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EXPLORING THE NONLINEAR EFFECT OF FINANCIAL DEVELOPMENT ON THE GLOBAL UNEMPLOYMENT RATE: EVIDENCE FROM BAYESIAN INFERENCE

EXPLORANDO O EFEITO NÃO LINEAR DO DESENVOLVIMENTO FINANCEIRO SOBRE A TAXA DE DESEMPREGO GLOBAL: EVIDÊNCIAS DA INFERÊNCIA BAYESIANA

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Abstract
This study aims to analyze the nonlinear effect of financial development on the unemployment rate of 117 countries in the world during the period from 2004 to 2022. The study uses the Bayesian inference method to test the nonlinear effect of financial development on the unemployment rate. The estimation results show that financial development has a positive effect on the unemployment rate. In addition, the financial development threshold is 0.73. When FD is below this threshold, it reduces the unemployment rate with a probability of 99.96%. In contrast, when financial development passes the threshold, it causes a negative effect on unemployment. These findings open policy directions in the context before and after the threshold, and this strengthens and opens the path to reduce the unemployment rate.

Keywords: Nonlinear Effect. Financial Development. Unemployment Rate. Bayesian Inference.

Resumo
Este estudo tem como objetivo analisar o efeito não linear do desenvolvimento financeiro sobre a taxa de desemprego em 117 países do mundo durante o período de 2004 a 2022. O estudo utiliza o método de inferência Bayesiana para testar o efeito não linear do desenvolvimento financeiro sobre a taxa de desemprego. Os resultados da estimação mostram que o desenvolvimento financeiro tem um efeito positivo sobre a taxa de desemprego. Além disso, o limiar de desenvolvimento financeiro é de 0,73. Quando o desenvolvimento financeiro está abaixo desse limiar, ele reduz a taxa de desemprego com uma probabilidade de 99,96%. Em contrapartida, quando o desenvolvimento financeiro ultrapassa o limiar, ele causa um efeito negativo sobre o desemprego. Essas descobertas abrem novas direções políticas no contexto anterior e posterior ao limiar, fortalecendo e abrindo caminho para a redução da taxa de desemprego.

Palavras-chave: *Efeito não linear. Desenvolvimento financeiro. Taxa de desemprego. Inferência Bayesiana.*

1 INTRODUCTION

Facing the goal of sustainable development, the United Nations has affirmed the essential role of financial development in reducing poverty, increasing social equity, and improving the economy's ability to cope with shocks (Van *et al*., 2025). Financial development (FD) not only provides capital but also acts as an important tool in supporting sustainable economic development (Dinh *et al*., 2025), creating job opportunities through the expansion and improvement of access to financial services. This encourages small and medium enterprises to operate and expand their business activities, thereby reducing unemployment (Van & Le Quoc, 2024). In addition, FD opens business opportunities for individuals, as access to credit and insurance allows them to improve their living conditions, reduce personal financial risks, and contribute to the economy (Çiftçioğlu and Bein, 2017). Furthermore, FD serves as a tool that reduces barriers to the non-financial sector, contributing to growth toward financial inclusion (Afonso and Blanco Arana, 2024). While previous studies have confirmed the positive role of financial development (Nyasha *et al*., 2022; Afonso and Blanco Arana, 2024), a new line of research has emerged and raised concerns that this relationship is gradually weakening (Chen *et al*., 2021). When examining global unemployment statistics reported by the World Bank (World Bank, 2025), some countries with highly advanced financial development such as Finland, Croatia, France, Italy, and Sweden still experience unemployment rates ranging from 6% to 10%. This can be explained in the context of rapid digital transformation, which requires strong infrastructure, while technological advancement may also create negative effects (Raifu *et al*., 2023, 2024). Although financial technology can improve access to financial services, it may also lead to automation, which can shrink or replace certain traditional sectors (Van *et al*., 2025). This directly affects industries that are highly sensitive to structural changes, such as financial services, banking, and manufacturing. Therefore, while FD can promote employment and reduce unemployment, it may also create significant challenges for the traditional labor market.

For this reason, the present study examines the nonlinear effect of FD on unemployment in the selected group of countries and identifies the FD threshold. These differences highlight the important role of FD in expanding the labor market. The study also determines the effect of FD when financial development is above the threshold. The study contributes to the literature in two main ways: (1) Providing additional evidence on the nonlinear impact of financial development on unemployment. (2) Demonstrating the presence of a financial development threshold, thereby offering suitable policy recommendations for countries.

2 THEORETICAL AND LITERATURE REVIEW

2.1 Theoretical foundation

The theory of the impact of financial development on unemployment can be approached through the following theories.

The information asymmetry theory of George in 1970 states that distinguishing between good borrowers and bad borrowers is a challenge because of the presence of information asymmetry, in which one party in the credit contract has more or better information than the other party. Financial development plays an important role in building and improving the financial system, helping individuals and businesses access and use financial services more easily. This promotes production and business activities, which then creates job opportunities and reduces unemployment. In the past, small and micro enterprises often faced difficulties in accessing finance, therefore the expansion of financial development helps provide capital for growth and job creation.

The financial intermediation theory of Diamond in 1984 explains that banks act as financial intermediaries that connect savers who hold capital with those who need capital such as firms or individuals seeking loans. Financial development encourages the formation and operation of financial institutions such as banks, insurance companies and investment funds as well as financial instruments in the economy. When financial institutions develop, capital allocation becomes more efficient, reduces information asymmetry and helps businesses especially small and medium enterprises access capital. This not only promotes economic development but also creates more job opportunities which may help reduce the unemployment rate.

The labor supply and demand theory of Marshall in 1920 states that the unemployment rate can be explained by the balance between labor supply and labor demand. In this context, financial development plays an important role in adjusting and promoting labor demand. A developed financial system helps firms access capital more easily, expand investment and adopt new technology which increases hiring demand. Financial development also improves market confidence and creates a more dynamic economic environment which expands production scale and strengthens job creation.

2.2 Literature review

Studies on the effect of FD on the unemployment rate reflect many views and different methods.

Çiftçioğlu and Bein (2017) explored the relationship between FD and the unemployment rate in 10 EU countries from 1991 to 2012. Using the Granger causality test to examine the causal link between FD and unemployment in each country, their findings show a negative relationship between the two factors. This implies that higher FD is related to lower unemployment in these countries. Chen *et al*. (2021) used the GMM estimate to analyze 97 OECD and non OECD countries from 1991 to 2015. Their study concluded that FD worsens the unemployment rate, showing that the relationship between FD and unemployment is not always positive. Nyasha *et al*. (2022) examined the effect of banking development on unemployment in Kenya from 1991 to 2019 using the ARDL method. Their results show that banking development, measured by liquid loans, bank deposits, bank assets and the banking development index, has a negative effect on unemployment in Kenya, showing that better access to banking services helps reduce unemployment. Afonso and Blanco Arana (2024) assessed the relationship between financial development and the labor market in OECD countries from 1990 to 2020. By applying the random effects model for panel data, the results show that financial development reduces the unemployment rate. Similarly, in the study of Tsaurai (2022), financial development and renewable energy were analyzed in relation to unemployment in the context of North African countries. The study used panel data analysis for the period 1992 to 2019 such as the fixed effects model, FMOLS and pooled OLS. The results show that financial development reduces unemployment in a significant way. Raifu *et al*. (2023) examined the effect of FD on unemployment in 19 emerging market economies from 1991 to 2019. Using OLS, dynamic OLS and quantile regression, they found that FD reduces unemployment across all age and gender groups. Their results show the need for long term financial policies to ensure economic growth and job creation for the working age population and young people, regardless of gender. Raifu *et al*. (2024)

extended their study to the MENA region by using the panel quantile method. Their findings show that FD has a significant negative effect on unemployment across all quantiles, showing a strong and consistent relationship between FD and lower unemployment in the MENA region.

From the review of the above literature, we identify some research gaps:

First, until now there are still few studies that assess at the same time the nonlinear effect of FD on unemployment. Previous studies focus on linear effects and do not explore the interaction or influence of this factor in different contexts. This leaves a large gap in understanding how FD contributes to unemployment when examined from a broader view.

Second, unlike previous studies that mostly use frequency based models, this study aims to assess the nonlinear effect of FD on the unemployment rate through the Bayesian regression model based on probability. Bayesian regression techniques allow researchers to clarify this nonlinear relationship. A notable challenge is the high correlation in assessing these factors, which easily leads to multicollinearity. This explains why previous studies rarely explored this relationship. Bayesian regression provides a strong solution for challenges related to multicollinearity and uncertainty (Kruschke, 2015; McElreath, 2020). This approach gives a more clear view of how FD affects UNE, creating a way for more effective policy recommendations.

Moreover, in previous methods, information is often summarized based on averages and percentages and does not consider the uncertainty related to the estimates. This situation may lead to biased results and inconsistency with the real changes of the factors that affect unemployment. In contrast, in Bayesian regression, each parameter is represented by a probability distribution (Le Quoc, 2024). This allows researchers not only to estimate the value of the parameter but also describe the uncertainty related to that value. In the context of modeling unemployment, this becomes very important because UNE can be affected by many unobserved or time varying factors, such as changes in policy, changes in technology or unexpected macroeconomic factors. Bayesian regression is a method that allows researchers to adjust or update their estimates over time by updating the probability distribution (McElreath, 2020). This not only gives a clearer view of the effect of FD on UNE but also shows the reliability of the estimates, which allows more accurate policy decisions.

3 METHODOLOGY

3.1 Research data

The selected countries are based on the available data. The research data are collected from three main sources: the World Development Indicators of the World Bank (WB) and the Financial Access Survey of the International Monetary Fund (IMF). The final sample includes a balanced panel of 112 countries from 2004 to 2022. The definitions and measurements of all variables are presented in Appendix 1.

The unemployment rate (UNE) is an appropriate and widely accepted measure to capture the level of unemployment in an economy. It is calculated as the percentage of the labor force that is actively looking for work but cannot find a job, making it a direct and clear indicator of the health of the labor market. This variable has been used in previous studies, such as Raifu *et al*. (2023); Raifu *et al*. (2024) and Çiftçioğlu and Bein (2017), further confirming its relevance and reliability as a measure in labor market research.

The construction of the FD index using 105 indicators from the Global Financial Development Database (GFDD) and 46 indicators from FinStats is a process with a strict methodology. By classifying these indicators into sub indices such as Financial Institution Depth (FID), Financial Institution Access (FIA), Financial Institution Efficiency (FIE), Financial Market Depth (FMD), Financial Market Access (FMA) and Financial Market Efficiency (FME), the index captures both the institutional and market dimensions of FD. The combination of these sub indices into a full FD index ensures a comprehensive representation of the structure and function of the financial system. This index is particularly relevant for analyzing its effect on unemployment. While FD often reduces unemployment by improving access to credit, encouraging entrepreneurship and allowing firms to expand, it can have opposite effects in the context of digital transformation. With the rapid progress of digital technology, FD can unintentionally lead to higher unemployment. This happens when automation and digital tools streamline financial operations, reducing the need for traditional labor in the financial sector.

Besides the three main variables, this study also includes five control variables, namely: Foreign Direct Investment (FDI), Urbanization Rate (UR), Population Growth (POP), Inflation Rate (INF) and Economic Growth (GDP). These variables play an important role in reducing error and increasing the accuracy of the model, strengthening the effect of FD on unemployment.

3.2 Bayesian regression method

The research model is as follows:

$$UNE_{i,t} = \beta o + \beta_1 FD_{i,t} + \beta_2 FD^2{}_{i,t} + \beta_x X_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where:

Xi;t: is the vector of control variables, *i* = 1, 2, . . . is country and *t* = 1, 2, . . . is time.

In addition, the Bayesian method also removes model problems such as endogeneity, heteroscedasticity and autocorrelation (Thach, 2020). In the Bayesian view, we build the linear regression by using the probability distribution as follows:

$$P(\beta|y,X) = \frac{P(y|\beta,X)(P(\beta|X)}{P(y|X)} \qquad (2)$$

in there:

P(β|y,X): Posterior distribution of model parameters given inputs and outputs
P(y|β,X): Likelihood of the data
P(β|X): Prior probability distribution
P(y|X): Normalizing constant that can be ignored

As a result, equation (2) is frequently reduced to:

$$P(\beta|y,X) = P(y|\beta,X)(P(\beta|X) \qquad (3)$$

Bayesian regression was used in the procedure to evaluate the impact of FD on UNE through a specific three-step process: First, to ensure the recorded estimates tend toward zero rather than away from it, and to avoid biasing the analysis in a positive or negative direction, prior distributions for the regression coefficients were established with a mean assumption of zero. For the next step of the process, based on the parameters extracted from the equation, the distribution for the likelihood functions of the coefficients was determined. The final step was to obtain the posterior distribution of the coefficients by applying Markov Chain Monte Carlo (MCMC) and Gibbs Sampler techniques. This was done through a process of estimating and simulating 30,000 samples based on the posterior distribution, with the first 5,000 samples removed. MCMC techniques are widely applied to refine complex models in various fields (Levy & Mislevy, 2017).

4 RESEARCH RESULTS

4.1 Overview of descriptive statistics

The average unemployment rate across the full sample is 7.64 %, with a notable standard deviation of 5.51. This shows that there is considerable variation in unemployment rates among the countries or regions in the dataset. The minimum observed rate is very low at 0.10 %, while the maximum rate reaches a high level of 37.85 %, showing that some countries face extremely high unemployment rates, while others have very low rates. Financial development (FD) has an average value of 0.3656 and a standard deviation of 0.2422, showing that the general level of financial development among the countries is still quite low but has large variation. The minimum value is 0.0061, reflecting very low financial development in some countries, while the maximum value of 0.9968 shows outstanding financial development in several countries.

Before running the regression, we use the U shape test by Lind and Mehlum (2010). The null hypothesis states that there is a monotonic linear relation or a U shaped nonlinear relation between GEG and SD. Table A1 presents the test results, showing that the test statistic is higher than 1 %, rejecting the null hypothesis. This suggests the existence of a U shaped or an inverted U threshold.

Table 1

Descriptive statistics for variables

Variables	Mean	Std. Dev.	Minimum	Maximum
UNE	7.6356	5.5114	0.1	37.852
FD	0.3656	0.2422	0.0071	0.9968
GDP	2.2082	4.7356	-34.2038	62.5282
FDI	5.7589	22.8990	-394.4716	449.0828
POP	1.2639	1.6350	-14.2570	19.3604
INF	4.9427	5.4408	-16.8596	59.1196
UR	60.2861	21.2748	9.139	100

Source: Authors' calculations

Besides that, we conduct a correlation matrix test to assess the effect of the variables in the dataset and to evaluate multicollinearity. The results of the correlation matrix are presented in Table 2, summarizing the main insights. The test results show that the coefficients between the independent variables are at low and medium levels, and no pair of variables has a correlation above 0.8, which is the level of serious multicollinearity. This implies an important point that the dataset does not show serious multicollinearity, and all research variables are included in the research model.

Table 2

Correlation Matrix

	FD	GDP	FDI	POP	INF	UR
FD	1.0000					
GDP	-0.1048	1.0000				
FDI	0.0473	0.0415	1.0000			
POP	-0.1906	-0.1469	-0.0255	1.0000		
INF	-0.3224	0.0579	-0.0441	0.1341	1.0000	
UR	0.5975	-0.1227	0.0621	-0.1360	-0.2609	1.0000

Source: Authors' calculations

4.2 Bayesian regression results and discusion

The Bayesian regression results of 117 countries are described in detail in Table 3, clarifying the main insights. The results show that the mean values of the variables are clearly presented, which is different from the approach that uses regression coefficients in traditional regression methods. In the Bayesian method, the mean reflects the expected value of the parameter after taking into account the probability distribution of the model, while the regression coefficient in traditional frequentist methods only gives a single value of the parameter without considering the uncertainty in the estimation. In particular, the results show that the mean of FD is -0.142, which can be explained as the average estimates showing the level of influence of these factors when applying the Bayesian method. These values reflect the probability distribution of the parameters and are not single values as in standard regression.

The tests with the Bayesian regression model show that the average acceptance rate is 0.7376, which lies in a stable range. The minimum efficiency of the MCMC chains is above the acceptable level of 0.01, showing that the sampling process is diverse enough to accurately estimate the target distributions. The posterior distribution built through the MCMC technique needs to ensure that the samples are representative of the target distribution. Therefore, MCMC diagnostic tools are required to test the convergence of the Markov chains and to determine the stopping point of sampling. In this study, the authors use the Gelman Rubin statistic (the Rc coefficient) to assess convergence and the efficiency index to check the quality of sampling. The results in Table 3 show that the Rc value is less than 1.1, meeting the convergence criteria given by Levy (2020). At the same time, all efficiency indices are above 0.01, proving the stability and high reliability of the MCMC estimates. Different from traditional statistical methods such as OLS, FEM or REM, which often rely on the p value less than 0.05 to identify statistical significance, the Bayesian method uses the Monte Carlo Standard Error (MCSE) to assess the accuracy of the estimates. MCSE measures the error between the estimate from the MCMC chain and the true value of the target distribution, rather than relying only on the p value. According to Flegal & Jones (2011), when MCSE moves closer to zero, the stability of the MCMC chain becomes higher; MCSE below 6.5% of the standard deviation is considered acceptable, and below 5% is optimal. Based on the results in Table 3, all variables in the model meet this criterion. In this context, the MCMC diagnostic indices—acceptance rate, efficiency, Rc coefficient and MCSE—all exceed the required thresholds, confirming the strength and reliability of the Bayesian simulation results in this study.

Table 3

Results Bayesian Regression

Variables	117 Countries		
	Mean	Std. Dev	MCSE
FD	-0.1420	0.0419	0.0008
FD2	0.0960	0.0343	0.0006
GDP	-0.0656	0.0214	0.0004
UR	0.0338	0.0272	0.0006
INF	-0.0152	0.0217	0.0004
POP	-0.2587	0.0217	0.0004
FDI	0.0098	0.0207	0.0003
C	-0.0000	0.0207	0.0001
Acceptance rate			0.7376
Efficiency: min			0.0156
Max Gelman–Rubin Rc			1.0030

Source: Authors' calculations

Table 3 also shows that FD has a positive effect on UNE with a probability of 99.96% (Table 4). This implies a U shaped relationship between the effect of financial development on the unemployment rate. Specifically, this threshold is α = 0.73. Below this threshold financial development reduces the unemployment rate, while when FD passes this threshold it increases sustainable development, and the probability that this threshold occurs is 99.96% (Table 5).

Table 4

Probability of impact

Probability	**117 Countries**		
	Mean	Std. Dev	MCSE
{UNE: FD} < 0	0.9996	0.0187	0.0001
{UNE: FD2} > 0	0.9999	0.0077	0.0001
{UNE: GDP} < 0	0.9989	0.0329	0.0003
{UNE: UR} > 0	0.8930	0.3091	0.0030
{UNE: INF} < 0	0.7581	0.4281	0.0042
{UNE: POP} < 0	1.0000	0.0000	0.0000
{UNE: FDI} > 0	0.6820	0.4656	0.0046
{UNE: CONS} > 0	0.5008	0.5000	0.0050

Source: Authors' calculations

Based on the financial development threshold of 0.82, the study divides the countries into two groups: financial development below and above the threshold. The results are shown in Table 6. From the results it implies that the relationship between financial development and the unemployment rate is not always linear. This highlights the complex relationship between FD and unemployment in the digital age. In the context of the digital economy, FD has multi dimensional effects. On one hand, FD increases access to capital, encourages technology investment and improves infrastructure, creating opportunities for job growth. On the other hand, it can lead to more automation and reduce demand for low skill labor. This shift to automation, which is encouraged by the digital transformation of industries, helps explain why FD can worsen unemployment in some situations, especially in countries where low skill labor makes up a large part of the labor force. When industries prefer workers with skills and technology knowledge, those who do not have these skills may be at a disadvantage, which can increase the unemployment rate, especially in countries that already have high unemployment. For example, countries such as Sweden, Switzerland, France and Italy, even though they have advanced financial systems and higher FD, also tend to have relatively high unemployment rates. This paradox may be due to automation and labor replacement in traditional industries that depend on low skill labor. When FD becomes more connected with technology, it can unintentionally leave behind workers who lack the technical skills required by new industries. In addition, the push for financial innovation, especially in digital finance and financial technology, can make the job market more competitive, where high skill workers are in demand while low skill workers face fewer opportunities. Therefore, the change in the job structure may contribute to higher unemployment, especially in countries that already have high unemployment rates. These findings strongly support the theories of Information Asymmetry Theory (George, 1970), Financial Intermediation Theory (Diamond, 1984) and Labor Supply and Demand Theory (Marshall, 2020), showing that the effect of FD on unemployment is not simple. Therefore, managing FD in the digital age requires a careful balance, encouraging innovation while ensuring that job opportunities remain available and accessible for all parts of the population.

Table 5

Table of countries above and below the financial inclusion threshold

117 Countries			
Countries below FD threshold (0.73) APPENDIX A2	Countries above FD threshold (0.73) Switzerland, Australia, Canada, Spain, Japan, Korea, Rep., France, Sweden, Netherlands, Italy, Luxembourg, Germany.		
Probability above threshold 0.73	Mean	Std. Dev	MCSE
Probability 0.73 < Prob (UNE:FD) < 1	0.9996	0.0187	0.0001

Source(s): Authors own creation

5 CONCLUSION

This study explores the nonlinear effect of financial development on the unemployment rate. The study focuses on 117 countries during the period from 2004 to 2022. By using the Bayesian regression model, we find that there is a nonlinear relationship between FD and UNE with a threshold of 0.73 (with a probability of 99.96%). This implies that below this threshold FD reduces unemployment. In contrast, if it passes this threshold FD increases the unemployment rate. These results confirm the importance of FD in the process of reducing UNE. This finding adds to the ongoing discussion about how FD has complex effects on unemployment. By adding to the existing sources, the study not only increases a better understanding of how FD affects UNE but also adds more empirical evidence. It provides information that helps policymakers make more suitable policies to improve and encourage the reduction of unemployment. Based on these findings, we recommend that countries below the threshold focus on maximizing the benefits of financial development, expanding the coverage of financial services to vulnerable groups, especially people in rural and remote areas. In addition, banks should expand and strengthen support programs so that businesses can access capital more easily, as well as individuals who want to start a business, thereby expanding the labor market and reducing unemployment. For countries above the financial development threshold, it is necessary to implement vocational education programs in the digital age. Financial development needs to go together with improving labor skills to avoid unemployment caused by automation and structural change. It is important to promote vocational education, digital skill training and build retraining programs to help workers adapt to new requirements of the market.

However, we find that there is no single policy that is suitable for all countries at all stages of development. Instead, policymaking needs to be based on a deep understanding of the effect of FD on UNE. By applying flexible and targeted measures, it will create opportunities for development and international integration for the countries.

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APPENDIX

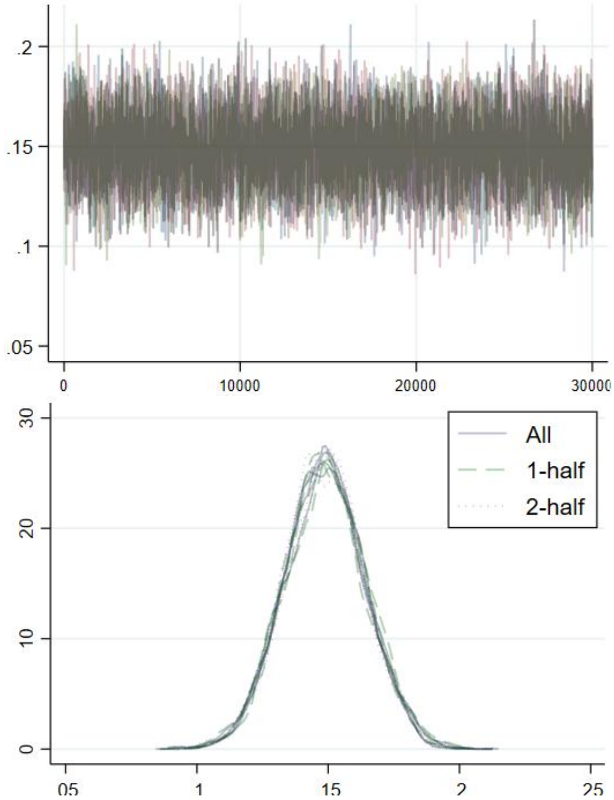
Appendix 1

Variable Description Table and Sources

Code	Indicator	Measurement	Source
Dependent Variable			
UNE	Unemployment rate	In this study unemployment is measured based on the Unemployment indicator, total percent of the total labor force. It shows the percent of the labor force that is unemployed and actively looking for work.	WB
Independent Variable			
FD		This study uses 105 indicators from GFDD and 46 from Finstats. Experts have built the	IMF

	Financial development index	indexes (FID, FIA, FIE, FMD, FMA, FME, FI, FM) and combined them into the overall FD index.	
Control Variable			
GDP	Economic growth	GDP per capita growth (%).	WDI
INF	Inflation rate	Percent change of CPI each year.	WB
UR	Urban population	Urban population percent of total population.	WB
FDI	Foreign direct investment	Foreign direct investment, net inflows percent of GDP.	WB
POP	Population growth rate	Annual population growth (%)	WB

Appendix 2. Posterior Distribution Plots and Trace Plots of FD and UNE



APPENDIX A1

Table A1

The U-shaped test result

Relationship	Overall examination for the existence of an inverted U-shaped or U-shaped relationship
FD vs UNE	*t*-value: 0.65***, *p*>|t|: 0.000

Source(s): Authors own creation

APPENDIX A2

Table A2

List of countries below the FD threshold (0.73)

Countries	Threshold
Albania, Algeria, Angola, Armenia, Austria, Azerbaijan, Bahamas, The, Bangladesh, Barbados, Belgium, Belize, Benin, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Chad, Chile, Colombia, Congo, Dem. Rep., Costa Rica, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, Egypt, Arab Rep., El Salvador, Estonia, Eswatini, Fiji, Finland, Gambia, The, Georgia, Ghana, Greece, Guinea, Guyana, Honduras, Hungary, Iceland, India, Indonesia, Ireland, Israel, Jamaica, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Latvia, Lesotho, Lithuania, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, New Zealand, Nicaragua, Nigeria, North Macedonia, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Saudi Arabia, Serbia, Slovak Republic, Slovenia, South Africa, Suriname, Thailand, Trinidad and Tobago, Tunisia, Uganda, Ukraine, United Arab Emirates, Uruguay, Vietnam, Zambia	FD < 0.73

Source(s): Authors own creation

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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