Future of Work in the Global South: Digital Labor, New Opportunities and Challenges

Working Paper

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Acknowledgments

This working paper is part of the Future of Work in the Global South initiative supported by the International Development Research Centre (IDRC) and coordinated by the Center for the Implementation of Public Policies Promoting Equity and Growth (CIPPEC).

The After Access dataset (www.afteraccess.net) is one of the main inputs to carry out this research. It consists of nationally representative surveys conducted by sister-networks across the Global South with support from the International Development Research Center (IDRC) of Canada, the Swedish International Development Cooperation Agency (SIDA) and the Ford Foundation (for Asia). The networks build on over a decade of experience in using rigorous research to inform ICT policy and regulation in their respective regions.

We thank the suggestions received from Ayesha Zainudeen but all errors remain ours.

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Abstract

Increases in access to Internet have led to the emergence of a new world of work, with an important potential of gig work to contribute in significant ways to marginalized populations in the Global South, especially in contexts of high unemployment rates, informality, less secure forms of employment and limited opportunities. Despite the potential benefits that can be derived from digital labor platforms as an alternative to find and perform income-generating activities, there are several barriers for populations of developing countries to take advantage of this global resource. In this context, we characterize digital workers of the Global South, with special attention to gender aspects and social inequalities; we also estimate the main determinants of entry decisions to digital labor markets (by gender), as well as the main determinants that explain pay gaps between men and women (gender pay gap) and between women that participate and women that do not participate in the digital labor market. We find that inequality of opportunities related to gender is also present in the digital world (digital divide) and that this inequality goes beyond the access barrier. Observable characteristics (such as having a computer, labor experience, and education) in women and men only explain 6% of the gender pay gap, leaving a space of unexplained effects that the literature generally attributes to discrimination. Finally, our results show a positive impact of working through digital platforms over income levels and potential income gains for women. Nevertheless, the income premium for working over digital platforms is 16% higher for women, but the potential gains for women are 14% less than the income gains for men.

Keywords: Digital platforms, gig economy, gender, Global South

JEL codes: D83, J16, O33

FUTURE OF WORK IN THE GLOBAL SOUTH AFTER ACCESS RESEARCH ICT AFRICA LIRNEasia Pro-poor. Pro-market. IEP INSTITUTO DE ESTUDIOS PERUANOS

1. Introduction

More than one billion people will enter the job market in less than three years, most of them from low-and lower-middle-income countries of the Global South (ILO, 2018b); however, structural unemployment in many countries, especially amongst the youth, will expand (ILO, 2017a; OECD, 2014). Moreover, increases in access to the Internet have led to the emergence of a new world of work (digital labor), with major international institutions suggesting that workers could compete in a frictionless global marketplace through online platforms (ILO, 2018a; S4YE, 2018). In this context, digital labor and related phenomena have the potential of offering an alternative to traditional employment under these global conditions (ILO, 2018b; Gillwald et al., 2018; World Bank, 2016).

While Information and Communications Technologies (ICT) have the potential to contribute to the attainment of sustainable development goals of equality and social inclusion, paradoxically as more people are connected and use the Internet more productively, digital inequality increases not only between those offline and online but also between those passively consuming the Internet and those who are more active, for purposes of entrepreneurialism and innovation or to enhance their well-being. This new labor market segment offers benefits such as autonomy, flexibility, and time management. Some studies highlight microwork as an opportunity for job creation, particularly for traditionally excluded minorities, such as women, youth, poor, racial minorities and people that live in rural areas) (Rossotto et al., 2012; Maselli et al., 2016). However, online workers are exposed to risks like social isolation, lack of work-life balance, discrimination, predatory intermediaries, and even basic internet threats to security and privacy (Bukht & Heeks, 2018). As a result, digitization processes that significantly affect the nature of work will have long-lasting impacts on development outcomes, such as participation, wages, and flexible work schedules. Yet, these impacts have not been broadly studied, particularly in the Global South.

In this context, this paper aims to contribute to a better understanding of the implications of changes in the nature of work (digital labor) for developing countries of the Global South, particularly among marginalized groups, to foster equitable growth and inclusive social development. We identify the characteristics of digital workers in countries in Africa, Asia, and Latin America, as well as the main barriers to digital labor market participation, focusing on the differences between men and women. We also analyze the determinants of entry decisions into the digital labor market, and the main drivers of the gender pay gap between male and female digital workers, and between females outside and inside the digital labor market.

Most studies examine how digital labor is building up in developing countries through big data approaches consisting of quantitative data extraction from work platforms and stakeholders' interviews (Graham, Lehdonvirta, et al., 2017; S4YE, 2018). These kinds of studies are based on data extraction from one specific online platform and could show bias. Most of the information compiled about people involved in digital labor (i.e. sellers or customers) is based on invisible profiles, which can create a statistical bias in the sample of data collected towards "less successful" workers (Graham, Lehdonvirta, et al., 2017). Given that this is an emerging research field, appropriate methodologies are still underdeveloped: there is a lack of data about the real profile of digital workers and the level of digital work in developing countries. This is precisely the kind of information that our study offers, therefore differing from previous ones.

For this purpose, we use a nationally representative survey from the After Access[1] project, conducted in 2017/18 by three think tanks in the Global South: Research ICT Africa (RIA) in Africa[2], LIRNEasia in Asia[3] and the Institute of Peruvian Studies (through the Regional Dialogue on Information Society-DIRSI) in Latin America[4]. This unique dataset includes comparable information on individuals' participation in the digital economy, the type of digital work activities they undertake, and the reasons for participating in such activities; in addition, there is information on different ICT use and socioeconomic data.

[1] See: http://afteraccess.net/
[2] Countries included are: Kenya, Mozambique, Ghana, Nigeria, Rwanda, South Africa, Tanzania, Uganda, Lesotho and Senegal.
[3] Countries included are: Pakistan, India, Bangladesh, Cambodia, Sri Lanka, and Nepal.
[4] Countries included are: Argentina, Colombia, Ecuador, Guatemala, Paraguay, and Peru.

1. Introduction

We seek to find a causal effect between individual characteristics (as well as current labor positions) and the probability of participating in digital labor, broken down by digital labor categories (i.e. ride-sourcing, delivery, online task, and cleaning tasks). Two approaches are used to examine participation in the digital labor market and its effect over relevant labor market outcomes (income). On the one hand, we analyze the difference in income between men and women that fall within the digital labor market (gender pay gap in the gig economy). On the other hand, we analyze the difference in income between women that participate and do not participate in the digital economy (the gig economy effect on women's pay).

The results show that gender inequalities are not limited to the 'connected' and 'unconnected' categories; they are also present among those who are already online (digital divide). Observable characteristics in women and men only explain 6% of the gender pay gap, leaving a space for the impact of other variables that the literature attributes to discrimination and social values to explain gender gaps. Also, even if men and women have identical labor experience, the existing gender pay gap only decreases by 0.8%, and the gender pay gap is reduced by 79% and 9% if educational level and social capital, respectively, were the same in men and women. Finally, our results justify the design of different public policies to address these gender gaps. Working through digital platforms has a positive impact on income levels and potential income gains among women. Nevertheless, the income premium for working through digital platforms is 16% higher for women, but the potential gains for women are 14% less than the income gains perceived by men.

2. Platform economy and gender issues in the Global South

The growth of the digital economy[5] in developing countries has been hindered by digital exclusion and digital inequality. The digital divide remains a critical problem: involvement in the digital economy typically requires not only Internet access but also digital skills and literacy. Even with inflated supply-side figures roughly half the planet's population is not yet connected (UNCTAD, 2017); moreover, this group disproportionately representing the world's traditionally excluded minorities in developing countries.

In particular, in the labor sector, despite increasing global workforce participation rates, traditionally excluded populations are still disadvantaged in terms of their share in employment, wages, and working conditions (ILO, 2018a). Today's labor market is still marked by pervasive inequality; according to Blau & Kahn (2017) women work in occupations that are different from those of men and get paid less for apparently the same personal and job characteristics, and those in the Global North earn more than those in the Global South. Furthermore, a significant percentage of the female global workforce earn their livelihood in the informal economy as "dependent" wage earners and self-employed entrepreneurs in a wide range of workplaces (ILO, 2016). Young people encounter serious problems in their work life, with three out of four youths worldwide engaged in informal employment. They face high rates of poverty and are exposed to non-standard, informal and less secure forms of employment, with a lack of social and legal protection, and limited opportunities for training (ILO, 2020). In this context, digital platforms offering the opportunity to find potential employers and clients and to perform income-generating activities constitute an important tool, especially for disadvantaged populations in places where job opportunities are very limited or simply do not exist.

According to Graham et al. (2020), a digital labor platform could be defined as a set of digital resources—including services and content—that enable value-creating interactions between consumers and individual service-providing workers. Gig work and new virtual job opportunities include writing, graphic design, data entry, transcriptions, social media marketing, translating online content into other languages, website curation, e-hailing, and online delivery (Wood et al., 2019; Graham et al., 2017). Common online digital labor platforms include Amazon Mechanical Turk, which enables workers to choose and perform simple tasks through a digital platform, report directly through the online platform, and receive payments in exchange. Other microwork online platforms include Samasource and Juna (Graham et al., 2017; Ford et al., 2015; World Bank, 2015; Horton, 2010). It should be noted that there is a distinction between online gig work—which is transacted and delivered via digital platforms because the product of work is digital information and can circulate through the Internet—and non-online gig work, where the product or service must be provided locally, such as Uber or Airbnb (Graham et al., 2017).

Online tasks vary according to type, targeted workers, and compensation (Broughton et al., 2018). Several factors have been identified as drivers or determinants of participation in the digital labor market: payment or reward, digital skills, awareness, access to the Internet or devices and electricity availability (Gillwald et al., 2018; Mtsweni & Burge, 2014).

Despite the potential benefits that can be derived from digital labor platforms there are several barriers for populations of developing countries to take advantage of this global resource. The majority of the online digital platforms that are available are hosted and only accessed only through the Internet. This creates an access challenge for many countries where Internet penetration is low. For instance, less than a third (28%) of individuals 15 years and older in Africa uses the Internet (Gillwald et al., 2018). Furthermore, people living in developing countries do not have devices such as computers and laptops which are necessary for meaningful participation in the digital labor market and are restricted to tasks that can be performed on smartphones such as e-hailing and online delivery with very limited coding, tagging, and categorization of content (Gillwald et al., 2018).

[5] Following (Bukht & Heeks, 2017) and (Broughton et al., 2018), we define digital economy as the exchange of labor for money between individuals or companies via digital platforms that actively facilitate matching between providers and customers, on a short-term and payment basis.

2. Platform economy and gender issues in the Global South

Digital labor platforms depend on ICT infrastructure. However, in many developing countries the majority of rural areas have yet to be connected and cannot participate in the digital economy (Roomaney et al., 2018). Other barriers identified by the literature include lack of ICT education, digital skills, and the non-visibility of digital labor platforms in developing countries. As a result, populations in these areas are unaware of the opportunities available online (IADB, 2018; Roomaney et al., 2018). Furthermore, the majority of people in developing countries are financially excluded (Gillwald et al., 2018) and the lack of payment mechanisms is a significant problem that is affecting the growth of online work in developing countries (Galperin & Alarcon, 2018).

The existing literature shows that online labor platforms compound market frictions that result in inferior labor outcomes for the poor, particularly for women, ethnic minorities, and other disadvantaged groups (Galperin & Greppi, 2017). While there is evidence that digital labor platforms might exacerbate the historical inequalities, most of the studies have remained descriptive and fail to quantify these disparities. Hence, much more research is needed about the connection between new forms of digital labor and traditional employment, and the distributional impact of these changes on relevant development outcomes.

2.1 Africa

Given the potential of the Internet to contribute to economic growth and job creation and the huge investment made in this sector, there have been several initiatives in Africa, such as Digital Jobs Africa, a USD 100-million initiative of the Rockefeller Foundation in partnership with the World Bank aimed at improving the lives of Africans by accelerating ICT-enabled employment and skills training for high-potential African youth. The digital space has also seen a growth in the number of digital platforms including Amazon Mechanical Turk, Short Task, Text Eagle and Clickworker, Uber, Lyft, TaskRabbit, eBay, and Alibaba, which outsource microwork to users and provide supplementary income to global virtual workers[6] .

The adoption of microwork or online work in Africa, however, is minimal. According to Gillwald et al. (2018), 2% of Africans are online workers, representing 3% of the economically active population. Based on their research, the authors conclude that the majority of these online workers are doing manual work like domestic tasks or e-hailing, which is simply sourced online, not the kind of online work understood in the context of microwork, namely, piecemeal online work that is distributed among geographically

untethered freelancers. Even in countries that directly benefited from the World Bank and Rockefeller Foundation online job generation initiatives (South Africa, Kenya, Nigeria, and Ghana), online platform participation is very low. For instance, the Digital Jobs Africa initiative undertook many activities to increase and enhance opportunities for digital job creation in Africa. This included the development of an Information Technology (IT) park in Ghana and online microwork awareness building and training in Nigeria. Despite these initiatives, only a small proportion of Internet users in these countries are microworkers (Roomaney et al., 2018; Gillwald et al., 2018).

The low uptake of digital work in Africa is attributed to the low levels of Internet use in the continent. The After Access[7] surveys show that about 72% of the African population do not use the Internet. Furthermore, even among those who use the Internet, usage disparities exist, with the majority of Internet users in Africa accessing only social networking sites.

[6] See https://blogs.worldbank.org/ic4d/education/ic4d/partnerships-and-opportunities-digital-jobsividuals or companies

[7] See www.afteraccess.net

2.2 Asia

The nature of work in Asia has changed dramatically in the last few decades. Rapid economic growth has led to better paying and more productive jobs, driven by international trade and new technology. The Asian Development Bank estimates the labor force in Asia will increase by 16 million each year between 2015–2030. This will increase the pressure for job seekers. New technologies will fundamentally change business models and how people work. Balancing prosperity against the challenges that come along with it will be a daunting task. Globally, the fourth industrial revolution led to the growth of less stable forms of employment, where protection and benefits associated with conventional employment are not a given (Asian Development Bank, 2017). This increasingly puts workers at risk as labor markets evolve as well as in the face of economic shocks. The growth of the online gig economy in much of Asia is also leading to better paying and more productive jobs.

Large segments of the developing Asian population have gained mobile connectivity in recent years, many still connected on basic phones. For example, the After Access surveys show that 56% of those that got connected in 2015-2017 in India are basic phone owners and only 31% of this group have smartphones. Computer ownership is still low in countries like India, Myanmar, Bangladesh, and even higher income countries from the region like Sri Lanka (where just 12% of the 15–65 population has a computer in their home). The surveys show that low numbers are venturing beyond basic voice use, and if they do get online, it is mostly on social media. For instance, in 2018, less than one-fifth of the population aged 15-65 years in India, Pakistan, and Bangladesh were online. Furthermore, those that do get online are skewed toward the urban, male, and lower age categories. As such, on the whole, many lack digital skills, particularly those from these digitally marginalized groups (LIRNEasia, 2019).

Supply-side data indicates that India, Bangladesh, and Pakistan are among the top suppliers of workers to the major digital work platforms of the world (Oxford Internet Institute, 2020). However, demand-side research shows a contrasting picture where awareness levels are sparse. For example, among internet users (already a low base in most developing Asian countries), less than one-third were aware of microwork possibilities (close to none, in some cases) by 2018. A separate survey of the population aged 15-40 years in Sri Lanka showed that just 26% were aware of the concept of digital work (again, skewed toward males, urban, younger and higher socioeconomic groups). Those open to or willing to engage in such work were less than half of those aware. This is pitiful in a country that boasts some of the highest connectivity levels in the developing Asian region (LIRNEasia, 2019) and a literacy rate of 92% (Ministry of Higher Education, Technology and Innovation, n.d.).

In contrast to the Global North experience where digital work is sometimes seen as an informalization of formal workers, in the Asian Global South, it has been an opportunity for informal workers to become formal. Data entry, online marketing, writing, and translation are popular forms of digital work in these contexts. Social media plays an important role in the process of finding digital work in some countries like Myanmar. Often digital work is not the primary source of a person's income but rather taken on while studying or in addition to a full-time job. In this regard, the flexibility to work where and when the worker chooses has been a key advantage for digital workers. Women value the flexibility that allows them to earn money while continuing with their care responsibilities and the sense of financial independence gained (Galpaya et al., 2018; Bandaranayake et al., 2020).

It is important to highlight perceptions and socio-cultural attitudes about platform-based work on the rise. In some Asian countries, 'informal' work has long been associated with unskilled work. This leads to seeing digital work as socially 'unacceptable' by workers' families, particularly in India (ICRIER, 2017). Similar sentiments have been seen among Sri Lankan male digital workers, while among female digital workers the opposite was observed since digital work enables women to make a living without having to leave the home (Galpaya et al., 2018). How countries define 'formal' and 'informal' work can influence the necessary shift in perceptions to make use of new earning opportunities, combined with concerted efforts to make non-conventional work arrangements more 'acceptable.' In India, the government's launch of Digital India, a platform to provide computer literates with freelance work opportunities, is an example of such efforts (ICRIER, 2017).

Research has also indicated the need to update legal and policy frameworks, particularly those which can facilitate payment of workers. For example, in Sri Lanka and Myanmar, inward remittance regulations prevented online workers from cashing out their earnings seamlessly; workers have to resort to workarounds in many cases. Furthermore, the lack of recognition of digital work as a 'formal' form of employment precludes workers from accessing formal financial services such as loans (Galpaya et al., 2018). There is an expanding scope and scale for digital work in developing Asia. Countries like India have a large pool of informal workers, especially women. Flexible platform-based work could be a good fit and provide a source of income for many people, given the right infrastructure, skills, and policy framework.

2.3 Latin America

Latin America is characterized by various aspects of gender inequality that impede the full development of women and girls. The structural factors that limit their rights include: (a) socioeconomic inequality and persistence of poverty; (b) discriminatory and violent patriarchal cultural patterns; (c) sexual division of labor and unjust social organization of care; and (d) concentration of power and hierarchical relations in the public sphere. In particular, regarding socioeconomic inequality and poverty, women face access barriers to productive resources, such as credit, land, water, training, technologies, and time (CEPAL, 2017).

Time-use surveys carried out in recent decades in the region have helped to illustrate female labor market participation: they spend two-thirds of their time doing unpaid work, whereas men spend two-thirds of their time doing paid work (CEPAL, 2019). In addition, national household surveys show that, on average, 43.4% of women 20–59 years old cite family responsibilities (pregnancy, childcare, domestic work, and some other restrictions) as the main reason they are not actively seeking or performing paid work (CEPAL, 2017). The unequal distribution of responsibilities for domestic work and care which falls mainly on women operates as a barrier to participation and reproduces inequalities in the labor market.

Regarding gender differences in the field of technology, Barrantes et al. (2018) analyze the factors that determine the gender gap in ICT use in five Latin American countries (Argentina, Colombia, Paraguay, Guatemala, and Peru), examining different dimensions of ICT use. The authors show that factors like occupation, education, and age do play a relevant role in explaining the gender gap in ICT use in Paraguay and Argentina; whilst, unobserved factors (e.g., culture and gender stereotypes) come into play in Peru and Guatemala. These results highlight factors that are deeply entrenched in the digital divide from social and cultural norms to attitudes toward women that need to be considered when analyzing women's access and use of ICT. According to the Agüero et al. (2020), women in six Latin American countries make more limited use of digital devices—mobile phones, computers, laptops—and the Internet, including their participation in the platform economy. This lag in digital skills limits their ability to reap the benefits that

2. Platform economy and gender issues in the Global South

technology could provide. On the other hand, occupational segregation trajectories in the digital labor market are evident in the region, in the type of companies (one-person businesses led by women have a greater presence in care, commerce and services sectors, while those led by men have a greater presence in communication, technology, and finance) and in the type of tasks (women participate more in platforms for cleaning services and purchase/delivery of household items, and men have a higher presence on platforms offering taxi services).

These gender disparities in the digital labor market are also affected by social and economic structural problems, in particular the lack of strong institutions and legislation. Notwithstanding that platform work has already been operating in the region for several years, the absence of legislation is a critical problem that could increase the gaps and obstacles for women in this new labor market segment. A legal framework is needed to reconfigure the rights and working conditions faced by workers, making it possible to design new public policies that address traditional labor market issues but in a new scenario that includes technology-enabled jobs. Currently, in countries like Argentina, Colombia, Ecuador, Guatemala, Paraguay, and Peru, digital platforms can obtain operating permits but although there are legislative bills no laws have been passed to regulate digital job modalities.

3. Data

Most studies that examine how digital labor is expanding in developing countries use big data approaches consisting of quantitative data extraction from work platforms and interviews with stakeholders (Graham, Lehdonvirta, et al., 2017; S4YE, 2018). These studies have been based on data extraction from one specific online platform, but there is some research bias. Most of the information compiled about the people involved in digital labor (i.e., sellers or customers) come from invisible profiles, which can create a statistical bias in the sample of data collected toward "less successful" workers (Graham, Lehdonvirta, et al., 2017). Because it is an emerging research field, appropriate methodologies are still underdeveloped: there is a lack of data about the real profile of digital workers and penetration levels of online gig work in developing countries.

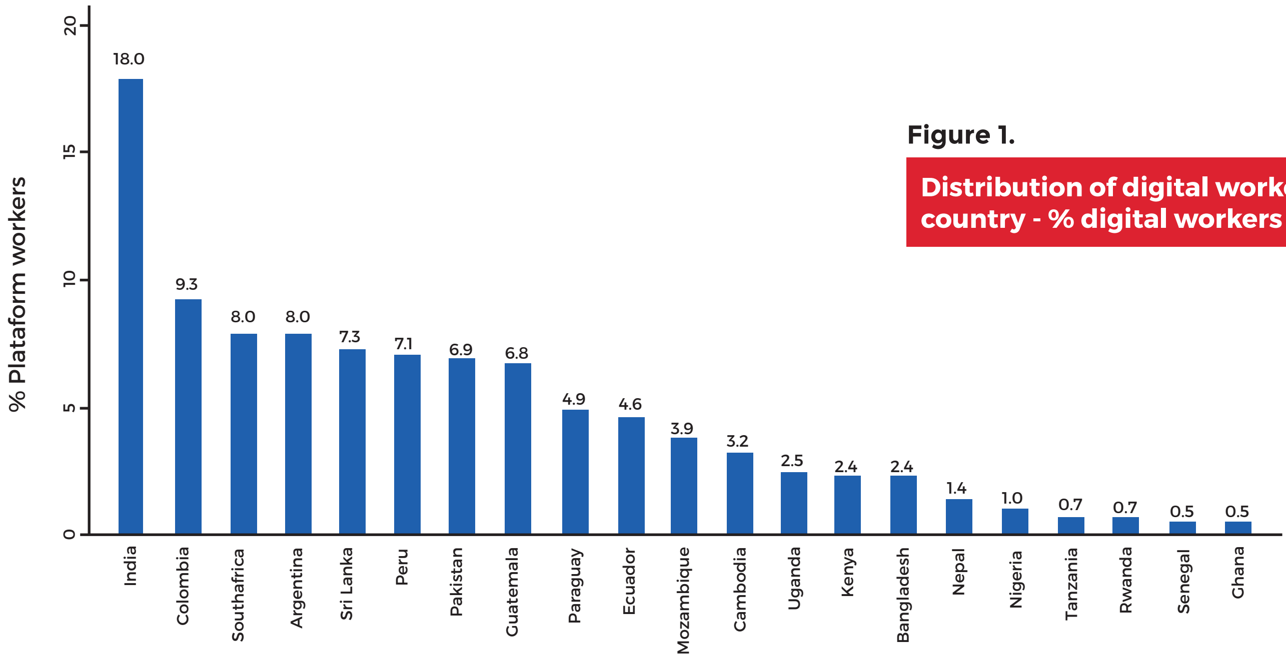
The data used in this paper is part of the After Access project[8], carried out since 2017 in the Global South, in Africa, Asia, and Latin America by RIA (Research ICT Africa), LIRNEasia and the Institute of Peruvian Studies (through the Regional Dialogue on Information Society), respectively. The focus of this project was on the demand-side of ICT, access, and use of new technologies, with nationally representative data. Surveys provide information about three main components of digital work in these Global South countries. First, the After Access Survey identifies people that participate in the digital economy by asking if they earn money doing microwork activities. Second, it makes it possible to identify the kind of digital work activity performed (driving, delivery, online tasks, or housekeeping activities). Finally, there is information about the reasons for participating in the digital labor market (income, flexible work hours, job experience, or lack of other job opportunities). Besides, After Access collected information about access and use of different ICT, that permits the characterization of digital workers by their digital skills and experience level.

In total 33,161 people were interviewed across the three regions, 12,777 in Africa, 11,214 in Asia and 9,170 in Latin America[9]. As mentioned above, digital platforms can only be accessed by those who have access to or use the Internet. As such, individuals who do not use the Internet are excluded from the final sample. This significantly reduces the sample size: 13,741 respondents who reported using the Internet, 51% of which are female.

Even though online platforms could potentially provide much-needed jobs to the majority of unemployed people in developing countries, their potential is hampered by low levels of Internet penetration, especially in Africa and Asia. For instance, the survey shows that countries with the lowest Internet penetration have the lowest uptake of microwork among the surveyed countries. Senegal and Ghana, two of the African countries with the lowest level of Internet use, have the fewest micro-workers among the surveyed countries at 0.5% of the sample used for the analysis **(see Figure 1)**.

Figure 1.

Distribution of digital workers, by country - % digital workers



Source: Authors based on After Access data.

[8] See www.afteraccess.net

[9] In Lesotho, information on microwork was not included on the questionnaire and was excluded from the final sample.

3. Data

However, in some countries, like India, the rise of bots and Artificial Intelligence (AI) has generated new job opportunities in established industries. These new technologies have not only had a positive impact on knowledge-intensive sectors like medicine, education and other professional services but they have also created jobs for informal workers who use digital technologies to perform virtual work locally and globally. This is evidenced by an exponential growth in the number of digitally driven start-ups in India (ICRIER, 2017). Among the surveyed countries, India has the largest share of digital workers (18%), followed by Colombia (9%), and South Africa and Argentina (8% each) of the sample used for the analysis.

There are noticeable differences between men and women in the type of digital work being performed. As table 1 shows, 29% of men work in ride-sourcing versus only 20% of women, marking a statistically significant difference of 9%. The differences are less noticeable in other types of work, except for cleaning tasks in which 30% of women engage in these activities, compared to 21% in the case of men (a statistically significant difference). Of the main reasons for securing work through digital platforms, the most important for women is control over their schedules due to child care, school, and/or other obligations, as well as to gain work experience for future job opportunities. However, when they cited “fill in gaps or fluctuations in other sources of income” as a reason to undertake digital work, the difference is not significant between men and women. These results pertaining to motivation show the perception about what benefits women and men expect when they decide to work in the digital economy.

Table 1. Descriptive statistics

Variables	Male(1)		Female(2)		Difference	P-Value
	Mean	N	Mean	N	(1) - (2)	
Participation in the digital labor market						
Ride-sourcing	0.294	347	0.198	243	0.096	0.0081
Delivery	0.406	347	0.420	243	-0.013	0.7451
Task	0.268	347	0.296	243	-0.028	0.4521
Cleaning	0.207	347	0.296	243	-0.089	0.0134
Other	0.228	347	0.193	243	0.034	0.3186
Motivation						
Control his/her time	0.251	347	0.490	243	-0.239	0.0000
Extra income	0.326	347	0.362	243	-0.036	0.3582
Gain work experience	0.357	347	0.473	243	-0.116	0.0047
Fun/leisure time	0.207	347	0.362	243	-0.077	0.0485
Lack of labor opportunities	0.239	347	0.366	243	-0.127	0.0008
Other	0.256	347	0.140	243	0.117	0.0006
Digital skills						
Solve tech problems by him/herself	0.455	347	0.502	243	-0.047	0.2640
Years of experience using the Internet	6.011	347	6.276	243	-0.265	0.5081
Gain work experience	0.357	347	0.473	243	-0.116	0.0047
ICT assets						
Smartphone	0.755	347	0.737	243	0.018	0.6130
Computer/Laptop	0.501	347	0.432	243	0.069	0.0972
Occupation and labor market						
Student	0.150	347	0.119	243	0.031	0.2899
Unpaid houseworker	0.049	347	0.152	243	-0.103	0.0000
Unemployed searching for work	0.069	347	0.103	243	-0.034	0.1446
Employed	0.282	347	0.243	243	0.040	0.2846
Independent worker with employees	0.104	347	0.045	243	0.058	0.0098
Independent worker without employees	0.259	347	0.198	243	0.062	0.0810
Unpaid family worker	0.009	347	0.107	243	-0.098	0.0000
Labor experience	7.448	347	5.935	243	1.513	0.0320
Social capital						
Socializing with friends (hours)	8.362	347	8.280	243	0.082	0.9397
Socializing with social network (hours)	4.051	347	3.391	243	0.660	0.2423
Socioeconomic characteristics						
Total income	1259.726	347	911.089	243	348.637	0.0014
Education level	2.334	347	2.251	243	0.083	0.1504
Married	0.432	347	0.358	243	0.074	0.0704
Single	0.473	347	0.416	243	0.057	0.1714
Age	31.977	347	32.140	243	-0.163	0.8668
Rural	0.271	347	0.235	243	0.036	0.3205

Note: Agricultural, property rental, government transfers, pension, allowances, scholarships, and investment income excluded. Income is expressed in 2015 international US dollars converted using PPP exchange rates. Source: Authors based on After Access data.

3. Data

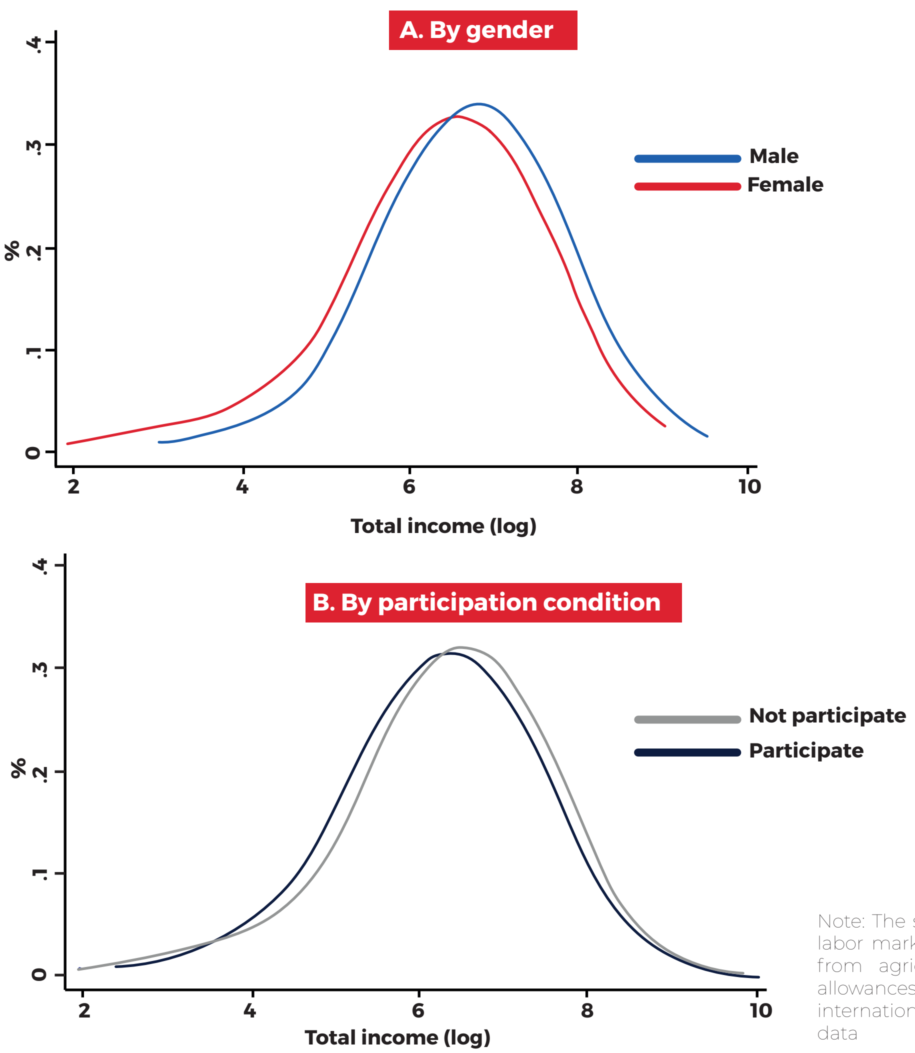
While there are no statistically significant differences in digital skills and having ICT assets between men and women, more gender differences are found in terms of occupations. Fifteen percent of women reported unpaid housework (mostly housewives) as their main occupation, compared to only 5% of men. This indicates the possibility that women are

engaging in the digital economy while still doing house-related activities. The percentage of paid occupations (such as employed and independent occupations) is higher among men, whereas more women reported unpaid occupations (unemployed and unpaid family worker). Finally, men have more job experience reinforcing gender penalties showed by the literature about gender inequalities in the labor market.

It is also important to mention that we did not find gender-related statistically significant differences in individual covariates (socioeconomic characteristics), which make our estimates robust due to a strong balance in individual characteristics: the effect over income levels could not be attributed to differences in education or age between men and women but to their participation in the digital labor market (after controlling for the main occupation categories).

Panel A in **Figure 2** illustrates the differentials in income between males and females who participate in the digital labor market. As the data shows, there is a gender pay gap in favor of men, that is, males who participate in the digital labor market tend to have a relatively higher income than their female counterparts participating in the same labor market. Similarly, Panel B in **Figure 2** shows the differentials in income between women who participate and those who do not participate in the digital labor market. There is a slight gender income gap in favor of women who participate in the digital labor market.

Figure 2. Income distribution - % digital workers



Note: The sample in Panel A includes only participants in the digital labor market. The sample in Panel B includes only women. Income from agriculture, property rent, government transfers, pension, allowances, scholarships, and investments are excluded. Income is in international 2015 PPP USD. Source: Authors based on After Access data

4. Methodology

We seek to find a causal effect between individual characteristics (as well as current labor positions) and the probability of participating in digital labor activities, broken down by digital labor categories (i.e., ride-sourcing, delivery, online tasks, and cleaning tasks). We use two kinds of analysis to examine participation in digital labor markets and its effect on relevant labor market outcomes (income). On the one hand, we analyze the difference in income between men and women within the digital labor market (gender pay gap in the gig economy). On the other hand, we analyze the difference in income between women that participate and women who do not participate in the digital economy (the gig economy effect on women's pay).

4.1 The Gender Pay Gap in the Gig Economy

The methodology to assess the gender pay gap in the gig economy involves two approaches. First, we aim to analyze the main drivers of participation in the digital economy broken down by individual characteristics (in particular, gender). The factors that drive a person to participate in the digital labor market are different for men and women. According to ILO (2016), it is important to separate the factors influencing female participation in a specific labor market segment from those influencing men, in order to avoid gender-specific bias. Hence, we estimate a conditional logit model to assess the main determinants of the probability of participation in the digital labor market. Following Gillwald et al. (2018), we estimate the following model: [11]

$$P_i = \sum_{n=1}^{n} \beta_n X_n + u_i \qquad [1]$$

where P_i is a dummy variable equal to 1 if the individual participates in the digital labor market (0 otherwise); $\boldsymbol{X}$ is the vector of control variables that influence the participation decision which includes the following five group of variables: main occupation, work experience, digital skills, ICT assets, social capital, and individual socioeconomic characteristics. u is the standard normal error term.

In the second part of this strategy, the model focuses on those individuals who have already entered the digital labor market in order to analyze the gender pay gap in this particular segment. In this regard, the model denotes a static approach to gender income inequalities. Following (Shahiri & Osman, 2015; Bech & Tyrowicz, 2017), we estimate a Mincer income equation:

$$\boldsymbol{log\ (income_i) = \beta_0 + \beta_1 sex_i + \beta_2 X_i + \beta_3 digiskills_i + \beta_4 digiwork_i + \beta_5 country_i + \beta_6 \lambda_i + \varepsilon_i} \qquad [2]$$

where $\boldsymbol{income}$ refers to the log-income level of individual $\boldsymbol{i}$, $\boldsymbol{sex}$ is a dummy variable equal to 1 if the individual is a woman (0 if male), $\boldsymbol{X}$ is a vector of individual and household characteristics, $\boldsymbol{digiskills}$ is a vector of individual digital skills, $\boldsymbol{digiwork}$ and $\boldsymbol{country}$ denotes digital and country fixed effects, and $\boldsymbol{\varepsilon}$ is the standard error term. Equation **[2]** was estimated using a Heckman model to correct for self-selection issues between the independent and dependent variables: the Inverse Mills Ratio (IMR) ($\boldsymbol{\lambda}$) is obtained from the logit model previously used (equation **[1]**). The IMR is used to account for the self-selection bias of digital labor participation and income level (Heckman, 1979; Heckman & Sedlacek, 1985; Shahiri & Osman, 2015).

Finally, to estimate unobservable effects in the gender pay gap, we follow guidelines set by Jann (2008) and Springel (2011). Thus, we estimate two Mincer equations (both for women and men in equation **[2]**) and then we subtract both using a Generalized Blinder-Oaxaca Decomposition with Heckman self-selection model, as follows:

$$\boldsymbol{log\ (\underline{income}_m) - log\ (\underline{income}_f) = \underline{X}_m(\widehat{\beta}_m - \widehat{\beta}_0) + \underline{X}_f(\widehat{\beta}_f - \widehat{\beta}_0) + (\underline{X}_m - \underline{X}_f)\widehat{\beta}_f + (\widehat{\beta}_m \widehat{\lambda}_m - \widehat{\beta}_f \lambda_f)} \qquad [3]$$

The first three terms of the decomposition represent the unexplained and explained differentials between men and women based on worker characteristics. The first and second terms capture the difference between the actual and the pooled earnings for male and female digital workers. The first term measures the advantage of male digital workers, which is computed as the income that

[11] We estimate two logit models. First, in the general model we study the probability of work in the digital labor market without distinguishing by type of digital work. Second, in the specific model we consider the differences in digital jobs by estimating four logit models for each type of digital job (ride-sourcing, delivery, online tasks, and cleaning activities).

4. Methodology

men receive above what would be due if their sample characteristics were to be rewarded under the income structure β_0 The second term measures the disadvantage of female digital workers, which is equivalent to the ratio between the income women should receive if income structure β_0 were enforced and the income they actually receive. The third term is the pay gap attributable to differences in gender characteristics. Finally, the fourth term of the decomposition accounts for the contribution of selection bias to the income differential between male and female digital workers.

4.2 The gig economy effect on women's pay

As mentioned above, we need to control for self-selection bias before doing an examination of a causal effect in labor market decisions (Heckman, 1979; Heckman & Sedlacek, 1985). Thus, based on Lokshin & Sajaia (2004), we implement an Endogenous Switching Regression (ESR) model to estimate both the decision of participating in the digital economy controlling by individual and labor characteristics (among them, gender), in order to assess the gig economy effect on women's pay[12].

A person's decision to participate in the digital economy and the benefits obtained in terms of income can be modelled using a two-stage method. In the first stage, we develop a selection model for the decision to participate or not in the digital labor market. We assume that individuals are risk-averse agents that decide strategically whether to participate or not based on an expected benefit (i.e., an income premium versus a cost of participation). Following Maddala (1986) and Antle (2011), we adopt a moment-based approach that allows a flexible representation of the risk production function. In the present study, the dependent variable (log-income) can be defined as follows:

$$\boldsymbol{log\ (income_i) = f(T, X, \theta) + u} \qquad [4]$$

where $\boldsymbol{income_i}$ represents the income level of women $\boldsymbol{i}$. $\boldsymbol{T}$ refers to the decision to participate in the digital labor market, which takes the value of 1 if the individual participates, and the value of 0 otherwise. In addition, $\boldsymbol{X}$ is the set of explanatory variables that include: (1) individual and household characteristics; (2) digital skills; (3) type of digital job (ride-sourcing, delivery, online tasks, and cleaning activities); and (4) digital platform and country-fixed effects (dummies at the digital platform and country level to control for specific labor market factors that differ for each platform and country, respectively). Finally, $\boldsymbol{\theta}$ is a vector of parameters to be estimated and $\boldsymbol{u}$ is the error term that captures the uncertainty faced by individuals.

Nevertheless, estimating equation **[4]** poses two econometric challenges when estimating the relationship between income and the decision to participate in the digital labor market ($\boldsymbol{T}$) First of all, there is an endogeneity problem in the relationship between the individual income level and participation in the digital labor market because the most productive individuals may be the ones that decide to participate in the digital economy, precisely because they are the most productive. On the other hand, it is possible to observe a sampling selection bias due to unobservable heterogeneity in the differences between both groups of analysis (those who participate and those who do not participate in the digital labor market). For instance, variables like labor market experience, social capital, education level, and ICT assets can generate the opportunity for those individuals to participate in the digital economy with better (pre)conditions; they are self-selected within the participants in the digital market. Therefore, to deal with both problems we use an ESR to identify the impact of the decision to participate in the digital labor market on wage levels (in the two models described above).

In the ESR model, individuals are divided into two groups according to their decision to participate or not in the digital labor market (T =1 and T = 0, respectively). These individuals decide whether or not to participate in the digital economy based on an analysis of the expected net benefits that could be obtained when doing this type of activity. Thus, we can model the participation decision of individual $\boldsymbol{i}$ as a latent variable T_i^* as follows (the selection equation):

$$\boldsymbol{T_i^* = g(X, Z, \alpha) + \nu_i} \qquad [5]$$

[12] For this strategy, we select a subsample of the After Access 2017 Survey conformed only by women. Also, we run the same model but for the male sample.

4. Methodology

where $T_i = 1$ if $T_i^* > 0$ (0 otherwise). That is, individual i decides to participate in the digital labor market $(T_i = 1)$ only if the expected net benefits are positive $(T_i^* > 0)$. In addition, Z represents the set of determinants of T (similar to instrumental variables), which include ICT assets, digital skills and social capital variables. Likewise, the implications of the vector of control variables X are similar to those explained in equation **[1]**. Finally, α represents the vector of parameters to be estimated and v the error term with zero mean and variance σ_v^2 that controls the effect of unobservable factors (for example, the individual's motivation or ambition to participate in the digital labor market).

In the second stage of the ESR model, the effect of (not) participating in the digital labor market over the individual's income level is analyzed. A simple approach to assess this relationship is to include in equation **[4]** a dummy variable equal to 1 if an individual decides to participate in the digital labor market, and estimate this equation by Ordinary Least Squares (OLS). However, this model might be biased because it is assumed that the decision to participate in the digital labor market is exogenously determined, when it is an individual's endogenous decision. Therefore, we estimate separate equations for each state (regime on the ESR model) to estimate the effect over the income level: one for participants and another for non-participants. The structural equation is:

$$income_{1i} = X_{1i}\beta_1 + \epsilon_{1i} \quad , \quad if\ T_i = 1 \qquad [6a]\ \text{(Regime 1)}$$

$$income_{2i} = X_{2i}\beta_2 + \epsilon_{2i} \quad , \quad if\ T_i = 0 \qquad [6b]\ \text{(Regime 2)}$$

where $income_i$ is the level of an individual's income in regime 1 (participants) and regime 2 (not participants), X_i represents the vector of control variables (including Z variables of equation **[5]**). Parameters of interest are β_1 and β_2. Finally, it is assumed that the error terms of equations **[5]**, **[6a]** and **[6b]** have a trivariate normal distribution, with mean equal to 0 and a covariance matrix Σ with the following structure (i.e., $(v, \epsilon_1, \epsilon_2) \sim N(0, \Sigma)$):

$$\Sigma = [\sigma_v^2\ \sigma_{v1}\ \sigma_{v2}\ \sigma_{1v}\ \sigma_1^2\ .\ \sigma_{2v}\ .\ \sigma_2^2\ ]$$

where σ_v^2 the variance of the error term of the selection equation **[1]** (i.e., $Var(v) = \sigma_v^2$), σ_1^2 and σ_2^2 are the variances of the error terms of structural equations of regimes **(6a)** (i.e. $Var(\epsilon_1) = \sigma_1^2$) and **(6b)** (i.e. $Var(\epsilon_2) = \sigma_2^2$), respectively. Similarly, σ_{v1} and σ_{v2} are the covariances of v_i with ϵ_{1i} and ϵ_{2i}, respectively. It is important to mention that Y_{1i} and Y_{2i} are not observed simultaneously; therefore, the covariance between ϵ_1 and ϵ_2 is not defined.

An important implication of the error term structure is that the selection bias generates a non-zero covariance between the error term of the selection equation **[5]** and the structural equation **[6a and 6b]** (Maddala, 1986). The expected values of the error terms ϵ_{1i} and ϵ_{2i} conditional on sample selection in participants and not participants (i.e., T) take the following form:

$$E[\epsilon_{1i}|T_i = 1] = \sigma_{1v}\frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} = \sigma_{1v}\lambda_{1i}$$

$$E[\epsilon_{2i}|T_i = 0] = -\sigma_{2v}\frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} = \sigma_{2v}\lambda_{2i}$$

where $\phi(.)$ is the normal probability density function, $\Phi(.)$ is the normal cumulative density function, and $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)}$ and $\lambda_{2i} = \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$ are the Inverse Mills Ratios evaluated in the selection equation **[5]** and incorporated in structural equations (**[6a]** and **[6b]**) to address the selection bias problem. Thus, if the estimated covariances are statistically significant, the decision to participate in the digital labor market of individuals are correlated, which allows us to state an endogenous switching and reject the null hypothesis of the absence of selection bias problem. This model is defined as a switching regression model with endogenous switching (Maddala, 1986; Lokshin & Sajaia, 2004).

The ESR model can be used to compare expected individual income levels between participants and non-participants in the digital labor market. Furthermore, with the ESR model, we can estimate the treatment effect (T) using counterfactuals by

4. Methodology

calculating the expected values of income conditional on the regime chosen by the individual. Although the methodology employed by impact evaluation techniques cannot be carried out in the present research, the ESR model allows us to compare participants and non-participants and in the counterfactuals of i participants of the digital labor market decide not to participate and (ii) non-participants decide to participate in the digital labor market, as follows:

$$E[income_{1i}|T_i = 1] = X_{1i}\beta_1 + \sigma_{1v}\lambda_{1i} \quad [7a]$$

$$E[income_{2i}|T_i = 0] = X_{2i}\beta_2 + \sigma_{2v}\lambda_{2i} \quad [7b]$$

$$E[income_{2i}|T_i = 1] = X_{1i}\beta_2 + \sigma_{2v}\lambda_{1i} \quad [7c]$$

$$E[income_{1i}|T_i = 0] = X_{2i}\beta_1 + \sigma_{1v}\lambda_{2i} \quad [7d]$$

Equations **[7a]** and **[7b]** (also see **Table 1**) represent the conditional expected values that are already observed in the After Access sample. Equations **[7c]** and **[7d]** (also see **Table 1**) represent the counterfactuals cases. On the other hand, following Heckman et al. (2005) we can obtain treatment effects that allow us to analyze the influence of participation on the income level of women. In this way, we calculate the treatment effect on the treated as the difference between **[7a]** and **[7c]**:

$$ATT = E[income_{1i}|T_i = 1] - E[income_{2i}|T_i = 1] =$$
$$X_{1i}(\beta_1 - \beta_2) + (\sigma_{1v} - \sigma_{2v})\lambda_{1i} \quad [8]$$

which represents the effect of participation over the income level of women. Similarly, we can obtain the treatment effect on the untreated (ATU) for non-participants as the difference between **[7d]** and **[7b]**:

$$ATU = E[income_{1i}|T_i = 0] - E[income_{2i}|T_i = 0]$$
$$= X_{2i}(\beta_1 - \beta_2) + (\sigma_{1v} - \sigma_{2v})\lambda_{2i} \quad [9]$$

Therefore, the selection bias is corrected through _1i λ_{1i} d λ_{2i} equations **[7a]** – **[7d]**, and thus, ATT and ATU provide unbiased estimates of the effect of participation in the digital labor market on the income level of women.

Table 2. Conditional expected values and treatment effects

Sample	Participation decision T=1	T=0	Effect
Participants	(a) $E[income_{1i}|T_i = 1]$	(c) $E[income_{2i}|T_i = 1]$	ATT
Non-participants	(d) $E[income_{1i}|T_i = 0]$	(b) $E[income_{2i}|T_i = 0]$	ATU

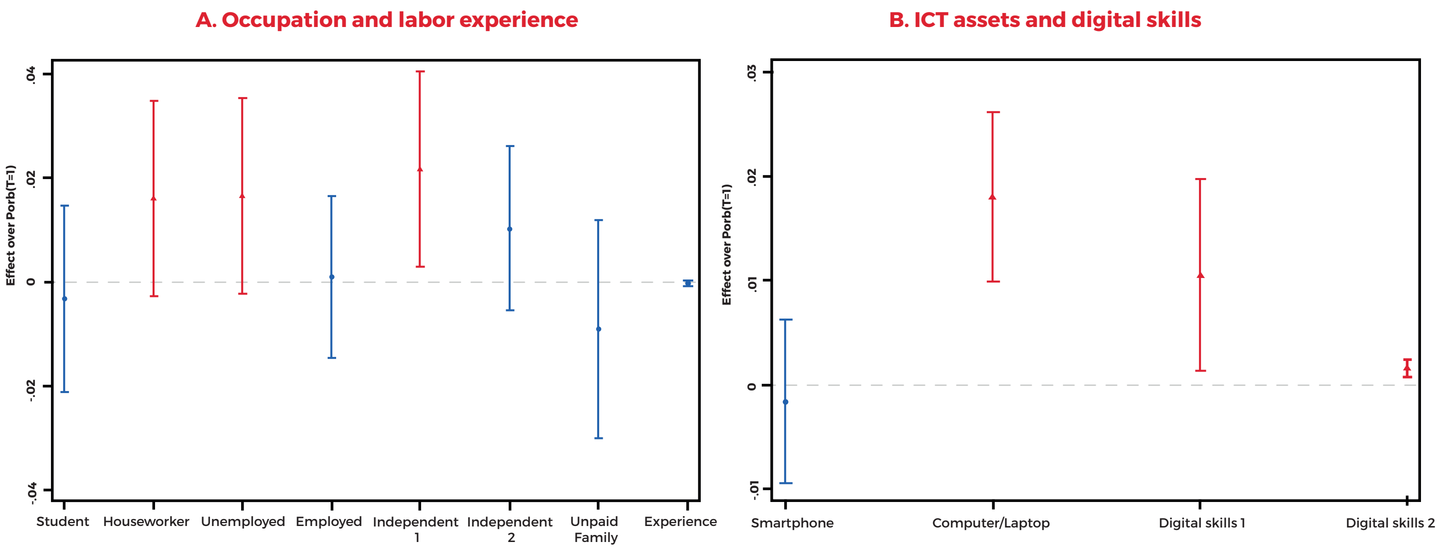
Source: Authors.

5. Results

5.1 Decision to participate

Results from the behavioral model to assess determinants of participation in the digital economy (**Figure 3 and Table A1**) suggest a positive and significant relationship between digital skills (measured by years of experience using the Internet and the ability to solve technical problems by him/herself) and participation in the digital labor market (Panel B). This shows that digital exclusion and inequality issues are not limited to the 'connected' and 'unconnected' categories; both problems are also present among those who are already online (second level of the digital divide). In addition, the availability of devices, more specifically computers or laptops, is a critical determinant of participation in the digital labor market; this is not the case of smartphones (even after including platform fixed-effects). Individuals who own computers are more likely to participate in digital work than those who do not have them, and having a smartphone does not play a key role in securing working through digital platforms. These issues should be further analyzed considering conditionalities on particular digital jobs. For instance, to secure work through digital ride-sourcing platforms, the individual must have access to a vehicle (car, motorcycle, etc.). This also is true for digital delivery platforms[13].

Figure 3. Determinants of participation in the digital labor market – Logit marginal effects



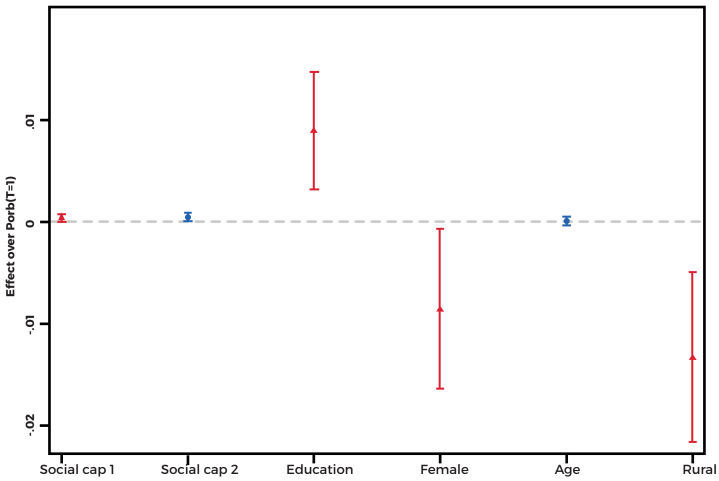
Note: Independent 1 = independent with employees, Independent 2 = independent without employees.

Note: Digital skills 1 = solve technological problems by him/herself, Digital skills 2 = Years of experience using the Internet.

[13] Unfortunately, the After Access survey does not include a question to identify the name of the ride-sourcing, delivery, online tasks, and cleaning digital platform used, which would make it possible to consider the conditionalities mentioned above.

5. Results

C. Social capital and socioeconomic characteristics



Note 1: Social capital 1 = Socializing with friends (hours), Social capital 2 = Socializing with social network (hours).

Note 2 : Red marginal effects mean statistically significant coefficients at 99%, blue marginal effects mean non-statistically significant coefficients. All models include country fixed effects. Source: Authors based on After Access data.

Furthermore, results show that digital work and formal labor (being employed) are not complements but rather substitutes: estimates for individuals who are unpaid houseworkers, unemployed and independent with employees point to an increase in the probability of work through digital platforms (Panel A). This suggests that digital work is still regarded as an inferior good/choice to formal labor. This could be attributed to payment structure and the lack of contractual obligations and rights in some of the online digital work activities. Hence, individuals with formal employment contracts are less likely to switch to these platforms because the rewards are lower and risky. However, unemployed people without basic income are more likely to consider online jobs as complements. For instance, about 34% stated that digital platform work provides them with extra income and 41% stated that it is important to get more work experience, an outcome which shows the potential of microwork to provide the necessary and much-needed job opportunities and real income to those who cannot find employment in the formal traditional labor market.

Finally, similar to Gillwald et al. (2018), digital inequalities tend to build on and exacerbate historical social disparities. Results show a positive and significant relationship between participation in digital labor platforms and educational level, whilst being female decreases the probability of participation in the digital labor market by 9%; living in rural areas is a barrier to participation in this new labor market.

5.2 The Gender Pay Gap in the Gig Economy

To quantify the gender pay gap in the gig economy, we use the Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973). The Blinder-Oaxaca decomposition model is used to study digital labor market outcomes by groups. Specifically, in this study, it permits the decomposition of mean log-incomes by gender, based on counterfactual regression models as shown in **Table 3.**

The results from the Blinder-Oaxaca decomposition model are consistent with the existing literature (Blau & Kahn, 2017) which shows that digital technologies tend to build on the existing inequalities between males and females. Overall, the difference in income between males and females is statistically significant: the mean log-income is 9 (810 USD/month) for males and 6 (403 USD/month) for females, resulting in a significant mean log-income gap of 3.4 (407 USD/month) (see Table 3, Panel 1). These results indicate that even after surpassing connection barriers (i.e., Internet access), females still face different challenges in the digital labor market. These results are consistent with the findings of Gillwald et al., (2018) who conclude that women are less likely to be hired in the digital labor market because of existing patriarchal values and norms which exclude them from most market labor segments.

The gender pay gap is further divided into two components. Firstly, the explained component reflects the changes in women's mean long-income if they had the same characteristics as men. Results show that by adjusting women's endowments (observable characteristics) to the same levels of men, female mean log-income would increase by about

5. Results

22%. However, a large percentage of differences in incomes between men and women is accounted for by the unexplained component (93% of the gender pay gap), which is usually attributed to gender stereotypes and discrimination. It is important to mention that this unexplained component also captures all potential effects of differences in unobservable variables (i.e., motivation, self-value of working, etc.). Therefore, unobservable factors such as discrimination and other unobserved characteristics might be responsible for differences in incomes between men and women who secure work through digital platforms.

Table 3. The gender pay gap in the gig economy – Oaxaca-Blinder-Heckman decomposition

Variables	(01)	(02)	(03)
	Dependent = Log-income		
	Overall	Explained	Unexplained
Male	9.393*** (0.331)		
Female	5.921*** (0.741)		
Difference	3.472*** (0.811)		
Explained	0.215*** (0.063)		
Unexplained	3.258*** (0.811)		
Occupation and labor market			
Student		0.003 (0.007)	0.001 (0.062)
Unpaid houseworker		0.021 (0.024)	0.028 (0.061)
Unemployed		0.004 (0.007)	0.048 (0.047)
Employed		0.021 (0.020)	0.085 (0.111)
Independent with employees		0.050** (0.021)	-0.020 (0.033)
Independent without employees		0.025 (0.018)	0.150 (0.102)
Unpaid family worker		-0.001 (0.023)	0.076* (0.043)
Labor experience		0.008** (0.010)	-0.065 (0.092)
ICT assets			
Smartphone		0.006 (0.011)	-0.049 (0.150)
Computer/Laptop		0.021 (0.014)	-0.155* (0.084)
Social capital			
Socializing with friends (hours)		0.000 (0.003)	0.008 (0.059)
Socializing on social network (hours)		-0.004 (0.007)	-0.094* (0.051)
Socioeconomic characteristics			
Education		0.017 (0.013)	-0.785*** (0.300)
Age		-0.002 (0.012)	-0.127 (0.351)
Rural		-0.003 (0.007)	0.066 (0.048)
Platform FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	590	590	590

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Results

Panel 2 of **Table 3** also shows that when women have similar characteristics to men, the main source of difference in mean income is due to differentials in occupation (being an independent worker with employees or unpaid family worker, and labor experience) ICT assets (having a computer or laptop), social capital (socializing with their social networks) and socioeconomic characteristics (educational level). Even if both women and men are independent workers with employees it would explain 5% of the existing gender pay gap, and when the number of years of labor experience of men and women is identical, the existing gender pay gap would decrease only 0.8%. Furthermore, adjusting women's characteristics to the level of males increases the mean log-income of female self-employed workers with employees by 5% and that of female unpaid family workers by 7.6%. However, our results indicate that adjusting women's characteristics to reflect those of men reduces the pay gap by 79%, and by 9% if the educational level and social capital were the same in men and women.

5.3 The Gig economy Effect on Women's Pay

Table 4 shows the results for the gig economy effect on women's pay. Column (1) presents the selection equation (which is similar to the results discussed in section 5.1 above), column (2) shows the results of the mincer function for regime 0 (women who do not participate in the digital labor market), and column (3) shows the results of the mincer function for regime 1 (women who do participate in the digital labor market).

The ESR model requires a set of instrumental variables to solve identification issues. In particular, we have to use a vector of variables that are directly correlated with the participation decision (selection equation) but do not affect (at least directly) the studied outcome variable (income). Following Barrantes et al. (2018) and Gilldwald et al. (2018), we use digital skills and ICT assets as determinants of the decision to secure work through digital platforms.

The suitability of using the ESR model depends on the existence of separated self-selection parameters between income and the two regimes of participation and no participation in the digital labor market.

According to Maddala & Nelson (1975), ρ_1 and ρ_2 are the correlations between the error term of the selection and the structural equations. If these correlations are not statistically significant, there will be no self-selection bias and the use of OLS would be enough, and if both correlations are statistically significant, it means that the self-selection bias goes in the same direction, and the use of a Two-Stage Heckman model would be sufficient. However, if the correlations are of different magnitude and only one is statistically significant, there would be a self-selection bias specific and different for the two regimes, validating the use of the ESR. **Table 4** shows that the correlation parameter is only statistically significant for no participation and it is positive, which means that there is endogeneity in the decision of working through digital platforms and income levels, justifying the use of the ESR model.

5. Results

Table 4. The gig economy effect on women's pay – ESR (female sample)

Variables	(01) Selection eq.	(02) Participation = 0	(03) Participation = 1
Dependent variable	Participation 0/1	Log-income	Log-income
Occupation and labor market			
Student	0.060 (0.191)	-0.714*** (0.190)	0.003 (0.392)
Unpaid houseworker	0.277 (0.179)	0.447** (0.202)	-0.486 (0.433)
Unemployed	0.484** (0.191)	-0.349 (0.214)	-0.547 (0.425)
Employed	0.262 (0.170)	3.590*** (0.178)	0.250 (0.370)
Independent with employees	0.506** (0.222)	3.599*** (0.243)	0.584 (0.443)
Independent without employees	0.333** (0.169)	3.128*** (0.182)	-0.262 (0.410)
Unpaid family worker	0.048 (0.182)	-1.004*** (0.186)	-0.535 (0.377)
Labor experience	-0.006 (0.005)	0.030*** (0.006)	0.012 (0.010)
ICT assets			
Smartphone	-0.025 (0.068)		
Computer/Laptop	0.146** (0.073)		
Digital skills			
Solve tech problems by him/herself	0.121* (0.082)		
Years of experience using Internet	0.029*** (0.008)		
Social capital			
Socializing with friends (hours)	0.006** (0.003)	-0.004 (0.003)	0.001 (0.005)
Socializing on social network (hours)	0.005 (0.004)	0.017*** (0.006)	0.012 (0.011)
Socioeconomic characteristics			
Education	0.008 (0.050)	0.109** (0.047)	0.250*** (0.082)
Age	0.001 (0.004)	0.008** (0.004)	0.014* (0.008)
Rural	-0.133* (0.075)	0.035 (0.069)	-0.091 (0.165)
σ_i		0.050	0.235
ρ_i		0.862***	-0.132
Platform FE	No	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	7,038	7,038	7,038

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Results

Table 4 shows the results of the ESR model for the female sample (the gig economy effect on women's pay), while Table A2 (Appendix) for the male sample (the gig economy effect on men's pay). Results for the selection equation show no differences in the determinants of the probability of participation in the digital labor market between men and women, except for occupation and education level, which means that for men education does play a role in the decision to participate in the digital economy, while for women it does not. Also, participating in the digital labor market is a substitute for formal labor occupations for females, but not for men where most of the occupation's categories are not statistically significant.

Regarding the impact over income levels, we confirm the substitution relationship between formal labor and digital labor as an income source generator: most of the job categories have an impact on the income level (similar to the labor literature) in the no-participation scenario, but it is not the case for participants (i.e., there are no other sources of income for women if they are securing work through digital platforms). Conversely, microwork is a complementary income source for men. Table A2 shows that the occupation variable does influence the income level for participants and non-participants in the digital labor market. Finally, for women, education level is a relevant variable (in particular, for policy design). Table 4 shows that a higher education level not only increases the income level of both groups, but the effect is stronger for those who participate in the digital labor market. Relating education results with the model for men, the importance of this dimension is reinforced: the effect of education on income levels is smaller for men in both groups.

In addition to analyzing the determinants of securing work through digital platforms and differentiating the impact on income by regimes, it is important to know what the real gains from participating in the digital labor market are. These gains could be analyzed from two points of view: (1) in the group of women who do participate, how much more they earn compared to a situation in which they would not have participated; and (2) in the group of women that do not participate, how much they would have earned if they had participated. These situations are counterfactuals: created scenarios to evaluate the effect of a treatment variable (participation in the digital labor market). Following Heckman et al. (2011), we create these counterfactuals based on the expected conditional values of the estimated coefficients, in which the ESR model is useful because it estimates different coefficients for each regime.

Table 5 shows the potential income gains of working through digital platforms for the counterfactuals mentioned above. The dependent variable (income) is in log-values, and the mean difference corresponds to the log-ratio between the two groups' income levels. Results show that the effect in both aspects—participation in the digital labor market and the potential gains of participation—is positive and statistically significant. Also, we transform these log-income values into exponential ones for a clearer interpretation. Therefore, for women who do participate, securing work through digital platforms represents an increase in their income of 74 USD/month; and for women who do not participate, working through digital platforms would have a potential increase in their income of 127 USD/month. Comparing these expected income gains with the results of the male model (Table A3), for men who do participate, working through digital platforms means an increase in their income of 62 USD/month (16% less than women); and for men who do not participate, working through digital platforms would have a potential increase in their income of 145 USD/month (14% more than women).

Table 5. Treatment Effects – ESR (female sample)

A. ATT Effect		
Conditional expected values	**Mean**	**95% CI**
$(a)\ E[Y_{1i}\|T_i = 1]$	6.553	[5.415 ; 7.464]
$(c)\ E[Y_{2i}\|T_i = 1]$	4.139	[3.424 ; 4.486]
Difference	2.414***	[1.973 ; 2.997]

B. ATU Effect		
Conditional expected values	**Mean**	**95% CI**
$(d)\ E[Y_{1i}\|T_i = 0]$	6.695	[5.619 ; 6.806]
$(b)\ E[Y_{2i}\|T_i = 0]$	4.221	[3.862 ; 4.872]
Difference	2.474***	[2.023 ; 3.757]

Note: *** p<0.01, ** p<0.05, * p<0.1.

6. Conclusion and recommendations

Despite the potential benefits that can be derived from digital labor platforms as an alternative to find and perform income-generating activities, there are several barriers for populations in developing countries to take advantage of this global resource. This paper characterizes digital workers of the Global South, with special attention to gender aspects and social inequalities. We estimate (a) the main determinants of entry decisions to digital labor markets (by gender) and (b) the main determinants that explain pay gaps between men and women (gender pay gap).

Using the Blinder-Oaxaca decomposition corrected for self-selection bias, which permits analyzing differences in labor market outcomes (income) by gender, the results show that gender inequalities are not limited to the 'connected' and 'unconnected' categories; they are also present among those who are already online (digital divide). Observable characteristics in women and men only explain 6% of the gender pay gap, leaving a space for the impact of other variables that the literature attributes to discrimination and social values to explain gender gaps. Also, even if the labor experience between men and women is identical, the existing gender pay gap would only decrease in 0.8%, and the gender pay gap would be reduced by 79% if the educational level was the same for men and women and by 9% in the case of social capital. Finally, these results indicate that there are unobservable characteristics critical to understanding the source of the gender pay gap in work through digital platforms. Thus, there is a need to conduct qualitative research to discern other factors such as employment discrimination and stereotypes in order to contribute to the formulation of more accurate public policies that seek to reduce social inequalities.

Moreover, the results justify the call for the design of differentiated public policies for men and women. We find positive impacts of securing work through digital platforms over income levels and potential increases in income. Nevertheless, the income premium for securing work through digital platforms is higher for women than men, but the potential gains for women is 14% less than the income gains for men.

Preparing for the future of work demands a rearrangement of gender roles and the closing of existing gaps. The technological revolution must be accompanied by an educational transformation and technical training in order to adequately respond to the new labor market demands. These policies will drive the development of greater autonomy for women, which will have a significant impact on economic growth and development by improving income levels and reducing current levels of inequality. The scope of labor policies and institutions considering the role of new technologies is relevant for the equal exercise of rights regarding the new market labor scene. Labor policies must be articulated with the development of new legislation and programs that facilitate and encourage the balance between the labor and family demands facing female and male workers in order to have a positive impact on women's income and time distribution.

Although having effective legislation is a necessary condition to achieve equal opportunities in the digital labor market, it is insufficient without effective labor inspection services that eliminate discrimination in paid work using surveillance mechanisms to ensure equal compensation for women and men, expanding opportunities for hiring and promoting women, and compliance with labor regulations and rights. On the other hand, to reduce gender inequalities in the labor market, public policies must promote the formalization of work and diminish the attractiveness of the informal economy. Furthermore, Global South countries face the challenge of undertaking reforms to end the prolongation of policies that deliberately use women's labor at a lower market value (lowest paying jobs) to boost the economy and to obtain competitive advantages.

Finally, in order to reduce labor market gender disparities and take advantage of the new opportunities that will arise with the fourth technological revolution, public policies will be required to enable the transitions between the school or university and the labor market, combining different job demands, reduce gender stereotypes, and promote greater female participation in STEM areas. There is also an urgency for the design of human capital training and technological innovation programs that anticipate the demands of the labor market (centered on digital skills), reverse the existing imbalance, and improve women's skills and employability levels. In addition, it is essential to promote reinsertion and reorientation policies that allow women to return to the labor market and/or to change job tasks at different stages of their lives, without this implying a high degree of risk for their future career and salary.

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Appendix

Table A1. Determinants of participation in the digital labor market – Logit marginal effects

Variables	(1) Participation =1
Occupation and labor market	
Student	-0.003 (0.009)
Unpaid houseworker	0.016* (0.010)
Unemployed	0.016* (0.010)
Employed	0.001 (0.008)
Independent worker with employees	0.022** (0.010)
Independent worker without employees	0.010 (0.008)
Unpaid family worker	-0.009 (0.011)
Labor experience	-0.000 (0.000)
ICT assets	
Smartphone	-0.002 (0.004)
Computer/Laptop	0.018*** (0.004)
Digital skills	
Solve tech problems by him/herself	0.010** (0.005)
Years of experience using the Internet	0.002*** (0.000)
Social capital	
Socializing with friends (hours)	0.000** (0.000)
Socializing with social network (hours)	0.000 (0.000)
Socioeconomic characteristics	
Education level	0.009*** (0.003)
Female	-0.009** (0.004)
Age	0.000 (0.000)
Rural	-0.013*** (0.004)
Country FE	Yes
Observations	13,741

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix

Table A2. The gig economy effect on women's pay – ESR (male sample)

Variables	(01) Selection eq.	(02) Participation = 0	(03) Participation = 1
Dependent variable	Participation 0/1	Log-income	Log-income
Occupation and labor market			
Student	-0.106 (0.128)	-2.013*** (0.167)	0.029 (0.273)
Unpaid houseworker	0.489*** (0.184)	-0.099 (0.341)	-0.517 (0.362)
Unemployed	-0.007 (0.142)	-1.230*** (0.199)	-0.076 (0.281)
Employed	-0.109 (0.110)	2.600*** (0.150)	0.589*** (0.228)
Independent worker with employees	0.190 (0.132)	2.607*** (0.170)	0.540** (0.262)
Independent worker without employees	0.034 (0.112)	1.979*** (0.154)	0.474** (0.219)
Unpaid family worker	-0.210 (0.351)	-0.478 (0.374)	2.101* (1.091)
Labor experience	-0.003 (0.005)	0.021*** (0.006)	0.002 (0.010)
ICT assets			
Smartphone	-0.005 (0.062)		
Computer/Laptop	0.249*** (0.062)		
Digital skills			
Solve tech problems by him/herself	0.056** (0.060)		
Years of experience using the Internet	0.014*** (0.005)		
Social capital			
Socializing with friends (hours)	0.002 (0.003)	0.001 (0.003)	0.002 (0.005)
Socializing with social network (hours)	0.005 (0.003)	-0.000 (0.004)	-0.014 (0.009)
Socioeconomic characteristics			
Education	0.184*** (0.043)	0.044* (0.045)	0.088* (0.101)
Age	-0.001 (0.003)	0.015*** (0.004)	0.010 (0.008)
Rural	-0.173*** (0.064)	-0.060 (0.064)	0.154 (0.125)
σ_i		0.814***	0.408***
ρ_i		-0.016	-1.837***
Platform FE	No	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	6,703	6,703	6,703

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A3. Treatment Effects – ESR (male sample)

A. ATT Effect		
Conditional expected values	**Mean**	**95% CI**
$(a)\ E[Y_{1i}\|T_i = 1]$	8.691	[7.277 ; 8.968]
$(c)\ E[Y_{2i}\|T_i = 1]$	6.865	[6.461 ; 7.232]
Difference	1.826***	[0.582 ; 1.904]
B. ATU Effect		
Conditional expected values	**Mean**	**95% CI**
$(d)\ E[Y_{1i}\|T_i = 0]$	8.270	[7.423 ; 8.914]
$(b)\ E[Y_{2i}\|T_i = 0]$	5.593	[5.240 ; 6.010]
Difference	2.677***	[1. 101 ; 3.073]

Note: *** p<0.01, ** p<0.05, * p<0.1.