment	5,187,067	0.08	0.08	1.00	1.00	5.94	2.67	70.50	17,262.25
Wage per worker (US dollars)	5,187,067	0.00	1,500.00	4,080.00	4,684.08	5,239.41	5,158.00	16,423.70	1,603,815.75
Firm size (dummies):									
Micro	10,007,276	0.00	0.00	1.00	1.00	0.92	1.00	1.00	1.00
Small	10,007,276	0.00	0.00	0.00	0.00	0.07	0.00	1.00	1.00
Medium	10,007,276	0.00	0.00	0.00	0.00	0.01	0.00	1.00	1.00
Large	10,007,276	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Internet intensity sector (dummies):									
Low	10,007,276	0.00	0.00	0.00	0.00	0.33	1.00	1.00	1.00
Medium-low	10,007,276	0.00	0.00	0.00	0.00	0.09	0.00	1.00	1.00
Medium-high	10,007,276	0.00	0.00	0.00	0.00	0.40	1.00	1.00	1.00
High	10,007,276	0.00	0.00	0.00	0.00	0.18	0.00	1.00	1.00

Notes: For each outcomes, P1, P25, P75, and P99 are, respectively, the 1st, 25th, 75th and 99th percentile. P50 is the median. Values cover the years 2012-2022. Details and sources for the outcomes are provided in Section 3.1.

Table A4: Descriptive statistics per time of 4G deployment (final sample)

	4G deployed in:									
	2013	2015	2016	2017	2018	2019	2020	2021	2022	Never
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Economic variables										
Number of firms	103,281.95	4,296.85	2,606.21	1,488.33	908.31	398.22	262.93	180.73	73.12	78.26
	(26,312.84)	(5,417.06)	(2,171.04)	(2,704.68)	(706.91)	(345.91)	(276.49)	(87.44)	(35.63)	(35.91)
Total employment	337,289.09	12,533.44	6,944.05	3,763.92	2,504.38	1,089.72	694.31	409.59	203.96	206.78
	(63,110.94)	(16,183.54)	(5,700.97)	(6,504.29)	(1,780.32)	(959.29)	(729.01)	(145.05)	(78.64)	(88.45)
Average number of employees per firm	3.68	3.21	2.98	3.43	3.25	3.13	2.95	2.70	3.55	3.02
	(0.47)	(0.77)	(0.46)	(0.96)	(0.93)	(0.93)	(0.98)	(0.69)	(1.01)	(0.70)
Wage per worker (US dollars)	6,584.06	6,196.99	6,545.22	6,437.53	6,611.33	6,954.39	7,097.49	6,900.22	7,388.02	8,000.33
	(401.75)	(666.03)	(1,092.78)	(758.87)	(1,006.43)	(1,223.79)	(1,172.35)	(1,257.86)	(1,065.20)	(1,602.63)
Covariates										
Population (2010)	2,632,636.02	139,967.68	110,319.11	56,255.96	55,582.48	27,086.49	18,672.92	10,231.03	4,864.73	5,548.18
	(127,908.58)	(133,390.90)	(86,274.62)	(63,660.51)	(34,729.07)	(18,153.09)	(14,442.35)	(6,986.29)	(1,394.46)	(1,987.20)
Population density (per sq. km., 2010)	565.23	353.38	137.25	102.92	71.89	61.50	53.41	54.20	18.67	27.06
	(7.61)	(715.52)	(170.53)	(57.92)	(84.94)	(50.71)	(85.93)	(62.11)	(4.64)	(32.91)
GDP (in millions, 2012)	40,681.10	1,463.00	1,229.08	501.37	405.29	108.61	99.60	33.81	139.01	14.41
	(5,081.95)	(1,688.50)	(1,064.93)	(686.42)	(858.13)	(126.67)	(142.32)	(27.57)	(186.19)	(4.75)
GDP per capita (2012)	14,877.15	9,083.38	15,501.04	7,780.37	8,602.57	3,865.73	5,408.84	3,727.97	23,165.39	2,742.52
	(1,380.57)	(6,762.86)	(14,616.96)	(7,063.48)	(25,295.43)	(2,795.04)	(7,167.34)	(2,642.23)	(28,858.50)	(683.79)
Average slope (in degrees)	9.48	10.46	5.96	6.27	10.00	12.82	11.14	12.82	17.34	19.82
	(7.43)	(7.02)	(6.45)	(6.09)	(6.81)	(6.56)	(7.02)	(4.31)	(6.60)	(3.60)
Average lightning flash rates (per 100 sq. km. per year, period 1998-2013)	3.33	3.72	6.96	2.50	3.52	3.76	4.79	3.31	7.16	1.93
	(1.85)	(5.34)	(8.68)	(2.04)	(3.50)	(5.35)	(5.66)	(3.80)	(9.30)	(2.01)
Number of tourism sites (2018)	7.00	2.33	1.64	0.17	1.52	0.82	0.46	0.17	0.00	0.00
	(4.09)	(4.98)	(2.65)	(0.38)	(3.66)	(3.04)	(0.98)	(0.55)	(0.00)	(0.00)

Notes: Values for the outcomes in 'Economic variables' are for the years 2012-2022. Details and sources for the outcomes are provided in Section 3.1.