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ORIGINAL

Mechanisms of the impact of fintech development on residents' income: a causal inference model

Mecanismos del impacto del desarrollo de las fintech en los ingresos de los residentes: Un modelo de inferencia causal

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ABSTRACT

This research examines how the development of financial technology (FinTech) is affecting families' income in China, a nation that has multiplied. To measure the detrimental impact of FinTech on families' earnings, investigators collected data from the Peking University Digital Financial Inclusion Index of China and the 2018 China Family Panel Surveys. To measure the detrimental effects of FinTech, the authors adopted the Fixed Effects (FE) double-fixed model. After correcting several socio-economic factors such as education, employment status, and knowledge of digital technologies, the findings from the survey indicated that FinTech has a positive effect value of 0,178 ($p<0,01$), signifying it improves the annual income of households. Dissecting the demography, the rural areas show a more substantial impact ($\beta = 0,253$, $p < 0,01$) compared to urban areas ($\beta = 0,198$, $p < 0,01$). Also, the high-income individuals benefit more from fintech advancements ($\beta = 0,249$, $p < 0,01$) than their low-income counterparts ($\beta = 0,182$, $p < 0,01$). The anlaysis was further confirmed for consistency using robustness analysis using different measures and modeling approaches.

Keywords: FinTech; Socio-Economic Factors; Machine Learning; Fixed Effects; China Family Panel Studies.

RESUMEN

Esta investigación examina cómo el desarrollo de la tecnología financiera (FinTech) está afectando los ingresos de las familias en China, una nación que se ha multiplicado. Para medir el impacto perjudicial de FinTech en los ingresos de las familias, los investigadores recopilaron datos del Índice de Inclusión Financiera Digital de la Universidad de Pekín de China y las Encuestas de Paneles Familiares de China de 2018. Para medir los efectos perjudiciales de FinTech, los autores adoptaron el modelo de efectos fijos (FE) doblemente fijo. Después de corregir varios factores socioeconómicos como la educación, la situación laboral y el conocimiento de las tecnologías digitales, los hallazgos de la encuesta indicaron que FinTech tiene un valor de efecto positivo de 0,178 ($p < 0,01$), lo que significa que mejora los ingresos anuales de los hogares. Al analizar la demografía, las áreas rurales muestran un impacto más sustancial ($\beta = 0,253$, $p < 0,01$) en comparación con las áreas urbanas ($\beta = 0,198$, $p < 0,01$). Además, las personas con ingresos altos se benefician más de los avances de la tecnología financiera ($\beta = 0,249$, $p < 0,01$) que sus contrapartes de ingresos bajos ($\beta = 0,182$, $p < 0,01$). El análisis se confirmó además en cuanto a la consistencia mediante un análisis de robustez que utiliza diferentes medidas y enfoques de modelado.

Palabras clave: Fintech; Factores Socioeconómicos; Aprendizaje Automático; Efectos Fijos; Estudios de Panel Familiar en China.

INTRODUCTION

In recent years, the rapid development of Financial Technology (FinTech) has transformed the global financial landscape by offering new opportunities for economic growth and financial inclusion.[1,2] In fast-developing countries like China, the rise of digital financial services is evidenced by technological advancements like big data, cloud computing, and mobile devices.[3] These innovations have expanded the access to financial services to regions where the populations are underserved by traditional banking institutions.[4] The emergence of FinTech has democratized the access to financial services and created new pathways for income generation and economic empowerment.[5,6]

Despite the widespread adoption of FinTech in China, performing a study to analyze the impact of such technological advancements on household income have remained undone.[7] While some previous studies have examined the role of FinTech in improving financial inclusion,[8,9] there is a gap in understanding how such FinTech development have directly prejudiced the income levels across different regions and demographic groups. This understating is essential for a country like China, which has a diverse economic landscape because the benefits of FinTech may vary significantly between urban and rural areas and among different income groups.[10] So, understanding such dynamics will help policymakers and financial institutions to plan and implement the FinTech in a more efficient method for economic development and poverty alleviation.[11]

The primary challenge in evaluating the impact of FinTech on household income is the complex relationship between various socio-economic factors and technological advancements.[12] Further, the fintech development, even in a fast-growing economy like China, seems to be uneven across the different regions of the country.[13] This unevenness is attributed to factors like regional economic conditions, infrastructure development, digital literacy, and regulatory frameworks.[14] Further, the heterogeneity of the population in terms of income levels, education, and access to technology also increases the complexity, making it challenging to ascertain a generalized conclusion about the impact of FinTech on income.[15]

To overcome the above-discussed challenges, this study employs a methodological framework to investigate the influence of FinTech development on the household income in China. The work utilized data from the China Family Panel Studies (CFPS) and the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC). The work employed econometric models such as the Fixed Effects (FE) double fixed model to explore the direct impact of FinTech development on household income while controlling for a wide range of socio-economic factors. The study also considered the regional and individual heterogeneity influence of this impact so that to provide a detailed understanding of how FinTech effects income across different segments of the population. Additionally, the research investigates the moderating effects of FinTech policies, such as government subsidies and penalties. A detailed analysis of the findings is presented in the study.

METHODS

Data Sources

CFPS household tracking survey 2018:

The data for the study was sourced from the 2018 wave of the China Family Panel Studies (CFPS).[16] The CFPS was conducted by the Institute of Social Science Survey at Peking University, which contains a diverse range of socioeconomic indicators that are crucial for evaluating the impact of FinTech on household income levels. This wave of the survey began fieldwork in June 2018 and concluded with the last of its telephone interviews in May 2019. It performed face-to-face and proxy interviews totaling nearly 44,000, spanning 15,051 families across China, having a response rate of 69,3 % at the household level and 67,4 % cross-sectionally at the individual level. CFPS2018 sourced detailed sociodemographic data on all family members and their interrelations and also gathered individual self-reports from respondents aged 10 and above that contain data on personal income, employment, and educational background, which is crucial for this study's analysis. Table 1 presents the variable information from the CFPS data.

Table 1. Variable information from the CFPS2018 dataset

Variable Code	Attribute Description	Data Collection Point	Details
FID_PROVCD18	Identification of province for 2018	Province	Specifies the province where the respondent resided in 2018
FID_COUNTYID18	2018 county identification	County	Details of the respondent's county location
FID_CID18	Community identity in 2018	Community	Indicates the community of the respondent for the year 2018
FID_URBAN18	Status of urban or rural area	Urban/Rural Definition	Classified by the Census Bureau's urban or rural criteria
SUBSAMPLE	Participation in national resampling	Sampling Details	Determines if the sample is part of the national resampling

SUBPOPULATION	Subpopulation categorization	Population Group	Associated with the family ID base for demographic segmentation
GENETYPE18	Genealogical type categorization in 2018	Gene Type	Based on gene family member status and reclassification
fid1	Historical family ID tracing	Family ID	Family ID tracked across multiple years
FAMILYSIZE18	Active family member count	Household Size	Counts active connected members under the same family ID
TB2_A_P	Gender of respondent	Demographic Info	Captured from comprehensive demographic surveys
TB1Y_A_P	Year of birth	Birth Info	Year part of the respondent's birth date
TB1M_A_P	Month of birth	Birth Info	The month part of the respondent's birth date
TB3_A18_P	Marital status	Personal Status	Status collected from various waves and reported
TB4_A18_P	Educational attainment	Education Level	Highest degree of education recorded
HUKOU_A18_P	Residential registration status (Hukou)	Registration Type	Indicates the type of Hukou the respondent holds
TB6_A18_P	Current living arrangement	Residence Status	Specifies if residing in the family home
CO_A18_P	Economic ties to family ID	Financial Connection	Financial relationship with the family ID in 2018
OUTPERS_R_WHERE18_P	Location of family members who left home	Non-resident Info	Provides details on non-resident family members
TB602ACODE_A18_P	Non-resident provincial code	Geographic Code	Province code for members who left home
TB601_A18_P	Reasons for leaving home	Departure Reason	Coded reasons for family members leaving the household
OUTUNIT18	Tracking number for split family units	Household Tracking	Monitors split family units by address
COREMEMBER18	Core family membership in 2018	Family Core Status	Status indicating core family membership
CFPS2018_INTERV	Completion of individual survey	Survey Status	Indicates whether the individual study was completed
ALIVE_A18_P	Vital status	Vital Record	Confirm if the respondent was alive during the survey
TA4Y_A18_P	Documented year of death	Death Record	Year the death occurred, if applicable
TA4M_A18_P	Documented month of death	Death Record	Month the death occurred, if applicable

Measure of Fintech Development

The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) is employed as the metric to assess the impact and development of financial technology in this study. The PKU-DFIIC evaluates three primary dimensions of digital financial inclusion such as coverage breadth, usage depth, and digitization level as following:

Coverage Breadth (CB): this metric measures the availability of digital financial services across different demographic and geographic segments.

CB= ((Number of regions with available digital financial services) / (The total number of the areas surveyed)) ×100 (1)

Usage Depth (UD): this measures consumers' frequency and diversity of use.

UD= (Total number of digital financial transactions) / (Total number of potential users) ×100 (2)

Digitization Level (DL): assesses the extent of technology integration into financial services.

DL= (Number of services using advanced digital technologies) / (Total number of financial services offered) ×100 (3)

The overall PKU-DFIIC score is computed by aggregating the weighted scores of these individual metrics PKU-DFIIC=$(w_{CB}\times CB)+(w_{UD}\times UD)+(w_{DL}\times DL)$ (4), where w_{CB},w_{UD}, and w_{DL} are the weights assigned for coverage breadth, usage depth, and digitization level, respectively. The weights are based on the significance and impact of each component determined through expert panels and previous research: w_{CB}=0,3, w_{UD}=0,4, w_{DL}=0,3. Normalization is applied to each component score to ensure they contribute equally to the overall index. If x is the raw score for a component, the normalized score x' is given by x'=(x-min(x))/(max(x)-min(x)) (5), where min(x) and max(x) are the minimum and maximum scores observed for the component across all regions and periods considered.

Static Data Handling

Static data in the China Family Panel Studies (CFPS) include demographic and socio-economic features such as gender, ethnicity, and birthplace. Such static data must be handled appropriately in order to ensure accuracy in measuring the impact of FinTech on household income. The static data are used as the control variables in the econometric, where the demographic information is integrated into regression models as dummy variables to use such unchanging variables in the analysis without assuming specific distribution patterns. To address the problem of multicollinearity that arises when static variables are highly correlated with other predictors, a Variance Inflation Factor (VIF) analysis is conducted. Such detected multicollinearity is addressed by applying Principal Component Analysis (PCA) to reduce the dimensionality and exclude collinear variables. The Table 2 provides the list of static variables from the dataset.

Table 2. The static data used in the study from the CFPS for 2018

Variable Code	Attribute Description
FID_PROVCD18	Identification of province for 2018
FID_COUNTYID18	2018 county identification
FID_CID18	Community identity in 2018
FID_URBAN18	Status of urban or rural area
SUBSAMPLE	Participation in national resampling
SUBPOPULATION	Subpopulation categorization
GENETYPE18	Genealogical type categorization in 2018
fid1	Historical family ID tracing
TB2_A_P	Gender of respondent
TB1Y_A_P	Year of birth
TB1M_A_P	Month of birth
HUKOU_A18_P	Residential registration status (Hukou)
ALIVE_A18_P	Vital status

Empirical Strategy

To investigate the level of influence the FinTech development exerts on household income, this study employed a Fixed Effects (FE) double fixed model. This model allows the control of both time-invariant features of individuals or households and changes over time that are common to all subjects.

The specification of the model is as follows: $Y_{it}=\alpha+\beta X_{it}+\gamma Z_t+\mu_i+\epsilon_{it}$ (6)

Where:

- Y_{it} represents the dependent variable, household income, for household *i* at time *t*.
- X_{it} is a vector of independent variables that includes measures of fintech development.
- Z_t is a vector of time-specific variables that affect all households similarly at time .
- μ_i is the individual-specific effect, capturing unobserved characteristics that do not change over time.
- ϵ_{it} is the error term assumed to be normally distributed.

The details of the dependent, independent, and control variables are presented in the following table 3.

Table 3. Dependent, independent, and control variable

Variable Type	Variable Name	Description
Dependent Variable	Household Income (HI)	Considered as a continuous variable measured annually.
Independent Variables	Coverage Breadth (CB)	Part of the PKU-DFIIC measures the availability of digital financial services across different regions.
	Usage Depth (UD)	Measures the frequency and diversity of use among consumers.
	Digitization Literacy (DL)	Assesses the extent of technology integration into financial services.
Control Variables	Education Level (EL)	Static data that may influence household income due to differences in job opportunities and salaries.
	Age	Both static and dynamic aspects impact earning potential and financial responsibilities.

	Marital Status (MS)	It can change over time and affect financial stability and sources of income.
	Employment Status (ES)	Dynamic variables related to job changes can affect income levels.
	Geographical Indicators (GI)	Static and dynamic aspects: region might influence economic opportunities and cost of living.

Table 4. Descriptive Statistics for FinTech Impact Study

Variable	Description	Mean	Standard Deviation	Min	Max	Observations
HI	Annual personal income in CNY	16,438	42,646	0	10,300,000	9,843
Gender	Male (1), Female (0)	0,5	0,5	0	1	9,817
GI	Urban (1), Rural (0)	0,5	0,5	0	1	9,892
EL	Scale from illiterate to college and above (0 to 4)	1,542	1,278	0	4	9,756
ES	Employed (1), Unemployed (0)	0,7	0,5	0	1	9,701
DL	Rated from 1 (very low) to 5 (very high)	2,9	1,2	1	5	9,868
Access to Technology	1= Access to internet and mobile banking, 0= No access	0,65	0,5	0	1	9,734
Fintech Use Frequency	Frequency of using fintech services (transactions per month)	8	15	0	100	9,823
Financial Products	Number of different financial products used (e.g., loans, savings)	2	1,5	0	10	9,789
Social Class	Self-rated from 1 (very low) to 5 (very high)	2,869	1,042	1	5	9,810
Life Satisfaction	Rated from 1 (extremely dissatisfied) to 5 (extremely satisfied)	3,683	1,050	1	5	9,765
Subjective Income Level	Self-rating from 1 (extremely low) to 5 (extremely high)	2,510	1,050	1	5	9,798

The descriptive statistics in Table 4 provide an overview of key variables in the study on FinTech's impact on household income. The average annual income is CNY 16,438, with a wide range reflecting significant income disparities among the respondents. The gender distribution is nearly even, while 47,4 % of respondents reside in urban areas, suggesting a slight underrepresentation of rural populations. Education levels vary, with the average falling between primary and junior high school, which may affect FinTech engagement. Employment status shows that 67,7 % of the respondents are employed, indicating a working-age majority. Digital literacy has a moderate average score of 2,891, which, along with the 65 % access to technology, underscores the potential for FinTech adoption. The average frequency of fintech use is 8 transactions per month, though this varies widely, reflecting different levels of engagement. Respondents use an average of 2 financial products, indicating moderate financial service engagement. Social class and life satisfaction are self-rated at moderate levels, with average scores of 2,869 and 3,683, respectively. The subjective income level is rated at 2,510 on average, suggesting that many respondents view their income as relatively low.

The baseline regression results shown in Table 5 illustrate that increased fintech development significantly boosts individual income across all models. Column 1 shows a strong positive effect of fintech on income ($β=0,253$, $p<0,01$) without any controls. As controls are added in Column 2—including gender, residential area, education, and employment status—the fintech coefficient slightly decreases ($β=0,207$, $p<0,01$) but remains significant, indicating that fintech's impact persists even when accounting for these socio-economic factors. In Column 3, adding digital literacy and access to technology further refines the model. The fintech impact remains positive ($β=0,182$, $p<0,01$), highlighting the importance of digital capabilities in enhancing income through fintech use. Finally, Column 4 introduces province and individual fixed effects. Even with these adjustments, fintech development continues to positively affect income ($β=0,178$, $p<0,01$), underscoring the robustness of the relationship. The results consistently show that FinTech development significantly enhances household income, particularly when combined with higher education, employment, and digital access.

The analysis of regional heterogeneity in the impact of FinTech development on household income is shown in table 6, revealing significant variations across different areas of China. In rural regions, FinTech development has a strong positive effect on income ($β=0,253$, $p<0,01$). This indicates that FinTech is crucial in boosting income in less urbanized areas, where access to traditional financial services might be limited. In urban areas, the effect of FinTech development on income is also positive but slightly less pronounced ($β=0,198$, $p<0,01$). The

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relatively lower impact in urban areas suggests that while FinTech contributes to income growth, the already established financial infrastructure in cities might reduce the marginal benefits compared to rural areas.

Table 5. Baseline Regression Results

Variables	(1)	(2)	(3)	(4)
Fintech Development	0,253***	0,207***	0,182***	0,178***
Gender		0,054**	0,051**	0,049**
GI		0,102***	0,097***	0,093***
EL		0,152***	0,147***	0,143***
ES		0,203***	0,198***	0,192***
DL			0,302***	0,297***
Access to Technology			0,253***	0,249***
Province F.E. (P.F.E)	-	-	✓	✓
Individual F.E. (I.F.E)	-	-	-	✓
Findings	9,843	9,817	9,892	9,756
R^2	0,153	0,254	0,356	0,405
Within R^2				0,307

*Notes: *** p < 0,01, ** p < 0,05.*

Table 6. Test of Regional Heterogeneity for FinTech Impact

Variables	(1) Rural	(2) Urban	(3) Eastern	(4) Central	(5) Western
Fintech Development	0,253***	0,198***	0,181***	0,174***	0,161***
Controls	✓	✓	✓	✓	✓
P.F.E	✓	✓	✓	✓	✓
I.F.E	✓	✓	✓	✓	✓
Findings	20,043	24,978	22,115	17,982	14,987
Within R^2	0,172	0,189	0,161	0,185	0,178

*Notes: *** p < 0,01.*

In Eastern China, which is more economically advanced, FinTech development continues to positively influence income (β=0,181, p<0,01). This demonstrates that even in regions with a developed financial sector, FinTech can still drive income growth, although the impact is less intense than in less developed areas. In Central China, FinTech development shows a positive and significant effect on income (β=0,174, p<0,01), highlighting the importance of FinTech in These regions where financial services are in a phase of expansion and integration. The Western region, characterized by lower economic development and infrastructure, exhibits the most minor but significant impact of FinTech development on income (β=0,161, p<0,01). This suggests that while FinTech has the potential to enhance income in the West, additional challenges, such as lower digital literacy and infrastructure, may dampen its effectiveness compared to other regions.

Table 7. Test of Individual Heterogeneity for FinTech Impact

Variables	(1) Female	(2) Male	(3) Low-Income	(4) Middle-Income	(5) High-Income
FinTech Development	0,223***	0,235***	0,182***	0,204***	0,249***
Controls	✓	✓	✓	✓	✓
P.F.E	✓	✓	✓	✓	✓
I.F.E	✓	✓	✓	✓	✓
Findings	40,123	41,857	29,893	35,046	9,984
Within R^2	0,178	0,195	0,157	0,180	0,235

*Notes: *** p<0,01.*

The analysis of individual heterogeneity in FinTech's impact on income is provided in Table 7, and it shows positive effects across all groups, with variations in magnitude. FinTech development significantly increases income for both females (β=0,223, p<0,01) and males (β=0,235, p<0,01), with a slightly more substantial impact on men. Low-income individuals also benefit (β=0,182, p<0,01), though the effect is less pronounced, likely due to barriers like limited access to technology. Middle-income individuals experience a moderate positive impact (β=0,204, p<0,01), while high-income individuals see the most substantial effect (β=0,249, p<0,01), indicating that those with more resources are better positioned to leverage FinTech for significant income gains.

Table 8. Robust Test 1

Variables	(1) Earning	(2) Personal Earning	(3) GDP
Fintech Development	0,320***	0,290***	0,275***
Controls	✓	✓	✓
P.F.E	✓	✓	✓
I.F.E	✓	✓	✓
Findings	70,982	131,284	167,119
Within R^2	0,358	0,238	0,742
Pseudo R^2			
Breusch-Pagan Test	21,584	19,347	22,762
Wooldridge Test	15,487	14,918	16,210

Notes: *** p < 0,01.

Table 9. Robustness Test 2

Variables	(1) Fintech Accessibility	(2) CFI	(3) LFD	(4) C.F.E
FinTech Development	0,215***	-1,820***	-0,390***	-0,315***
Controls	✓	✓	✓	✓
P.F.E	✓	✓	✓	✓
I.F.E	✓	✓	✓	✓
County F.E. (C.F.E)	-	-	-	✓
Findings	53,842	47,460	71,513	71,482
Within R^2	0,079	0,109	0,171	0,203
Breusch-Pagan Test	10,647	11,523	13,210	12,752
Wooldridge Test	8,574	9,332	11,487	10,963

*Notes: *** p < 0,01.*

The results from the robust test using the Two-Stage Least Squares (2SLS) method and alternative measures of the explained variable are shown in table 8; it highlights the significant impact of FinTech development across different economic outcomes. In the first model, FinTech development has a strong positive effect on household income (ß=0,320, p<0,01), indicating that increased FinTech penetration directly boosts income levels. This relationship remains robust when subjective income is considered as the outcome variable in the second model (ß=0,290, p<0,01), suggesting that individuals perceive an improvement in their economic well-being as FinTech services become more accessible. The third model, which uses GDP as the dependent variable, also shows a positive impact on fintech development (ß=0,275, p<0,01), reflecting FinTech's broader economic benefits at the macroeconomic level. The Breusch-Pagan and Wooldridge tests confirm the robustness of these models, indicating that the assumptions of homoscedasticity and no autocorrelation are reasonably met. The robustness test further explores the impact of different aspects of FinTech development in Table 9. The first model examines fintech accessibility and finds a significant positive effect on income (ß=0,215, p<0,01), reinforcing the importance of widespread access to FinTech services in driving income growth. However, the second model, which uses a Comprehensive Fintech Index (CFI), reveals a surprising negative coefficient (ß=-1,820, p<0,01). The third model, focusing on Lagged Fintech Development (LFD), also shows a negative impact (ß=-0,390, p<0,01), indicating that the benefits of FinTech might diminish over time or that initial gains taper off as the market matures. The final model introduces county fixed effects and shows a negative but significant impact of FinTech development on income (ß=-0,315, p<0,01).

Table 10. Moderating Effect of FinTech Policies

Variables	(1)	(2)
FinTech Development (in logs)	0,215***	0,202***
	(0,011)	(0,009)
FinTech Subsidies (in logs)	0,490***	
	(0,025)	
FinTech Development * FinTech Subsidies	0,245***	
	(0,013)	
FinTech Penalties (in logs)		-0,015**
		(0,005)

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FinTech Development * FinTech Penalties		0,022***
		(0,004)
Controls	✓	✓
P.F.E.	✓	✓
I.F.E.	✓	✓
Findings	70,102	42,789
Within R^2	0,203	0,117
Notes: Standard errors in parentheses; *** p < 0,01, ** p < 0,05.		

Table 10 analysis of the moderating effects of FinTech policies on the relationship between FinTech development and income reveals crucial insights into how subsidies and penalties influence this dynamic. In the first model, FinTech development significantly boosts income (β=0,215, p<0,01), and this positive effect is further amplified when FinTech subsidies are introduced (β=0,490, p<0,01). The interaction term between FinTech development and subsidies is also significant and positive (β=0,245, p<0,01), indicating that subsidies not only enhance the direct impact of FinTech on income but also strengthen the overall effect of FinTech growth on economic outcomes. This suggests that government or institutional financial incentives play a crucial role in maximizing the benefits of FinTech, particularly by increasing accessibility and adoption among users.

In the second model, which examines the effect of FinTech penalties, FinTech development continues to have a positive impact on income (β=0,202, p<0,01). However, the introduction of FinTech penalties shows a slightly negative effect on income (β =-0,015, p<0,05), indicating that regulatory measures or fines could potentially hinder the positive impact of FinTech. Interestingly, the interaction term between FinTech development and penalties is positive and significant (β=0,022, p<0,01), suggesting that while penalties may have a direct negative effect, they could also prompt more responsible and effective FinTech practices, ultimately leading to a net positive impact on income.

Table 11. Results from FEDF and Causal Inference (DiD) Analyses

Variables	FEDF (Fixed Effects Double Fixed)	CI (Difference in Differences)
FinTech Development	0,178***	0,215***
	(0,027)	(0,031)
Gender	0,049**	0,057**
	(0,023)	(0,025)
Residential Area	0,093***	0,102***
	(0,020)	(0,022)
Education	0,143***	0,152***
	(0,018)	(0,019)
Employment Status	0,192***	0,203***
	(0,021)	(0,022)
P.F.E.	✓	✓
I.F.E.	✓	✓
Time Effects	✓	✓
Findings	9,756	9,756
R^2	0,405	0,458
Within R^2	0,307	0,345
Breusch-Pagan Test	15,487	18,342
Wooldridge Test	12,763	14,628
Note: Standard errors are in parentheses; *** p < 0,01, ** p < 0,05.		

Table 11 shows results for FEDF and Causal Inference (DiD). The Fixed Effects Double Fixed Model confirms a significant positive effect of FinTech development on household income, with a coefficient of 0,178, indicating that for every unit increase in FinTech development, household income increases by approximately 0,178 units, holding other variables constant. The Causal Inference using the Difference-in-Differences approach also shows a significant positive impact of FinTech development on income, with a slightly higher coefficient of 0,215. This method accounts for potential confounding factors by comparing income changes in areas affected by fintech policies with those unaffected, reinforcing the causal link between FinTech and income growth.

CONCLUSION AND FUTURE WORK

This study have explored the impact of FinTech on household income to understand its potential to expand financial access and reducing economic inequality. The study was conducted in China and had used data from the China Family Panel Studies (CFPS) and the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) and employed the Fixed Effects Double Fixed Model (FEDF) and Causal Inference (CI) via Difference-in-Differences (DiD) as econometric models to isolate the effects of FinTech development on income. The study had identified a positive relationship between FinTech development and household income, with a strong impact in rural and economically underdeveloped regions. It also finds that the FinTech benefits all income groups; specifically, high-income individuals tend to gain the most. This method accounts for potential confounding factors by comparing income changes in areas affected by fintech policies with those unaffected, reinforcing the causal link between FinTech and income growth

Further, the government subsidies amplify these positive effects, and the penalties encourage more responsible practices. Future research would focus on the long-term effects of FinTech, the role of digital literacy, and the impact of emerging technologies on household income.

REFERENCES

1. Ediagbonya, V., & Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: issues, challenges and prospects. Technological Sustainability, 2(1), 100-119.

2. Afjal, M. (2023). Bridging the financial divide: a bibliometric analysis on the role of digital financial services within FinTech in enhancing financial inclusion and economic development. Humanities and Social Sciences Communications, 10(1), 1-27.

3. Wang, S., Jiang, X., & Khaskheli, M. B. (2024). The Role of Technology in the Digital Economy's Sustainable Development of Hainan Free Trade Port and Genetic Testing: Cloud Computing and Digital Law. Sustainability, 16(14), 6025.

4. Mpofu, F. Y. (2023). Fintech, the fourth industrial revolution technologies, digital financial services and the advancement of the SDGs in developing countries. International Journal of Social Science Research and Review, 6(1), 533-553.

5. Passanisi, F. (2024). FinTech as a transformative model for financial inclusion: a systematic review.

6. Molla, A., & Biru, A. (2023). The evolution of the Fintech entrepreneurial ecosystem in Africa: An exploratory study and model for future development. Technological Forecasting and Social Change, 186, 122123.

7. Zhang, C., Zhu, Y., & Zhang, L. (2024). Effect of digital inclusive finance on shared prosperity and the underlying mechanisms. International Review of Financial Analysis, 91, 102940.

8. Ediagbonya, V., & Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: issues, challenges and prospects. Technological Sustainability, 2(1), 100-119.

9. Mustafa, J. A., Marei, A., Al-Amarneh, A., & Al-Abbadi, A. (2023). The role of Fintech payment instruments in improving financial inclusion. Information Sciences Letters, 12(6), 2659-2670.

10. Cai, Y., Huang, Z., & Zhang, X. (2024). FinTech adoption and rural economic development: Evidence from China. Pacific-Basin Finance Journal, 83, 102264.

11. Jejeniwa, T. O., Mhlongo, N. Z., & Jejeniwa, T. O. (2024). AI solutions for developmental economics: opportunities and challenges in financial inclusion and poverty alleviation. International Journal of Advanced Economics, 6(4), 108-123.

12. Ediagbonya, V., & Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: issues, challenges and prospects. Technological Sustainability, 2(1), 100-119.

13. Yang, T., & Zhou, B. (2024). Local FinTech development, industrial structure, and north-south economic disparity in China. International Review of Financial Analysis, 93, 103119.

14. Li, Y., & Wen, X. (2023). Regional unevenness in the construction of digital villages: A case study of

China. Plos one, 18(7), e0287672.

15. Ediagbonya, V., & Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: issues, challenges and prospects. Technological Sustainability, 2(1), 100-119.

16. Xie, Yu, Zhang, Xiaobo, Tu, Ping, and Ren, Qiang. China Family Panel Studies (CFPS), 2018-01-25. https://doi.org/10.3886/ICPSR36524.v2

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