J-naker
Jurnal Ketenagakerjaan

Jurnal Ketenagakerjaan
Volume 20 No. 1, 2025
Online ISSN: 2722-8770
Print ISSN: 1907-6096

Analysis of Socioeconomic and Demographic Characteristics of Female Participation in The Labor Market in Indonesia

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Abstract

Indonesia has the third lowest FLFP with the second highest gender gap in Southeast Asia in the labor market dimension despite an almost equal male and female population. This study analyzes the short-run and long-run relationship between socioeconomic and demographic characteristics on female participation in the labor market. The method used is the Error Correction Model (ECM). The results show that wage/salaried workers, female average years of schooling, and net migration have short-run and long-run effects on FLFP. Meanwhile, the unemployment rate, female participation in higher education, and child population have no impact in the short-run but have a significant effect in the long-run. The adjustment process from short-run to long-run equilibrium is 55.2% in the first year, while 44.8% in the following years has an adjustment time of 1.81 years. This study suggests the need to strengthen quality and flexible employment policies, inclusive education, and support gender-friendly policies, such as childcare services and maternity leave, to increase female participation in the labor market.

Keywords: FLFP, sosioeconomic, demographic, labor market, error correction model.

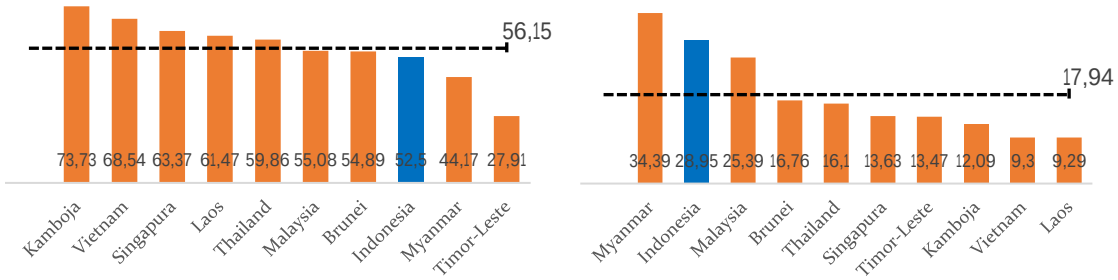
DOI:10.47198/naker.v20i1.464 Received: 2-25-2025 Revised: 4-21-2025 Accepted: 6-30-2025

1. Introduction

The labor market plays a vital role in a country's economy. An economy that continues to grow and develop will encourage national development, which impacts the labor market, improving the community's quality of life (Karim et al., 2019). However, various problems still arise in the labor market, such as the low participation of females. Female labor force participation (FLFP) measures female participation in the labor market. Socioeconomic and demographic conditions can affect FLFP so that females' participation in the labor market is lower than males' (ILO, 2024). Males and females have equal rights and opportunities to enter the labor

market (Radha & Uwiyono, 2023). When the labor market can provide equal access for males and females without discrimination, a country has ensured female's equal rights in accessing economic resources.

Female's equal rights in accessing economic resources is one of the *Sustainable Development Goals* (SDGs) covered in goal 5, namely gender equality (Bappenas, 2018). In goal 5 of the SDGs, by 2030, Indonesia is expected to reform to realize female economic empowerment through equal access to economic resources. Efforts that the government can make to achieve female economic empowerment reforms are to increase FLFP (Silva & Herrera-Idáraga, 2023). However, Indonesia is one country still encountering the problem of low female participation. Indonesia ranked 3rd out of 11 Southeast Asian countries with the lowest FLFP in 2022, at 52.50%. This figure is still far below Cambodia and Vietnam, with FLFP of 73.73% and 68.54%, respectively. In addition, Indonesia shows a high gap between the labor force participation of males and females, so Indonesia ranks 2nd with the highest gender gap in the labor market dimension, reaching 28.95% (BPS, 2024a). Indonesia is also one of the three countries with a gender gap above the Southeast Asian average. Almost 50% of Indonesia's population is female, so there should be no significant gap between male and female participation in the labor market. Both have equal opportunities to develop skills and knowledge through equal access to education and decent work (Hendrizal et al., 2024). Meanwhile, Laos, a country still categorized as less developed, shows a much lower gender gap than Indonesia, only 9.29%, with female participation reaching more than 60% (BPS, 2024a). This contrast shows that countries with more advanced development do not guarantee that female workers can achieve the same position as males in the labor market due to gender discrimination (Nuraeni & Suryono, 2021).



(a) (b)

Figure 1. *Overview of Gender Inequality in Southeast Asian Countries in the Labor Market Dimension*: (a)*FLFP*; and (b)*Gender Gap*

Source: BPS (2023); Processed

FLFP in Indonesia has shown gradual improvement but remains below the national target. As of 2024, FLFP reached 54.52%, falling short of the 55% target outlined in the 2020–2024 National Medium-Term Development Plan (RPJMN) (Prastyo, 2022). The low rate of FLFP contributes to lower female income levels, with female income contributing only 37.09% to household earnings, a slight decline from the previous year (BPS, 2024c). Limited labor market

access for females has led to higher female unemployment and greater dependency on male income, indicating that female economic empowerment remains suboptimal and contributes to broader economic inequality (Yunara et al., 2023). As a result, females are more vulnerable to poverty, with 9.20% of the female population living below the poverty line compared to 8.86% of males (BPS, 2024b).

Labor economic theories help explain these trends. The *discouraged worker effect* posits that persistent unemployment can dissuade individuals, particularly females, from seeking work due to perceived job scarcity (Mincer, 1962). Conversely, Mincer's *absolute income hypothesis* suggests that declining household income, often driven by reduced male earnings, can motivate females to enter the workforce to help stabilize finances. These dynamics are supported by empirical studies showing that high unemployment correlates with decreased FLFP, both in Indonesia (Triggs & Urata, 2020) and across the European Union (Altuzarra et al., 2019), where labor market pessimism has a disproportionately negative effect on female participation.

Another key socioeconomic factor influencing FLFP is education. Human capital theory argues that education is an investment that enhances individual skills, productivity, and competitiveness in the labor market (Becker, 1975). For females, attaining higher education equips them with the skills needed for professional roles, thus improving their prospects in the labor market (Altuzarra et al., 2019; Kiani, 2013; Suhaib & Kartiasih, 2024). However, the relationship between education and FLFP is more complex than a linear one. According to the U-curve hypothesis, the impact of education on FLFP follows a non-linear pattern (Boserup, 1970; Boserup et al., 2013). Females with low levels of education often enter the labor market out of necessity, as economic demands drive them to work. In contrast, females with moderate education may temporarily withdraw from the labor force to pursue further education, leading to a decrease in FLFP during that period. Finally, highly educated females are more likely to re-enter the labor force because the return on their education is higher, which increases their motivation to work (Cools et al., 2017; Pratomo, 2017).

Demographic shifts, particularly migration, also influence FLFP. The *immigration surplus theory* suggests that migration can increase labor productivity and employment opportunities when migrant skills complement the native workforce (Borjas, 1999). However, structural and cultural factors such as gender norms, inadequate childcare, and household responsibilities can limit the extent to which females benefit from these opportunities (Fadayomi & Olurinola, 2014; Pederzini & Meza, 2024). Time allocation theory further explains how caregiving responsibilities reduce female labor participation (Becker, 1965). Studies in Indonesia confirm that the presence of children in the household is a significant barrier to female employment (Schaner & Das, 2016; Utomo, 2018; Triggs & Urata, 2020). Despite these findings, few macro-level analyses fully integrate care responsibilities with broader labor market dynamics, leaving a critical gap in policy design.

The presence of children in the household is one of the most significant demographic barriers to female employment. Time allocation theory explains how females must balance

household production (such as childcare) with market work, often sacrificing the latter (Becker, 1965). Empirical findings consistently show that having more children reduces females' labor force participation (Utomo, 2018; Hosney, 2016). In Indonesia, Schaner & Das (2016) and Triggs & Urata (2020) found that childcare responsibilities are a key reason females leave wage employment or choose not to enter the labor market at all. However, few macro-level studies have integrated this variable with broader dynamics—such as urbanization, migration, or changing labor demand—despite their potential to reshape how females navigate work-family tradeoffs over time.

To date, no studies have simultaneously examined the role of socioeconomic and demographic characteristics such as the unemployment rate, percentage of wage/salaried workers, participation of females in higher education, female average years of schooling, migration, and child population in influencing female labor force participation (FLFP). Moreover, existing research has not explored the short- and long-run effects of these factors on FLFP, particularly in the Indonesian context. This study offers novelty by employing the Error Correction Model (ECM) approach, which captures long-run dynamics that may not be evident in the short run but emerge through gradual adjustment toward equilibrium. The study aims to analyze how socioeconomic and demographic factors influence FLFP in Indonesia over the short- and long run, thereby offering insights for formulating long-run policies that effectively and sustainably empower females economically.

2. Research Method

2.1. Data and Data Sources

The data used are secondary data from annual periods. This study used 32 observations from 1991 to 2022. The details of the data analyzed are as follows.

Table 1. Data and Data Sources

Variables	Description	Unit	Data Source
FLFP	Female Labor Force Participation	Percent (%)	ILO
UR	Unemployment Rate	Percent (%)	IMF
WSW	Percentage of wage/salaried workers	Percent (%)	ILO
SCH	Female participation Rate in Higher Education	Percent (%)	UNESCO
AYS	Female Average Years of Schooling	Year	UNESCO
MIG	Net Migration	People	UN DESA
CHILD	Percentage of Child Population	Percent (%)	UN DESA

2.2. Method

This study uses descriptive analysis to see the general picture of socioeconomic and demographic characteristics from 1991 to 2022, as well as inferential analysis with the Error Correction Model (ECM) method using Eviews 12 software. The ECM method was chosen because it is suitable for time series data, which is generally non-stationary at its level, so an approach is needed that can avoid pseudo regression. ECM allows the analysis of short-run relationships between variables while still considering long-run equilibrium through cointegration tests. With analysis stages that include stationarity tests, cointegration tests, model estimation, and assumption tests, ECM is expected to be able to capture the influence of socioeconomic and demographic characteristics on FLFP, both in the short and long run, validly and comprehensively.

2.2.1. Stationarity Test

Time series data are considered stationary when their mean, variance, and covariance remain constant over time. The Augmented Dickey-Fuller (ADF) test is commonly employed to assess stationarity by detecting the presence of a unit root, which indicates non-stationarity (Lütkepohl & Kratzig, 2004). A time series is deemed stationary if the absolute value of the ADF test statistic exceeds the MacKinnon critical value (Widyarta et al., 2024). This study tests two hypotheses: the null hypothesis (H_0), which posits $\delta = 0$, suggesting the presence of a unit root and thus non-stationarity; and the alternative hypothesis (H_1), which posits $\delta < 0$, indicating the absence of a unit root and therefore stationarity, possibly around a deterministic trend. Rejection of H_0 confirms that the series is stationary (Gujarati & Porter, 2009).

$$\Delta Y_t = (Y_t - Y_{t-1}) = u_t \quad (1)$$

Equation (1) shows that the first change (ΔY_t) of the variable Y_t is the difference between the value of Y_t at time t and the value of Y_{t-1} in the previous period.

2.2.2. Cointegration Test

Granger states that cointegration tests can be considered pre-tests to avoid 'spurious regression' situations (Gujarati & Porter, 2009). When two or more time series variables have a stationary linear combination, even though each variable itself is not stationary, the variables can be said to be cointegrated (Ziegel & Enders, 2015). Variables that are said to be cointegrated will have a long-run relationship between them.

$$Y_t = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon_t \quad (2)$$

Cointegration testing can be carried out using the same method as when testing variable stationarity with the Augmented Dickey-Fuller (ADF) test. The difference is that the cointegration test is carried out on the residual estimates (ε_t) from the regression equation (2), the long-run equation in ECM analysis. This method is known as the Augmented Engle-Granger (AEG) test. The cointegration test posits that the residuals from the long-run equation should be stationary at the level (Kartiasih & Setiawan, 2020). If the residuals of the long-run equation are

stationary at the level, then the equation is cointegrated. So, the resulting parameters are cointegration parameters, or it can be said that the variables have a stable or cointegrated long-run relationship (Gujarati & Porter, 2009).

2.2.3. Error Correction Model

Error Correction Model (ECM) can correct short-run imbalances towards long-run balance. Apart from that, ECM also has the advantage of connecting short-run and long-run relationships of each variable analyzed (Kartiasih & Setiawan, 2020). ECM is built by regressing the lag of the dependent variable against the lag of each independent variable plus the residual lag from the cointegrated model. The residual lag of the cointegrated model is called the error correction term (ECT). ECT plays a role in correcting short-run fluctuations so that the variables in the model can return to a stable long-run balance (Barsua et al., 2024). The following is the model in this research.

$$FLFP_t = \beta_0 + \beta_1\, UR_t + \beta_2\, WSW_t + \beta_3\, SCH_t + \beta_4\, AYS_t + \beta_5\, MIG_t + \beta_6\, CHILD_t + \varepsilon_t \quad (3)$$

$$\Delta FLFP_t = \beta_0 + \beta_1\, \Delta UR_t + \beta_2\, \Delta WSW_t + \beta_3 SCH\, \Delta_t + \beta_4\, \Delta AYS_t + \beta_5\, \Delta MIG_t + \beta_6\, \Delta CHILD_t + \beta_7\, ECT_{t-1} + u_t \quad (4)$$

Equation (3) is a long-run equation where t is time, β_0 is a constant, β_i is the long-run coefficient on the variable, and ε_t is the error term. Equation (4) is a short-run equation, where $t-1$ is the previous year period, β_0 is a constant, Δ is the first difference, β_i is the short-run coefficient on the variable, ECT is the error correction term with a value between -1 to 0, and u_t is the error term. In the short-run, the residual observed via ECT must be negative. This negative value of ECT shows how quickly the variable moves towards equilibrium.

2.2.4. Classical Assumption Test

2.2.4.1. Multicollinearity Check

Multicollinearity occurs in a regression model when some or several independent variables exhibit a perfect linear relationship. The following formula, the Variance Inflation Factor (VIF), is used to identify multicollinearity in the model.

$$VIF = \frac{1}{1 - R_i^2}, i = 1,2, \dots, t \quad (5)$$

where:

R_i^2 = coefficient of determination of the regression.

When $VIF_i > 10$, the i-th independent variable is highly correlated with other independent variables. When perfect multicollinearity arises, the regression coefficients of the independent variables become undefined, and their standard errors approach infinity. However, if multicollinearity is not perfect but still present, the regression coefficients can be estimated, though they will be accompanied by significant standard errors, making the estimates less precise (Gujarati & Porter, 2009).

2.2.4.2. Normality Test

The normality assumption states that the residuals from the regression model should follow a normal distribution with a mean of zero and a constant variance. The normality test ensures the validity of statistical tests that rely on a normal distribution to produce accurate conclusions (Gujarati & Porter, 2009). In this study, the normality test was obtained using the Jarque-Berra method. The hypothesis of this test is as follows.

H_0: $\varepsilon_t \sim N(0, \sigma^2)$ or residuals are normally distributed

H_1: $\varepsilon_t \nsim N(0, \sigma^2)$ or residuals are not normally distributed

Test statistics:

$$JB = \frac{n}{6}(S^2 + \frac{(K-3)^2}{4}) \quad (6)$$

where:

n = sample size,
S = skewness,
K = kurtosis.

Residuals are normally distributed when the value is more than the specified significance level, which in this study used a significance level of 5%. If a violation of normality is found, it is desirable to apply a data transformation (such as logarithm) or use a robust approach such as bootstrapping (Park, 2006).

2.2.4.3. Homoscedasticity Test

The homoscedasticity test is a procedure in regression analysis that aims to detect whether there are unequal residual variances between observations. Failure to fulfill this assumption can cause parameter estimates to be inefficient and statistical efficiency to be invalid. Several standard methods are used to detect heteroscedasticity, including residual graph analysis and Glejser, White, and Breusch-Pagan tests. In this research, the Breusch-Pagan-Godfrey test was used to see the condition of the residual variance with the hypothesis that there is no heteroscedasticity, or in other words, the model has the same residual variance (Gujarati & Porter, 2009). The hypothesis of this test is as follows.

H_0: $var\ (\varepsilon_t | X_1, X_2, \dots, X_n) = \sigma^2$ or homoscedastic

H_1: $var\ (\varepsilon_t | X_1, X_2, \dots, X_n) \neq \sigma^2$ or heteroscedastic

Test statistics:

$$nR^2 \sim \chi^2_{(n)} \quad (7)$$

where:

n = sample size,
R^2 = coefficient of determination.

The decision for this test is if $BP > \chi^2_{critical}$ or $p - value <$ 5% significance level, then reject H_0 or there is heteroscedasticity.

2.2.4.4. Autocorrelation Test

Autocorrelation arises when the residuals in period t correlate with those from the previous period $(t-1)$ in the obtained regression model. A well-constructed regression model lacks autocorrelation. This research conducted this test using the Breusch-Godfrey Correlation LM test. The hypothesis of this test is as follows.

$H_0: \rho_1 = \rho_2 = \cdots = \rho_p = 0$ or there is no autocorrelation

$H_1: \rho_i \neq 0; i = 1,2, \ldots, p$ or there is autocorrelation

Test statistics:

$$BG = (n-p)R^2_{(m)} \sim \chi^2_{(\alpha,p)} \quad (8)$$

where:

n = sample size,
m = number of lags in the error term,
R^2 = coefficient of determination.

In this test, researchers hope to find no correlation between errors in the former model. Therefore, the test must meet the criteria of not rejecting H_0 when $BG < \chi^2_{critical}$ or $p - value >$ 5% significance level, indicating that the non-autocorrelation assumption is satisfied.

3. Results and Discussion

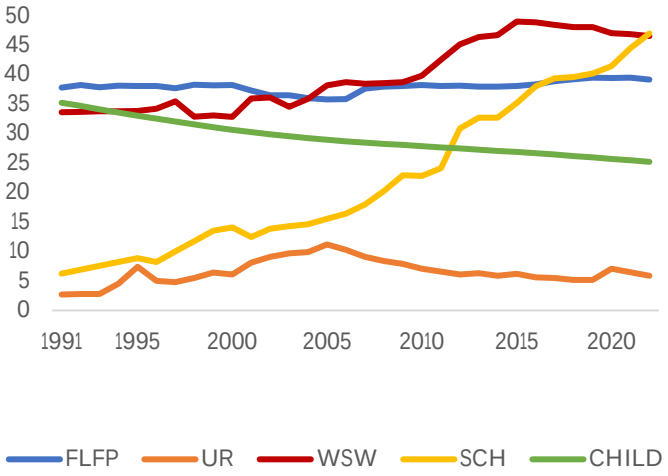
Results and discussion include descriptive analysis using line charts and inferential analysis using the Error Correction Model (ECM). However, before carrying out inferential analysis, stationarity and cointegration tests must first be carried out as pre-estimation tests.

3.1. Descriptive Analysis

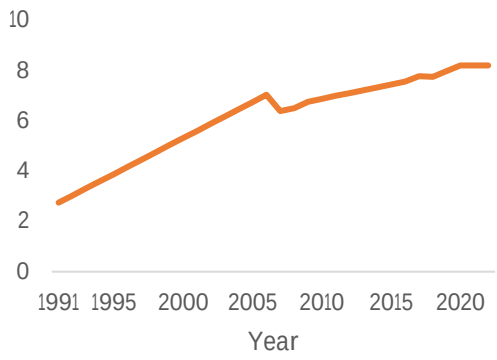
Figure 2 depicts various important trends related to socioeconomic and demographic characteristics in Indonesia during 1991–2022. Figure 2a shows changes in socioeconomic indicators expressed as percentages. Female labor force participation shows fluctuations, with a decline in the early 2000s before increasing gradually and steadily approaching 2022. The unemployment rate peaked in the early 2000s but declined until 2022, although there was a slight increase towards the end of the period, possibly related to economic dynamics. The percentage of salaried workers shows a significant upward trend, reflecting a shift to formal employment. Female participation rates in higher education have consistently increased, marking significant progress in females' access to higher education. In contrast, the percentage of the child population continued to decline during this period, which can be attributed to the demographic transition due to urbanization and the increasing participation of females in education and the world of work.

The average years of schooling for females (Figure 2b) shows a significant increase, reflecting the improvement in the quality of female human resources in Indonesia. Meanwhile, the net

migration graph (Figure 2c) shows sharp fluctuations, with a migration deficit in the early 2000s, where more people left than entered, followed by a migration surplus in recent years, indicating the attractiveness of specific regions as social and economic centers. These trends reflect significant improvements in female education and economic participation, although challenges such as unemployment and migration fluctuations require further attention.



(a)



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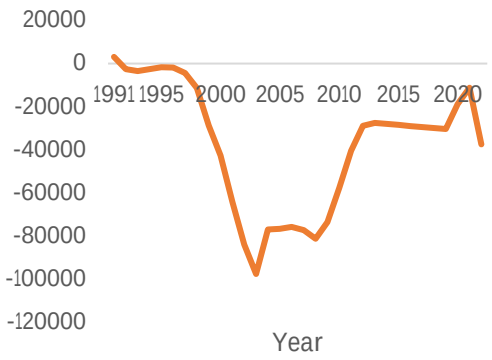

(c)

Figure 2. *Trends*: (a)*Female Labor Force Participation, Unemployment Rate, Percentage of Wage/Salaried Workers, Female Participation Rate in Higher Education, Percentage of Child Population*; (b)*Female Average Years of Schooling*; and (c)*Net Migration*

Source: Processed

3.2. Stationarity Test

The stationarity test in this research is the Augmented-Dickey-Fuller (ADF) test, which has a confidence level of 90% (alpha 10%). The model is stationary (does not contain unit roots) when

the t-ADF is less than the MacKinnon critical value. The unit root is tested at both the level and first difference.

Table 2. Summary of Stationarity Test Results

Variable	Level	First Difference
	Probability	Probability
FLFP	0,534	0,002**
UR	0,259	0,000**
WSW	0,879	0,001**
SCH	0,999	0,001**
AYS	0,054	0,001**
MIG	0,297	0,097*
CHILD	0,932	0,003**

Notes: *significant at α = 10%; **significant at α = 5%.

Source: Eviews 12 (Processed)

Based on Table 2, all variables are found to be non-stationary at the level but become stationary after taking the first difference. Therefore, the conditions necessary for a cointegrated regression relationship have been fulfilled.

3.3. Cointegration Test

The cointegration test ensures that the conditions for a cointegrated regression relationship are met. Subsequently, the residuals of the long-run regression equation (ε_t) should be stationary at the level, as verified using the ADF test.

Table 3. Summary of Cointegration Test Results

Augmented Dickey-Fuller Test	
t-Statistic	-3,891
Probability*	0,006

Notes: *MacKinnon (1996) one-sided p-value.

Source: Eviews 12 (Processed)

Based on Table 3, the residuals of the long-run regression equation are stationary at 1% alpha. This result indicates that the seven variables contained in the model are cointegrated, meaning that there is a long-run relationship between the FLFP and the unemployment rate, percentage of wage/salaried workers, percentage of female participation in higher education, female average years of schooling, migration, and child population.

3.4. The Effect of Socioeconomic and Demographic Characteristics on Female Participation in the Labor Market in Indonesia

Table 4 shows the effect of the unemployment rate, percentage of wage/salaried workers, percentage of female participation in higher education, female average years of schooling, migration, and child population on the FLFP in the long-run.

Table 4. Cointegrated Regression Estimation (Long-run)

Variables	Coefficient	Std. Error	t-Statistics	Probability
C	89,515	10,124	8,842	0,000**
UR	-0,137	0,075	-1,821	0,081*
WSW	-0,123	0,036	-3,408	0,002**
SCH	0,067	0,027	2,485	0,020**
AYS	-1,889	0,480	-3,934	0,001**
MIG	0,001	0,0004	2,501	0,019**
CHILD	-1,205	0,263	-4,580	0,000**
Adjusted R-Square				0,8892
F-Statistics				42,466
Prob. F-Statistics				0,000

Notes: *significant at α = 10%; **significant at α = 5%.

Source: Eviews 12 (Processed)

Based on Table 4, the long-run equation can be written as follows.

$$FLFP_t = 89{,}515 - 0{,}137UR_t^{*} - 0{,}123WSW_t^{**} + 0{,}067SCH_t^{**} - 1{,}889AYS_t^{**} + 0{,}001MIG_t^{**} - 1{,}205CHILD_t^{**} \quad (9)$$

Equation (9) is a cointegrated regression equation that shows the effect of the unemployment rate, percentage of wage/salaried workers, percentage of female participation in higher education, female average years of schooling, net migration, and percentage of child population on FLFP in the long-run. Based on Table 4, all independent variables significantly affect FLFP, both simultaneously and partially.

This research found that the unemployment rate hurt FLFP. This result is in line with previous research, which states that unemployed people tend to lack sufficient skills to support their work, especially in the era of the Industrial Revolution 4.0, so workers who have lower qualifications will increasingly be excluded from the world of work (Triggs & Urata, 2020). The percentage of wage/salaried workers hurts FLFP, which is in line with previous research that when the husband's salary meets family income as a wage worker, the female will choose not to enter the labor market because they take care of the household (Qinfen Ma, 2017). Then, the percentage of female participation in higher education has a positive effect because, in the current world of work, higher education graduates are needed because they tend to have better abilities

in jobs that require special skills (Altuzarra et al., 2019). Female average years of schooling negatively influence FLFP. This result is in line with the U-curve hypothesis, which states that females with low levels of education tend to be more involved in the world of work. On the other hand, females with a secondary level of education have lower participation in the labor market. Finally, the participation rate increases again at a higher level of education (Pratomo, 2017). However, the female average years of schooling in Indonesia is still at around 8 years, which is in the medium category, in contrast to Malaysia, Singapore, and the Philippines, where the female average years of schooling tends to be high, reaching more than 10 years (UNESCO, 2024). This condition indicates that Indonesia has not yet reached a turning point as in the U-curve hypothesis, so female labor force participation tends to stagnate at a lower level. Furthermore, net migration, which has a positive effect on FLFP, is in line with previous research where when the number of people entering a country increases, it will provide benefits for the country they are visiting, one of which is through increasing employment opportunities (Pederzini & Meza, 2024). Finally, the percentage of the child population hurts FLFP because females who have many children tend to choose to take care of their children as a mother's obligation, so they decide not to work (Utomo, 2018).

The short-run equation describes adjustments to the long-run balance through the error correction term (ECT). ECT shows the extent to which the long-run balance can be corrected over a certain period of time. The estimation of short-run regression can be shown in Table 5.

Table 5. ECM Estimation (Short-Run)

Variables	Coefficient	Std. Error	t-Statistics	Probability
C	0,235	0,166	1,416	0,170
D(UR)	-0,047	0,050	-0,928	0,363
D(WSW)	-0,173	0,041	-4,230	0,000**
D(SCH)	0,010	0,036	0,290	0,775
D(AYS)	-1,813	0,319	-5,678	0,000**
D(MIG)	0,002	0,000	3,157	0,004**
D(CHILD)	-0,696	0,466	-1,492	0,149
ECT (-1)	-0,552	0,191	-2,892	0,008**
Adjusted R-Square			0,690	
F-Statistics			10,556	
Prob. F-Statistics			0,000	

Notes: *significant at α = 10%; **significant at α = 5%.

Source: Eviews 12 (Processed)

Based on Table 5, the short-run equation can be written as follows.

$$\Delta FLFP_t = 0{,}235 - 0{,}047\Delta UR_t - 0{,}173\Delta WSW_t^{**} + 0{,}010\Delta SCH_t - 1{,}813\Delta AYS_t^{**} + 0{,}002\Delta MIG_t^{**} - 0{,}696\Delta CHILD_t - 0{,}552ECT_{t-1}^{**} \quad (10)$$

Based on equation (10), the error correction term (ECT) is statistically significant at the 5% level and has a negative coefficient. This finding confirms the validity of the model specification, as the ECT coefficient reflects the speed at which short-run deviations are corrected toward long-run equilibrium. A non-negative ECT coefficient would indicate divergence from the long-run equilibrium, rendering the model spurious. The ECT coefficient represents the adjustment rate, illustrating how quickly short-run fluctuations are corrected to restore stability in the long-run. The resulting ECT coefficient of -0.552 means that short-run equilibrium fluctuations will be adjusted towards long-run equilibrium, with an adjustment process of 55.2% occurring in the first year while the remaining 44.8% occurs in subsequent years. The adjustment process from the short to the long-run spans several years.

This study found that the unemployment rate does not affect FLFP in the short-run but has a negative and significant effect in the long-run. This finding is consistent with previous research showing a long-run relationship between unemployment and FLFP. Unemployment has a long-run influence on FLFP because it is found that there is hidden unemployment for females, so they need to adjust the economic structure first to be able to take employment opportunities (Taşseven et al., 2016). This study also found that female participation in higher education affects FLFP in the short-run and the long-run. According to the findings of previous research, namely in developing countries that are in the stage of development towards a modern economy, education will continue to increase until the completion of the transition so that in the long-run in the labor market, female participation will increase (Altuzarra et al., 2019). The findings of this study align with previous research that explores the long-run relationship between female fertility and education in shaping females' decisions to participate in the workforce, where females who take care of children will keep themselves out of the labor market so that FLFP decreases (Hosney, 2016). Other studies have also found that couples prefer to have children of different genders. Therefore, those with same-sex children increase the likelihood of having more children in a way that is not related to factors affecting labor force participation that are directly observable in the short-run but over the long-run (Cools et al., 2017).

3.5. Classical Assumption Test

This research checks multicollinearity using VIF, normality using the Jarque-Bera test, heteroscedasticity using the Breusch-Pagan-Godfrey test, and autocorrelation using the Breusch-Godfrey Correlation LM test. Table 6 below presents the results of the multicollinearity and classical assumption tests.

Table 6. Classical Assumption Test Results

Multicollinearity		Normality Probability	Homoscedasticity Probability	Non-Autocorrelation Probability
Variable	VIF			
D(UR)	1,260	0,488	0,990	0,542
D(WSW)	1,139			
D(SCH)	1,167			
D(AYS)	1,481			
D(MIG)	1,322			
D(CHILD)	1,662			
ECT	1,148			

Source: Eviews 12 (Processed)

Based on the results presented in Table 6, all VIF values are below the threshold of 10, indicating that the predictive model is not affected by multicollinearity. The Jarque-Bera test for normality yields a probability value of 0.488, which exceeds the 1% significance level (α), suggesting that the residuals are normally distributed. The Breusch-Pagan-Godfrey test returns a probability value of 0.990, also above the 1% significance level, indicating the absence of heteroscedasticity and confirming that the residuals have constant variance. Furthermore, the Lagrange Multiplier (LM) test yields a chi-square probability value of 0.542, which exceeds the 1% significance threshold, demonstrating that the model is free from autocorrelation.

Although this study has provided a number of relevant findings and broadened our understanding of females' labor market participation, some limitations need to be considered. The scope of the analysis is still limited to certain socioeconomic and demographic variables, so it does not include other factors such as cultural, psychological, political, and environmental that can also affect female labor force participation in a complex manner. In addition, the analysis was conducted at the national level without more specific data segmentation. Hence, the findings are general and cannot be directly generalized to specific groups of females, such as housewives, young females, or females with disabilities. These limitations indicate the importance of further studies with a more comprehensive and contextual approach, both in terms of variable coverage and diversity of target groups, in order to produce a more complete and in-depth understanding.

4. Conclusion and Recommendations

This study finds that hidden unemployment is a key challenge for females. Many are not officially unemployed but remain out of the workforce due to limited job opportunities or reliance on a spouse's income. Females with children also tend to withdraw from the labor market to focus on caregiving. Education shows a non-linear effect: those with low education often work out of necessity. In contrast, those with secondary education are more likely to leave the workforce due

to unmet job expectations. Participation rises again at higher education levels, where better job matches are more accessible. Based on the findings, the government should focus on creating quality jobs for females to reduce the long run. Enhancing work incentives and flexibility, such as part-time or remote work, is essential. Efforts to improve female access to higher education through scholarships and gender-inclusive policies should align with labor market demands. Additionally, the government can leverage in-migration by providing gender-friendly job opportunities and expanding childcare and maternity support to help females remain in the workforce.

Future research can be directed to explore other factors that influence the level of females' participation in the workforce, such as cultural values, gender roles, and social norms prevailing in society. In addition, it is important to analyze the influence of post-COVID-19 on the pattern of females' involvement in the workforce to find out whether these changes are temporary or have created new patterns in females' work participation. By examining cultural factors and post-pandemic social transformation, further studies are expected to provide deeper insights into the factors that influence FLFP and support the formulation of policies that are in line with the real conditions of females in the labor market.

References

Altuzarra, A., Gálvez-Gálvez, C., & González-Flores, A. (2019). Economic Development and Female Labour Force Participation: The Case of European Union Countries. *Sustainability*, *11*(7), 1962. https://doi.org/10.3390/su11071962

Bappenas. (2018). *Kesetaraan Gender: Mencapai Kesetaraan Gender dan Memberdayakan Kaum Perempuan*. Kementerian Perencanaan Pembangunan Nasional/Badan Perencanaan Pembangunan Nasional Republik Indonesia. https://sdgs.bappenas.go.id/17-goals/goal-5/

Barsua, N. P. E. U., Harum, N. S., Boeaya, M. A., & Gurusinga, W. U. (2024). Analisis Determinan Nilai Ekspor Kopi Indonesia (Dampak Nilai Tukar Rupiah, Investasi Asing Langsung dan Harga Kopi Dunia). *JIA (Jurnal Ilmiah Agribisnis) : Jurnal Agribisnis Dan Ilmu Sosial Ekonomi Pertanian*, *9*(4), 327–337. https://doi.org/10.37149/jia.v9i4.1338

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, *75*(299), 493. https://doi.org/10.2307/2228949

Becker, G. S. (1975). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education* (2nd ed.). National Bureau of Economic Research. http://www.nber.org/books/beck75-1

Borjas, G. J. (1999). *The Economic Analysis of Immigration* (Vol. 3, pp. 1697–1760). Elsevier Science B. V. https://doi.org/10.1016/S1573-4463(99)03009-6

Boserup, E. (1970). *Woman's Role in Economic Development* (1st ed.). St. Martin's Press.

Boserup, E., Tan, S. F., & Toulmin, C. (2013). *Woman's Role in Economic Development*. Routledge. https://doi.org/10.4324/9781315065892

BPS. (2023). *Indeks Ketimpangan Gender 2022* (Vol. 1). BPS.

BPS. (2024a). *Indeks Ketimpangan Gender*.

BPS. (2024b). *Persentase Penduduk yang Hidup di Bawah Garis Kemiskinan Nasional, Menurut Jenis Kelamin (Persen), 2024*.

BPS. (2024c). *Sumbangan Pendapatan Perempuan (Persen), 2022-2023*.

Cools, S., Markussen, S., & Strøm, M. (2017). Children and Careers: How Family Size Affects Parents' Labor Market Outcomes in the Long Run. *Demography*, *54*(5), 1773–1793. https://doi.org/10.1007/s13524-017-0612-0

Fadayomi, T., & Olurinola, I. O. (2014). Determinants of Labour Force Participation in Nigeria: The Influence of Household Structure. *Journal of Economics and Development Studies*, *2*(2), 169–190. https://doi.org/10.15640/jeds

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th ed.). McGraw-Hill/Irwin.

Hendrizal, Joni, M., Hijrat, K., Wandi, J. I., & Afnita, N. (2024). Investasi Pendidikan dalam Meningkatkan Kesejahteraan Ekonomi Masyarakat. *El-Kahfi: Journal of Islamic Economics*, *5*(01), 81–90. https://doi.org/10.58958/elkahfi.v5i01.232

Hosney, S. H. (2016). *Factors Influencing Female Labor Force Participation in Egypt and Germany: A Comparative Study* (826; SOEPpapers on Multidisciplinary Panel Data Research).

ILO. (2024, February 6). *Labor Force Participation Rate, Female (% of Female Population Ages 15+) (Modeled ILO Estimate)*. International Labour Organization. https://ilostat.ilo.org/data/

Karim, M. Al, Utomo, G. J., & Fauziah, B. (2019). Kualitas Hidup dan Pertumbuhan Ekonomi, Studi Kasus DKI Jakarta dan Daerah Penyangganya. *Jurnal Pembangunan Wilayah & Kota*, *15*(3). https://doi.org/10.14710/pwk.v15i3.22287

Kartiasih, F., & Setiawan, A. (2020). Aplikasi Error Correction Mechanism Dalam Analisis Dampak Pertumbuhan Ekonomi, Konsumsi Energi Dan Perdagangan Internasional Terhadap Emisi Co2 Di Indonesia. *Media Statistika*, *13*(1), 104–115. https://doi.org/10.14710/medstat.13.1.104-115

Kiani, A. Q. (2013). Determinants of Female Labor Force Participation. *ASEAN Marketing Journal*, *1*(2). https://doi.org/10.21002/amj.v1i2.1986

Lütkepohl, H., & Kratzig, M. (2004). *Applied Times Series*.

Mincer, J. (1962). *Labor Force Participation of Married Women: A Study of Labor Supply*. Princeton University Press. http://www.nber.org/books/univ62-2

Nuraeni, Y., & Suryono, I. L. (2021). Analisis Kesetaraan Gender dalam Bidang Ketenagakerjaan di Indonesia. *Nakhoda: Jurnal Ilmu Pemerintahan*, *20*(1). https://doi.org/10.35967/njip.v20i1.134

Park, H. M. (2006). Univariate Analysis and Normality Test Using SAS, STATA, and SPSS. *Measurement*, *January*, 1–67.

Pederzini, C., & Meza, L. (2024). Labor Force Participation of Central American Migrant Women in Mexico. *Social Sciences*, *13*(3), 135. https://doi.org/10.3390/socsci13030135

Prastyo, M. Y. (2022, January 20). Partisipasi Angkatan Kerja Perempuan Ditargetkan Capai 55% di 2024. *DetikFinance*, 1–6.

Pratomo, D. S. (2017). Pendidikan Dan Partisipasi Angkatan Kerja Wanita Di Indonesia: Analisis Terhadap Hipotesis Kurva-U. *Jurnal Ekonomi Kuantitatif Terapan*. https://doi.org/10.24843/JEKT.2017.v10.i01.p01

Qinfen Ma. (2017). Female Labor Force Participation in Malaysia: Time-Series Evidence. *South East Asia Journal of Contemporary Business, Economics and Law*, *14*(3), 1–7.

Radha, N., & Uwiyono, A. (2023). Perbandingan Kesetaraan Hak Pekerja Perempuan dalam Ruang Lingkup Ketenagakerjaan di Indonesia dan Amerika Serikat. *COMSERVA Indonesian Jurnal of Community Services and Development*, *2*(11), 2771–2789. https://doi.org/10.59141/comserva.v2i11.669

Schaner, S., & Das, S. (2016). Female Labor Force Participation in Asia: Indonesia Country Study. In *SSRN Electronic Journal* (474; ADB Economics Working Paper Series, Issue 474). https://doi.org/10.2139/ssrn.2737842

Silva, H. G., & Herrera-Idáraga, P. (2023). *Culture, Gender, and Labor Force Participation: Evidence from Colombia*. https://doi.org/10.2139/ssrn.4575892

Suhaib, A. M., & Kartiasih, F. (2024). Pengaruh Teknologi Digital terhadap Partisipasi Perempuan dalam Angkatan Kerja di Provinsi Papua. *Jurnal Ketenagakerjaan*, *19*(2), 218–232. https://doi.org/10.47198/jnaker.v19i2.342

Taşseven, Ö., Altaş, D., & ÜN, T. (2016). The Determinants of Female Labor Force Participation for OECD Countries. *International Journal of Economic Studies*, *2*(2), 27–38.

Triggs, A., & Urata, S. (2020). *Achieving Inclusive Growth in the Asia Pacific*. Australian National University Press. https://doi.org/10.22459/AIGAP.2020

UNESCO. (2024, June 16). *Mean Years of Schooling (ISCED 1 or Higher)*. UNESCO Institute for Statistics.

Utomo, A. (2018). Revisiting the Trends of Female Labour Force Participation in Indonesia. *Jurnal Perempuan*, *23*(4), 193. https://doi.org/10.34309/jp.v23i4.274

Widyarta, I. K. P., Samosir, C. P. D., Aysyah, P., & Kartiasih, F. (2024). Revisiting Unemployment in Indonesia: Error Correction Model (ECM) Analysis . *Jurnal Akuntansi, Manajemen, Bisnis Dan Teknologi*, *4*(2), 222–241. https://doi.org/10.56870/4q9ctm59

Yunara, E., Yeni, I., & Irfan, M. I. (2023). Pengaruh Pemberdayaan Perempuan Dalam Ekonomi Dan Politik Terhadap Pembangunan Perempuan di Provinsi Sumatera Barat. *Jurnal Kajian Ekonomi Dan Pembangunan*, *5*(2), 79. https://doi.org/10.24036/jkep.v5i2.14862

Ziegel, E. R., & Enders, W. (2015). Applied Econometric Time Series. In *Technometrics* (Vol. 37, Issue 4). https://doi.org/10.2307/1269759