EXPLORING THE IMPACT AND RISKS OF FINTECH ADOPTION ON INCOME INEQUALITY: A GLOBAL CROSS-SECTIONAL STUDY

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OPEN ACCESS

How to cite this paper: Imeraj, J., Hoda, N., Bica, K., Prenaj, V., & Gjoni, L. (2025). Exploring the impact and risks of fintech adoption on income inequality: A global cross-sectional study. *Risk Governance & Control: Financial Markets & Institutions, 15*(2), 92–102.
https://doi.org/10.22495/rgcv15i2p8

ISSN Online: 2077-4303
ISSN Print: 2077-429X

Received: 29.09.2024
Revised: 23.01.2025; 22.04.2025
Accepted: 09.05.2025

JEL Classification: D31, G21, J11, O33, O40
DOI: 10.22495/rgcv15i2p8

Abstract

The rapid expansion of financial technology (fintech) has transformed financial services, offering innovative solutions that promote financial inclusion and economic growth. However, its impact on income inequality remains debated (Beck et al., 2018). This study investigates the relationship between fintech adoption and income inequality across 150 countries for the years 2014, 2017, and 2021 using secondary data from the Global Findex database. Income inequality is measured by the share of pre-tax national income held by the top 10 percent, while fintech adoption is captured by the percentage of the population using mobile payments. Key control variables include inflation, financial depth, trade openness, population growth, education level, government expenditure, and gross domestic product (GDP) growth. A quadratic model reveals a non-linear relationship, suggesting that fintech reduces inequality only beyond a certain threshold. Findings indicate that financial depth and population growth exacerbate inequality, while GDP growth mitigates it. The study underscores the importance of inclusive financial systems and regulatory measures to mitigate risks and optimize fintech's potential in reducing inequality (Demir et al., 2022).

Keywords: Fintech, Income Inequality, Financial Depth, Population Growth, Gross Domestic Product Growth

Authors' individual contribution: Conceptualization — J.I. and K.B.; Methodology — J.I. and K.B.; Formal Analysis — J.I., N.H., and K.B.; Data Curation — K.B. and L.G.; Writing — Original Draft — J.I. and K.B.; Writing — Review & Editing — N.H., V.P., and L.G.; Supervision — J.I. and K.B.; Project Administration — J.I.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

Acknowledgements: This study is funded by the University "Aleksandër Moisiu", Durrës, Albania.

1. INTRODUCTION

Fintech, an acronym for financial technology, refers to businesses primarily using technology to carry out essential financial services operations that impact consumers' ability to transfer, pay, save, borrow, invest, and safeguard their money. (McKinsey & Company, 2024). Fintech encompasses various technological innovations in the financial services sector, including mobile banking, digital payment systems, blockchain technology, and peer-to-peer lending platforms. These innovations have greatly changed how people and businesses access financial services, offering unparalleled convenience, efficiency, and accessibility (AlBaker, 2024; AlHares & AlBaker, 2023; Al-Matari et al., 2023; Arner et al., 2015). Traditional financial systems have been criticized for aggravating income inequality by often excluding low-income individuals and small businesses from essential financial services (Demirgüç-Kunt et al., 2018). Income inequality, defined as the unequal distribution of income within a population, presents significant socioeconomic challenges, potentially leading to social unrest, limiting economic growth, and perpetuating poverty (Stiglitz, 2012). Fintech has the potential to overcome these limitations by providing inclusive financial solutions. By reducing transaction costs, providing microloans, and facilitating mobile money transfers, fintech can empower underserved populations, enhance financial inclusion, and potentially reduce income inequality (Suri & Jack, 2016). However, the effect of fintech on income inequality is complex and varies across different contexts and regions (Beck et al., 2018). Understanding the association between fintech and economic inequality is crucial for several reasons. Policymakers need strong evidence to design regulations that leverage the advantages of fintech while managing its potential risks. Understanding how fintech impacts income inequality can guide policies promoting inclusive economic growth (Zalan & Toufaily, 2017). Economic progress is significantly influenced by financial inclusion. Examining how fintech affects income inequality helps in determining how to use fintech to support sustainable development objectives, especially those related to poverty and inequality reduction (Beck et al., 2018). Investors and financial institutions benefit from understanding the socioeconomic impacts of fintech, guiding investment strategies that align with social responsibility goals, and promoting inclusive economic growth (Haddad & Hornuf, 2019). Moreover, studying fintech's impact on income inequality can spur further innovation. By highlighting areas where fintech has successfully reduced inequality, entrepreneurs and developers can create more targeted and effective financial solutions (Suri & Jack, 2016).

The objectives of the study are:

- to analyze the effect of fintech adoption on income disparity across different countries;
- to identify key factors influencing the relationship between fintech and income inequality;
- to assess regional variations in fintech's impact on income disparity, focusing on low-income and upper-middle-income countries;
- to provide policy recommendations based on findings to promote inclusive economic growth through fintech.

The structure of this paper is as follows. Section 2 reviews the relevant literature. Section 3 analyses the methodology used to conduct empirical research on fintech adoption and income inequality. Section 4 presents and discusses the empirical results. Finally, Section 5 provides conclusions, policy recommendations, implications for further research, and study limitations.

2. LITERATURE REVIEW

Financial technology, or fintech, has rapidly evolved over the last few decades, fundamentally transforming the financial services landscape. The development of fintech can be linked to the rise of the internet and the digital revolution that took place in the 1990s. Early fintech innovations focused on online banking and electronic payments, but the sector has since expanded to include a wide array of services and technologies (Arner et al., 2015). One of the most prominent components of fintech is digital payments, which include mobile payments, online transactions, and digital wallets. Services like PayPal, Alipay, and mobile money platforms such as M-Pesa have transformed how individuals and businesses carry out financial transactions (Demirgüç-Kunt et al., 2018). Fintech has also transformed the lending industry through peer-to-peer lending platforms and online loan services. Companies such as LendingClub and Prosper have democratized access to credit, allowing people and small enterprises to secure loans without traditional financial intermediaries (Iyer et al., 2009). Meanwhile, traditional financial systems have been criticized for aggravating income inequality by often excluding low-income individuals and small businesses from essential financial services (Demirgüç-Kunt et al., 2018).

Inequality of income refers to the uneven distribution of income within a population (Stiglitz, 2012). Theoretical perspectives on income inequality include the Kuznets curve theory, which posits that income inequality rises in the initial phases of economic progress, peaks at intermediate stages, and eventually decreases as a country becomes more developed (Kuznets, 1955). Some theories emphasize the impact of institutions, global economic integration, and technological advancement in shaping income inequality. For instance, institutional theories underline the impact of labor market institutions, tax policies, and social safety nets on income distribution (Stiglitz, 2012). Globalization theories investigate how increased trade and investment flows affect income inequality within and across countries (Milanovic, 2016). Technological advancements exhibit a complex relationship with income inequality. On the one hand, technology can enhance productivity, create new economic opportunities, and improve living standards. On the other hand, technological change can aggravate income inequality by primarily advantaging highly skilled workers and capital holders while displacing low-skilled workers (Acemoglu & Autor, 2011; Goldin & Katz, 2018). As a subset of technological advancements, fintech has the capacity to both mitigate and exacerbate income inequality. Fintech can promote financial inclusion and reduce inequality by providing inclusive financial services. However, if access to fintech services is uneven, it may reinforce existing disparities (Philippon, 2016).

Understanding how fintech impacts income inequality can guide policies aimed at promoting inclusive economic growth (Zalan & Toufaily, 2017) and can help identify ways to leverage fintech to support sustainable development goals, particularly those related to decreasing impoverishment and inequality (Beck et al., 2018). Investors and financial institutions benefit from understanding the socioeconomic impacts of fintech, guiding investment strategies that align with social responsibility goals, and promoting inclusive economic growth (Haddad & Hornuf, 2019). Moreover, studying fintech's impact on income inequality can spur further innovation.

While theoretical perspectives on fintech provide essential insights into its potential influence on income inequality and socioeconomic outcomes, empirical studies provide tangible evidence of these impacts in real-world contexts. Empirical studies on fintech and its socioeconomic impacts have highlighted both positive and negative effects. Research has demonstrated that fintech can significantly enhance financial inclusion, particularly in low-income and emerging economies. For instance, the introduction of mobile banking solutions like M-Pesa in Kenya has been linked to increased savings, investment, and poverty reduction (Suri & Jack, 2016). Additionally, several studies have explored the effects of fintech on financial stability and consumer protection. While fintech innovations can contribute to financial stability by diversifying financial services, they also present legal and regulatory risks, as well as risks related to cybersecurity and consumer privacy (Thakor, 2020). Research on digital lending platforms further suggests that fintech can improve loan access and lower lending fees. Yet, it also raises concerns about over-indebtedness and the adequacy of regulatory frameworks to protect borrowers from predatory lending practices (Balyuk & Davydenko, 2023).

The relationship between fintech adoption and income disparity has attracted growing academic interest, and several studies have explored the potential non-linear relationship between these two dimensions. Specifically, some studies suggest that fintech adoption initially reduces income inequality, but beyond a certain threshold, it may exacerbate it, leading to a non-linear effect. In their International Monetary Fund (IMF) working paper, Sahay et al. (2020) explore the relationship between fintech and income disparity. The study finds evidence of a non-linear relationship, showing that while fintech adoption initially promotes financial inclusion and reduces inequality, in certain instances, increased fintech penetration may disproportionately benefit higher-income groups, ultimately reversing the initial positive effects.

Beck et al. (2018) investigated the dual nature of financial innovation, highlighting both the benefits and potential risks. Their study suggests that while fintech can enhance economic efficiency, it may also introduce new forms of financial exclusion if not properly managed. Ozili (2018) investigates the effects of fintech on financial inclusion and stability, concluding that digital financial services can enhance financial access but may introduce risks to financial stability.

Frost (2020) explores how fintech can help mitigate economic disparity by enhancing access to financial services and extending credit to underserved populations. However, the author also cautions that fintech could worsen existing inequalities without equitable access. The author identifies several key factors influencing fintech adoption globally-higher levels of economic development correlate with greater fintech use, driven by better infrastructure and internet access. A supportive regulatory environment is essential for fostering innovation, while countries with significant unbanked populations often turn to fintech for financial inclusion. Changing consumer preferences, especially among younger, tech-savvy individuals, also boosts demand for fintech services. Additionally, economic crises, like the COVID-19 pandemic, have expedited the integration of alternative financial solutions (Frost, 2020). Overall, the article highlights that fintech adoption varies significantly across countries due to a mix of economic, regulatory, and social factors.

Demir et al. (2022) examine the interplay among fintech, access to financial services, and income disparity using a quantile regression approach. Their study highlights that fintech significantly expands financial services accessibility, particularly for marginalized populations, which helps enhance financial inclusion. They also ascertain that greater fintech adoption correlates with lower levels of income inequality, which is particularly evident in lower-income quantiles, suggesting that fintech can effectively reduce income disparity. The influence of fintech varies depending on the income level of different population segments. Lower-income groups benefit more from fintech innovations compared to higher-income groups (Demir et al., 2022). They also suggest that promoting fintech could be a crucial strategy for policymakers aiming to foster financial inclusion and narrow the income gap.

Additionally, Piketty (2017), Saez and Zucman (2019), and Chancel et al. (2022) have explored income inequality, particularly focusing on the concentration of wealth at the top and the growing disparity in income distribution. Their studies show how wealth is increasingly concentrated among the top 1% or 10% of the population, and they highlight the potential role of fintech in exacerbating these disparities. If fintech adoption is not properly regulated, it could disproportionately benefit wealthier individuals and further widen the income gap (Piketty, 2017). In contrast, studies like Beck et al. (2007) and Svirydzenka (2016) demonstrate that financial depth, measured by the share of credit in the monetary sector allocated to the private sector as a percentage of gross domestic product (GDP), supports economic development. However, as fintech deepens financial systems by expanding access to credit and financial services, it is critical to ensure that such financial deepening does not further concentrate wealth in the hands of a few (Svirydzenka, 2016; Beck et al., 2007).

In terms of broader economic factors, Beck et al. (2007), Turégano and Herrero (2018), and Lacalle-Calderon et al. (2019) have explored trade openness and population growth as key determinants of economic performance. The effects of population growth (Beck et al., 2007) on economic outcomes depend on how countries harness human capital and manage resources. In these areas, fintech adoption could make a significant difference by providing greater access to educational and financial resources for growing populations.

Finally, education level, as discussed by Beck et al. (2007), Lacalle-Calderon et al. (2019), and Demir et al. (2022), is another important factor. Education impacts human capital development and influences both economic growth and income distribution. Fintech has the potential to enhance educational access and provide financial resources to individuals, making it an essential tool in addressing global disparities in education and ultimately improving economic mobility for disadvantaged groups (Beck et al., 2007; Lacalle-Calderon et al., 2019).

Despite a growing body of research, several gaps remain. Many studies focus on developed economies, with limited attention to developing countries where fintech adoption is rapidly increasing. Additionally, extended research is required to evaluate the long-term effects of fintech on income inequality. More detailed data on fintech adoption and usage are necessary to comprehend the specific impacts of fintech on various demographic groups.

3. RESEARCH METHODOLOGY

This chapter summarizes the methodology employed to utilize the effects of the fintech adoption rate on income inequality. Based on the Global Findex database 2021 data, this cross-sectional study spans 2014, 2017, and 2021. Particularly interesting is the evidence for a non-linear relationship between the fintech adoption rate and income inequality found by Sahay et al. (2020) and Demir et al. (2022). We establish a quadratic equation to determine the threshold level, if any. It may exploit any possible effect of financial depth adoption at higher rates than the actual ones.

We aim to examine the potential effects of adopting financial depth at higher rates than currently observed. To do this, we will incorporate the squared variable of fintech into the existing equation of the underlying model and assess its statistical and practical significance. We can use the beta coefficients to determine the turning point or threshold level if we find statistical significance.

Besides the robust results obtained from this study, it is essential to underline the methods' limitations. Firstly, the model encounters barriers of homogeneity with the ordinary least squares (OLS) estimation — that is, it fails to account for diverse socio-economic properties within our group of interest. The data includes over 150 countries, ranging from low to upper-middle income. Still, due to missing information in many countries, not all of them could be included in the Global Findex database 2021.

Most of the data used for this analysis are expressed in percentages and annual terms. They are quantitative and retrieved from the World Bank and other reliable sources. Given that this study focuses on several low- and middle-income countries with many missing values on some variables, it was challenging to index them correctly. We opted to use the average from previous years if there was no considerable variability, or otherwise, we excluded the countries from the analysis.

Among other estimation alternatives and techniques, a cross-sectional quadratic model finds strong support in two elements. First, given the diverse exposure of countries incorporated in our sample, it highlights the nuanced and non-linear relationship between the fintech adoption rate and income inequality. Second, it does not oversimplify the complexity of this relationship, indicating that the impact of fintech on income inequality is not spread equally among our cross-sections. In addition, we utilized a large sample of more than 150 countries, which has considerable implications on the robustness of the anticipated results — this method balances the simplicity and flexibility on which we develop our paper framework. The variables used in the study are shown in Table 1.

Table 1. Measurement of the study variables

Variable	***Variable code***	***Measurement***	***Authors***
Fintech adoption	*FINTECH*	Made or received a digital payment (% age 15+)	Suri and Jack (2016), Demirgüç-Kunt et al. (2022), Demirgüç-Kunt et al. (2018)
Income inequality	*INCOME_INEQUALITY*	Pre-tax national income / Top 10% share	Piketty (2017), Saez and Zucman (2019), Chancel et al. (2022)
Inflation rate	*INFL*	Inflation, GDP deflator (annual %)	Barro (1996), Beck et al. (2007), World Development Indicators[a]
Financial depth	*F_DEPTH*	Monetary sector credit to private sector (% of GDP)	Beck et al. (2000), Svirydzenka (2016)
Trade openness	*TRADE_OPENESS*	(Exports + imports) / GDP (%)	Beck et al. (2007), Turégano and Herrero (2018), Lacalle-Calderon et al. (2019), Demir et al. (2022)
Population growth	*POP*	Annual population growth rate (%)	Beck et al. (2007), Demir et al. (2022), Lacalle-Calderon et al. (2019)
Education level	*ED_LEV*	School enrollment, primary (% gross)	
Government expenditure	*GOV_EXPENDITURE*	General government final consumption expenditure (% of GDP)	Turégano and Herrero (2018), Lacalle-Calderon et al. (2019), Demir et al. (2022)
Real GDP growth	*REAL_GDP_GROWTH*	Annual % change	Beck et al. (2000), Demir et al. (2022), Lacalle-Calderon et al. (2019)

Note: [a] https://databank.worldbank.org/source/world-development-indicators
Source: Authors' elaboration.

The variable of interest in this study is defined as income inequality. It captures the share of pre-tax national income held by the top 10% of the population. The alternative measure, that is, the Gini coefficient from the World Bank, had insufficient information to complete the data for this study. Therefore, we considered our proxy a relevant representation for capturing wealth distribution. Descriptive statistics provide an important outline of the differences in wealth distribution between the two sub-groups included in the study. For instance, in Namibia, 2014, 65% of the total income is held by 10% of the population, while this ratio is only 29% of the national income in the Czech Republic[1].

The fintech adoption rate is measured based on the digital payments made or received by the population above 15 years old. It is assigned as a percentage by the Global Findex database. Among the other indicators, it is the most appropriate to capture fintech access. In addition, we use other financial metrics to control inequality distributions among the elements of this study. Financial depth is considered an important indicator for the financial inclusion and development of fintech itself, and the expectations are to have a strong correlation with the fintech adoption rate.

The inflation rate is measured on a percentage scale based on the GDP deflator obtained from the World Bank. Most low-middle-income countries

[1] https://wid.world/data/

have undergone significant economic transformations in the past decades, leading to political instability and economic downturns. In 2021, the inflation rate in Zimbabwe reached almost 92%, threatening a recurrence of the events of 2000 when the economy was hit by hyperinflation. This data has meaningful information about the country's economic performance. Low to middle-income countries have an average inflation rate of 5.65%, approximately two times higher than the 2.31% annual rate observed in middle-high-income countries (World Bank, n.d.).

In addition, educational level measures the gross primary school enrolment as a percentage of the population. As for 20217, the gap between low-middle-income countries and middle-high-income countries is almost negligible. The primary school enrolment average is close to 60% and 70%, respectively (World Bank, n.d.). A higher educational level is assumed to smooth the growing income inequality. However, there are doubts about the accuracy and effectiveness of education data in low-middle-income countries, which might violate the expected outcomes.

Government expenditure and real GDP growth capture the final consumption of the general government and the annual change in GDP growth per annum, respectively. In fact, upper-middle-income countries tend to spend more, as, on average, their government expenditure is 4.5% higher than that of low-middle-income countries. This gap is proportionally opposite to the real GDP growth of the regions. Libya reached its peak government expenditure in 2017, nearly 41% of the GDP (World Bank, n.d.).

Trade openness expresses the sum of exports and imports of goods and services measured as a share of GDP. It represents a fundamental determinant of income inequality at the international level. Increasing trade activity can lead to higher economic growth and productivity, as well as increased labor demand. Yet again — just like all elements analyzed so far — there is strong evidence of differences between upper and lower-income countries. Low- to middle-income countries have, on average, 36% less trade openness than upper-middle-income countries. China leads the ranking with 425% in 2014, while Sudan ranks last with 20% trade openness in 2014 (World Bank, n.d.).

The real economy grew by an average of 4% and more than 65% in 2021, attributed to the post-recovery of COVID-19. Nonetheless, descriptive statistics reveal some extreme values of economic decline among low-middle-income countries. In 2014, Ukraine experienced an economic decline of 10%, while Bangladesh experienced a decline of more than 20% as of 2021. On the other hand, the highest growth rates were recorded in developed economies; specifically, in 2021, real GDP in Luxembourg increased by 33%. The tabular presentation of descriptive statistics is included in the Appendix. Table 2 provides a detailed list of variable descriptions and their respective sources.

Table 2. Study variables and source of data

Variable code	*Unit of measurement*	*Source*
FINTECH	Annual %	The Global Findex database 2021
INCOME_INEQUALITY	Annual %	World Inequality Database
INFL	Annual %	World Bank database
F_DEPTH	Annual %	World Bank database
TRADE_OPENESS	Annual %	World Bank database
POP	Annual %	World Bank database
ED_LEV	Annual %	World Bank database
GOV_EXPENDITURE	Annual %	World Bank database
REAL_GDP_GROWTH	Annual %	World Bank database

Source: Authors' elaboration.

The present study comprises a cross-sectional model of over 150 countries, examined every three years from 2014 to 2021. The selection of regressors is based on an extensive literature review, incorporating quantitative data from macroeconomics and social welfare. The regression analysis is conducted using EViews 10, and the findings are robust to any potential biases associated with regression restrictions.

The cross-sectional method delivers a snapshot of the entire population at a specific point in time. We analyze the coefficient changes between three periods and evaluate the impact of various factors on the targeted group. It is essential to consider that cross-sectional studies may fail to account for the dynamic relationships between variables, which we perceive as a limitation. The OLS technique, generally, is a robust estimator that generates unbiased estimates with the most minor variance. However, it is not robust to heteroskedasticity in its natural settings and is sensitive to outliers — they may affect the result's accuracy. We define the equation for the impact of the fintech adoption rate on income inequality as defined below in Eq. (1).

$$Y = \beta_0 + \beta_1 FINTECH + \beta_2 FINTECH^2 + \beta_3 F\_DEPTH + \beta_n X_n + \mu \tag{1}$$

where,

- Y: the dependent variable;
- β_0: the constant coefficient;
- β_1: the slope coefficient of the fintech adoption rate;
- β_2: the slope coefficient of the squared fintech adoption rate;
- β_n: the slope coefficient of independent variables;
- X_n: set of independent variables;
- μ: the error term.

From Eq. (1), we can, therefore, define the turning point of the fintech impact on income inequality as follows:

$$\frac{\beta x}{2 * (\beta x^2)} \tag{2}$$

The anticipated results are robust, and all tests utilized to check the reliability of the coefficients are listed in the Appendix. The model is robust to heteroskedasticity. The probability value obtained from the white test is 0.2761 — it fails to reject the homoscedastic hypothesis. We have used the Ramsey regression equation specification error test (RESET) test to control model specification, and from the results, it is correctly specified, and the model is linear in parameters. Most regressors have a correlation coefficient between -0.5 and 0.36. Only fintech and financial depth have a correlation coefficient of 0.60, which does not violate the multicollinearity assumption. The normality assumption is satisfied. The residual term has an average close to zero with a normal distribution checked by the Jarque-Bera test. This research is treated by conducting three different models for each year, and their robustness checks are included in the Appendix. In addition to them, we have listed the respective datasets. Table 3 below illustrates the estimated coefficients and their probability values.

Table 3. Estimation coefficients, fintech impact on income inequality

Variables	*2014*	*2017*	*2021*
FINTECH	0.3737 (0.0001)***	0.4025 (0.0014)***	0.7042 (0.0001)***
FINTECH^2	-0.0042 (0.0000)***	-0.0048 (0.0000)***	-0.0067 (0.0000)***
F_DEPTH	-0.0072 (0.6621)	0.0422 (0.0158)**	0.0571 (0.0019)***
REAL_GDP_GROWTH	0.3806 (0.1431)	-0.3364 (0.0593)*	0.0532 (0.7875)
POP	1.5515 (0.0002)***	2.4441 (0.0001)***	2.9160 (0.0000)***
TRADE_OPENESS	-	-0.0131 (0.2661)	-0.0031 (0.8202)
INFL	-	-	0.1248 (0.0715)*
GOV_EXPENDITURE	-	-	0.0902 (0.6313)
ED_LEVEL	0.0591 (0.1182)	-	-
Turning point	44.5	41.4	51.8
R-squared	0.402783***	0.408998***	0.504441***
Adjusted R-squared	0.373412***	0.381295***	0.462266***

*Note: The table reports the estimation coefficients and, in parentheses, the associated probability values. *, **, and *** denote the significance at 10%, 5%, and 1% levels.*
Source: Authors' elaboration.

The results confirm a strong overall goodness of fit, with the model's explanatory power exceeding 40% annually and peaking at 50% in 2021. Most of the variables have statistical significance, although some are excluded from here due to a lack of correlation to the dependent variable. Each column represents the anticipated results for the specific year assigned to it. Variable coefficients expressed with a line are missing from the calculation for that period; they are utilized in another year.

4. EMPIRICAL RESULTS

The results presented in this section support most of the findings in the existing literature. Our variable of interest — fintech adoption rate — is statistically significant in the abovementioned estimates. After squaring the fintech adoption rate, the non-linear relationship is verified with a function of a U-shaped convex form. In 2014 and 2017, the threshold level was approximately equal, with negligible variations between 44.5% and 41.4%. Each unit increase above 45% of the fintech adoption rate — the percentage of the population that has made or received a payment using a mobile phone — would have a positive effect by declining income inequality by 0.0042%. In addition, one must notice that along with the turning point, the magnitude of the impact of fintech on income inequality has changed, too.

Until this turning point is reached, each unit increase in the fintech adoption rate exacerbates income inequality by 0.4%. This threshold limit increased by approximately 10% in 2021, increasing the target beyond which the positive effects of fintech inclusion are to be seen. Specifically, until the fintech adoption rate reaches the 52% threshold limit, each percentage point increase in value is associated with a 0.7% increase in income inequality, confirming a strong correlation between the variables.

These results are within expectations, as the more access to financial services, the more the expected profit for the underserved population that may have been excluded from participating in the formal economy. Therefore, they are more capable of managing their personal and familiar finances and have more opportunities to use financial resources, allowing them to utilize their capital. By doing so, they can increase incomes and accumulate wealth as they have more opportunities and raise more funds to fulfill their investment needs.

In addition, small entrepreneurs can profit from finance digitalization as they have more tools to access capital, tools that they would not have by using traditional banking restrictions. They can grow and have a meaningful impact on the job market, increasing the demand for labor and thereby impacting overall income inequality. Another element is related to transaction costs; having more opportunities and a higher number of financial services suppliers makes them cheaper and more accessible to the general population.

These facilities, which are easily accessible to users, make financial transactions more transparent, so there are no financial frictions or unrecorded economic activities. All of these factors have a considerable impact on the effective allocation of financial resources and their utilization to their most effective use. However, special attention is required to adopt fintech, as, in some circumstances, it may have a negative effect.

For every unit increase in financial depth, there is, on average, a 0.05% rise in income inequality. While this may initially seem perplexing, these findings align with those observed for the fintech adoption rate. In addition, their correlation coefficient was strong, as measured by descriptive statistics. On average, financial depth was 75% for the entire population during our estimation period, and we assume that the relationship between financial depth and income inequality is non-linear — following the inverse function (convex) to what we found for fintech. We did not extend further, not to exceed the scope of this paper.

Estimates of real GDP growth do not disclose any relevant information for income inequality, at least on our estimates. Only in 2017 did the variable have minor effects, and for the rest of the estimates, it failed to explain income inequality. Furthermore, the rest of the control variables, including trade openness, government expenditure, and education levels, did not have a statistically significant impact on income inequality. The inclusion of the inflation rate had a minimal additional impact, increasing income inequality by 0.12% for each percentage increase. Our estimates align with existing literature; the one-sided effect of inflation on wealth distribution is well known, and these findings support it further.

Lastly, the estimations have revealed that population growth has a sizable effect on wealth distribution. This effect has continuously increased from period to period. For instance, in 2014, if population growth increased by one percentage point, income inequality would increase by 1.55%. The income inequality coefficient increased by approximately one unit in 2017 and nearly doubled in 2021 — it mounted at a 2.91% increase for each added percentage in population growth.

These results are justifiable as population growth can lead to higher competition in the job market, and it may oversaturate market needs. This, on the other hand, increases unemployment rates and cuts salaries for the unskilled labor force — the gap between the rich and other society layers deepens even more. Moreover, a higher population can mean less available resources on average if other things are constant. Hence, some groups of society would prevent fundamental services such as education, health care, and even financial benefits. The income inequality gap will expand significantly if the population growth rate is not matched by real economic growth and utilitarian services.

5. CONCLUSION

We want to confirm the complexity between the rate at which fintech is adopted and the varying levels of income inequality within different scales of the economy. From the empirical evidence, it is found that the threshold level — at which fintech exacerbates income inequality — and its magnitude of impact have changed notably from one period to another. This is due to the fintech adoption rate rising significantly from 2017 to 2021, reaching around 43% more. Consequently, it may be unclear how this rapid growth could affect the income distribution in such a short time. The average fintech adoption rate in 2021 is nearly 67%, while the turning point found in our analysis is 52%. This means that — besides low-middle income regions — most of the countries taken into the study have reached the level above which they experience the positive effects of fintech.

Financial depth is another indicator that has essential implications on the wealth distribution in the economy. From the empirical evidence, it is found that it has a negative effect on effective wealth distribution. Financial deepening might be sufficient to encourage investment, employment, and economic growth, but in terms of income inequality, it must be accompanied by complementary measures. One is through increased access to fintech services and a supportive credit policy for the vulnerable layers of the economy. This is done through inclusive economic institutions and can genuinely affect income redistribution.

Economic growth has essential implications for curbing income inequality. The results show that GDP immediately impacted curbing economic inequality in 2017. If the output increases, it will positively impact the economy by boosting consumption, increasing employment rates, and encouraging higher wages due to market competition for skilled labor. Hence, it should be considered as a basis for the mitigation of income inequality across the world. Even though we lack statistical evidence for inflation, educational level, and government expenditure are essential to our issue. We noticed that countries experiencing low-income inequality are those that have higher levels of education, stable inflation, and higher government spending, although the latter cannot be taken for granted.

Based on the results, we argue that annual population growth has notably impacted wealth distribution. Each percentage point increase in population growth is associated with an average of a 2.3% increase in income inequality. The data are concerning, considering the increasing trend of the global population. This effect may vary among different regions, but it was impossible to observe this discrepancy due to insufficient information. Population growth must be accompanied by complementary measures that enhance labor force productivity and generate economic output. Otherwise, there will be a persistent gap in wealth distribution.

In addition, we suggest that fintech adoption is a crucial indicator in smoothing income inequality. The more inclusive financial systems are, the more return there is regarding effective wealth distribution in society. However, this process must be accompanied by the influence of a sustainable institutional and legal framework that ensures a smooth transition from traditional banking to fintech services. Rapid and unmonitored fintech adoption can bring risks related to the loss of jobs due to the automation of some processes, which can worsen wealth distribution.

Fintech adoption rates in low-to-middle-income countries have ranged from 21.53% in 2014 to 48.3% in 2021, coming close to the estimated threshold of 51.8%. Yet, some countries within this group must take further steps to accelerate adoption levels by stimulating e-banking and access to finance. As a result, they could afford financial liberalization and broader access for new enterprises and low-income citizens who could benefit from access to finance. Policymakers must encourage financial institutions to invest in online banking infrastructure and promote e-banking operations to adjust accordingly.

These conclusions contribute to the existing literature by providing recent insights on the dynamic relationship between fintech and income inequality. Given the research limitations, we recommend the inclusion of some demographic indicators for future research, as they would distinguish the effects between the two subgroups analyzed in this research.

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APPENDIX

Table A.1. Estimated results 2014

Dependent variable: *INCOME_INEQUALITY* Method: least squares Sample: 1129 Included observations: 129				
Variable	***Coefficient***	***Std. error***	***t-statistic***	***Prob.***
FINTECH	0.373751658	0.095725192	3.904423151	0.0001553
FINTECH^2	-0.004202775	0.000853415	-4.924655005	0.0000
ED_LEV	0.059174311	0.037612988	1.573241432	0.1182527
POP	1.551599093	0.408254503	3.800568224	0.0002267
REAL_GDP_GROWTH	0.380635585	0.258277721	1.473745327	0.1431258
F_DEPTH	-0.007299909	0.016665704	-0.438019858	0.6621464
C	31.85501376	4.47050551	7.125595457	7.90E-11
R-squared	0.402783996	Mean dependent variable		44.131008
Adjusted R-squared	0.373412717	S.D. dependent variable		8.8054817
S.E. of regression	6.970178591	Akaike info criterion		6.7738945
Sum squared resid	5927.173531	Schwarz criterion		6.9290782
Log likelihood	-429.9161974	Hannan-Quinn criterion		6.8369488
F-statistic	13.71353279	Durbin-Watson statistic		2.0909094
Prob. (F-statistic)	7.34E-12			

Source: Authors' elaboration.

Table A.2. Estimated results 2017

Dependent variable: *INCOME_INEQUALITY* Method: least squares Date: 09/05/24 Time: 20:34 Sample: 1135 Included observations: 135				
Variable	***Coefficient***	***Std. error***	***t-statistic***	***Prob.***
FINTECH	0.402514	0.122915	3.274724	0.0014
FINTECH^2	-0.004867	0.001056	-4.610586	0.0000
F_DEPTH	0.042279	0.017285	2.44607	0.0158
REAL_GDP_GROWTH	-0.336459	0.176792	-1.903132	0.0593
POP	2.444173	0.598931	4.080893	0.0001
TRADE_OPENESS	-0.013149	0.011772	-1.116997	0.2661
C	37.8742	3.6423	10.39843	0
R-squared	0.408998	Mean dependent variable		44.44081
Adjusted R-squared	0.381295	S.D. dependent variable		9.237586
S.E. of regression	7.266082	Akaike info criterion		6.854771
Sum squared resid	6757.88	Schwarz criterion		7.005414
Log likelihood	-455.697	Hannan-Quinn criterion		6.915988
F-statistic	14.76358	Durbin-Watson statistic		2.064524
Prob. (F-statistic)	0			

Source: Authors' elaboration.

Table A.3. Estimated results 2021

Dependent variable: *INCOME_INEQUALITY* Method: least squares Date: 09/06/24 Time: 15:43 Sample: 1103 Included observations: 103				
Variable	***Coefficient***	***Std. error***	***t-statistic***	***Prob.***
FINTECH	0.704211393	0.179934536	3.913708889	0.000171899
FINTECH^2	-0.006797273	0.001495311	-4.54572593	1.628E-05
F_DEPTH	0.057102332	0.017901192	3.189861926	0.001934721
INFL	0.12481312	0.068492868	1.822279084	0.071592288
REAL_GDP_GROWTH	0.053270999	0.197111145	0.270258684	0.787553723
POP	2.916085806	0.700047153	4.165556265	6.892E-05
TRADE_OPENESS	-0.003130412	0.013736606	-0.227888289	0.820228055
GOV_EXPENDITURE	0.090233389	0.187464482	0.481335924	0.631396384
C	23.40944543	6.431266352	3.639943387	0.000445777
R-squared	0.504441391	Mean dependent variable		43.67417476
Adjusted R-squared	0.462266191	S.D. dependent variable		9.581557093
S.E. of regression	7.026187954	Akaike info criterion		6.820488751
Sum squared resid	4640.527814	Schwarz criterion		7.050707789
Log likelihood	-342.2551707	Hannan-Quinn criterion		6.913735344
F-statistic	11.96061626	Durbin-Watson statistic		1.971103679
Prob. (F-statistic)	1.25E-11			

Source: Authors' elaboration.

Table A.4. Multicollinearity/correlation matrix

Panel A: Year 2014						
	FINTECH	***ED_LEV***	***POP***	***REAL_GDP_FROWTH***	***F_DEPTH***	***INFL***
FINTECH	1					
ED_LEV	-0.521164	1				
POP	-0.390382	0.25518	1			
REAL_GDP_FROWTH	-0.346752	0.33853	0.31005	1		
F_DEPTH	0.618608	-0.34983	-0.20555	-0.29993	1	
Panel B: Year 2017						
	FINTECH	***F_DEPTH***	***REAL_GDP_FROWTH***	***POP***	***TRADE_OPENESS***	***INFL***
FINTECH	1					
F_DEPTH	0.607356	1				
REAL_GDP_FROWTH	-0.141951	-0.10722	1			
POP	-0.414437	-0.35565	0.07688	1		
TRADE_OPENESS	0.387721	0.28535	-0.01437	-0.18863	1	
Panel C: Year 2021						
	FINTECH	***F_DEPTH***	***INFL***	***REAL_GDP_FROWTH***	***POP***	***TRADE_OPENESS***
FINTECH	1.000000					
F_DEPTH	0.573185	1.00000				
INFL	-0.103829	-0.22269	1.00000			
REAL_GDP_FROWTH	0.126588	0.02198	0.00616	1.00000		
POP	-0.558082	-0.40026	0.16636	-0.29541	1	
TRADE_OPENESS	0.339289	0.20939	-0.13062	0.16761	-0.32453	1
GOV_EXPENDITURE	0.515893	0.34088	-0.15213	-0.08191	-0.36443	0.21607

Source: Authors' elaboration.

Table A.5. Stability diagnostics — Ramsey reset test

Ramsey RESET test Equation: UNTITLED Specification: *INCOM_INEQUALITY L_FINTECH L_FINTECH^2 L_ED* POP GDP LOG_T C Omitted variables: Squares of fitted values						
Statistic	***2014***		***2017***		***2021***	
	Value	***Probability***	***Value***	***Probability***	***Value***	***Probability***
t-statistic	0.5201202	0.6039301	0.638863	0.5241	0.444089	0.658
F-statistic	0.270525	0.6039301	0.408146	0.5241	0.197215	0.658
Likelihood ratio	0.288089	0.5914477	0.43316	0.5104	0.21819	0.6404

Source: Authors' elaboration.

Table A.6. Zero conditional mean

RESID01	***2014***	***2017***	***2021***
Mean	2.42E-15	-2.57E-14	-4.88E-15
Median	-0.819685264	-0.198771	0.017399
Maximum	19.32756687	20.95693	18.8098
Minimum	-17.00091758	-22.18707	-16.25068
Std. dev.	6.804854385	7.101545	6.745026
Skewness	0.224833997	0.026695	0.081908
Kurtosis	2.962731329	3.455518	2.817523
Jarque-Bera	1.094297641	1.183204	0.258073
Probability	0.578597145	0.55344	0.878942
Observations	129	135	103

Source: Authors' elaboration.

Table A.7. Zero conditional mean

RESID01	***2014***	***2017***	***2021***
FINTECH	9.67E-16	6.48E-15	-1.98E-15
ED_LEV	8.67E-16	-	-
POP	-1.12E-15	4.90E-15	-3.20E-16
REAL_GDP_FROWTH	-1.87E-15	2.10E-15	-5.66E-15
F_DEPTH	2.54E-15	1.45E-15	-1.14E-15
TRADE_OPENESS	-	6.40E-15	-1.33E-15
INFL	-	-	1.24E-15
GOV_EXPENDITURE	-	-	8.37E-15
RESID01	1	1	1

Source: Authors' elaboration.

Table A.8. Homoskedasticity check

2014		*Heteroskedasticity test: White*	
F-statistic	1.177892	Prob. F(26,102)	0.2761
Obs*R-squared	29.78808	Prob. Chi-square(26)	0.2765
Scaled explained SS	26.1465	Prob. Chi-square(26)	0.4551
2017		*Heteroskedasticity test: Breusch-Pagan-Godfrey*	
F-statistic	1.202223	Prob. F(6,128)	0.3094
Obs*R-squared	7.201956	Prob. Chi-square(6)	0.3026
Scaled explained SS	7.949065	Prob. Chi-square(6)	0.2419
2021		*Heteroskedasticity test: Breusch-Pagan-Godfrey*	
F-statistic	0.347243	Prob. F(8,94)	0.9449
Obs*R-squared	2.956541	Prob. Chi-square(8)	0.9371
Scaled explained SS	2.237768	Prob. Chi-square(8)	0.9728

Source: Authors' elaboration.