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The impact of Internet Para Todos (IPT) in providing connectivity in Peru

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ABSTRACT

Access to the internet in isolated areas is still a challenge for many developing countries, especially in those that present a complex geography such as Peru. In 2018, the Internet Para Todos (IPT) initiative was launched in the country as a public-private organization aimed at reducing the digital divide through an innovative business model based on interoperable technological infrastructure. This study analyzes the impact that IPT has had on the country's connectivity using differences-in-differences regression models. We rely on department-level coverage data provided by IPT, as well as on outcome variables from the National Institute of Statistics and Informatics (INEI). Our results demonstrate that IPT has had a positive impact on reducing the digital divide in Peru, according to several metrics. Moreover, the territories more favored by the initiative seemed to be those with lower income, lower education levels, the less connected ones and those facing more difficult geographic conditions. These results provide support to initiatives aimed at replicating the IPT model in other countries with similar connectivity issues and characteristics to those of Peru.

1. Introduction

Currently, one of the challenges most countries face in terms of connectivity is the digital divide that exists mainly in distant and isolated areas. As reported by the International Telecommunications Union (ITU), there has been a lack of progress in bridging the urban-rural divide, as globally, an estimated 83 % of individuals living in urban areas were internet users in 2024, compared with only 48 % of the population in rural areas. Moreover, of the estimated 2.6 billion offline people in the world during 2024, 1.8 billion live in rural areas (ITU, 2024).

In Peru, this situation is fairly critical because of the geographic and economic complexities associated with deployment in rural and isolated areas.[1] The country has an area of 1285,215 km^2, it is the third-largest country in Latin America. Politically, Peru is divided into 24 departments and 1 constitutional province (Government of Peru, 2024). The territory of Peru is composed of a diverse geography, including plains, mountainous terrain from the Andes Mountain range, and the Amazonas Forest. Like many other developing countries, Peru is affected by a digital divide between urban and rural areas. The complex geography, as well as the dispersion of the population in remote areas, are two of the many reasons why this country suffers from the digital divide (Flores-Cueto et al., 2020).

The departments of Peru can be classified in three categories: Coast, Mountain, and Forest.[2] The Coast regions concentrate 65.80 % of the population resides, while 25 % reside in the Mountain regions 25 %, and 9.20 %in the Forest regions (INEI, 2024). However, the distribution in terms of land surface is not equivalent since most of the population is concentrated in a small share of Peruvian territory. In the Coast regions, there is a higher percentage of urban population, while in the Mountain and Forest regions, the rural population increases significantly. This is mainly due to the geographic characteristics of these areas, which are an impediment to urbanization.

Both the Mountain region, due to its irregular geography, and the Forest region, due to its dense vegetation, encourage population dispersion, and therefore, low population density stands out in these departments. These complex geographies not only hinder accessibility and the concentration of communities but also significantly increase the costs of deploying technological infrastructure. As a result, connectivity in these areas is limited, accentuating the digital divide between

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[1] In Peru, rural areas are defined as those where fewer than 2000 inhabitants live.

[2] See Table A1 in Appendix for details

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territories.

In addition to the geography, socioeconomic factors are also determinants of the digital divide in Peru. As expected, people living in rural areas are characterized by having lower incomes than those living in large cities, which is an impediment to purchasing internet plans and technological devices (Alarco et al., 2019). Additionally, the rural population is also characterized by having a lower level of education, which hinders the development of digital skills. The characteristics described generate different levels of digital divide, related to both access and usage.

The Internet Para Todos (IPT)[3] initiative emerged as a public-private project aimed at providing broadband connectivity to the entire country, particularly to the most remote or isolated areas. According to data provided by the ITU, when the IPT initiative was announced in 2018, only 2.1 % of rural households in the country had internet access, a figure that increased to more than 20 % by 2022.

In this context, the focus of this research is to analyze the impact that the IPT initiative has had on connectivity in Peru since its implementation. IPT was launched in 2018, with deployments beginning in 2020 and continuing today. Having been implemented for more than five years so far, it seems propitious to conduct an evaluation of the program and to analyze how much it has contributed to addressing the digital divide in those areas where it has been deployed. The outcome variables considered to analyze the IPT impact are the share of the population that uses internet, the share of households with mobile phones and computers, and the gender parity in internet usage. The contribution of such study is relevant since no analysis has been done to date on this initiative, which, on the other hand, is being considered with interest by other countries to implement.

Methodologically, the analysis will be made using two-way fixed effects models (TWFE), as well as some of the novel differences-in-differences techniques that have been recently developed to overcome the limitations of the former approach. In particular, we will follow De Chaisemartin and D'Haultfoeuille (2020) as our baseline estimator, with further robustness checks conducted following Sun and Abraham (2021) and Borusyak et al. (2024) approaches.

The remaining of this paper is structured as follows. Section 2 provides a literature review on the digital divide in Peru. In turn, Section 3 explains the specific features of the IPT initiative. Section 4 presents the study dataset and methodology. Section 5 provides the baseline results. Section 6 develops some robustness checks and extensions. Finally, Section 7 ends with some conclusions and implications.

2. Literature Review

The process of global digitalization has not occurred uniformly across all geographies. The concept of the digital divide underlies social inequality. Initially, the digital divide was defined as "*the difference between those who have access to digital ICTs and those who do not*" (Camacho, 2005). However, over time, this concept has become increasingly complex, giving rise to different dimensions, including aspects such as the quality of internet connection or the different uses made of it (Van Dijk, 2006). To better understand the reasons explaining the digital divide in some regions, it is necessary to explore the different supply and demand factors related, such as network coverage and service affordability (Leaning and Averweg, 2019).

Supply factors are related to the availability and accessibility of ICTs. Millions of people living in rural or underdeveloped areas lack internet connection due to the absence of technological infrastructure. Technological infrastructure refers to "all the physical and digital components necessary for a technological system to function" (Sánchez et al., 2017). For a specific area to have technological connectivity, various infrastructure types are required. Among the basic ones, we first find communication networks, supported by a variety of technologies ranging from fiber optics, copper cabling, mobile networks (2 G, 3 G, 4 G, and 5 G), to satellite links, as well as the components required for them to operate. The lack of one or these infrastructures results in total or partial technological service in the affected areas. The providers of these infrastructures are responsible for deciding whether to invest capital to offer service in each geography. It is often the case that they consider that investing in rural areas does not yield sufficient returns to cover the initial investment and operating expenses. This is mainly due to the low population density in rural areas and the low-income potential of potential consumers, which, combined with the high investment costs, often makes the implementation of this infrastructure economically unfeasible. All of this represents a financial risk that infrastructure providers choose to avoid, focusing instead on urban areas with higher customer density and greater profit potential (Bagchi, 2005).

Among the supply factors, we also find government policies and regulations that affect infrastructure providers (Katz, 2009). The telecommunications sector is subject to high-cost regulations, including spectrum licenses, permits, and price regulation policies. These impositions directly affect the willingness of infrastructure companies to provide technology and digital services in different geographic areas. This is mainly because they can restrict competition and establish strict standards without sufficient incentives, which promotes the extension of digital inequalities, leading to a geographic digital divide.

Demand factors driving the digital divide include those related to the characteristics and needs of users to access digital technologies and the internet. This category includes education level and purchasing power (Katz, 2009; Elena-Bucea et al., 2021). For example, a link exists between access and use of ICTs, on the one hand, and the education level of users, on the other. People with a higher education level are more likely to have access to the internet and to make extensive use of it. On the other hand, people with a lower education level often lack physical access to digital technologies and also lack the basic digital skills needed to make use of the internet. Even if the access divide is addressed, the lack of skills to use digital technologies generates a second and third-level digital divide (Gorski, 2005). For the case of European Union members, Elena-Bucea et al. (2021) found education to be a critical factor in determining the adoption of e-services. In addition, people with higher purchasing power have a greater ability to acquire both devices and internet access, and they perceive them as a basic necessity. However, for people with low income, access to ICTs might be initially perceived as a luxury item than a necessity. In cases where they can afford internet access, the connection is usually of low quality, which makes it difficult to fully benefit from online services.

Another demand-side determinant of the digital divide is the generational difference (Elena-Bucea et al., 2021). Young people who have grown up with the internet as a fundamental part of their daily lives tend to be more familiar with digital technologies. In contrast, older people, who did not grow up in a digital environment from an early age, often perceive the internet and other technological resources as unnecessary in their daily lives, leading to lower adoption of these tools. The generational divide in this sense can create digital inequalities.

Geographic conditions aggravate the digital divide, generating inequality between urban and rural areas. Urban areas are characterized by high population density, easier conditions for deployment of technological infrastructure, greater economic and social diversity, a high concentration of educational institutions, and better-quality public services. In contrast, rural and remote areas are characterized by low population density, limited transportation and technological infrastructure, economic and geographical constraints, and low literacy levels. Currently, approximately 56 % of the world's population (4.4 billion people) live in urban areas (World Bank, 2024). The remaining 44 %, or 3.5 billion people, live in rural areas and face daily disadvantages, including the lack of technological infrastructure, which leads to

[3] In English, the name of the initiative means "*Internet for All*"

digital divide. Moreover, even in developed countries that enjoy high-connectivity infrastructure and population skill levels, there is still the case of some important digital divides when it comes to rural or isolated areas, such as in the case of Korean farmers (Suh, 2025) or some locations in Spain (Pontones-Rosa et al., 2021; Ruiz-Rodríguez et al., 2023) and Italy (Capello et al., 2025).

The existence of digital divide is a concern for both governments and affected individuals, mainly due to its socioeconomic consequence. As argued by Helsper (2021), social and digital inequalities are linked in several aspects. The impact of digital divide on education is significant for various reasons. The lack of access to the internet limits students' access to educational resources, such as online documents, tutorials, or educational platforms. Consequently, a lack of access to technological resources negatively impacts students' academic performance. Students with access to ICTs are in a more advantageous position compared to those who do not. Moreover, the main socioeconomic characteristics that cause the digital divide will affect digital literacy. As shown by Aydin (2021), gender, parents' level of education, internet connection and computer experience were found to be relevant predictors of computer and information literacy in Korea and Chile. Additionally, job opportunities are more limited for people without internet access, not only because of the difficulty in accessing job opportunities but also due to the lack of training and skills for the position. A lack of connectivity presents limitations for affected individuals, putting them at a disadvantage (Miras et al., 2023). This was highlighted during the COVID-19 pandemic (Dyba and Di Maria, 2024; Ruiz-Rodríguez et al., 2025).

Another consequence of the digital divide is the limits in accessing healthcare services for people who are not connected to the internet. Telemedicine services are becoming increasingly common, especially for treating medical cases that are difficult to access or for urgent consultations (Misbori and Antono, 2020). To request these services, the patient must be connected to the internet and be able to access the platforms that offer these types of services (Wang et al., 2011). In addition, digital divide often leads to social isolation. When the digital divide affects an entire region, the consequences are even worse since they may lead to community isolation, leading to unequal development between areas with and without internet connectivity (Valadez and Duran, 2007).

Overall, the social gains of connecting the unconnected areas are expected to be significant, as Bahia et al. (2024) show for the case of Nigeria, where mobile coverage was found to reduce poverty, increase consumption, and increase labor force participation; being these effects especially relevant in poorer and rural areas. In addition, digitalization was found to be relevant for regional development in China (Guo et al., 2025).

The most common regulatory approach to addressing the digital divide problem in isolated and rural areas are the Universal Service Funds (USFs), a mechanism that typically is funded by the telecommunications operators and can be used for deploying networks and for subsiding demand in unconnected areas. However, this traditional regulatory solution has not always been able to deliver satisfactory results, according to some research conducted in the literature. To provide some examples of critical evaluation of these programs, we can cite ESCAP (2017), that studies the role of USFs in providing affordable and accessible telecommunication and broadband services in the Asia-Pacific region. Through a series of country case studies and econometric analysis, they conclude that countries with universal service funds targeting internet expansion have not experienced better results in fixed-broadband and internet growth than the countries without such funds. This can be explained due to weaknesses in the design, structure and implementation of these programs. Similarly, Boik (2017) studied the case of North Carolina in the United States, arguing that a policy of universal high speed wired broadband service would be unlikely to achieve universal adoption, as it will result in costly services in some areas. Beyond USFs, Gerli and Whalley (2021) analyzed how community networks and public-private partnerships have contributed to promoting the delivery and adoption of superfast broadband across the rural areas in the United Kingdom. They conclude that public-private partnership did not solve the access divide afflicting the hardest-to-reach areas. While some of them have been served by community networks, there are doubts regarding the scalability of this approach.

Considering these mixed results according to some of the empirical research conducted to date, it seems worth to study the impact of the IPT initiative promoted in Peru, due to its novelty and uniqueness. A robust evaluation of this initiative can provide evidence to other countries considering adopting similar frameworks.

3. The IPT initiative

The IPT project was officially launched in 2018 and began to be implemented in mid-2019, with the first deployment taking place in 2020. The initiative was created with the goal of reducing the digital divide in Peru between urban and rural areas. The project embodied an innovative vision: "*to be the leading and reference provider of technological solutions that allow narrowing the digital divide in rural areas of Peru*" (source: IPT). Its main objective has been to connect the unconnected and provide connectivity to promote the economic, social, and personal development of those who, due to living in rural areas, lack it.

The initiative results from the combined inputs of several private and public actors (see Fig. 1). The telecommunications operator Telefónica has been a key contributor to the launch of IPT. Its participation has resulted in cost savings since IPT could rely on the operator's existing network infrastructure (Telefónica, 2018). Additionally, Telefónica has built 3130 base stations, with an invested capital of $75 million. This positions the operator as the key owner of the IPT project, with 54 % of the capital structure (Katz et al., 2023). Telefónica also collaborates in the operation of the infrastructure and allows the connection of external mobile operators without them having to make large monetary investments.

Another shareholder is Meta, who owns 21 % of the capital structure, placing it behind Telefónica in terms of capital investment (Katz et al., 2023). Additionally, the technology player has introduced advanced technologies such as Open RAN and planning tools in IPT's operations. This has allowed for the construction of more flexible and less costly networks, contributing to the sustainability and scalability of the IPT model to rural areas.

In addition, the Peruvian government plays an important role in the IPT project, by facilitating the implementation of the initiative through regulatory support. The Peruvian state helps reduce administrative barriers and promotes digital connectivity as part of national objectives and social and economic development policies. Additionally, it allows the placement of antennas and equipment on state properties and provides access to radio spectrum in rural areas, (source: IPT).

There is also an important involvement of multilateral institutions as

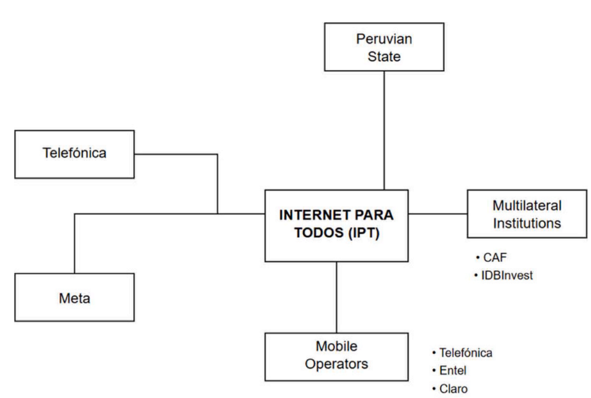

Fig. 1. IPT formation diagram.
Source: Katz et al. (2023)

well. The participation of institutions such as the Development Bank of Latin America (CAF), and the Inter-American Development Bank (IDB) is crucial, as they provide financing. Each of these two institutions controls 12.5 % of the capital structure (Katz et al., 2023).

Finally, four mobile operators participate in the initiative by relying on the IPT network to provide end-user services: Telefónica, Entel, Claro, and Bitel. These operators use IPT's rural infrastructure under a wholesale access model, which allows them to reach rural areas without having to assume infrastructure deployment costs. The price of the services offered under the wholesale model is negotiated based on the regional average revenue per user (ARPU), meaning the price is adjusted according to the average revenue generated by each user in a specific region. As a result, prices are generally higher in more developed areas, favoring residents of rural and underdeveloped areas.

The implementation of this solution is facilitated by an open and collaborative model among the different entities detailed above. On May 1, 2019, this project began with the creation of various Rural Mobile Infrastructure Operators (OIMR), which are local companies operating their own infrastructure (Telefónica, 2018) but allowing the connection of other operators. This rendered the overarching model operating as a shared and neutral solution, since the infrastructure allows the connection of different mobile operators. All the services and technologies offered by IPT are based on an infrastructure block that allows the deployment of connectivity in Peru. This includes the construction of telecommunications towers, mobile towers, fiber optic networks, and microwave radio link equipment (Telecom Infra Project, 2022). IPT also implements network technologies such as Open RAN and a NaaS model, which stands for Network as a Service (CAF, 2019).

The services implemented by IPT in Peru are as follows. First, thanks to the OIMR set-up model, IPT enables 3 G and 4 G mobile connectivity. This improves connectivity in remote areas and provides internet access to more than 2.8 million people who benefit from this initiative. Additionally, IPT provides fixed Layer 2 connectivity, meaning a LAN-to-LAN data connection, and last-mile connections for telecommunications operators. It also offers fixed internet through a network that combines fiber optics and microwave radio. Finally, for the most remote areas, IPT provides satellite internet through Starlink LEO, a solution that covers the entire country, focusing on areas where other services and technologies such as fiber optics or microwaves cannot be deployed.

The key empirical question to be tackled is top understand how this innovative operating model contributes to addressing the digital divide in Peru. Its relevance is not only relative to the local environment but, if proven successful, it can be extended to other countries.

4. Data and methods

Based on the key empirical question, the purpose of the following analysis is to test to what extent the IPT initiative has been successful in increasing digital connectivity indicators in those departments that receive the service.

4.1. The Database

The database used for the study covers the 24 departments of Peru over 5 years (2018–2022), before and after the IPT deployments. We would have liked to expand the analysis to 2024. However unfortunately there is no data on IPT coverage available after 2022. Two main sources have been used to build the database. The data on the IPT coverage variable is sourced from IPT itself.[4] while the remaining dataset has been compiled from the National Institute of Statistics and Informatics (INEI). Descriptive statistics are presented in Table 1.

Four outcome variables have been selected, each measuring a specific aspect of access and use of technology in each department over the four years. They include the share of population that uses internet (Internet variable), the percentage of households with at least one mobile phone (Mobile variable), the percentage of households with at least one computer (PC variable), and finally an indicator of gender gap in internet access, measured as the ratio between share of females and males that use internet (Gender variable).

Table 1
Variables to be used in the empirical analysis.

Group	Variable	Description	Source	Mean	Std. Dv.
Outcome	Internet	Population that uses internet (every 100 people)	INEI	57.060	15.372
	Mobile	Households with at least 1 member with a mobile phone (every 100 households)	INEI	92.004	4.091
	PC	Households with at least 1 member with a computer (every 100 households)	INEI	28.388	10.588
	Gender	Ratio between share of females / males using internet	INEI	0.909	0.072
Treatment	IPT	Binary variable that takes value of 1 if IPT has been deployed, 0 otherwise	IPT	0.536	0.501
	IPT (%)	Persons covered by IPT services (every 100 people)	IPT	3.147	5.181
Controls	Employment	Persons employed, as a share of total population	INEI	0.521	0.121
	Education	Average years of education received	INEI	9.856	0.751
	Income	Average income (in thousand soles)	INEI	1.226	0.267

Source: authors' analysis

The independent variable IPT will be defined in two formats. First, as a binary variable indicating the existence of IPT coverage (it takes values of 1 or 0 depending on whether there is IPT coverage in that department and year), and second, as a continuous variable indicating the percentage of the population covered by IPT by department and year. These two variables allow for a comprehensive analysis of the effect of IPT coverage. As for control variables, we included factors that can drive technological adoption according to the literature reviewed above, such as Education (average number of years of study completed by the population), Income (average monthly income from work) and Employment (persons employed, as a share of total population).[5]

As mentioned above, the initial IPT deployment took place in 2020. Fig. 2 presents a map showing the departments with the highest percentages of IPT coverage in their initial year of implementation, mostly departments facing connectivity barriers. In Fig. 2, the departments marked in different shades of blue represent different ranges of IPT coverage during 2020. Dark blue indicates the departments with the highest coverage values, Pasco with 11.2 % coverage and Apurímac with 9.15 %. Medium blue represents intermediate upper ranges such as Ayacucho with 8.89 % IPT coverage and Amazonas with 8.3 %. Finally, the departments in light blue represent the lowest IPT coverages, Cusco with 5.4 %, Huánuco with 5.2 %, and San Martín with 4.6 %.

[4] See detail by department in Table A2 in Appendix

[5] Theoretically, price variables should also be included. However, in this case, prices are excluded because of lack of data. This should not be a serious limitation, as prices in different departments should not vary significantly, with temporal variations absorbed by the year fixed effects.

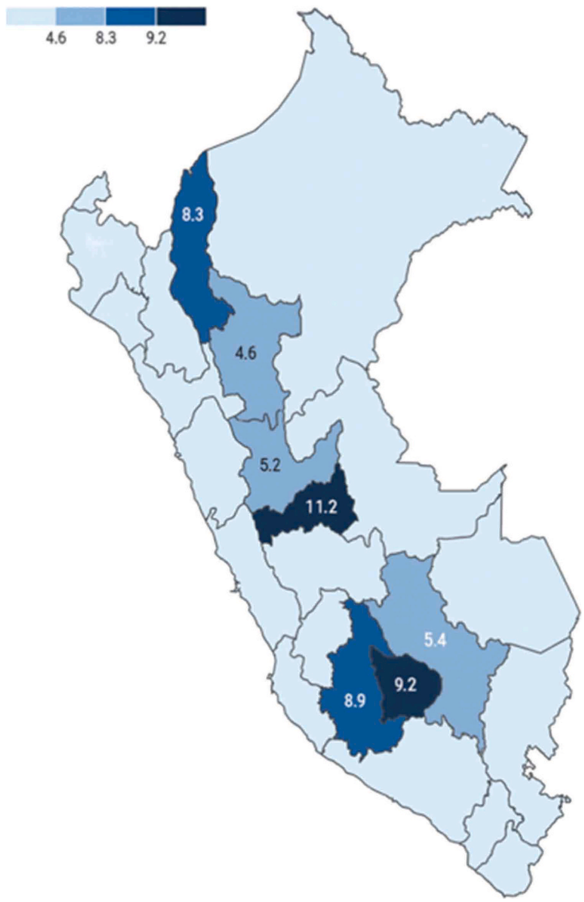

Fig. 2. IPT coverage map in 2020 (%).
Source: IPT, authors' analysis

Initially, IPT coverage was concentrated in certain regions that faced technological infrastructure challenges due to geographic factors. The regions of Pasco, Apurímac, Ayacucho, and Cusco are characterized by being in mountainous areas as they are crossed by the Andes Mountain range. On the other hand, the regions of Amazonas and San Martín belong to the Amazon forest, where dense tropical jungle predominates. Finally, the Huánuco region combines characteristics of the Mountain and the Forest, placing it in an intermediate position in terms of access difficulty.

4.2. Methods

The empirical approach is based on the generalization of the difference-in-difference approach to the cases where the treatment is staggered over different periods, as was the case of IPT deployments across Peruvian departments. The treatment effect is typically recovered using TWFE specifications such as:

$$\log(Internet_{it}) = \quad \alpha_i + \delta_t + \beta IPT_{it} + \gamma X_{it} + \varepsilon_{it}$$

Where sub-indices i and t denote department and year, respectively. α_i are department-level fixed effects, while γ_t represent year fixed effects. On the other hand, X_{it} is the vector of covariates described in the previous section. If all departments were treated in the same period, a TWFE estimation of the parameter β associated with the treatment variable in the previous equation should be an appropriate approximation of the treatment effect of interest. However, this is not the case when treatment is staggered or when its effects evolve over time (Goodman-Bacon, 2021). The standard TWFE estimator represents a weighted sum of the average treatment effects, where weights can be negative in these situations, affecting the estimated regression coefficient (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021). Considering the limitations of TWFE, the empirical strategy will be complemented with differences-in-differences approaches designed to overcome its shortcomings.

We will work primarily with the De Chaisemartin and D'Haultfoeuille (2020), an estimator designed to be valid for situations where the treatment effect is heterogeneous over time and across groups. The advantage of the De Chaisemartin and d'Haultfoeuille (2020) estimator over other novel approaches is that it allows using both discrete and continuous treatment variables, as in our sample. This methodology relies on several key assumptions underlying its identification and interpretation of treatment effects:

- Parallel trends, meaning that the groups would have evolved similarly over time in the absence of treatment and under treatment, respectively.
- No Anticipation, meaning that groups' outcomes at any time depend only on current and past treatment status, not future treatment.
- Existence of "switchers" and "stayers", meaning that some groups switch treatment status over time (from untreated to treated) and some groups to remain untreated across the same periods.
- Common support and overlap: there must be overlap in timing and treatment across groups to form meaningful comparisons.

For robustness checks, we will also work with the estimators proposed by Sun and Abraham (2021) and Borusyak et al. (2024). Sun and Abraham (2021) focus on estimating average treatment effects with what they call reasonable weights, defined as those which sum to one and are non-negative. They propose an interaction-weighted estimator, in which the weights they consider are sample shares of each cohort in the relevant periods. The method is robust to treatment effect heterogeneity across cohorts. Borusyak et al. (2024), in turn, is based on an imputation procedure, in which they estimate in a first step unit and period fixed effects using only untreated observations before using them to impute the untreated potential outcomes and, therefore, obtain an estimated treatment effect for each treated unit, before calculating a weighted sum of these effects.

5. Econometric results

The focus of this section is to analyze the specific effect of IPT on the selected outcome variables. As explained above, results will be presented using both TWFE and other differences-in-differences approaches that have been specifically designed to overcome its shortcomings.

5.1. Estimations using TWFE

Table 2 presents the results for the TWFE estimations of IPT on the different outcomes. Estimates include robust standard errors clustered at department level.

For the Internet variable (column (i)), the coefficient β is 0.116 and is significant at 1 %. This implies that, on average, the implementation of IPT is associated with an 11.6 % increase in people using the internet in those departments that were covered compared to those that did not. For the Mobile variable (column (ii)), the coefficient β is 0.015 and is significant at 1 %. It suggests that the implementation of IPT translates to an average increase of 1.5 % in households with at least one mobile phone. It is worth remembering that disparities in mobile penetration were already low in the year of implementation, meaning that gains in this field are naturally more limited. For the case of the PC variable (column (iii)), the coefficient β is 0.097 and is significant at 1 %. It indicates that the presence of IPT implies a 9.7 % increase in households with at least one computer. This suggests that the arrival of IPT coverage triggered unconnected individuals to acquire a computer in order to take advantage of digitization. However, the estimate for the gender ratio

Table 2
TWFE estimates.

Dep. Var:	(i) Log(Internet)	(ii) Log(Mobile)	(iii) Log(PC)	(iv) Log(Gender)	(v) Log(Internet)	(vi) Log(Mobile)	(vii) Log(PC)	(viii) Log(Gender)
IPT	0.116***	0.015***	0.097***	0.029				
	[0.023]	[0.004]	[0.017]	[0.026]				
IPT (%)					0.018***	0.001*	0.011***	0.003
					[0.003]	[0.000]	[0.003]	[0.002]
Income	0.200	0.043*	0.299	-0.092	0.168	0.044**	0.287*	-0.093*
	[0.126]	[0.023]	[0.178]	[0.057]	[0.119]	[0.021]	[0.150]	[0.053]
Employment	0.205	0.031	-0.540	0.164**	0.239	0.044	-0.485	0.184***
	[0.147]	[0.044]	[0.353]	[0.061]	[0.174]	[0.042]	[0.323]	[0.066]
Education	0.323***	0.019	0.425***	-0.020	0.176**	0.014	0.344***	-0.039
	[0.091]	[0.012]	[0.100]	[0.042]	[0.068]	[0.012]	[0.097]	[0.029]
Dep. FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.883	0.762	0.520	0.533	0.936	0.763	0.579	0.545
Observations	124	124	124	124	124	124	124	124

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets.
Source: authors' analysis

indicator (column (iv)) exhibits not significant coefficient associated with IPT, meaning that the early evidence points to no impact in that field. In addition, the results when using the continuous IPT treatment are consistent in terms of the significance and sign (columns (v) to (viii)).

As for the control variables, there is evidence that income increases drive both mobile and PC adoption, although that is not the case for internet use. Employment growth is, in turn, associated with reduced gender disparities. Finally, education is linked to both internet usage and PC adoption.

5.2. Estimations using alternative differences-in-differences approach

Considering the limitations of TWFE models, estimations in this section are conducted using the novel differences-in-differences methodology proposed by De Chaisemartin and d'Haultfoeuille (2020). Results are presented in Table 3.

The comparison with respect to the TWFE estimator suggests that once the limitations of the traditional methodology are corrected, the effects increase in magnitude. All the coefficients presented in Table 3 are higher than the corresponding values of those presented in Table 2. Moreover, now the deployment of IPT seems to have contributed significantly to reduce gender inequalities in the use of the technology across Peruvian departments. In addition, pre-trends are not significant in all cases (except for the Internet outcome when using the IPT continuous variable, where it is significant at 10 %), validating the results.

Next, in Fig. 3 we present the results by period for the event study. For the case of Internet, the positive effects of IPT go beyond the first period of implementation. This is also evident for the impact on the gender indicator, and to a less extent, for the case of PC adoption. On the other hand, for the case of mobile penetration, where the lower impact levels were verified in Tables 3 and 4, the effect is mostly associated with the first period, diminishing later.

Overall, this evidence points to a significant overall effect of the IPT initiative, which results in improving digitization levels across Peruvian departments. This evidence is also robust to the use of a technique specifically designed to overcome the methodological limitations of the traditional TWFE regression models.

6. Further checks

In this section we expand the analysis in two directions. First, by providing a robustness check using alternative differences-in-differences methodologies. Second, by exploring heterogeneous effects by department characteristics.

6.1. Robustness analysis using other methodologies

The robustness check is done through two other differences-in-differences methodologies developed recently to overcome the limitations of the conventional TWFE estimator. In the first place, the procedure developed by Sun and Abraham (2021) will be considered. Second, the empirical strategy will also rely in the estimator proposed by Borusyak et al. (2024). These estimations had to be done only for the binary IPT variable, as they are not designed for continuous treatments. Results are presented in Table 4.

Overall, results following these methodologies validate those reported in the De Chaisemartin and d'Haultfoeuille (2020) estimator. The only exception is that the effect over gender gap is not significant under Sun and Abraham (2021). In addition, the Borusyak et al. (2024) estimator provides up to two pre-trends which, in all cases, are never significant, validating the results.

Table 3
Differences-in-Differences average total effects using methodology of De Chaisemartin and d'Haultfoeuille (2020).

Dep. Var:	(i) Log(Internet)	(ii) Log(Mobile)	(iii) Log(PC)	(iv) Log(Gender)	(v) Log(Internet)	(vi) Log(Mobile)	(vii) Log(PC)	(viii) Log(Gender)
IPT	0.171***	0.021***	0.107***	0.060***				
	[0.031]	[0.005]	[0.036]	[0.017]				
IPT (%)					0.029***	0.004***	0.018***	0.010***
					[0.003]	[0.000]	[0.005]	[0.002]
Pre-trend 1 (p-value)	0.106	0.339	0.461	0.617	0.092	0.213	0.456	0.593
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Dep. FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets.
Source: authors' analysis

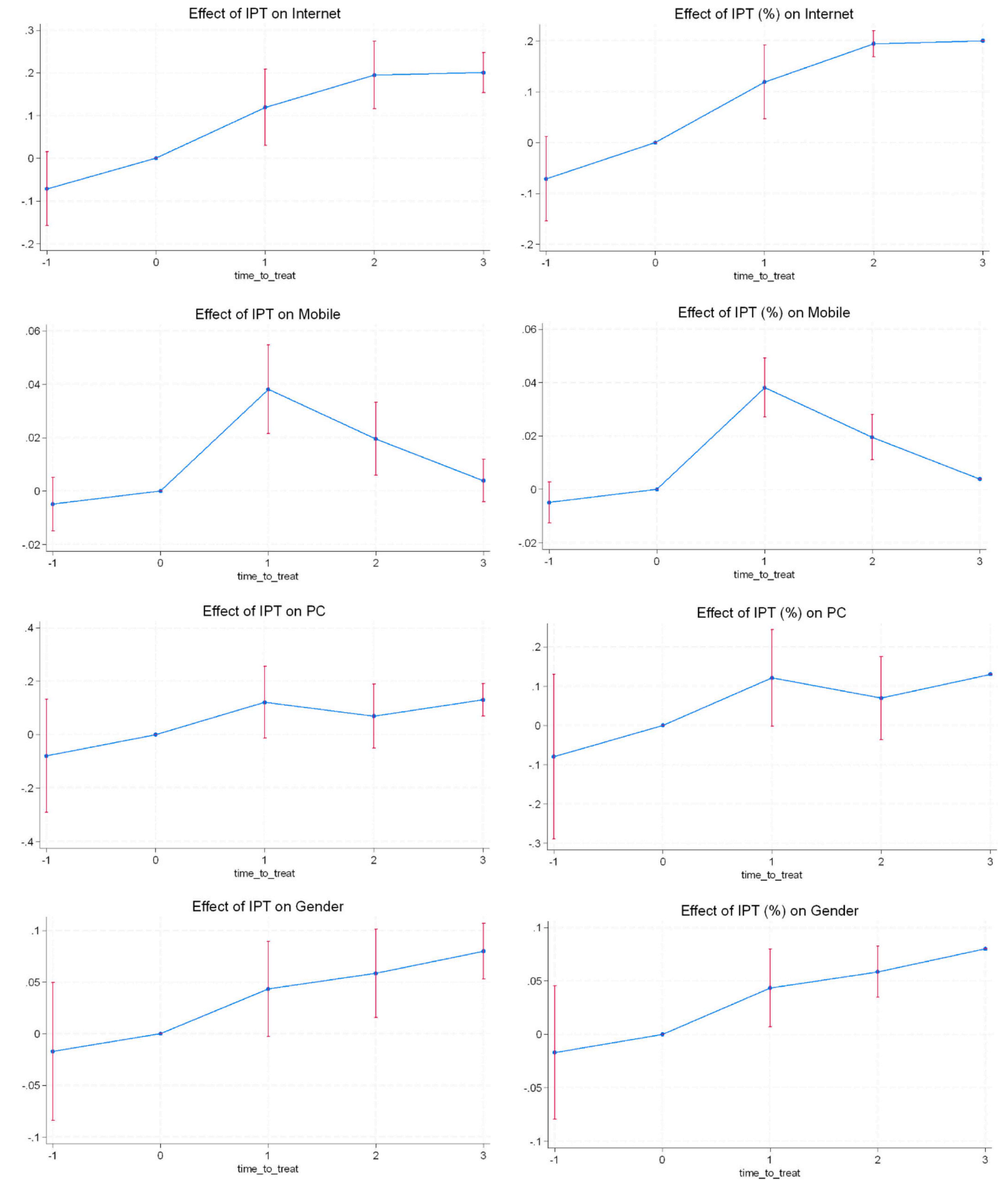

Fig. 3. De Chaisemartin and d'Haultfoeuille (2020) event study by periods.
Source: Authors' analysis

6.2. *Analysis of heterogeneous effects by department*

In this section heterogeneous effects by department are explored. The aim is to understand if all the departments that received IPT deployments experienced similar treatment effects, or if on the contrary, some departments were more benefited than others.

The analysis of the heterogeneous effects will be done interacting the treatment variable with some department-level characteristics. All

Table 4
Differences-in-Differences average total effects.

Dep. Var:	(i) Log(Internet)	(ii) Log(Mobile)	(iii) Log(PC)	(iv) Log(Gender)	(v) Log(Internet)	(vi) Log(Mobile)	(vii) Log(PC)	(viii) Log(Gender)
IPT	0.132***	0.017***	0.105***	0.032	0.185***	0.024***	0.091***	0.069***
	[0.026]	[0.005]	[0.018]	[0.028]	[0.032]	[0.005]	[0.022]	[0.020]
Pre-trend 1 (p-value)	NR	NR	NR	NR	0.962	0.959	0.877	0.166
Pre-trend 2 (p-value)	NR	NR	NR	NR	0.184	0.544	0.437	0.242
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Dep. FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Method	SA	SA	SA	SA	B	B	B	B

*Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets. SA refers to Sun and Abraham (2021), B to Borusyak et al. (2024), NR denotes not reported.*
Source: authors' analysis

variables to be interacted with IPT are dummies that capture certain department conditions. The estimates conducted in this section will be carried out using TWFE, as differences-in-differences latest techniques are not suitable for interactions. In any case, the comparison of the above-presented results using TWFE, and the reported differences-in-differences models show that the former slightly underestimates the effects of IPT, being then a conservative approach or a lower bound reference to continue the analysis. Results for heterogeneities by income and educational level of departments are presented in Table 5.

Both income and educational dummies to be interacted with IPT consist in indicators identifying the sample by thirds in the distribution of the respective variable: low, medium and high (being this latest one omitted as is the baseline effect).

We begin by analyzing heterogeneities by income level. From column (i), it seems clear that IPT increased internet use in all departments where it has been deployed, although the effects were larger the lower the income of the department. On the other hand, the impact on mobile devices (column (ii)) is only significant for the low-income case, but not for other departments. The number of PCs increased in all departments where IPT was deployed, but more so in low-income ones (column (iii)). In turn, the effect over gender gap was only visible in low and medium-income departments (column (iv)).

On the other hand, low education departments seem to be the most benefited in terms of internet users and mobile penetration (columns (v) and (vi)), although there are no differences by educational level with respect to the PC indicator (column (vii)). IPT is not significant in any case to explain the gender gap when splitting the effect by educational level (column (viii)). Table 6 presents heterogeneous effects by internet use levels, also divided in three groups.

As seen in columns (i) and (ii), the effect of IPT on internet usage and mobile penetration is the highest in those departments with the larger

Table 6
Heterogeneous effects by internet use level.

Dep. Var:	(i) Log (Internet)	(ii) Log (Mobile)	(iii) Log (PC)	(iv) Log (Gender)
IPT	0.026	0.004	0.079***	0.013
	[0.021]	[0.005]	[0.027]	[0.027]
IPT x Low internet	0.214***	0.027***	0.024	0.017
	[0.042]	[0.009]	[0.047]	[0.022]
IPT x Mid internet	0.116***	0.014**	0.033	0.030*
	[0.039]	[0.006]	[0.035]	[0.017]
Income	0.131	0.034	0.296*	-0.092*
	[0.132]	[0.021]	[0.166]	[0.052]
Employment	0.020	0.008	-0.576	0.134**
	[0.136]	[0.038]	[0.348]	[0.063]
Education	0.218***	0.005	0.421***	-0.021
	[0.071]	[0.013]	[0.089]	[0.033]
Dep. FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.919	0.805	0.524	0.547
Observations	124	124	124	124

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets.
Source: authors' analysis

Table 5
Heterogeneous effects by income and education level.

Dep. Var:	(i) Log(Internet)	(ii) Log(Mobile)	(iii) Log(PC)	(iv) Log(Gender)	(v) Log(Internet)	(vi) Log(Mobile)	(vii) Log(PC)	(viii) Log(Gender)
IPT	0.032*	0.005	0.097***	0.011	0.060*	0.007	0.093***	0.028
	[0.018]	[0.006]	[0.024]	[0.027]	[0.030]	[0.005]	[0.029]	[0.029]
IPT x Low income	0.271***	0.025***	0.080**	0.043*				
	[0.030]	[0.007]	[0.036]	[0.024]				
IPT x Mid income	0.081**	0.013	-0.033	0.026*				
	[0.033]	[0.009]	[0.040]	[0.013]				
IPT x Low education					0.156***	0.021**	-0.030	0.030
					[0.046]	[0.008]	[0.045]	[0.020]
IPT x Mid education					0.081	0.013*	0.041	-0.022
					[0.058]	[0.007]	[0.047]	[0.025]
Income	0.172	0.045*	0.246	-0.086	0.099	0.029	0.314*	-0.109*
	[0.131]	[0.022]	[0.162]	[0.053]	[0.127]	[0.021]	[0.180]	[0.058]
Employment	-0.058	0.002	-0.565	0.111*	0.104	0.018	-0.514	0.139*
	[0.146]	[0.038]	[0.373]	[0.062]	[0.133]	[0.040]	[0.361]	[0.068]
Education	0.140*	0.003	0.366***	-0.048	0.280***	0.013	0.429***	-0.026
	[0.075]	[0.012]	[0.093]	[0.032]	[0.081]	[0.012]	[0.098]	[0.034]
Dep. FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.940	0.795	0.562	0.556	0.904	0.790	0.537	0.575
Observations	124	124	124	124	124	124	124	124

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets.
Source: authors' analysis

digital divide, followed by those in a medium situation. No effects are visible for those departments that are at the most digitized. However, the same is not verified for the case of PCs (column (iii)) or gender gap (column (iv)).

Finally, in Table 7 we split the effects by geographical condition, by classifying the departments across the definitions presented in Table A1 in the Appendix: Forest, Mountain and Coast (baseline case). On average, the most benefited departments in terms of internet usage and PC diffusion are those classified as mountainous (columns (i) and (iii)), while on the other hand those facing a forest condition where the more benefited in terms of mobile penetration (column (ii)). No heterogeneities by geographical condition were found for the gender gap indicator (column (iv)).

Overall, the analysis of heterogeneous effects points to a larger impact on connectivity on those departments that were facing the more unfavorable conditions, thus contributing significantly to reduce internal gaps across regions.

7. Conclusions and recommendations

After studying the business model of IPT and conducting a quantitative analysis of the results in recent years of implementation, this study has been demonstrated that IPT has had a positive impact on reducing the digital divide in Peru through several metrics used. Moreover, those territories more favored by the initiative seemed to be those with lower income, lower education levels, less connected ones and those facing more complex geographical conditions. This means that the initiative has made a significant contribution to disadvantaged areas or populated segments, that in turn are expected to experience important socioeconomic gains from this increased connectivity.

The study faced some limitations that are worth mentioning. First, it would have been desirable to conduct the analysis at a more disaggregated geographic division, possibly at the municipal level. In addition, it would have been worth to incorporate in the analysis the coverage levels of the past two years, 2023 and 2024. Unfortunately, these data sets were not available, something that provided some constraints to our analysis. As a line for future research, it would be worth studying the economic effects of the IPT initiative beyond its adoption, particularly in terms of its impact on local income and productivity levels.

The success of IPT in Peru suggests that this model can be replicated in other countries with similar connectivity problems, provided that the appropriate conditions are met, ranging from regulatory to those related to industry coordination. This is relevant, in a context in which traditional solutions to address the digital divide problem, such Universal Service Funds (USFs), have not always proven to be successful to deliver the desired results (ESCAP, 2017; Boik, 2017).

A factor that could have contributed to the implementation of the IPT project in Peru is the existence of the regulatory figure of OIMR, which facilitates an open and collaborative model. However, we should be cautious before reaching firm conclusions regarding the specific regulatory figure, as we didn't study if an alternative framework would have led to higher or lower achievements.

The OIMR structure allows multiple mobile operators to share infrastructure, optimizing costs and ensuring greater coverage in rural areas. However, in most countries, there is no similar regulatory framework, which can represent an obstacle to the implementation of a model like IPT. For other countries to successfully replicate this initiative, it is essential that they adopt regulations that promote cooperation among operators, allowing shared infrastructure models such as OIMR. This would require the adoption of specific regulations that facilitate the deployment of shared networks and incentivize private investment in areas that may initially seem commercially unprofitable. Additionally, a flexible and transparent governance framework must be established to facilitate joint decision-making between the public and private sectors.

The IPT business model is based on a strategic alliance between technology companies, governments, and multilateral organizations, consolidating it as a public-private organization that drives innovation, cooperation, and the development of large-scale technological solutions. To ensure the replicability of this solution in different contexts, it is essential to have a flexible and transparent governance framework that facilitates joint decision-making, as well as sustainable financing mechanisms that guarantee its long-term viability. Additionally, an interoperable technological infrastructure must be available, allowing the integration of mobile operators and ensuring the scalability of the model to rural and disadvantaged areas, were, under normal circumstances, a private company would likely choose not to invest due to lack of profitability.

Only through the construction of an environment of trust and collaboration among the different actors involved is it possible to establish the necessary standards and regulations for the effective adoption of a solution like IPT. This trust is based on transparency, participation, and the commitment of all parties involved. In this sense, the willingness to collaborate of the different actors has been a key factor for the success of the alliance. The "willingness to collaborate" among competitive operators in view of achieving a common good is a non-trivial matter. Encouraging collaboration among multiple stakeholders is critical for success in partnerships tackling the digital divide. As a general concept, infrastructure sharing requires that competing organizations are willing to recognize that network sole ownership is not necessarily a source of competitive advantage. Service based competition in cases where infrastructure deployment costs are an insurmountable economic constraint is the sole framework that can allow tackling the digital divide.

How do operators migrate to this shared/collaborative model and buy-in to a shared project? IPT provides a useful case on how to address the usual coordination failures that affect multi-stakeholder partnerships. First and foremost, the model launch had to be facilitated by an agreement among three players that are essential to project success: a supplier of the starting infrastructure (Telefonica), a provider of capital acting as a bridging entity (the multilateral banks), and a technology provider (Meta). Secondly, the IPT experience indicates that it might not be advisable to bring multiple telecommunications service providers to agree at the point of launch of the collaborating entity. It is better to create the starting agreement as stipulated above and begin gradually enrolling the remaining operators, once the launching structure is set up and operating. Third, collaboration aimed at sharing infrastructure is usually affected by managerial complexity. IPT was successful because it created a separate organization, independent from any operator with its

Table 7
Heterogeneous effects by geographical condition.

Dep. Var:	(i) Log (Internet)	(ii) Log (Mobile)	(iii) Log (PC)	(iv) Log (Gender)
IPT	0.055*	0.007	0.079***	0.019
	[0.027]	[0.005]	[0.024]	[0.026]
IPT x Forest	0.090	0.020*	-0.039	0.025
	[0.064]	[0.010]	[0.053]	[0.019]
IPT x Mountain	0.137**	0.012	0.091**	0.015
	[0.052]	[0.007]	[0.036]	[0.024]
Income	0.220*	0.041*	0.340**	-0.094
	[0.128]	[0.022]	[0.158]	[0.063]
Employment	0.138	0.020	-0.541	0.150**
	[0.124]	[0.038]	[0.368]	[0.060]
Education	0.291***	0.023*	0.352***	-0.016
	[0.085]	[0.012]	[0.102]	[0.034]
Dep. FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.903	0.785	0.573	0.542
Observations	124	124	124	124

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered by department in brackets.
Source: authors' analysis

own operating model, resources, and management processes. This resulted in a unifying culture driven by unique critical success factors linked to addressing the digital divide.

CRediT authorship contribution statement

Raúl Katz: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources. **Montesinos Vidal Sofia:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Juan Jung:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table A1
Departments by Geography and Percentage of Population and Land

Department	Geography	Population (%)	Land area (%)
Amazonas	Forest	1.26 %	3.05 %
Ancash	Coast	3.53 %	2.79 %
Apurímac	Mountain	1.25 %	1.63 %
Arequipa	Mountain	4.72 %	4.93 %
Ayacucho	Mountain	1.97 %	3.41 %
Cajamarca	Coast	4.25 %	2.59 %
Cusco	Mountain	4.11 %	5.60 %
Huancavelica	Mountain	0.98 %	1.72 %
Huánuco	Mountain	2.19 %	2.90 %
Ica	Coast	3.12 %	1.66 %
Junín	Mountain	4.06 %	2.99 %
La Libertad	Coast	6.26 %	1.98 %
Lambayeque	Coast	4.00 %	1.13 %
Lima	Coast	33.21 %	2.72 %
Loreto	Forest	3.11 %	28.70 %
Madre de Dios	Forest	0.58 %	6.64 %
Moquegua	Coast	0.59 %	1.22 %
Pasco	Mountain	0.78 %	1.95 %
Piura	Coast	6.32 %	2.78 %
Puno	Mountain	3.55 %	5.21 %
San Martín	Forest	2.78 %	3.99 %
Tacna	Coast	1.16 %	1.25 %
Tumbes	Coast	0.78 %	0.37 %
Ucayali	Forest	1.88 %	7.95 %

Source: INEI, authors' analysis

Table A2
IPT coverage by department (every 100 inhabitants)

Departament	2018	2019	2020	2021	2022
Amazonas	0.00	0.00	8.33	11.21	10.98
Ancash	0.00	0.00	3.89	4.61	4.79
Apurimac	0.00	0.00	9.15	19.78	22.35
Arequipa	0.00	0.00	1.65	2.08	2.28
Ayacucho	0.00	0.00	8.89	15.92	16.73
Cajamarca	0.00	0.00	3.46	6.31	7.74
Callao	0.00	0.00	0.00	0.00	0.00
Cusco	0.00	0.00	5.39	11.12	11.44
Huancavelica	0.00	0.00	11.50	23.72	24.14
Huanuco	0.00	0.00	5.20	6.82	6.81
Ica	0.00	0.00	0.05	0.05	0.83
Junín	0.00	0.00	1.00	2.61	4.07
La Libertad	0.00	0.00	2.10	2.69	2.78
Lambayeque	0.00	0.00	0.00	0.00	0.27
Lima	0.00	0.00	0.18	0.19	0.20
Loreto	0.00	0.00	0.24	2.14	2.26
Madre de Dios	0.00	0.00	3.38	3.61	8.15
Moquegua	0.00	0.00	0.72	1.51	1.46
Pasco	0.00	0.00	11.22	11.81	11.68
Piura	0.00	0.00	2.14	5.29	6.24
Puno	0.00	0.00	3.33	4.68	5.08
San Martin	0.00	0.00	4.62	6.39	6.60
Tacna	0.00	0.00	0.57	0.63	0.97
Tumbes	0.00	0.00	0.00	0.00	0.00
Ucayali	0.00	0.00	1.16	2.07	2.12

(*continued on next column*)

Table A2 (*continued*)

Source: IPT

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