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Unveiling the impact of digital financial inclusion and financial development on global unemployment: A Bayesian quantile regression approach

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Abstract: This study investigates the impact of Digital Financial Inclusion (DFI) and Financial Development (FD) on Unemployment (UNE) across 112 countries from 2004 to 2022. Using the Bayesian Quantile Regression (BQR) method, the analysis reveals that DFI significantly reduces unemployment rates at all quantiles, including 0.1, 0.25, 0.5, 0.75, and 0.9. These findings suggest that DFI has a consistent and positive effect on lowering unemployment across different levels, making it an effective tool for tackling unemployment globally. In contrast, the impact of FD on unemployment is more nuanced. The study shows that FD reduces unemployment at the lower quantiles (0.1 and 0.25), but its effect turns negative at higher quantiles (0.5, 0.75, and 0.9). This indicates that while financial development may have a beneficial effect in countries with lower unemployment rates, its impact becomes less favorable or even exacerbates unemployment in countries with higher unemployment rates. These results suggest that focusing on expanding digital financial inclusion, rather than emphasizing traditional financial development, could be a more effective strategy for reducing unemployment, especially in countries with higher unemployment levels. The study recommends that policymakers prioritize digital financial inclusion as a means to enhance financial access and inclusivity, thus contributing to greater employment opportunities and reduced unemployment in the long run.
Keywords: *Digital financial inclusion, Financial development, Unemployment.*

1. Introduction

In the context of globalization and the continuous development of the global economy, the pursuit of sustainable development has become a top priority for nations and international organizations. Sustainable development not only requires economic growth but also demands a strong emphasis on environmental protection, improving people's quality of life, and addressing social issues such as unemployment and inequality. To achieve these goals, responsive resources — including financial instruments — play a crucial role. One of the essential factors in promoting sustainable development is Financial Inclusion (FI) [1]. FI is not just about providing basic financial services but also serves as a crucial tool for supporting sustainable economic development, offering opportunities for marginalized groups to engage in formal financial activities. When individuals have access to credit, insurance, savings, and other financial services, they can improve their living conditions, reduce personal and business financial risks, and subsequently contribute to the economy [2]. In particular, in the context of the rapidly advancing global digital transformation [3] the robust development of the Internet and the widespread adoption of digital solutions have led to profound changes in all aspects of life [4]. Digital Financial Inclusion (DFI) has become a critical factor in driving economic growth and addressing issues

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of equity in society [5]. DFI not only enhances access to financial services for disadvantaged groups but also has the potential to reduce barriers to credit, investment, and other financial services [6, 7]. Digital financial platforms, such as e-wallets, digital banking, and online payment applications, have enabled people in rural and remote areas to access financial services that were previously out of reach. This is particularly important in supporting the growth of small and medium-sized enterprises (SMEs), creating additional job opportunities, and reducing unemployment rates.

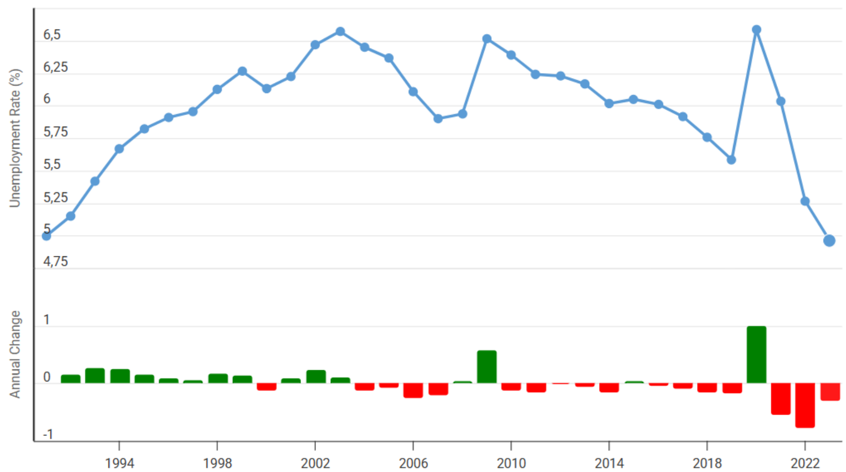

Figure 1.
Unemployment Rate and Its Growth Trend.
Source: World Unemployment Rate [8].

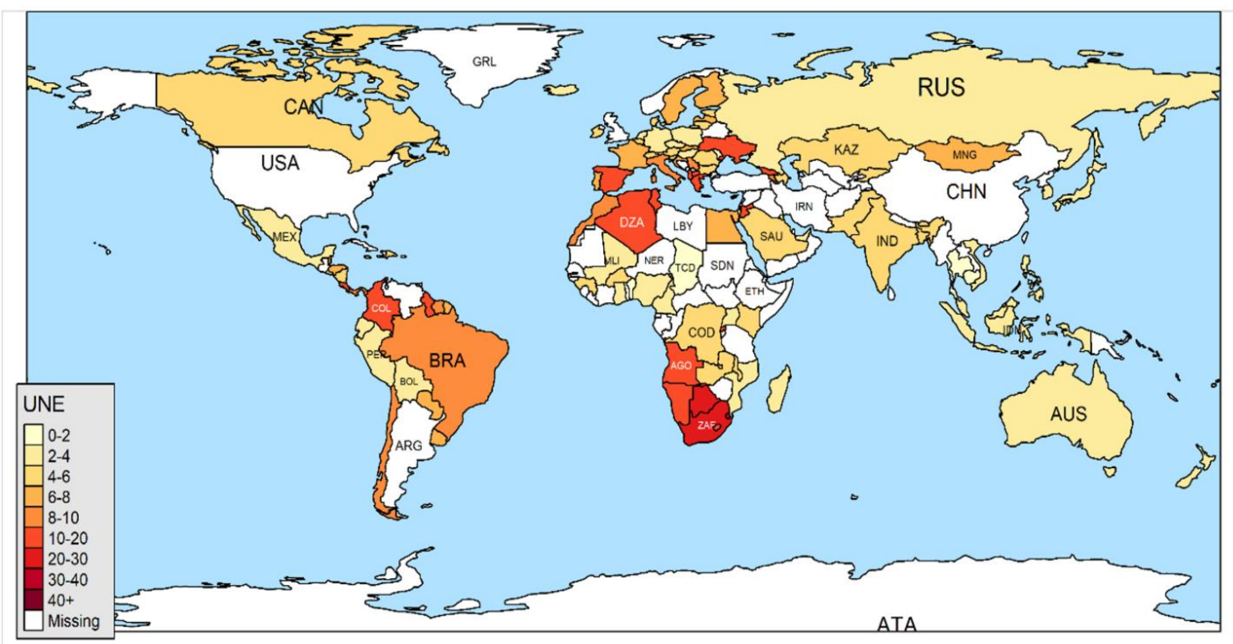

Figure 2.
Unemployment Rates of Countries Worldwide in 2022.

Figure 1 presents the average unemployment rate across countries worldwide from 1994 to 2021. Three notable periods can be identified: Period 1 (1991-2003) shows an increase in the unemployment

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rate from 5% to 6.57%. Period 2 (2004-2020) is marked by the widespread implementation of financial inclusion policies, with a downward trend in unemployment from 6.4% to 5.58%, except for two periods affected by the global economic crisis and the COVID-19 pandemic. Period 3 (2020-2022), following the COVID-19 pandemic, saw a reduction in the unemployment rate from 6.59% to 4.96%. Overall, the trend in the average unemployment rate from 1991 to 2022 is downward. However, as shown in Figure 2, unemployment rates across countries in 2022 are unevenly distributed. Some countries have very low unemployment rates, such as Qatar (0.13%), Burundi (0.92%), Thailand (0.94%), and Benin (1.47%), while others experience high unemployment rates, such as Botswana (23.62%), South Africa (28.84%), and Eswatini (37.85%). Furthermore, countries with strong financial development, such as Finland (6.72%), Croatia (6.96%), France (7.31%), Sweden (7.39%), and Italy (8.07%), have unemployment rates ranging from 6% to 10%.

Therefore, in this study, we argue that the impact of DFI and FD on unemployment rates will differ significantly. Specifically, DFI is characterized by expanding access to financial services for individuals and groups that have been excluded from the formal financial system, particularly low-income individuals or those in remote areas [9-13]. By reducing barriers related to geography, cost, and procedures, DFI creates opportunities for these individuals to engage in formal economic activities, thereby improving employment opportunities and reducing unemployment rates. In contrast, in today's technological context, financial development requires a robust infrastructure, and technological advancements can have opposite effects. While financial technology may enhance efficiency, reduce costs, and expand access to financial services, it can also lead to the automation of processes, resulting in the downsizing or replacement of certain traditional sectors by technology. This can create a situation of "job displacement" in sectors that are vulnerable to technological replacement, particularly in industries such as financial services, banking, and manufacturing. Therefore, while financial development may generate new job opportunities through fostering innovation and entrepreneurship, it could also pose challenges in protecting jobs for traditional labor groups. Given these dynamics, it is crucial to examine whether DFI or FD should be the key focus in today's digital transformation context. Thus, this study aims to answer two critical questions: How will DFI and FD impact unemployment rates? And, which policy—DFI or FD—should be promoted by countries in the current digital transformation era?

To address these two questions, we use the Bayesian quantile regression method. The application of quantile regression provides a deeper insight into the impact of DFI and FD on unemployment rates in various contexts. However, when dividing into smaller quantiles, such as at the 0.10 quantile, the sample size becomes smaller, which reduces the reliability of the estimates. To overcome this issue, Bayesian quantile regression can be an effective solution, as this method can handle problems related to small sample sizes. Additionally, Bayesian quantile regression helps address issues such as autocorrelation, endogeneity, and multicollinearity, providing more accurate estimates [14-16].

Moreover, in the case of traditional quantile regression, statistical information is often consolidated into a single number, such as the mean or percentile, which does not reflect any uncertainty associated with such estimates. This situation may lead to the analysis results being inconsistent with the actual variability of the factors influencing unemployment rates. In contrast, in Bayesian quantile regression, each parameter is represented by a probability distribution [5]. This allows researchers not only to estimate the value of the parameter but also to describe the uncertainty associated with these values. In the context of modeling unemployment rates, this becomes especially important because unemployment can be influenced by many unobservable factors or factors that change over time, such as fluctuations in policies, technological changes, or unexpected macroeconomic factors. For instance, when there is volatility in unemployment rates due to factors such as the COVID-19 pandemic, policy changes, or economic crises. Bayesian quantile regression is a method that allows researchers to adjust or update their estimates over time by modifying the probability distribution [14]. This not only provides a clearer view of the impacts of financial policies on unemployment rates but also shows the reliability of the estimates, thereby enabling more accurate policy decisions.

This study contributes to the literature in the following aspects: First, it clarifies the differences between DFI and FD in their impact on unemployment rates; it applies the Bayesian quantile regression method to model unemployment rates, helping to describe uncertainty and variability in the influencing factors; it provides insights for effective financial policies aimed at reducing unemployment rates; and it proposes improvements in financial infrastructure, particularly in the context of digital transformation, to reduce unemployment rates.

The remainder of this article is organized as follows. The section "Literature Review" provides an overview of studies examining the impact of DFI and FD on UNE. Following that, the section "Research Methodology" offers a brief introduction to the data, variable descriptions, rationale, and an overview of descriptive statistics. In the subsequent section, "Empirical Results," we delve into the findings of our research. Finally, the section "Conclusion and Policy Implications" concludes the article and presents tailored policy recommendations.

2. Literature Review

2.1. The Theory of the Impact of DFI and FD on UNE

The theory regarding the impact of DFI and FD on unemployment can be approached through the following theories.

George [17] theory of information asymmetry suggests that distinguishing between good borrowers and bad borrowers is challenging due to the presence of information asymmetry, where one party in a credit contract has more or better information than the other. DFI, by providing digital financial services, helps mitigate information asymmetry between financial institutions and previously underserved individuals, especially those in rural areas or with low incomes. Previously, many individuals were unable to access financial services due to a lack of information about financial products or insufficient documentation to participate in the formal banking system. FD plays a crucial role in building and improving the financial system, enabling individuals and businesses to easily access and use financial services.

The Financial Intermediation Theory by Diamond [18] explains that banks function as "financial intermediaries" connecting savers (capital holders) with those who need capital (businesses or individuals seeking loans). DFI helps connect individuals without bank accounts to the formal financial system through digital financial services such as e-wallets, mobile money transfers, or online banking platforms. By doing so, DFI not only reduces geographical barriers but also mitigates information asymmetry in evaluating and allocating capital, supporting individuals and businesses in joining the formal economy, improving employment opportunities, and reducing unemployment rates. FD promotes the emergence and operation of financial institutions (banks, insurance companies, investment funds, etc.) and financial instruments in the economy. As financial institutions develop, capital allocation becomes more efficient, reducing information asymmetry and helping businesses, especially small and medium-sized enterprises (SMEs), access capital. This not only boosts economic development but also creates more job opportunities, potentially contributing to lower unemployment rates.

The Labor Supply and Demand Theory [19] suggests that unemployment rates can be explained through the balance between labor supply and labor demand. In this context, DFI helps reduce financial barriers for workers and businesses, increasing their ability to participate in the labor market. When individuals can easily access financial services, they can create job opportunities or start their own businesses, thereby reducing unemployment rates. FD also contributes to increasing job opportunities by fostering a more dynamic economic environment.

2.2. Studies Related to the Impact of DFI and FD on UNE

Amakor and Eneh [20] examine the impact of financial inclusion on unemployment in Nigeria from 1991 to 2021. Using the ARDL method, their results show that the variables affecting the unemployment rate are statistically significant at the 5% level. Their study recommends that the government should promote widespread financial literacy to help citizens access the benefits of financial services. Furthermore, monetary authorities should enhance their role in directing credit and lending channels toward the private sector to harness the benefits of financial inclusion. Sakanko, et al. [21] explore the impact of financial inclusion on poverty reduction, income inequality, and unemployment in Nigeria, using data from 2007 to 2018 and the ARDL method. Their results indicate that financial inclusion increases job opportunities while simultaneously reducing poverty in Nigeria. Mehry, et al. [22] investigate the effects of financial inclusion on unemployment in 35 developing countries from 2009 to 2018. Using the GMM method, they found that financial inclusion reduces unemployment rates in these countries. Alshyab, et al. [23] focus on non-oil-exporting Arab countries such as Egypt, Jordan, Lebanon, Morocco, and Tunisia from 2008 to 2018. Their results from a random effects model reveal a significant negative impact of both financial inclusion and real output growth on unemployment. Williams, et al. [24] study the impact of financial inclusion on illiteracy and unemployment in rural Nigeria from 2017 to 2022, using the ARDL method. They found that higher illiteracy rates are associated with lower financial inclusion and higher unemployment rates. Their findings suggest that a decrease in financial service provision in developing countries contributes to illiteracy and unemployment. They conclude that improving education and employment rates in rural areas is essential to achieving optimal financial inclusion of products and services. Okeke, et al. [25] also analyze the impact of financial inclusion on unemployment in Nigeria from 1991 to 2021. Using the ARDL method, they find a positive short-term relationship between financial inclusion and the unemployment rate. Recent studies by Wibowo, et al. [26] and Wu, et al. [27] further explore the relationship between financial inclusion and unemployment, contributing additional insights into the topic.

The studies on the impact of FD on unemployment rates reflect a variety of perspectives and methods.

Çiftçioğlu and Bein [28] explore the relationship between financial development and unemployment rates in 10 EU countries from 1991 to 2012. Using the Granger causality test to examine the causal relationship between FD and unemployment in each country, their findings show a negative correlation between the two. This implies that higher financial development is associated with lower unemployment rates in these countries. Chen, et al. [29] use GMM estimation to analyze 97 OECD and non-OECD countries from 1991 to 2015. Their study concludes that FD exacerbates unemployment rates, suggesting that the relationship between financial development and unemployment may not always be beneficial. Nyasha, et al. [30] study the impact of banking development on unemployment in Kenya from 1991 to 2019 using the ARDL method. Their results indicate that banking development, represented by liquidity loans, bank deposits, bank assets, and banking development index, has a negative impact on unemployment in Kenya, suggesting that better access to banking services helps reduce unemployment. Raifu and Afolabi [31] investigate the effect of FD on unemployment in 19 emerging market economies between 1991 and 2019. Using OLS, Dynamic OLS, and quantile regression, they find that FD reduces unemployment across all age groups and genders. Their results suggest the need for long-term financial policies that ensure economic growth and job creation for the working-age population and youth, regardless of gender. Raifu, et al. [32] extend their research to the MENA (Middle East and North Africa) region using quantile panel methods. Their findings show that FD has a significantly negative impact on unemployment across all quantiles, indicating a strong and consistent relationship between financial development and reduced unemployment in the MENA region.

Through the literature review, two research gaps can be identified:

First, no study to date has simultaneously evaluated the combined impact of DFI and FD on unemployment rates. Previous studies have typically focused on the isolated effects of either DFI or FD on unemployment, without exploring the interplay or joint influence of these two factors. This leaves a significant gap in understanding how DFI and FD, when considered together, contribute to addressing unemployment.

Second, unlike previous studies that predominantly employed traditional frequency-based methods, this research aims to reassess the impact of DFI and FD on unemployment rates through the Bayesian quantile regression approach (probability-based perspective). Bayesian quantile regression techniques enable researchers to analyze the effects of DFI and FD at different points in the unemployment distribution, shedding light on the nonlinear impacts of DFI and FD on unemployment dynamics. One notable challenge in evaluating the joint influence of DFI and FD on unemployment lies in their high correlation, which often leads to multicollinearity issues. This may explain why prior studies have rarely explored the combined effects of these variables. However, Bayesian quantile regression offers a robust solution to such challenges by addressing issues of endogeneity and multicollinearity [14]. This approach provides a more nuanced understanding of how DFI and FD interact across varying unemployment contexts, paving the way for more effective policy recommendations.

3. Research Methodology

3.1. Data and Sample

The countries were selected based on data availability. The research data were collected from three primary sources: the World Development Indicators Index from World Bank (WB) and the Financial Access Survey from the International Monetary Fund (IMF). The final sample consists of a balanced panel of 112 countries covering the period from 2004 to 2021. The definitions and measurements of all variables are presented in Appendix 1.

3.2. Variable Justification

The unemployment rate (UNE) is an appropriate and widely accepted measure for capturing the extent of unemployment within an economy. It is calculated as the percentage of the labor force that is actively seeking but unable to find employment, making it a direct and straightforward indicator of labor market health. This variable has been utilized in prior studies, such as Amakor and Eneh [20] and Alshyab, et al. [23] further validating its relevance and reliability as a measure in research on labor market dynamics.

In prior studies, the measurement of DFI has varied significantly. Nonetheless, the consensus is that DFI cannot be adequately represented by a single variable but requires a composite of indicators reflecting the breadth of financial access expansion [33]. Drawing on previous research, including Oanh and Dinh [6]; Quoc, et al. [11] and Dinh, et al. [10] this study develops a DFI measure encompassing the following eight components: the number of bank branches (BRA); the number of ATMs (ATM); the outstanding balance, including loans from commercial banks (OLB) and deposits at commercial banks (ODB); mobile cellular subscriptions (MCS); fixed broadband subscriptions (FBS); and the proportion of individuals using the Internet (INT).

$$DFI = W_1BRA + W_2ATM2 + W_3OLB + W_4ODB + W_5MCS + W_6FBS + W_7INT$$

Principal Component Analysis (PCA) is employed to condense a large set of closely interrelated variables into fewer uncorrelated components by transforming the original data [6, 7]. Tables 1 and 2 illustrate the PCA results for 112 countries worldwide, summarizing key insights. Table 1 shows that the first and second principal components have eigenvalues of 4.1477 and 0.944, respectively, accounting for 72.72% of the total variance. However, since the second component and the subsequent components have eigenvalues below the threshold of 1, the first principal component was selected to construct the DFI variable. Table 2 highlights that the weights for MCS and INT are relatively high, at 0.4559 and 0.3883, respectively, indicating the importance of these variables in constructing the digital financial index. The ATM variable has the highest weight at 0.5722, suggesting that the number of ATMs remains a key indicator for most countries. This may be attributed to the sample, which includes many developing nations where traditional financial inclusion methods are still dominant.

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Table 1.
Probability contribution of the variables.

Dim	Eigenvalue	Proportion	Cumulative
Dim.1	4.1477	0.5925	0.5925
Dim.2	0.9440	0.1349	0.7274
Dim.3	0.7532	0.1076	0.8350
Dim.4	0.4945	0.0706	0.9056

Table 2 - PCA results for the 7 variables with positive weights (W) are presented. And the overall DFI scores for 117 countries are calculated using the formula below.

DFI = 0.5722ATM + 0.1395CBB + 0.3295ODB + 0.4048OLB + 0.4559MCS + 0.1485FBS + 0.3883INT

Table 2.
PCA result.

DFI	ATM	CBB	ODB	OLB	MCS	FBS	INT
	0.5722	0.1395	0.3295	0.4048	0.4559	0.1485	0.3883

The construction of the FD index using 105 indicators from the Global Financial Development Database (GFDD) and 46 from FinStats is a methodologically rigorous process. By categorizing these indicators into sub-indices—such as Financial Institutions Depth (FID), Financial Institutions Access (FIA), Financial Institutions Efficiency (FIE), Financial Markets Depth (FMD), Financial Markets Access (FMA), and Financial Markets Efficiency (FME)—the index captures both the institutional and market dimensions of financial development. The aggregation of these sub-indices into a comprehensive FD index ensures a holistic representation of the financial system's structure and functionality. This index is particularly relevant for analyzing its impact on unemployment. While FD often reduces unemployment by improving access to credit, fostering entrepreneurship, and enabling businesses to expand, it may have counteracting effects in the context of digital transformation. With the rapid advancement of digital technology, financial development could inadvertently lead to higher unemployment rates. This occurs as automation and digital tools streamline financial operations, reducing the need for traditional labor in the financial sector.

Based on the arguments above, we propose the following two hypotheses.

Hypothesis 1: DFI reduces the unemployment rate.

Hypothesis 2: FD increases the unemployment rate.

Additionally, we include the following control variables: Gross Domestic Product (GDP), Urbanization Rate (UR), Inflation (INF), Foreign Direct Investment (FDI), and Population (POP). These control variables are important for accounting for other macroeconomic factors that may influence unemployment, ensuring a more accurate analysis of the relationships between DFI, FD, and UNE.

3.3. Research Methodology

The model for analyzing the impact of DFI and FD on the UNE is constructed as follows.

$$UNE_{i,t} = \beta_o + \beta_1 DFI_{i,t} + \beta_2 FD_{i,t} + \beta_x X_{i,t} + \varepsilon_{i,t} \quad (1)$$

Model 1 faces several key issues that need to be addressed: (1) the presence of high multicollinearity between DFI and FD, which can reduce the accuracy of the model's estimates and make it difficult to separately determine the effect of each variable. (2) There may be endogeneity issues between the independent variables and the error term $\varepsilon_{i,t}$, leading to biased estimates and raising concerns about the consistency of the results. To overcome these issues, we apply the Bayesian Quantile Regression (BQR) method. This method helps address multicollinearity and endogeneity by using probabilistic techniques to incorporate additional informational factors, improving the accuracy of the estimates. BQR allows for

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modeling the variation in the effects of explanatory variables at different quantiles of the dependent variable's distribution, providing more precise estimates, especially when the relationship between variables varies across the distribution. Additionally, this method handles endogeneity by utilizing prior distributions and enhancing the stability of the parameter estimates, thereby reducing errors in the model [14].

4. Research Findings

4.1. Overview of Descriptive Statistics

The average unemployment rate across the sample is 7.64%, with a significant standard deviation of 5.51%. This suggests that there is a considerable variation in unemployment rates across the countries or regions in the dataset. The minimum observed rate is very low at 0.10%, while the maximum reaches a notably high 37.85%, indicating that some countries face extremely high unemployment, whereas others have very low unemployment rates. The average DFI score is 0.38, with a standard deviation of 0.20, indicating considerable variation in digital financial inclusion across the sample. The DFI score ranges from 0 (indicating no DFI) to 1 (representing complete DFI). This suggests that many countries are still at the early stages of digital financial inclusion, although some countries have achieved significant levels of inclusion. The average financial development score is 0.37, with a relatively high standard deviation of 0.24. This indicates a diverse range of FD across the countries in the dataset. The minimum value of 0.01 suggests that some countries have extremely limited FD, while the maximum score of 3.92 indicates a high level of FD in some countries, showing a wide disparity between financial systems in the sample.

Additionally, Table 3 highlights three important issues that need to be addressed. Firstly, the assessment of cross-sectional dependence (CD) is essential in panel data analysis. To evaluate CD, we employed the Pesaran [34] test, as overlooking this aspect could lead to misleading conclusions. The results presented in Table 3 show a significant relationship among the countries ($p < 0.01$), indicating the presence of cross-sectional dependence. Secondly, the Jarque-Bera test results indicate that the variables in the study do not follow a normal distribution ($p < 0.01$). This suggests that the data may exhibit skewness or kurtosis, meaning the distribution is not symmetrical and may have outliers or heavy tails. Consequently, this necessitates the use of robust estimation methods to address these departures from normality. Lastly, the test statistics for both Delta and Adjusted [35] are significant, with values of 17.780 ($p < 0.01$) and 25.508 ($p < 0.01$), respectively. These findings indicate slope heterogeneity, meaning that the relationships between the variables differ across various units of observation. This is an important consideration in choosing the appropriate method for analysis. Given these challenges, the results strongly justify the application of Bayesian Quantile Regression (BQR). This method allows for more precise estimation of coefficients at different quantiles, taking into account the heterogeneity of slopes across the data. By doing so, BQR ensures that the unique characteristics of each unit are properly captured, providing more reliable and nuanced insights into the relationships among the variables.

Table 3.
Overview of descriptive statistics.

Variables	Mean	Std. Dev.	Minimum	Maximum	Pesaran CD Test	Jarque Bera Test
UNE	7.6357	5.5115	0.1000	37.8520	27.150***	598.68***
DFI	0.3803	0.2049	0.0000	1.0000	266.735***	489.33***
FD	0.3657	0.2423	0.0072	3.9165	79.397***	955.57***
GDP	2.2083	4.7356	-34.2039	62.5283	160.428***	127.85***
FDI	5.7589	22.8991	-394.4716	449.0828	28.117***	203.88***
POP	1.2639	1.6350	-14.2570	19.3604	46.183***	61.71***
UR	60.2861	21.2748	9.1390	100.0000	269.201***	61.71***
INF	4.9428	5.4409	-16.8597	59.1197	140.620***	128.05***
Slope heterogeneity						
Delta	17.780***					
Adj.	25.508***					

Note: *** indicates significance level of 1%.

Table 4.
BQR results.

Variables	Quantile: 0.10			Quantile: 0.25			Quantile: 0.50		
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
DFI	-1.5663	-2.8825	-0.1559	-2.3992	-3.6100	-1.2568	-2.4743	-3.5019	-1.4241
FD	-0.8097	-2.2353	0.6544	-0.0511	-0.0927	0.8495	0.0405	-0.7463	0.8710
GDP	-0.0284	-0.0640	0.0084	-0.0448	-0.0080	-0.0118	-0.0713	-0.1035	0.3431
FDI	0.0051	-0.0004	0.0096	0.0040	0.0006	0.0088	0.0003	-0.00032	0.0048
POP	-0.5749	-0.6837	-0.4635	-0.7648	-0.8750	-0.6580	-0.9944	-1.0988	-0.9064
UR	0.0315	-0.0013	0.0672	0.0384	0.0029	0.0476	0.0291	0.0213	0.0365
INF	0.0314	-0.0013	0.0672	0.0571	0.0367	0.0758	0.009	-0.0129	0.0291
C	2.0450	-4.6386	-1.6597	3.5754	3.0700	4.0717	6.6614	6.1401	7.2293
Variables	Quantile: 0.75			Quantile: 0.90					
DFI	-2.7814	-3.9562	-1.6497	-5.0631	-8.0491	-2.4610			
FD	0.0540	-0.8277	0.9261	1.2510	-0.4143	2.4098			
GDP	-0.0760	-0.1065	-0.0427	-0.1679	-0.2228	-0.1164			
FDI	0.0007	-0.0036	0.0053	0.0053	-0.0102	0.0173			
POP	-1.1064	-1.2148	-0.9828	-0.8218	-0.9333	-0.7204			
UR	0.0236	0.0160	0.0320	-0.0298	-0.0512	-0.0089			
INF	-0.0037	-0.0268	0.0168	0.0543	-0.0037	0.0986			
C	7.7315	7.1382	8.2827	19.1205	18.0919	20.4706			

4.2. BQR Results and Discussion

The results of the Bayesian Quantile Regression (BQR) regarding the impact of DFI and FD on UNE across 112 countries from 2002 to 2022 are presented in Table 4. We used five quantiles: 0.1, 0.25, 0.50, 0.75, and 0.9. As shown, DFI has a negative effect on UNE at all quantiles. This suggests that DFI contributes to a reduction in unemployment rates across these countries, indicating that digital financial inclusion plays a role in lowering unemployment levels, regardless of the specific quantile. The impact is consistent across the distribution of unemployment, implying that the benefits of DFI in enhancing financial access and fostering economic activities are broadly felt in both low and high unemployment contexts. When comparing these findings with previous studies by Amakor and Eneh [20]; Sakanko, et al. [21]; Mehry, et al. [22]; Okeke, et al. [25]; Wibowo, et al. [26] and Wu, et al. [27] which explored the impact of FI on UNE, this research provides additional evidence on the direct influence of DFI—a form of FI facilitated by digital means—on UNE. While earlier studies established a link between financial inclusion and unemployment reduction, this study expands on that by focusing specifically on the digital aspect of financial inclusion, offering a more nuanced perspective on its role in addressing unemployment in the modern economy. The findings support Hypothesis 1 (H1) initially proposed, aligning with the theories of Asymmetric Information Theory [17] Financial Intermediation Theory [18] and Labor Supply and Demand Theory [19]. These theories emphasize that better access to financial services can improve labor market outcomes by facilitating information flow, reducing financial barriers, and promoting efficient allocation of labor and capital, ultimately leading to lower unemployment.

The findings regarding the impact of FD on UNE indeed suggest a more complex relationship. As noted, while FD appears to reduce unemployment in countries with lower unemployment rates (quantiles 0.1 and 0.25), its impact becomes more adverse at higher quantiles (0.5, 0.75, and 0.9), particularly in nations with higher unemployment rates. This complexity can be further unpacked by considering the evolving dynamics of financial systems, especially in the digital age. In the context of the digital economy, the impact of financial development becomes multifaceted. On the one hand, financial development enhances access to capital, facilitates investment in technology, and improves infrastructure. However, on the other hand, it can also lead to increased automation and the reduction of demand for low-skilled labor. This shift towards automation, driven by the digitalization of industries, could explain why FD might exacerbate unemployment in certain contexts, particularly in countries where low-skilled labor constitutes a significant portion of the workforce. In the digital age, many sectors increasingly prioritize skilled, tech-savvy employees, which could marginalize individuals without these skills, thus contributing to higher unemployment rates, especially in higher unemployment countries.

For example, nations like Sweden, Switzerland, France, and Italy, which exhibit advanced financial systems and higher levels of financial development, also tend to have relatively high unemployment rates. This paradoxical situation can be attributed to the fact that these countries, despite their strong financial sectors, face challenges related to automation and the displacement of workers in industries that traditionally employed lower-skilled labor. As financial development increasingly integrates technology, it can unintentionally leave behind a segment of the workforce that is not equipped with the technical skills demanded by emerging industries. Moreover, in these economies, the push toward financial innovation, particularly digital finance and fintech, could lead to a more competitive job market, where high-skilled workers are in greater demand while low-skilled workers face more limited employment opportunities. The shift in employment patterns may thus contribute to rising unemployment, particularly at higher quantiles where unemployment rates are already more pronounced. Therefore, the complexity of FD's impact on unemployment suggests that financial development in the digital age requires a careful balance between fostering innovation and ensuring the availability of accessible, inclusive job opportunities for all segments of the population.

To ensure that the Bayesian inference based on the Markov Chain Monte Carlo (MCMC) samples is valid, the author tested the convergence of the MCMC estimates of the parameters through visual diagnostics using graphs. According to Balov and Altunkaynak [36] the MCMC convergence diagnostic plots include the trace plot and the posterior distribution histogram. These plots help monitor the history of a parameter value through successive iterations of the chain. Appendix 2 shows the convergence diagnostics results for two variables, DFI and FD, across five quantiles. The results indicate that all parameter plots in the model are reasonable, with consistent trace plot shapes, and the distribution plots exhibit a normal distribution, confirming the robustness of the Bayesian quantile regression.

5. Conclusion and Policy Implications

This study evaluates the impact of DFI and FD on UNE across 112 countries from 2004 to 2022. Using the BQR method, we find that DFI reduces unemployment at all quantiles, including 0.1, 0.25, 0.5, 0.75, and 0.9. These results suggest that digital financial inclusion plays a significant role in reducing unemployment, indicating a consistent impact across different unemployment levels. In contrast, FD reduces unemployment at lower quantiles (0.1 and 0.25) but exacerbates unemployment at higher quantiles (0.5, 0.75, and 0.9). This finding indicates that while financial development may positively impact unemployment reduction in countries with lower unemployment rates, its effects become less favorable or even detrimental in countries with higher unemployment rates. Based on these findings, we recommend that countries focus on expanding DFI to promote broader financial inclusion and address unemployment more effectively. Additionally, we recommend promoting FD in countries with low unemployment rates, as this may help further reduce unemployment levels. In contrast, for countries with high unemployment rates, a more tailored approach should be considered, as the effects of FD may not be as favorable and could potentially exacerbate unemployment. In such cases, expanding DFI may be a more effective strategy to address unemployment challenges and foster economic stability.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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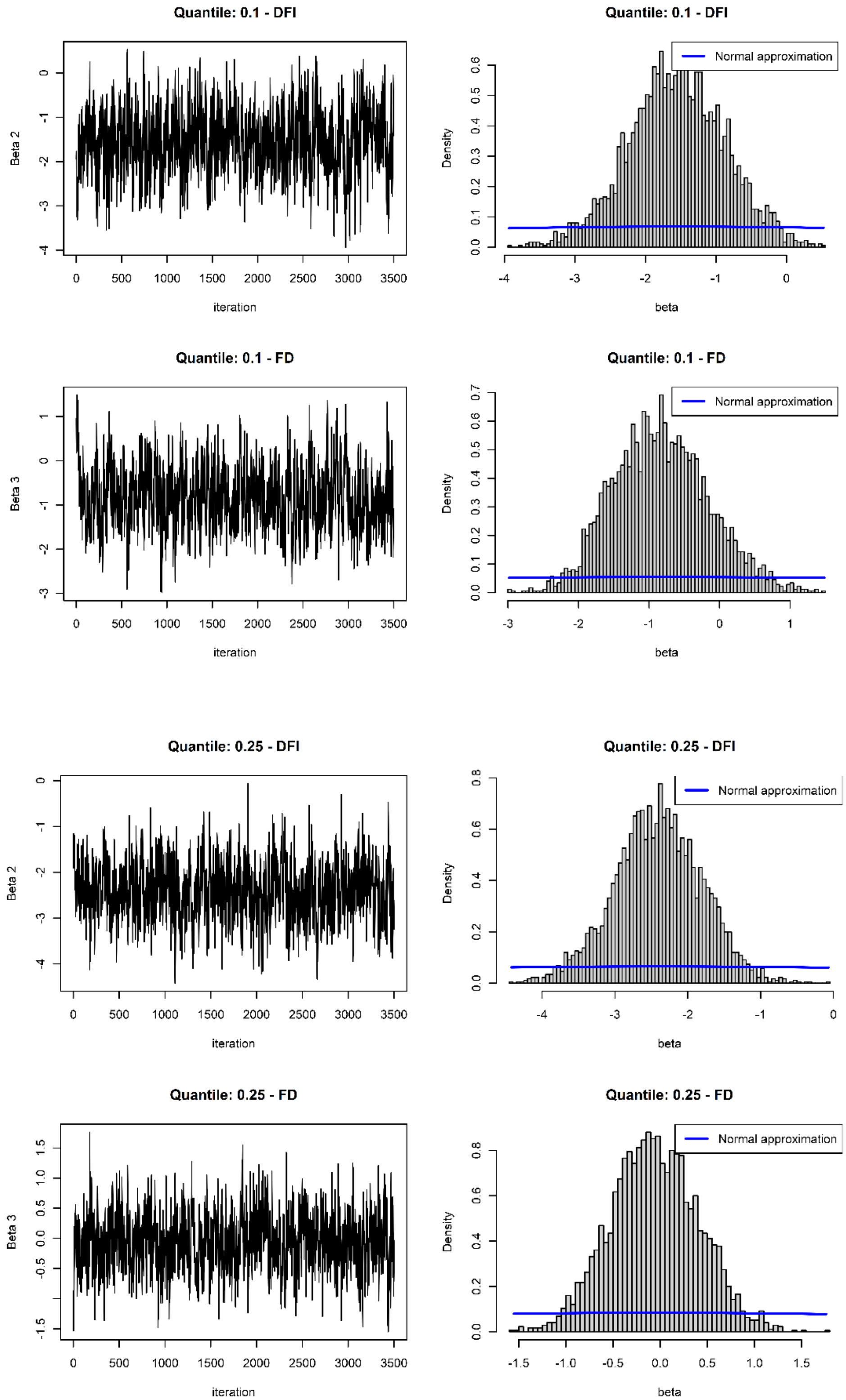
Appendix 1.
Variable description and source.

Symbol	**Indicator**	**Measurement**	**Source**
Dependent variable			
UNE	Unemployment Rate	The measurement of unemployment in this study is based on the indicator "Unemployment, total (% of total labor force)", which represents the percentage of the total labor force that is unemployed and actively seeking employment	WB
Independent variables			
DFI	Digital Financial Inclusion	We use the PCA technique to calculate DFI.	Authors
1. BRA	The number of bank branches.	Number of commercial bank branches per 100,000 adults.	WB, IMF
2. ATM	The number of ATMs	Number of ATMs per 100,000 adults.	WB, IMF WB, IMF
3. OLB	Outstanding loans from commercial banks	The percentage representing the total value of loans provided by commercial banks within a specific nation relative to its GDP.	WB, IMF
4. ODB	Outstanding balance of deposits at commercial banks	The percentage indicating the total value of deposits maintained within commercial banks within a given country in relation to its GDP.	WB, IMF
5.MCS	Mobile cellular subscriptions	Mobile cellular subscriptions per 100 people	WB
6. INT	Individuals using the Internet	The percentage of individuals in a specific country or region who have access to and utilize the Internet. (%)	WB
7. FBS	Fixed broadband subscriptions	Fixed broadband subscriptions (per 100 people)	WB
FD	Financial development index	Using 105 indicators from GFDD and 46 from FinStats, experts constructed sub-indices (FID, FIA, FIE, FMD, FMA, FME, FI, FM) and combined them into the overall FD index.	IMF
Control variables			
INF	Inflation Rate	Annual CPI growth rate (%) is the year-over-year percentage change in the Consumer Price Index (CPI).	WDI
UR	Urban population	Urban population (% of total population)	WDI
POP	Population growth rate	Annual population growth rate (%)	WDI
FDI	Foreign direct investment	Foreign direct investment, net inflows (% of GDP)	WDI
GDP	Economic growth	GDP growth per capita (%)	WDI


Quantile: 0.1 - DFI
Beta 2
iteration
Quantile: 0.1 - DFI
Normal approximation
Density
beta
Quantile: 0.1 - FD
Beta 3
iteration
Quantile: 0.1 - FD
Normal approximation
Density
beta
Quantile: 0.25 - DFI
Beta 2
iteration
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Beta 3
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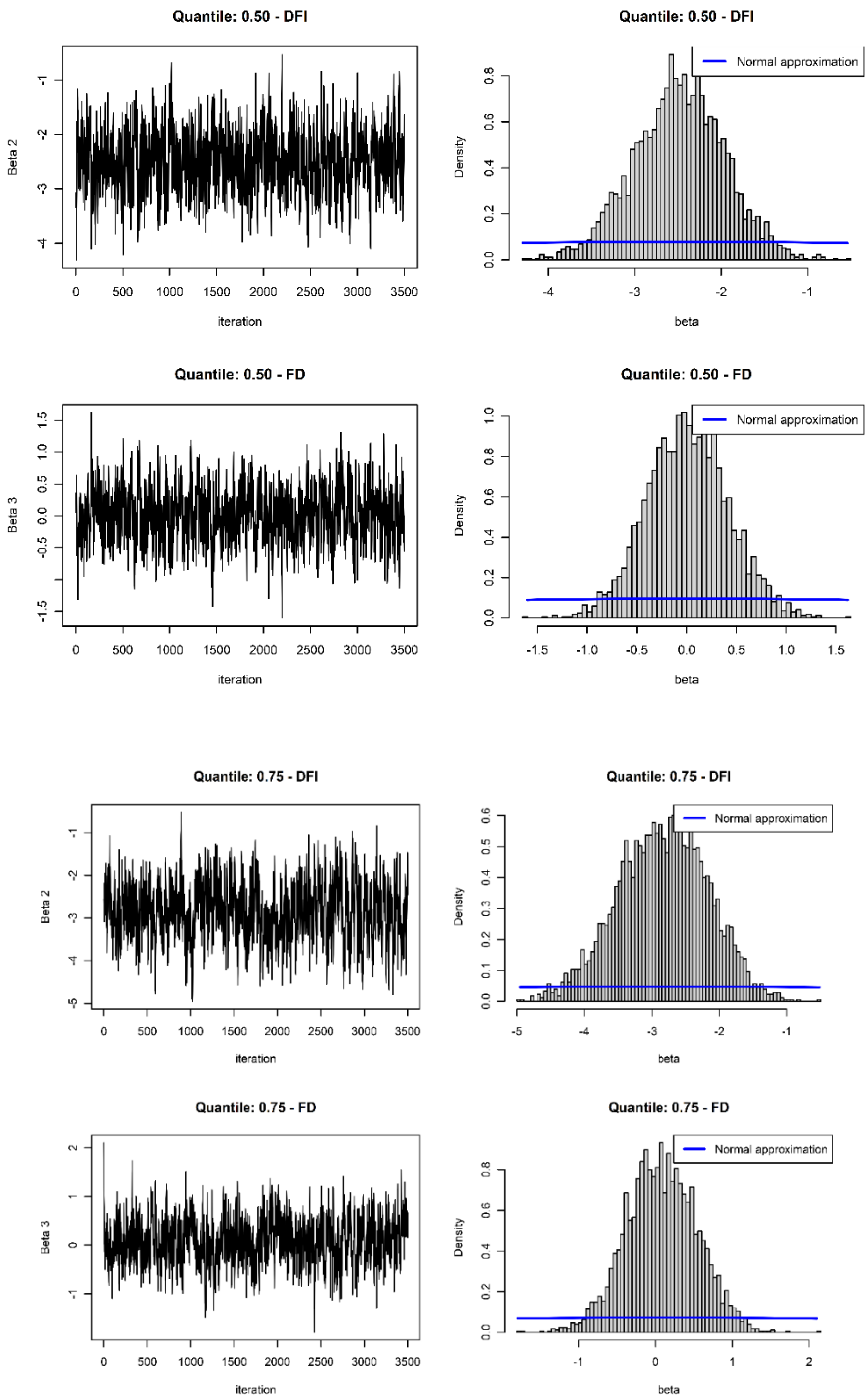

Appendix 2.
Trace Plot and Histogram of DFI at CO2 Quantiles.

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