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DIGITAL ADOPTION AND WOMEN IN THE LABOR MARKET: INDONESIA'S CASE

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ABSTRACT

Although the advantages of digitalization are frequently mentioned, there is still a persistent gender disparity in labor participation, especially in developing nations. This study examines the extent to which digitalization guarantees gender equality. Specifically, it aims to analyze the impact of internet usage on women's involvement in Indonesia's workforce. This study additionally examines the impacts in various parts of the country. Through the use of panel Tobit regression, utilizing district-level data obtained from SUSENAS-KOR, SAKERNAS, and INDO-DAPOER for the years 2017-2019, we have discovered a noteworthy and positive correlation between the utilization of the internet and the participation of women in the labor force. The observed effect remains strong even after accounting for additional factors. The heterogeneity analysis indicates that the correlation between internet usage and female labor force participation is more pronounced in the Java region than in areas outside Java. However, obstacles still prohibit women from accessing the advantages of digitalization. Hence, the proposed policy entails prioritizing equitable internet access and diminishing the obstacles to women's participation in the labor market to attain gender equality.

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Introduction

Indonesia, the most prominent Southeast Asian economy, effectively handled the 1998 Asian Financial Crisis, attaining substantial economic expansion and decreasing the poverty rate by over 50 percent in 2019 (World Bank, 2020a). Even with this remarkable accomplishment, there was still a persistent gender imbalance in Indonesia's employment force. Over the past thirty years, there has been little change in the disparity between the rates of women's and men's involvement in the workforce. The involvement rates for women and men remained stable at between 50 percent and 80 percent, respectively (World Bank, 2020b). Indonesia's labor force participation rate, which is a component of the Global Gender Gap Index, remained high in comparison to the Association of Southeast Asian (ASEAN) countries. In 2020, Indonesia was 115th out of 153 countries, placing it in the bottom three among the 10 ASEAN countries (World Economic Forum, 2019).

Simultaneously, as the digital economy expands, Indonesia is also confronted with the issue of the digital gender divide. The issue, as defined by the United Nations Educational, Scientific and Cultural Organization (UNESCO) and EQUALS (2019), is "… gender-biased coded into technology products, pervasive in the technology sector and apparent in digital skills education". The Organization for Economic Co-operation and Development (OECD) (2018) states that women's involvement in the digital economy is often hindered by limited access, inadequate education, insufficient skills, low digital literacy, and prevailing social-cultural norms. The disparity, however, may hinder women's engagement in the workforce and their production level. According to the Economist Intelligence Unit (2020), Indonesia ranked 50th out of 100 countries in terms of gender disparity in internet access. The gender gap score was 8.1 points, indicating that men in Indonesia have 8.1 percent more internet access than women.

The employment gender gap and the digital gender barrier have emerged as significant concerns for Indonesia, given that one of the Sustainable Development Goals (SDGs) for 2030 is to attain gender equality and empower women and girls. In addition, the digital economy presents a chance for Indonesia to attain a GDP of USD 150 billion or a 10 percent increase in economic growth by 2025, provided that digitalization is coupled with improved labor participation and productivity (McKinsey, 2016). Therefore, Indonesia needs to address the gender disparity in labor in the digital age to empower women in the workforce, particularly during the demographic bonus period when productive age surpasses non-productive age.

The impact of digitalization on gender disparity is a topic of debate. While digitalization offers flexibility in working hours, it may limit female labor due to preexisting obstacles. Women often face greater challenges in managing family care and professional commitments, leading to reduced participation and job quality. The International Labour Organization (ILO) (2018) found that women with toddlers in developing nations worked five hours less and engaged in nighttime employment using digital platforms. Additionally, women typically have less extensive access to the internet compared to men, with 184 million fewer women with mobile phones and 250 million fewer online than men (International Telecommunication Union, 2017). In Indonesia, internet access is limited to 20 percent of women (World Wide Web Foundation, 2016). Infrastructure availability, cultural norms, and social standards also impede women's access to the internet. Thus, notwithstanding the reverberations of the advantages of digitalization, the gender disparity may endure, specifically in developing nations.

Our study adds to the extensive literature on the impact of technological adoption, specifically on the participation of women in the labor sector. Studies conducted by Frey & Osborne (2017) and Watson et al. (2018) yield contrasting findings about the impact of digitalization on the workforce's ability to enter the labor market. While the evidence derived from prior research may be persuasive, there needs to be more understanding regarding the applicability of these findings at the subnational level in Indonesia. Another typical drawback of these studies is that they model female labor participation using linear specifications, which is inappropriate when working with such a small number of dependent variables. In order to close this gap, this paper examines if digitalization is a reliable means to achieve gender equality in the labor force. It also seeks to identify the factors that influence female labor force participation, with a specific focus on Indonesia, by analyzing the impact at the regional level. In order to accomplish this purpose, this study utilizes the Tobit model using panel district data. This study also examines the variation in characteristics between Java and non-Java islands.

The paper will be given in the following manner. Section II comprises a comprehensive examination of previous research projects and economic theory. Section III presents an econometric methodology and a strategy for identification. Section IV analyzes the extent of data coverage and the methods used to measure it. The findings obtained from the Tobit model are analyzed in Section V. Section VI serves as the final part of the text, where conclusions and inferences are drawn. Section VII promotes and supports further investigation.

Literature Review

Quantifying digitalization's direct effect on women's workforce involvement may provide challenges. Although digital transformation and labor gap stagnancy have been shown to have prospective benefits, the relationship between these two variables needs to be clearly evident due to conflicting results from past studies. This section begins by presenting a theoretical framework for understanding the impact of digitalization on job outcomes in a broad manner. The forthcoming literature review will be guided by examining the advantages of digitalization for women in the workforce to establish the fundamental structure for this study.

This study expands upon an extensive collection of literature investigating the impact of technical advancements on employment. On the downside, Frey & Osborne (2017) used Keynes's prediction to investigate how susceptible future employment will be to computerization. According to the statement, the prediction of widespread technological unemployment results from our ability to reduce the need for human labor faster than we can create new job opportunities. The researchers employ the Gaussian process classifier to gauge the likelihood of future computerization and evaluate its effects on labor market results in the United States (ibid). The researchers discovered that implementing technology, specifically called 'computerization' in their study, might result in significant reductions in employment (ibid).

Another strand of studies, exemplified by Kuhn & Skuterud (2004), provides impartial evidence of digitalization, specifically examining the internet's impact on decreasing the duration of unemployment. Utilizing the probit model, they discovered that in certain instances, internet job search can be related to a shorter duration of unemployment; however, in other cases, they observed the reverse trend (ibid). There are two possible explanations for the inconsistent results: internet use is inefficient in reducing unemployment length, or there is a negative selection bias in the choice to utilize the internet for job searches due to unobservable factors (ibid). The latter issue might have a major impact on the estimations; however, there is no further information on how to tackle it being presented in the paper.

Conversely, a study by Watson et al. (2018) purportedly presents empirical support for digitalization, specifically regarding its potential advantages for women in the workforce. Controlling for country-fixed effects, a time trend, and numerous other controls, they discovered a robust and statistically significant relationship between women's workforce participation and Internet usage using cross-country data between 2000 and 2016 (ibid). Similarly, Dettling (2017) discovered that the utilization of high-speed internet in the United States increased the labor force participation of married women by 4.1 percentage points from 2000 to 2009. The findings also suggest that college-educated married women with children experience the most substantial advantages (ibid).

Multiple studies have been conducted on the impact of technological adoption, specifically on the participation of women in the labor sector. For instance, a study conducted by Cavalcanti & Tavares (2008) suggests that reducing the cost of household appliances between 1975 and 1999 in the United Kingdom led to a 10 to 15 percentage point rise in women's workforce participation. Applying OLS analysis to data from OECD countries, the researchers utilize a panel model to examine the relationship between women's labor force participation and the relative price change index of household appliances. They control for various covariates, including country dummies, GDP growth, consumer price index, GDP per capita for males, a shared time trend, urban population, and the proportion of government spending in relation to GDP (ibid).

This study is also connected to the wider body of scholarship that explores the factors influencing women's engagement in the workforce. Goldin (1995) demonstrates a pattern of decreasing female employment involvement when a country transitions from low to middle-income status and increasing participation as the country progresses from middle to high-income status. It is a rational conclusion that the greater the wealth level of a country, the greater the opportunity cost for women in that country to exit the workforce. In addition, Watson et al. (2018) contend that poverty and necessity are the primary factors contributing to a significant female workforce involvement in a low-income country with a substantial agricultural sector. Furthermore, they highlight that certain countries, such as Indonesia, exhibit a 'within-country U-shaped link' between GDP and women's labor participation (ibid).

Asian Development Bank (2015) asserts that, apart from income level, increasing educational achievement and decreasing fertility rate are necessary but not enough to entice women to participate in the labor market in the Asia-Pacific region. They discovered that one of the most significant obstacles that discourage women from joining the workforce is the disparity in pay and job quality compared to men. In addition, there are prevailing social conventions that prioritize domestic labor as the primary role of women. On the contrary, Thevenon (2013) emphasizes the significance of declining fertility and educational attainment as the primary factors driving the rise in female labor force participation in OECD nations.

While the evidence presented in previous research appears to be persuasive, there needs to be more understanding regarding the practical implications of these findings at the subnational level, particularly in developing nations such as Indonesia, where diverse cultures and social norms continue to exist. These contradictory findings will also hold if any further unknown or unobservable confounding variables affect women's participation in the labor force. Furthermore, a prevalent drawback of these studies is that they model female labor force participation using linear specifications, which is less suitable when the dependent variable is limited. Therefore, this research aims to address this deficiency by utilizing more current and dependable data and more suitable criteria, which will be elaborated upon in the subsequent segment.

Empirical strategy

This analysis uses the following identification-based approach design. This study utilizes the Tobit model to analyze a censored dataset of a dependent variable. The variable in question is female labor participation, which ranges from zero to one hundred percent and has positive values. Under these circumstances, Tobit would provide a more accurate estimation that aligns closely with the range of values of the dependent variable, as opposed to the OLS model. Secondly, we add explanatory variables to each model individually until we estimate seven models. This approach finds the model specifications and offers a robustness assessment tool. In order to determine whether the digitalization effect varies between the two locations, we build two Tobit estimations for Java and non-Java using the covariates discovered in the previous phase. Lastly, the endogeneity test is run. Using the most reliable model definition, we investigate whether the estimation has an endogeneity problem.

A linear regression between the dependent variable y and the independent variables X in a model where the dependent variable y is a continuous, strictly positive probability equal to zero may produce questionable findings (Wooldridge, 2013). In addition to the possibility of receiving a negative fitted value from the variable range, the interpretation of the estimation coefficients may be misleading due to the constant partial impact (ibid). As a result, in order to interpret the partial effect of the independent variable X, it is essential to have a model that predicts values for variable y exclusively within a specified range (ibid). Thus, Tobit estimation provides a practical resolution for mitigating these concerns.

We subsequently utilize the Tobit model:

$$FLFP_{it} = \alpha + \beta fnet_{it} + \sum_{k=1}^{6} \gamma_k Controls_{kit} + u_{it} \tag{1}$$

i stands for district 1 to 514, and t stands for period. Both dependent and independent variables are continuous. Female labor force participation or FLFP and the proportion of females utilizing the internet $fnet$ are the variables of interest in this research. Several covariates are employed to account for additional confounding factors of FLFP, which will be elaborated upon in the following section. FLFP illustrates the attributes of censored data; the absence of a boundary hindered the observation of every value. Therefore, this paper will adhere to the censored Tobit protocol, as the exogenous variable could still be observed at a predetermined threshold.

This study aims to develop a robust model that explains how internet usage affects women's involvement in the labor force. In order to verify the robustness of each Tobit model, we add control variables one at a time until we find a model that exhibits a generally constant coefficient's size, direction, and significance.

Java and non-Java differ in many aspects, including social conventions, development, and infrastructure. While acknowledging that Java may offer superior internet infrastructure and access, this study aims to determine whether there are regional differences in the impact of female internet use on female labor force participation. Thus, we build two models using districts that are Java and those that are not, and we contrast the control variable's coefficient estimation.

In addition, we are concerned about the endogeneity of female internet usage based on earlier research. If the control variable and the error term are correlated, leading to inconsistent coefficient parameters, the model is said to be endogenous (Cameron & Trivedi, 2005). According to Nguyen (2019), there are three primary reasons for endogeneity: measurement error, omitted variables, and reverse causality or simultaneity. This study implements a variety of strategies to resolve these issues.

Initially, we are creating seven models that incorporate numerous control factors that are believed to influence female labor force participation. We will next examine the significance and stability coefficient of female internet utilization. This stage is analogous to the previously described robustness check. In undertaking this action, we aim to mitigate the potential for omitted variable bias. Furthermore, when considering potential measurement error, it is worth noting that the percentage of females utilizing the internet has been identified as the prevailing indicator for assessing digitalization, as evidenced by prior research. Moreover, this study utilizes reliable data sources, ensuring a substantial sample size that extends to the district level, thereby ensuring representativeness. Therefore, the issue of measurement error is no longer relevant to this investigation.

Lastly, regarding the issue of simultaneity, we acknowledge that a correlation between internet usage and the fluctuating participation of women in the labor force does not necessarily imply a causal relationship between the two. A statistically significant correlation between increasing female labor force participation and internet utilization, according to Watson et al. (2018), does not necessarily imply a causal relationship. They argue that the increase in internet usage may be attributed to greater female labor force participation, which they call 'demand-driven technical change'. However, it is improbable for both phenomena to happen simultaneously. Hence, we perform a test to confirm that simultaneity is, in fact, a concern in our data, as opposed to simply adopting this argument.

Data and Measures

This study employs panel data from 2017 to 2019, encompassing 514 districts in Indonesia. Data is acquired from multiple sources, including the World Bank-Indonesia Database for Policy and Economic Research (INDO-DAPOER), Central Bureau of Statistics (BPS), the National Labor Force Survey (SAKERNAS), and the National Socioeconomic Household Survey (SUSENAS-KOR).

FLFP, the dependent variable, is obtained from SAKERNAS. Since 1986, this annual survey has collected data on national labor market variables within the household sample. This survey has consistently furnished a representative sample size for estimation purposes, extending to the district level since 2017. By utilizing personal data, it is possible to discern which household women are categorized as labor force members. It enables us to compute the total participation rate at the district level. The labor force, as defined by Central Bureau of Statistics (2014), comprises gainfully employed individuals who sustain an ongoing job search during the two time periods surveyed.

To represent digitalization as a proxy for the independent variable of interest, we utilize the proportion of females who utilize the internet, derived from SUSENAS-KOR. This survey gathers data from every household member, encompassing their internet utilization for many objectives. Based on the previously specified notion of the labor force, we limit our sample to females who are 15 years of age or older. Subsequently, we calculate the total number of individuals at the district level.

To account for additional confounding variables, we employ five variables. The variable per capita Gross Regional Domestic Product (GRDP) and population density are transformed into natural logarithms to handle large magnitudes. Population density and per capita GRDP information are obtained from BPS-Statistics Indonesia. P0, the variable poverty head-count ratio, signifies the poverty rate obtained from the INDO-DAPOER. The variable women's mean years of schooling (MYS) is employed in this study as a measure of women's level of education. As a final variable, the equation incorporates the variable life expectancy (LE) of women, which measures their overall health. Life expectancy and average years of education are statistics gathered from BPS-Statistics Indonesia.

Descriptive Statistics

Table 1 presents the statistical summaries of the dependent and independent variables. Most variables exhibit a comparable range with standard deviation, minimum, and maximum values throughout the observation period. Female internet usage (*fnet*) exhibits a comparatively positive trend in its mean value throughout these periods, whereas the means of all other variables remain relatively stable. Between 2017 and 2019, the mean value of *fnet* increased from 27.685 percent to 40.978 percent.

Table 1: Summary Statistics of Variables

Variable	Units	Year	Obs.	Mean	Std. Dev.	Min	Max
(1)		(2)	(3)	(4)	(5)	(6)	(7)
FLFP	Percent	2017	514	53.482	11.626	22.578	97.100
		2018	514	55.011	11.305	34.043	96.115
		2019	514	54.084	10.393	30.274	97.379
fnet	Percent	2017	514	27.685	13.255	0.000	69.242
		2018	514	34.770	14.600	0.000	75.879
		2019	514	40.978	15.687	0.000	82.418
lnGRDPcap	-	2017	514	3.293	0.671	1.400	6.074
		2018	514	3.331	0.665	1.471	6.129
		2019	514	3.368	0.659	1.493	6.190
pov	Percent	2017	514	12.966	7.982	1.760	43.630
		2018	514	12.340	7.841	1.680	43.490
		2019	514	11.973	7.755	1.680	43.650
lnDENS	-	2017	514	5.185	1.996	-0.266	9.917
		2018	514	5.198	1.993	-0.223	9.931
		2019	514	5.211	1.990	-0.190	9.943
MYS	Years	2017	514	7.580	1.774	0.580	12.340
		2018	514	7.698	1.777	0.720	12.350
		2019	514	7.824	1.769	0.830	12.360
LE	Years	2017	514	70.802	3.609	56.190	79.450
		2018	514	71.007	3.559	56.380	79.500
		2019	514	71.269	3.484	56.740	79.520

Source: Authors' estimate (2020)

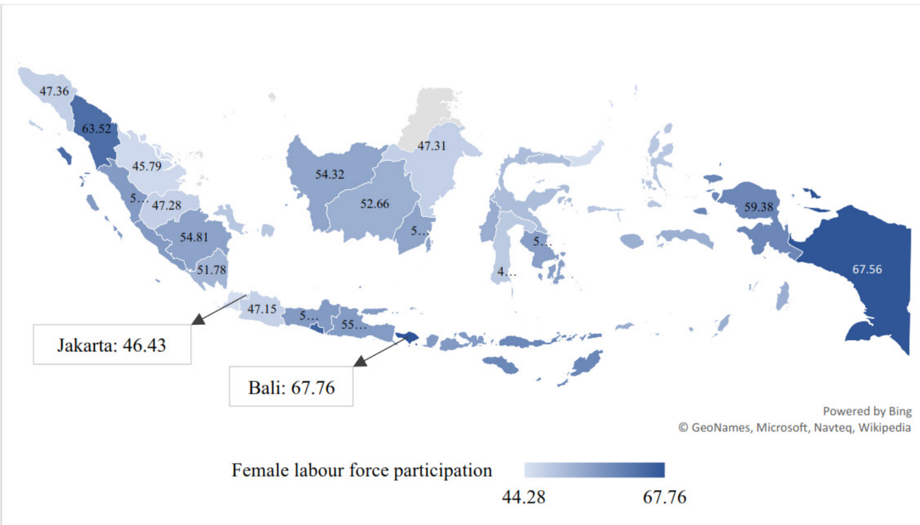

Figure 1: Average Female Labor Force Participation Per Province (%) in 2019

Source: SAKERNAS Data

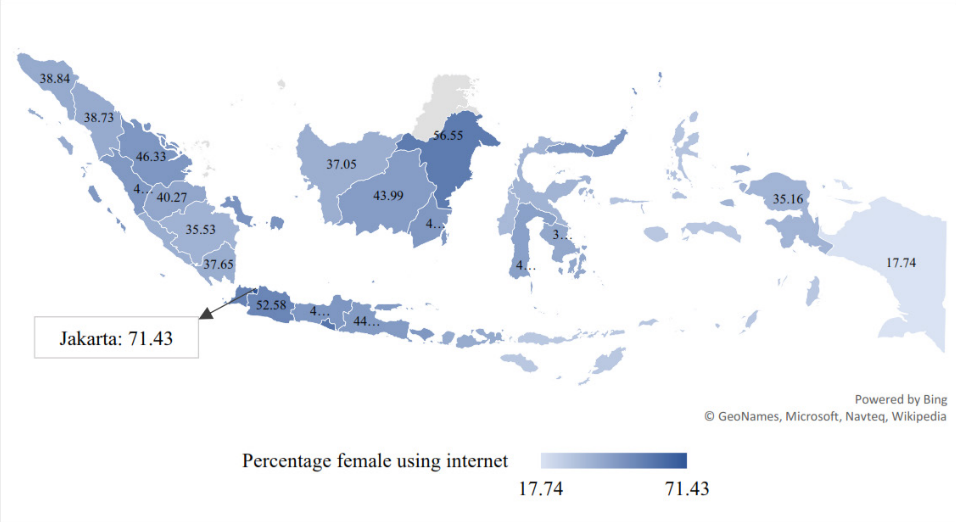

Figure: 2 Average Female Internet Utilization Per Province (%) in 2019

Source: SUSENAS-KOR Data

Figures 1 and 2 illustrate how female internet usage and labor force participation differ throughout provinces and islands. The provinces of Papua and West Papua have a relatively higher FLFP than Java, as indicated by the darkest hue in Figure 2. The capital city of Jakarta has a relatively low percentage of women working—roughly 46 percent—while Bali has the greatest percentage—roughly 67 percent. In contrast, Java, Sumatra, and Kalimantan Island account for the most female Internet users. With almost 71 percent, Jakarta has the largest percentage, while Papua has the lowest, at roughly 17 percent.

Results and Discussion

Main Result and Robustness Check

The Tobit regression model reveals the causal impact of women's internet utilization on their engagement in the labor market, as indicated by the coefficient *fnet* in Table 2. The model selection process commences by estimating the effect using the most basic functional form, which includes only one variable on the right-hand side of the model. The second specification incorporates an additional control variable into the model, the logarithm of per capita GRDP. The direction and amplitude of the coefficient of interest begin to alter in column 2. It suggests that more confounding unobservable could influence female labor force participation, which could bias the estimation.

Following Watson et al. (2018), the model's third specification incorporates the quadratic form of per capita GRDP to address the non-linear correlation between per capita GRDP and female labor force participation. Upon conducting tests for non-linearity, we discovered that lnGRDPcap2 also exhibits statistical significance. It suggests that the district's degree of development follows a U-shaped pattern concerning work participation. In order to enhance the accuracy of the estimates, we propose incorporating additional control variables. Consequently, we systematically include each covariate one at a time in specifications 3, 4, and subsequent iterations until the estimated coefficients reach a state of stability.

The coefficient sigma in the Tobit model can be used interchangeably as the residual standard error in OLS. Thus, considering there have been no significant alterations in magnitude, direction, and importance, particularly in the final two columns, model 7 is selected due to its minimal standard error of the estimate. In model 7, the impact of *fnet* on FLFP is statistically significant at a significance level of 0.01 percent. As predicted, this outcome demonstrates a modest yet favorable correlation between female internet usage and female involvement in the labor force. Simultaneously, this model selection process can function as a robustness check, indicating that the estimated effect remains robust even after accounting for five confounders.

Table 2: Panel Tobit Estimates of Determinants of Female Labor Force Participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FLFP	FLFP	FLFP	FLFP	FLFP	FLFP	FLFP
fnet	-0.0486**	0.00333	0.0165	0.0463*	0.0500**	0.0773***	0.0653**
	(-2.95)	(0.19)	(0.93)	(2.53)	(2.64)	(3.91)	(3.26)
lnGRDPcap		-5.405***	-22.58***	-13.23**	-13.57**	-10.15*	-11.70**
		(-7.70)	(-5.67)	(-3.12)	(-3.19)	(-2.39)	(-2.76)
lnGRDPcap2			2.326***	1.234*	1.270*	0.928	1.086*
			(4.38)	(2.23)	(2.28)	(1.68)	(1.98)
pov				0.363***	0.348***	0.281***	0.342***
				(5.66)	(5.16)	(4.15)	(4.92)
lnDENS					-0.177	0.0417	-0.388
					(-0.76)	(0.18)	(-1.47)
MYS						-1.420***	-1.345***
						(-4.62)	(-4.41)
LE							0.537***
							(3.44)
_cons	55.91***	72.12***	102.0***	77.93***	79.63***	81.90***	48.39***
	(77.01)	(32.93)	(14.26)	(9.50)	(9.37)	(9.78)	(3.78)
sigma_u							
_cons	9.934***	9.426***	9.220***	8.968***	8.971***	8.793***	8.693***
	(29.18)	(29.56)	(29.53)	(29.63)	(29.65)	(29.68)	(29.62)
sigma_e							
_cons	4.238***	4.226***	4.231***	4.221***	4.219***	4.216***	4.214***
	(44.60)	(45.01)	(45.06)	(45.21)	(45.22)	(45.30)	(45.29)
N	1542	1542	1542	1542	1542	1542	1542

Source: Authors' estimate (2020)
Note: z statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In terms of interpretation, this research adopts the approach outlined by Cameron & Trivedi (2009) to analyze the impact of the observed variable *y*, FLFP. The analysis utilizes the concept of marginal effects on the expected value of the censored outcome, as illustrated in Table 3.

Table 3 presents the marginal effects assessed using the left-censored mean, denoted as without censoring. Since there is no zero-valued dependent variable, as seen from the output in column *dy/dx*, the Tobit marginal effects reflect the absolute value similar to the original coefficients we had in model 7. Therefore, it is reasonable to conclude that a 1 percent increase in female internet users will result in a 0.065 percent rise in female labor force participation.

Table 3: Marginal Effects of Each Regressor on the Observed Variable (FLFP)

FLFP	(1)	(2)	(3)
	dy/dx	Std. error	Z
Fnet	0.065***	0.02	3.26
lnGRDPcap	-11.70**	4.23	-2.76
lnGRDPcap2	1.086*	0.55	1.98
Pov	0.342***	0.07	4.92
lnDENS	-0.388	0.26	-1.47
MYS	-1.345***	0.31	-4.41
LE	0.537***	0.16	3.44
N	1542	1542	1542

Source: Authors' estimate (2020)
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our study shows that internet usage has a small beneficial impact on FLFP. It may be attributed to social-economic factors affecting women's decision to enter the labor market besides the availability of the internet per se. The accessibility of the internet may facilitate women in quickly exploring employment prospects. Nonetheless, several obstacles that hinder women from accessing the advantages of digitalization continue to exist. Women in developing nations continue to encounter challenges in managing their professional obligations and caregiving duties (ILO, 2018). Women responsible for caring for senior family members also frequently miss career opportunities. Additionally, mothers' decisions to enter the workforce may be influenced by the accessibility of childcare facilities.

Table 3 further illustrates the impact of additional variables on female labor force participation in Indonesia. In addition to showing a non-linear relationship between female labor force participation and per capita GRDP, which is consistent with a study by Goldin (1995), the result also points to a positive and significant relationship—which accounts for 54 percentage points—between women's health—as measured by women's life expectancy—and FLFP. On the other hand, average years of education hurt women's employment. This finding seems to align with a study by Bawazir et al. (2022), which uses annual panel data for ten Middle Eastern nations from 1996 to 2018 to measure determinants affecting female labor force participation. It could be due to at least two factors. First, as a person's years of education increase, there may be a reduction in the number of pertinent employment opportunities; therefore, they would be better off remaining unemployed than working in an unattractive environment. Moreover, using mean years of instruction likely introduces a measurement error that may introduce bias into the outcome. Resosudarmo (2020a) argues that the average number of years spent in school does not necessarily correspond to an individual's true educational achievement, given that it disregards factors such as grade repetition and school retention.

It is also apparent that the female labor force participation level is not significantly affected by population density. This phenomenon refers to the uneven distribution of Female Labor Force Participation (FLFP) among different provinces, as depicted in Figure 1. For example, Jakarta, the province with the largest population density, has the lowest percentage of female workers. Similarly, other less populous locations like Riau also have similar ratios. Our data might corroborate these conclusions.

Simultaneously, the growing population of individuals residing below the poverty threshold has the potential to enhance the rate of female involvement in the workforce. These findings indicate that women experiencing poverty are more inclined to join the workforce to fulfill their fundamental requirements. This finding is consistent with a study undertaken in 20 African nations between 1990 and 2018, examining the factors influencing female workers' demand and supply (Idowu & Owoeye, 2019). Unfortunately, the lack of comprehensive information and data limitations prevent us from definitively discerning if the effect is truly advantageous for competent or unskilled women, regardless of whether they are employed in official or casual sectors.

Heterogeneity Analysis

This analysis aims to compare how other factors, such as digitalization, affect female labor force participation across subpopulations. Model 7 from the main result in Table 4 illustrates the comparative result when the sample is limited to whether the district is in Java or Non-Java Island. Female labor force participation is more strongly associated with internet usage in Java than in regions other than Java. This conclusion is consistent with evidence that digitalization is not yet widely adopted in Indonesia, as demonstrated by BTS Maps in Figure 3. The 2016 map depicting the deployment of Base Transceiver Stations (BTS) in Indonesia reveals that internet access remains unevenly distributed throughout the country, with most BTS stations located in and around Java Island.

Table 4: Heterogeneity Test between Java and Non-Java

FLFP	(1) Java	(2) non-Java
Fnet	0.0640*	0.0546*
	(2.22)	(2.15)
lnGRDPcap	8.076	-13.19**
	(1.26)	(-2.67)
lnGRDPcap2	-0.962	1.150
	(-1.20)	(1.76)
Pov	0.565***	0.275***
	(3.31)	(3.60)
lnDENS	-2.412*	0.192
	(-2.50)	(0.56)
MYS	0.313	-2.077***
	(0.42)	(-5.67)
LE	1.240***	0.618**
	(5.28)	(3.11)
_cons	-47.74*	51.75**
	(-2.44)	(3.26)
sigma_u	5.754***	8.857***
	(14.22)	(25.68)
sigma_e	2.774***	4.565***
	(21.76)	(39.68)
N	357	1185

Source: Authors' estimate (2020)
Note: z statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Apart from internet usage, it is discovered that in Java, as opposed to non-Java, the effects of population density, poverty rate, and life expectancy are more significant. Additionally, the relationship between the GRDP per capita and women's labor force participation in both regions does not inherently follow a U-shaped pattern. Besides, the result indicates that the mean number of years of education is negative and significant outside of Java but insignificant in Java.

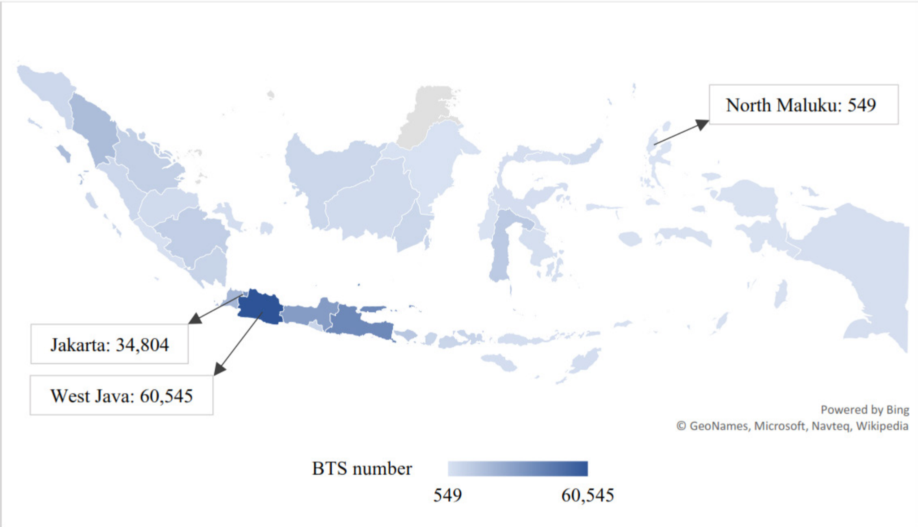

Figure 3: Number of Base Transceiver Stations (BTS) per province, 2016

Source: Ministry of Communication and Information Technology

Endogeneity in Internet Use

As was indicated in the preceding section, some research is concerned about the endogeneity problem when assessing the effects of digitalization. According to some research, the Granger Causality test can be used to determine whether endogeneity concerns are warranted. The goal of the test is to determine whether the regressor's historical values can explain any variation in the dependent variable (Granger 1969, quoted in Lopez & Weber 2017). Put another way, one may switch the roles of the independent and dependent variables to test for causality, which goes the other way. The test's shortcomings, however, are that it is based on a weaker theory than 'true' causality, which necessitates that the series remains stationary (ibid). Besides, to ensure that the test possesses sufficient power, it is ideal to have data encompassing a sufficient number of periods, which is not present in this study.

Alternatively, we can evaluate whether the coefficient of *fnet* is steady and add the lag value of FLFP, which is uncorrelated with internet use, to officially assess the reverse causality issue (Resosudarmo, 2020b). As Table 5 illustrates, the sign of *fnet* changes from positive to negative when the lag FLFP variable was added to model 7. It suggests that internet use may have historically been associated with FLFP, consistent with Watson's earlier claim. Thus, gainfully employed individuals have a higher probability of possessing internet connectivity than those who are unemployed. It suggests that the rise in labor force participation may also contribute to the demand for internet access.

Instrumenting internet usage with electricity access since internet access is inaccessible without electricity. This variable is additionally obtained from the district-level aggregation of the SUSENAS household survey. This variable is computed as a proportion of households in each district that have access to electricity, similar to *fnet*. As can be seen, however, the inclusion of an instrumental variable (IV) does not significantly enhance the estimation result due to the instrument's lack of dependability. The initial phase of 2SLS IV estimation reveals that the F-test yields a P-value greater than 5 percent and is only 0.61 (see Appendix 1). We can conclude that having access to power does not serve as a necessary component for using the internet, i.e., the initial stage is nonexistent. Given our inability to embrace the validity of IV estimation, we continue to suspect that our previous estimation result was impacted by endogeneity. Therefore, it is regarded as a constraint of our research.

Table 5: Assessing Reverse Causality

	Model 7	**Model with lag**
	FLFP	FLFP
fnet	0.065***	-0.087**
	(3.26)	(-3.44)
controls	Yes	Yes
L.FLFP	-	0.758***
		(45.34)
_cons	48.39***	8.202
	(3.78)	(1.40)
N	1542	1028

Source: Authors' estimate (2020)
Note: control variables include: lnGRDPcap, lnGRDP_pcap2, pov, lnDENS, MYS, LE;
* p < 0.05, ** p < 0.01, *** p < 0.001

Conclusions

As shown in Model 7 Table 2, this study discovered a positive and significant correlation between internet usage and female labor force participation at the subnational level despite the relative stagnation of female labor force participation in Indonesia. The result remains robust even after six covariates are controlled. Additionally, it is crucial to emphasize that the effects of digitalization on women's labor force participation differ by region. Specifically, within the region of Java, the correlation between internet usage and female labor force participation is more pronounced than in other regions of Java.

Based on the covariates, this study reveals various factors that substantially impact female labor force participation. The variable of women's health, as represented by women's life expectancy and the poverty rate, both positively impact female labor force participation. In contrast, the educational level, as represented by the mean years of schooling, had a negative impact on labor participation. This study further validates the U-shaped correlation between GRDP and female labor force participation.

Recommendation

The findings of this study may provide insight into the optimum approach to policy design. Poverty alleviation, the improvement of women's educational attainment, and the expansion of health facility access for women may all contribute to reducing the gender disparity in labor force participation. Furthermore, ensuring equitable internet access and diminishing obstacles (such as childcare facilities, flexible work schedules, and family-friendly work environments) throughout the country will aid in closing the wage disparity between Java and non-Java residents.

We acknowledge that our findings possess numerous limitations. The result may still be subject to endogeneity concerns; a more robust test utilizing potentially much lengthier time series is required. The current instrument employed in this research fails to adequately account for the variability observed in female internet usage. As a result, it has not yet contributed to an improved estimation. In order to enhance the accuracy of estimations in subsequent investigations, it is advisable to employ a more exogenous instrument, such as BTS by district level, which is not available for this study. Additionally, this study does not account for the potential effects of technological sector-specific differences in internet usage on female labor force participation. The variations may be contingent upon the sector and the extent to which its operations rely on digital technology. Further research is warranted to consider the wider socioeconomic ramifications of digitalization, including its effects on the gender wage disparity and women's income in the workforce.

Declaration

Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

Availability of Data and Materials

Data and material used in this study can be provided upon request. Data Sharing is not applicable to this article as no new data were created or analyzed in this study.

Authors' Contribution

RE conceptualized the study and developed the theory; WAS created the methodology and performed the computations; RE and WAS wrote, reviewed, and edited the manuscript. All authors discussed the results and contributed to the final manuscript.

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Appendices

Appendix 1: IV estimation result

```
FIXED EFFECTS ESTIMATION
------------------------
Number of groups =       514                    Obs per group: min =         3
                                                               avg =       3.0
                                                               max =         3

First-stage regressions
-----------------------


FIXED EFFECTS ESTIMATION
------------------------
Number of groups =       514                    Obs per group: min =         3
                                                               avg =       3.0
                                                               max =         3

First-stage regression of fnet:

Statistics consistent for homoskedasticity only
Number of obs =                  1542
------------------------------------------------------------------------------
        fnet |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 electricity |  -2.528389   3.226992    -0.78   0.434    -8.860684    3.803906
   lnGRDPcap |   81.97675   13.59258     6.03   0.000     55.30416    108.6493
  lnGRDPcap2 |  -4.033627   1.570556    -2.57   0.010    -7.115513    -.951741
         pov |  -1.788398   .1938516    -9.23   0.000    -2.168791   -1.408005
      lnDENS |   154.8069   10.50844    14.73   0.000     134.1863    175.4275
         MYS |   6.643641   1.076459     6.17   0.000     4.531316    8.755966
          LE |   1.766271   .8788781     2.01   0.045     .0416573    3.490885
------------------------------------------------------------------------------
F test of excluded instruments:
  F(  1,  1021) =     0.61
  Prob > F      =   0.4335
Sanderson-Windmeijer multivariate F test of excluded instruments:
  F(  1,  1021) =     0.61
  Prob > F      =   0.4335
```

```
Summary results for first-stage regressions
-------------------------------------------

                                           (Underid)            (Weak id)
Variable     | F(  1,  1021)  P-val | SW Chi-sq(  1) P-val | SW F(  1,  1021)
fnet         |       0.61    0.4335 |        0.62   0.4318 |        0.61

Stock-Yogo weak ID F test critical values for single endogenous regressor:
                                   10% maximal IV size            16.38
                                   15% maximal IV size             8.96
                                   20% maximal IV size             6.66
                                   25% maximal IV size             5.53
Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Sanderson-Windmeijer F statistic.


Underidentification test
Ho: matrix of reduced form coefficients has rank=K1-1 (underidentified)
Ha: matrix has rank=K1 (identified)
Anderson canon. corr. LM statistic       Chi-sq(1)=0.62     P-val=0.4319

Weak identification test
Ho: equation is weakly identified
Cragg-Donald Wald F statistic                                      0.61

Stock-Yogo weak ID test critical values for K1=1 and L1=1:
                                   10% maximal IV size            16.38
                                   15% maximal IV size             8.96
                                   20% maximal IV size             6.66
                                   25% maximal IV size             5.53
Source: Stock-Yogo (2005). Reproduced by permission.

Weak-instrument-robust inference
Tests of joint significance of endogenous regressors B1 in main equation
Ho: B1=0 and orthogonality conditions are valid
Anderson-Rubin Wald test           F(1,1021)=      0.44     P-val=0.5082
Anderson-Rubin Wald test           Chi-sq(1)=      0.44     P-val=0.5066
Stock-Wright LM S statistic        Chi-sq(1)=      0.44     P-val=0.5067

Number of observations               N  =       1542
Number of regressors                 K  =          7
Number of endogenous regressors      K1 =          1
Number of instruments                L  =          7
Number of excluded instruments       L1 =          1
```

```
IV (2SLS) estimation
--------------------

Estimates efficient for homoskedasticity only
Statistics consistent for homoskedasticity only

                                                      Number of obs =     1542
                                                      F(  7,  1021) =     0.96
                                                      Prob > F      =   0.4614
Total (centered) SS     =  18149.55222                Centered R2   =  -0.6720
Total (uncentered) SS   =  18149.55222                Uncentered R2 =  -0.6720
Residual SS             =  30345.15966                Root MSE      =    5.433

------------------------------------------------------------------------------
        FLFP |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        fnet |   1.056795   2.069018     0.51   0.610    -2.998406    5.111996
   lnGRDPcap |  -62.39893   170.8277    -0.37   0.715    -397.2151    272.4172
  lnGRDPcap2 |   2.031012   8.708336     0.23   0.816    -15.03701    19.09904
         pov |   1.998524   3.722607     0.54   0.591     -5.29765    9.294699
      lnDENS |  -183.7441   319.7616    -0.57   0.566    -810.4653    442.9771
         MYS |  -6.735446   13.80767    -0.49   0.626    -33.79797    20.32708
          LE |  -.9320148   3.766851    -0.25   0.805    -8.314907    6.450878
------------------------------------------------------------------------------
Underidentification test (Anderson canon. corr. LM statistic):          0.618
                                                   Chi-sq(1) P-val =    0.4319
------------------------------------------------------------------------------
Weak identification test (Cragg-Donald Wald F statistic):               0.614
Stock-Yogo weak ID test critical values: 10% maximal IV size             16.38
                                         15% maximal IV size              8.96
                                         20% maximal IV size              6.66
                                         25% maximal IV size              5.53
Source: Stock-Yogo (2005). Reproduced by permission.
------------------------------------------------------------------------------
Sargan statistic (overidentification test of all instruments):          0.000
                                                 (equation exactly identified)
------------------------------------------------------------------------------
Instrumented:         fnet
Included instruments: lnGRDPcap lnGRDPcap2 pov lnDENS MYS LE
Excluded instruments: electricity
------------------------------------------------------------------------------
```