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CAN FINTECH CURB INCOME INEQUALITY IN CHINA?

Kefu LIU[1], Yunping HAO[2*], Yuhang GE[1], Weiwei MU[3*]

[1]China School of Banking and Finance, University of International Business and Economics, Beijing, China
[2]College of Finance, Nanjing Agricultural University, Nanjing, China
[3]School of Finance, Hebei University of Economics and Business, Shijiazhuang, China

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Abstract. The effect of FinTech on income inequality in China and the characteristics of the existing thresholds are examined in this study based on China provincial panel data from 2011 to 2020 by combining dynamic panel differential GMM with panel threshold models. As revealed by this study, (1) FinTech can significantly curb income inequality. (2) FinTech can mitigate income inequality in all regions, and the degree of mitigation is more significant in the central and western regions of China. (3) The improvement of FinTech development can reduce income inequality in all quantiles. The regions with high-income inequality and low-income inequality are compared. The comparison results reveal that FinTech can reduce income inequality to a greater extent in regions with low-income inequality. (4) FinTech can restrain income inequality under different threshold variables, and the restraining effect of economic growth is the most significant. The policy significance of this study is to fully exploit the empowerment and income-generating role played by FinTech, build a more inclusive financial system, create a good financial environment, cultivate residents' financial knowledge level, enhance the ability of low-income groups to obtain income from financial services and reduce income inequality, to fulfill the development goal of common prosperity.

Keywords: FinTech, income inequality, differential GMM, threshold model, income distribution, financial inclusion, common prosperity.

JEL Classification: G10, G20, G3.

Introduction

China is the world's largest developing nation and has made great contributions to the narrowing of the income gap between urban and rural areas and reducing global poverty. They can lay a practical basis for solving income inequality, and it is of great significance for the world to reduce income inequality and achieve common prosperity. The continuous integration and innovation of cutting-edge technologies such as big data, blockchain, machine learning, and artificial intelligence have spawned new innovative formats of FinTech. FinTech

*Corresponding author. E-mails: *yunpingh2016@163.com; mvv_uibe@163.com*

has changed the structure of the existing financial industry, thus making the boundaries of the industry more blurred, while creating new possibilities for financial institutions' service methods. FinTech is capable of reducing information asymmetry, decreasing transaction costs, strengthening financial functions, and increasing financial service efficiency. They have been improving financial inclusion and financial coverage, which can stimulate savings, investment, and appropriate household consumption and the broad and undiscovered potential of poorer social classes. Demirguç-Kunt and Klapper (2013) suggested in the study that the seven nations of Philippines, Bangladesh, Pakistan, China, Vietnam, India, and Indonesia account for approximately 92% of the 1.5 billion unbanked population in developing nations, thus suggesting that the financial market that is a vast space for expansion. On that basis, FinTech development can play a greater role in developing nations, especially in China. The types of financial services and financial product innovations increased by the FinTech development can play a vital role in improving the efficiency of financial services and increasing income.

China has a vast territory, and the development gap tends to be significant, which is not only reflected in the regions but also in the urban and rural areas. From 2011 to 2020, the per capita disposable income of urban residents in China rose from US$3,355.354 to US$6,446.18, marking an increase of nearly 1.92 times, and the per capita income of rural residents increased from US$1,073.43 to US$2,519.27, marking an increase of approximately 2.35 times. Compared with urban residents, the per capita income of rural residents has grown faster, and the urban-rural income ratio has dropped from 3.126 in 2011 to 2.56 in 2020. The rate of decline is relatively significant, thus suggesting that the urban-rural income gap is significantly narrowing and improving the level of income inequality. This improvement originates from the fact that the income level of rural residents has increased faster than that of urban residents. The vital contributions of income increase consist of the improvement of financial efficiency, FinTech development, and the use of smartphones. China has the largest mobile payment market worldwide. The FinTech development affects the transformation of consumer behavior and payment methods to a certain extent. It also brings unprecedented challenges to traditional financial institutions and the financial industry. They have more effectively adapted to the advancement of the times to embrace the development trend of digital technology and FinTech. Active transformation and upgrading should be carried out, our development potential should be enhanced, and future development directions and strategies should be planned. FinTech can help social groups obtain financing, increase income, and improve access to financial services, whereas it will not reduce inequality among all groups (Philippon, 2020). However, FinTech is capable of providing unprecedented opportunities to overcome the high cost of financial services, physical distance, and financial access barriers, eliminating the remaining gap in the use of bank accounts, and making financial services more popular through the use of mobile technology. FinTech is increasingly considered as a critical driver of financial inclusion, while mobile financial services are considered with the greatest potential to integrate social groups with insufficient financial services into the formal financial system and ultimately achieve fairer growth (Demirgüç-Kunt et al., 2018). For this reason, researching the effect of FinTech on income inequality and the threshold characteristics of existence has certain theoretical value and practical significance, which is also the research goal of this study.

Based on the above analysis, the effect of FinTech on China's income inequality and the existing threshold characteristics is examined in this study based on inter-provincial panel data in China from 2011 to 2020 by combining dynamic panel differential GMM with panel threshold models. The research finds that it can significantly reduce income inequality, and the mitigation effect of FinTech on income inequality has certain threshold characteristics. The existing research on the effect of FinTech on income inequality mainly focuses on the empirical test of cross-border panel data. The data use is generally relatively broad. There is still a relative lack of research at the provincial level in China. Compared with the existing research, the possible contribution of this study is presented as follows. This study initially uses dynamic panel differential GMM and panel threshold models and quantile regression methods based on provincial-level data in China and performs a more detailed empirical test of the effect of FinTech on income inequality and threshold characteristics, as well as the saliency and heterogeneity of FinTech in reducing income inequality. This study provides a reference for the development of global FinTech to reduce income inequality in China.

The rest of the study is organized as follows. Section 1 literature review. Section 2 data and econometric model. Section 3 Empirical result analysis. Section 4 conclusion.

1. Literature review

Information and FinTech can play an essential role in reducing income inequality. Especially in developing countries, FinTech can create new jobs for the poor, improve taxation and government services, and reduce corruption (Aker & Mbiti, 2010). Asongu (2015) finds a negative correlation between mobile penetration and income inequality in 52 African nations sample. Using mobile phones can reduce the likelihood of families falling into poverty in Ghana (Abor et al., 2018; Billari et al., 2020; Lee et al., 2021; Ureta, 2008). The expansion of mobile phone coverage reduces extreme poverty while increasing household consumption in rural Peru (Asongu et al., 2023; Asongu, 2015; Bahia et al., 2023; Bhallamudi, 2022; Khan et al., 2022; Odhiambo, 2022; Rajkhowa & Qaim, 2022; Wei & Mukherjee, 2023). Asongu and Nwachukwu (2018) investigate the correlation between mobile banking and inclusive development (quality of growth, inequality, and poverty) in 93 nations. The study shows that using mobile phones to pay bills or send and receive money shows a significant negative correlation with income inequality, whereas this only happens in upper-middle-income nations. Mobile banking can reduce income inequality in the lowest or highest-income nations (i.e., 10% and 90% of the income inequality distribution) (Asongu & Odhiambo, 2018).

With the FinTech development, the effect of FinTech on income inequality shows an inverted U-shaped nonlinear relationship that first increases and then decreases (Zhang & Wang, 2021). Besides, FinTech can promote the development of the real economy through financial innovation and technological innovation (Tian et al., 2021). Fu and Liu (2023) investigate the relationship between income inequality and the accessibility of financial services, measured by the number of bank branches. Their findings reveal that there is a negative correlation between income inequality and the accessibility of financial services, especially in underdeveloped countries and regions. Brei et al. (2023) have also examined the relationship between finance and income inequality, discovering that increasing the amount of finance can reduce income inequality to a certain extent. They note, however, that when finance grows through market-based financing, it may lead to an increase in inequality, whereas finance that is sourced primarily through bank lending does not have such an impact. Another study by Hodula (2023) explores whether fintech has an impact on income inequality. The study reports that fintech's rise is associated with a decline in income inequality, but only in countries with higher levels of financial inclusion. Luo et al. (2022) investigate the relationship between fintech innovation and household consumption. Their findings show that fintech innovation contributes significantly to household consumption, with entrepreneurship and increased income being the primary channels of transmission.

FinTech can reduce inequality and poverty based on some mechanisms. For instance, FinTech can narrow the urban-rural income gap by promoting rural entrepreneurship (Zhang et al., 2018). As a form of FinTech, mobile money has lifted 2% of Kenyan households out of poverty and raised per capita consumption (Suri & Jack, 2016). As reported by studies in Nepal and India, digital government payments can reduce administrative costs and corruption, thus leaving more resources for social spending (Muralidharan et al., 2014). Demir et al. (2022) use the global Finex survey data in 2011, 2014, and 2017 to analyze the interrelationship between FinTech, financial inclusion, and income inequality in 140 nations and regions. Research suggests that FinTech directly or indirectly affects income inequality through financial inclusion. Using quantile regression to study whether this effect differs across countries with different levels of income inequality, they find that financial inclusion is the main channel for FinTech to reduce income inequality.

2. Data

2.1. Data source and variable selection

(1) FinTech development (lnFinTech). This study refers to the keywords in the literature of Li et al. (2020), and Sheng and Fan (2020). We combine with the availability of keywords and manually sort out the Baidu search index of FinTech to relate keywords in various provinces from 2011 to 2020 (Due to the availability of data, the data used does not consist of Hong Kong, Macao and Taiwan regions from China), and the entropy method is used to calculate the comprehensive FinTech index. We manually entered the Baidu index page and then searched by "keyword + province" to sort out the keywords of each province from 2011 to 2020. The total number of FinTech keywords is 33, specifically: big data, cloud computing, artificial intelligence, blockchain, biometrics, online payment, mobile payment, virtual reality, Internet banking, e-banking, voice recognition, NFC payment, third-party payment, direct banking, network banking, online banking, data visualization, data mining, online lending, Internet finance, deep learning, mobile internet, equity crowdfunding, mechanical learning, intelligent customer service, stream computing, business intelligence, digital currency, network connection, Internet of Things, credit investigation, natural language processing and FinTech. The calculation method based on Euclidean distance by Liu et al. (2018) is adopted to calculate the FinTech comprehensive index. The specific steps are as follows: (1) First,

the data is quantified without rigidity; (2) The coefficient of variation method is adopted to calculate the index weight:

$$\lambda_{ij} = \frac{\sigma_{ij}}{\overline{X}_{ij}},\ \rho_{ij} = \frac{\lambda_{ij}}{\sum_{i=1}^{j} \lambda_{ij}}, \tag{1}$$

where σ_{ij} denotes the standard deviation of the j-th index of the i-th dimension; $\overline{X}_{ij}$ expresses the mean value of the j-th index of the i-th dimension; λ_{ij} represents the coefficient of variation of the j-th index of the i-th dimension; ρ_{ij} is the j-th index of the i-th dimension Weights. (3) The comprehensive FinTech index is calculated by Eq. (2):

$$fintech_i = 1 - \frac{\sqrt{\rho_{i1}^2 (1 - X_{i1})^2 + \rho_{i2}^2 (1 - X_{i2})^2 + \ldots + \rho_{ij}^2 (1 - X_{ij})^2}}{\sqrt{\rho_{i1}^2 + \rho_{i2}^2 + \ldots + \rho_{ij}^2}}. \tag{2}$$

(2) Income inequality (lnini). The current indicators for measuring income inequality comprise the urban-rural income gap at the provincial level (Lu et al., 2005; Gong & Fan, 2012), and the Gini coefficient (Zhao & Fan, 2020). To be specific, the urban-rural income gap can explain more than 75% of the overall income gap in China (Gong & Fan, 2012). Accordingly, this study uses the urban-rural income gap as an indicator to measure income inequality, taking the ratio of the disposable income of urban residents to the disposable income of rural residents as measured in the logarithm.

(3) Control variables. Openness (lnopen): the proportion of total imports and exports to GDP is adopted as the logarithm; child dependency ratio (lncsr): the proportion of children's population in the total population is taken as the logarithm; infrastructure construction (lntroad): the number of railway operating mileage per 10,000 people is taken Logarithm; Communication Technology (lnict): The per capita mobile phone exchange capacity is the logarithm. Income inequality, openness, child dependency ratio, infrastructure, and communication technology data originate from the *China Statistical Yearbook* and the *Provincial Statistical Yearbook*. The article data is structured as balanced panel data for 2011 to 2020. Table 1 lists the descriptive statistical analysis of specific variables.

Table 1. Descriptive statistical analysis of variables

Variable	Name	Mean	S.D.	Min	Max	Median	Obs
ln*ini*	Income inequality	0.971	0.156	0.613	1.381	0.954	310
ln*FinTech*	FinTech	–1.723	1.027	–4.158	–0.280	–1.377	310
ln*open*	Openness	–3.646	0.949	–5.992	–1.428	–3.824	310
ln*csr*	Child dependency ratio	3.084	0.298	2.291	3.589	3.123	310
ln*troad*	Infrastructure	7.993	0.724	6.134	9.455	8.216	310
ln*ict*	Communication technology	0.451	1.277	–3.237	4.264	0.450	310

2.2. Model

Whether the FinTech development can suppress income inequality, the pro-poor and inclusiveness of FinTech need to be tested by building a model. This study uses the dynamic panel differential GMM regression method to investigate the effect of FinTech on income inequality. The benchmark model constructed is:

$$\ln ini_{it} = \alpha_0 + \alpha_1 \ln fintech_{it} + \alpha_2 control_{it} + \varepsilon_{it}, \tag{3}$$

where α_0 denotes a constant term, α_1 measures the effect of FinTech on income inequality, and α_2 measures the effect of other control variables on income inequality. Control variables consist of openness (lnopen), child dependency ratio (lncsr), infrastructure construction (lntroad), and Communication Technology (lnict). ε_{it} is a random disturbance item. There are obvious differences in the level of economic development, urbanization rate, and FinTech among regions in China, and there may be threshold characteristics. For instance, when economic development reaches a certain threshold, the effect of FinTech on income inequality will be different. FinTech and income inequality are not purely linear and may have non-linear characteristics. The threshold model threshold is generated by data. Given this, it can better reveal the correlation between FinTech and income inequality. To further examine the threshold characteristics of FinTech affecting income inequality, this study uses FinTech itself, economic development level (GDP and per capita GDP), and urbanization rate as threshold variables. The model constructed by Hansen (1999) threshold regression model is as follows:

$$\ln ini_{it} = \lambda_1 \ln x_{it} \times I(q_{it} \le \gamma) + \lambda_2 \ln x_{it} \times I(q_{it} > \gamma) + \varphi_1 control_{it} + \varepsilon_{it}, \tag{4}$$

where x_{it} is the explanatory variable affected by the threshold variable, in the text is the level of FinTech development, q_{it} is the threshold variable, γ is the specific threshold value, λ_1, λ_2 is the influence coefficient of the threshold variable $q_{it} \le \gamma$ and $q_{it} > \gamma$, the explanatory variable x_{it} on the income inequality of the explained variable, respectively, Is an indicative function.

3. Empirical result analysis

3.1. Benchmark regression analysis

In Table 2, the dynamic panel difference GMM model is adopted to examine the effect of FinTech on income inequality. To ensure the reliability of the empirical test results, the regression method is adopted to gradually add control variables, and the results in column (5) serve as the basis for the explanation. From the regression results in column (5) of Table 2, it can be seen that the estimated coefficient of lnFinTech is significantly negative at least at a significance level of 1%, thus suggesting that FinTech can alleviate income inequality. Under the circumstances, for every 1% increase in FinTech, the degree of income inequality will decrease by an average of 0.035%, which fully demonstrates the significant role played by FinTech in reducing income inequality. The FinTech development has improved the convenience of financial services, reduced transaction costs, diversified services, and diversified channels. It is easier for the general public to obtain financial services, especially by breaking the original physical distance constraint, dredging the last mile of financial services, and enabling Rural areas to have the same access to financial services as cities and towns. Notably, rural areas benefit more from financial services since most of the residents in rural areas start from nothing (sending charcoal in the snow), while towns have increased on the original basis (icing on the cake). Thus, rural residents benefit more from financial services and apply them to daily production and life; they expand reproduction, reserve capital, increase income levels, and narrow the income gap with urban residents, thus significantly reducing income inequality.

The estimated coefficient of the degree of openness (lnopen) is significantly negative at least at 1%, thus suggesting that the increase in the degree of openness is conducive to reducing income inequality. For every 1% increase in the degree of openness, the degree of income inequality will drop by 0.052% on average. Only by opening up can we gain more insights into the world, understand the world, and integrate into the world. We are enabled to acquire resources and information from the outside timely. Only by fully communicating can we facilitate the allocation and flow of resources, attract talents from developed regions, and make up for the shortcomings of our development, as well as Insufficiency. Besides, we can find the advantages and disadvantages of development faster. Accordingly, the increase in the degree of openness has enabled remote areas, especially rural areas, to obtain more information and resources, and the continuous integration with cities and towns has increased the income level of residents in rural areas. With the increase in the child dependency ratio (lncsr), income inequality will be exacerbated. The reason is that an excessively high child dependency ratio will take up most of the time and experience of the dependants on the one hand, and it is difficult for the dependants to spare time to work to increase family income. On the one hand, it will increase the living burden of rural residents, and it is difficult to guarantee the quality of life, and it will also negatively affect the healthy growth of children. For urban residents, most of them are primarily in commerce, selling daily necessities, or having a fixed job in the town and a fixed source of income, the impact is not very obvious. In contrast, the income gap between urban and rural areas has widened, thus increasing income inequality. The estimated coefficient of infrastructure construction (lntroad) is significantly negative at least at 5%, thus suggesting that the improvement of infrastructure construction can help alleviate income inequality. For every 1% increase in infrastructure construction, the level of income inequality will be even down-regulated by 0.168%, thus proving that infrastructure construction plays an essential role in reducing income inequality. With the continuous improvement of infrastructure, urban-rural exchanges are more convenient, transportation costs between urban and rural areas are reduced, freight logistics are more convenient, and the express delivery industry can rapidly expand the rural market, rural residents can also enjoy the convenience of online shopping, and the role played by infrastructure construction cannot be ignored. The estimated coefficient of communication technology (lnict) is significant by at least 5%, thus suggesting that the improvement of communication technology is conducive to suppressing income inequality. Communication technology makes information transmission in rural areas more accessible. Impacted by the information spillover effect, rural residents have access to more abundant information, information is not only wealth, it significantly increases the income of rural residents, effectively alleviates the income gap between urban and rural areas, and reduces income inequality.

Table 2. Benchmark regression results

Variable	(1)	(2)	(3)	(4)	(5)
ln*FinTech*	-0.041^{***}	-0.048^{***}	-0.055^{***}	-0.036^{***}	-0.035^{***}
	(−7.83)	(−8.07)	(−8.25)	(−3.17)	(−2.96)
ln*open*		-0.053^{***}	-0.045^{***}	-0.054^{***}	-0.052^{***}
		(−3.06)	(−3.41)	(−4.01)	(−2.92)
ln*csr*			0.439^{***}	0.465^{***}	0.314^{*}
			(3.70)	(3.27)	(1.66)
ln*troad*				-0.165^{**}	-0.168^{**}
				(−2.38)	(−2.35)
ln*ict*					-0.027^{**}
					(−2.37)
obs	279	279	279	279	279
AR(2) *p* Value	0.961	0.320	0.506	0.250	0.038
Hansen *p* Value	0.199	0.162	0.374	0.160	0.354

Note: The regression coefficient is outside the brackets, and the *z* value is inside the brackets. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

3.2. Robustness test

To ensure the robustness of the benchmark regression results, this paper adopts the digital financial inclusion index of the Digital Finance Research Centre of Peking University as a proxy variable for fintech development brought into the benchmark regression model to re-regress the results of the empirical test to check the robustness of the empirical test results. As can be seen from the results in Table 3, the main conclusion that FinTech can significantly suppress income inequality has not changed, indicating the robustness of the regression results.

Table 3. Robustness test

Variable	(1)	(2)	(3)	(4)	(5)
ln*FinTech*	-0.100^{***}	-0.126^{***}	-0.148^{***}	-0.156^{***}	-0.157^{***}
	(−8.00)	(−9.25)	(−9.04)	(−4.91)	(−4.70)
ln*open*		-0.073^{***}	-0.062^{***}	-0.059^{***}	-0.060^{***}
		(−4.36)	(−3.60)	(−3.35)	(−3.37)
ln*csr*			0.579^{***}	0.591^{***}	0.597^{***}
			(3.03)	(3.24)	(3.36)
ln*troad*				0.029	0.032
				(0.32)	(0.34)
ln*ict*					0.002
					(0.21)

End of Table 3

Variable	(1)	(2)	(3)	(4)	(5)
obs	279	279	279	279	279
AR(2) *p* Value	0.026	0.433	0.662	0.586	0.570
Hansen *p* Value	0.191	0.159	0.209	0.187	0.197

Note: The regression coefficient is outside the brackets, and the *z* value is inside the brackets. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

3.3. Analysis of Regional Heterogeneity

The regression results of the sub-regions in Table 4 suggest that there is a certain difference in the degree of FinTech's alleviation of income inequality in various regions. For the effect of equality, every 1% increase in FinTech can alleviate income inequality in the eastern, central, and western regions by 0.02%, 0.045%, and 0.063%, respectively. The mitigation effect is even more significant in the western region, followed by the central region, and limited in the eastern region, which did not pass the significance level test. The above result also shows from another level that FinTech development is inclusive, which can alleviate the income inequality between urban and rural areas while alleviating the development gap between regions.

Table 4. The effect of FinTech on income inequality by region

Variable	East	Central	Western
	(1)	(2)	(3)
ln*FinTech*	–0.020	–0.045**	–0.063***
	(–1.09)	(–2.35)	(–4.76)
ln*open*	–0.013	–0.131***	–0.049***
	(–0.48)	(–5.25)	(–2.99)
ln*csr*	0.206*	0.319***	0.448***
	(1.84)	(2.64)	(4.49)
ln*troad*	–0.168**	–0.095	–0.020
	(–2.01)	(–1.04)	(–0.27)
ln*ict*	–0.009	–0.018*	–0.005
	(–1.32)	(–1.72)	(–0.83)
obs	99	72	108
AR(2) *p* Value	0.295	0.059	0.871
Hansen *p* Value	0.999	1.000	0.985

Note: The regression coefficient is outside the brackets, and the z value is inside the brackets. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

3.4. Investigation of different quantile results

To examine the effect of FinTech on income inequality at different quantiles, this study uses the quantile regression method to estimate. The quantile regression results show that basically at all quantiles, the improvement of FinTech can alleviate Income inequality is significant at least at 1%, but the degree of influence varies at different quantiles. From the results in Table 5, it can be seen that in the region in the 10th quantile of income inequality, a 1% increase in FinTech will reduce income inequality by 0.052%, and at the 90th quantile, FinTech will increase by 1% It will reduce income inequality by 0.057%. At the 25th quantile, a 1% increase in FinTech will reduce income inequality by 0.061%, showing an N-curve path of influence. The lower the degree of equality, the greater the degree of FinTech's alleviation of income inequality, the higher the degree of integration of urban and rural residents, and the development of integration in the direction. In regions with higher income inequality, FinTech development has a relatively limited effect on alleviating income inequality. The reason may be the consolidation of the urban-rural dual structure, and the FinTech development is difficult to break the existing development pattern in the short term.

Table 5. The effect of different quantiles of FinTech on income inequality

Variable	Q10	Q25	Q50	Q75	Q90
	(1)	(2)	(3)	(4)	(5)
ln*FinTech*	–0.052***	–0.061***	–0.050***	–0.049***	–0.057***
	(–5.45)	(–6.99)	(–5.50)	(–3.64)	(–5.06)
ln*open*	–0.075***	–0.046***	–0.060***	–0.064***	–0.087***
	(–5.11)	(–3.37)	(–4.27)	(–3.06)	(–4.96)
ln*csr*	0.198***	0.225***	0.153***	0.135**	0.050
	(5.28)	(6.49)	(4.22)	(2.53)	(1.12)
ln*troad*	–0.017	–0.015	–0.018	–0.006	–0.021
	(–0.87)	(–0.83)	(–0.96)	(–0.20)	(–0.88)
ln*ict*	0.011	0.006	0.003	–0.011	–0.003
	(1.11)	(0.60)	(0.29)	(–0.81)	(–0.24)
constant	–0.012	0.039	0.326*	0.369	0.739***
	(–0.07)	(0.24)	(1.91)	(1.47)	(3.50)
obs	279	279	279	279	279
Pseudo R^2	0.3397	0.2747	0.2669	0.2685	0.3086

Note: The regression coefficient is outside the brackets, and the t value is inside the brackets. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively.

3.5. Threshold feature analysis

By the data structure and variable settings, this study estimates a single threshold regression model. There are only two reasons for estimating a single threshold. One reason is that the panel data interval is short, and the possibility of multiple threshold features is less likely. The other reason is that according to the test results of the threshold effect, the double threshold and the triple threshold are not significant, so there are no double and triple threshold features. With the use of the identification and testing method of the threshold regression model, the single threshold model is estimated to be returned to the self-sampling process after 200 times of Bootstrap, and the F value, P value, and 95% confidence interval of the threshold estimation result are achieved. Table 6 suggests that the single threshold of per capita GDP and urbanization rate is at least significant at 10%. When GDP and FinTech development themselves serve as threshold variables, the P values are 0.11 and 0.14, respectively. For FinTech and GDP, the first thresholds of per capita GDP and urbanization rate are 0.0608, 12512.2998, 49558, and 51.83, respectively.

Table 6. Panel threshold effect test and threshold value and confidence interval

Variable	*FinTech*	*gdp*	*pgdp*	*ubr*
	(1)	(2)	(3)	(4)
F Statistics	22.11	26.73	27.10	35.34
P Value	0.1100	0.1400	0.0900	0.0750
Threshold estimate	0.0608	12512.2998	49558	51.83
95% Confidence interval	[0.0552–0.0612]	[12069.1499–12582]	[46436.35–50160]	[51.655–51.990]
BS number of times	200	200	200	200

Note: The number of BS refers to the number of times that the self-sampling Bootstrap can be replaced.

Table 7 lists the regression estimation results of the panel threshold model. As revealed by the results, under the regression of different threshold variables, FinTech development can alleviate income inequality, and it is basically at least at the 1% significance level. The above is significant, whereas the degree to which FinTech suppresses income inequality under different threshold variables shows a certain degree of heterogeneity. When the FinTech development itself, GDP, GDP per capita, and urbanization rate cross a single threshold, the FinTech development can significantly suppress income inequality, but due to the existence of the law of diminishing margins, the mitigation effect of FinTech on income inequality is weakening. From the perspective of the absolute value of the regression estimation coefficients under different threshold variables, when the single threshold is not crossed, the coefficients of the effect of FinTech on income inequality are −0.023, −0.042, −0.034, and −0.036, respectively. The increase in gross product (GDP), that is, economic growth, has a more significant mitigation effect of FinTech on income inequality, followed by the urbanization rate, GDP per capita, and the FinTech development itself has the least mitigation effect as a threshold variable. Moreover, when the threshold is crossed, the relative order of the mitigation effects of FinTech on income inequality under different threshold variables has not undergone a fundamental change. The degree of openness (lnopen), infrastructure construction (lntroad), and communication technology (lnict) all alleviate income inequality, and the child dependency ratio (lncsr) will exacerbate income inequality. The detailed analysis has been carried out above, and we will no longer Go into details.

Table 7. Regression estimation results of the panel threshold model

Threshold variable	*FinTech*	*gdp*	*pgdp*	*ubr*
	(1)	(2)	(3)	(4)
ln*open*	-0.058^{***}	-0.064^{***}	-0.060^{***}	-0.058^{***}
	(−6.13)	(−6.83)	(−6.36)	(−6.21)
ln*csr*	0.163^{***}	0.121^{**}	0.143^{***}	0.141^{***}
	(3.46)	(2.53)	(3.06)	(3.00)
ln*troad*	-0.226^{***}	-0.175^{***}	-0.191^{***}	-0.188^{***}
	(−7.49)	(−5.66)	(−6.32)	(−6.24)
ln*ict*	0.002	−0.000	−0.001	−0.000
	(0.52)	(−0.03)	(−0.17)	(−0.07)
$\ln fintech_{it} \times (M_{it} \le \tau)$	-0.023^{***}	-0.042^{***}	-0.034^{***}	-0.036^{***}
	(−5.50)	(−8.28)	(−7.96)	(−8.18)
$\ln fintech_{it} \times (M_{it} > \tau)$	-0.010^{*}	-0.024^{***}	-0.015^{***}	-0.019^{***}
	(−1.71)	(−5.83)	(−3.23)	(−4.35)
constant	2.032^{***}	1.710^{***}	1.786^{***}	1.779^{***}
	(7.05)	(5.99)	(6.30)	(6.30)
obs	279	279	279	279
R^2	0.7127	0.7176	0.7180	0.7203
F	87.22	89.38	89.56	90.57
$F(P)$	0.0000	0.0000	0.0000	0.0000
Width	200	200	200	200
BS number of times	200	200	200	200

Note: The regression coefficient is outside the brackets, and the *t* value is inside the brackets. ***, **, and * indicate the significance levels of 1%, 5%, and 10%, respectively, M_{it} is the threshold value.

Conclusions

Financial market deficiencies such as information asymmetry and transaction costs will restrict low-income groups' access to formal financial services. However, with the advent of FinTech, low-income groups usher in the dawn. FinTech can reduce information asymmetry, reduce transaction costs, enhance financial functions, and improve financial efficiency. FinTech will provide unprecedented opportunities to overcome the high cost of financial services, physical distance, and financial access barriers, eliminate the remaining gap in the use of bank accounts, and make financial services more popular by using mobile technology. Based on the inter-provincial panel data from 2011 to 2020, this paper uses dynamic panel differential GMM and panel threshold model to investigate the impact of FinTech on income inequality and the existing threshold characteristics. The research results find that: (1) FinTech can significantly inhibit income equality. (2) FinTech can mitigate income inequality in all regions, and the degree of mitigation is more significant in the central and western regions. (3) Basically, in all quantiles, the increase in the level of FinTech development can reduce income inequality. Compared with regions with high-income inequality, the degree of FinTech's alleviation of income inequality in regions with low-income inequality is bigger. (4) With the FinTech development itself, GDP, GDP per capita, and urbanization rate as threshold variables, FinTech can inhibit income inequality, and economic growth has the most significant inhibitory effect.

By the conclusions drawn in this study, the policy recommendations are given as follows:

First, relevant national-level financial policy-making departments should place stress on the restraining effect of FinTech development on China's income inequality. It is necessary to gain insights into the needs of financial market services, build a bridge between the supply and demand of financial services, provide a relatively loose market supervision atmosphere, and boost sound and orderly FinTech development. Relevant FinTech companies should be encouraged to strengthen FinTech (e.g., big data, cloud computing, and artificial intelligence), integrate their business with financial services, develop more inclusive financial products, help low-income groups enjoy financial services at an affordable cost, and proactively fulfill corporate social responsibilities. Financial infrastructure construction should be strengthened, and residents' financial knowledge should be properly trained. The government is required to create a good financial environment and lay a solid basis for FinTech development to better serve low-income groups. Financial policies should be combined with monetary and fiscal policies. Financial inclusion should be based on the redistributive effect of fiscal policy to fulfill the policy goal of common prosperity.

Second, for China's central and western regions and regions characterized by low-income inequality, we should actively embrace FinTech. The conclusions of this study suggest that FinTech more significantly inhibits China's central and western regions and regions with low-income inequality, which is a vital development opportunity for them in the digital economy era. Relevant functional departments in the above regions can strive to obtain higher-level policy support on the one hand, set up corresponding FinTech pilots under the framework of the regional free trade pilot zone, encourage first pilots, and fully explore the policy dividend and the restraining effect of FinTech's income inequality. Besides, it is necessary to actively learn the development experience of advanced areas in FinTech development, and combine the absorption and enrichment of regional scenarios to create FinTech application scenarios with regional characteristics. Furthermore, the above regions should grasp the role played by FinTech in consolidating the results of poverty alleviation and efficiently connecting rural areas. The vital role played by revitalization has caused the FinTech market to sink.

Lastly, the restraining effect of regional economic development, urbanization, and consumer consumption, as well as the FinTech development on regional income inequality should be exploited fully. Local governments are required to focus on economic development, strive to boost regional economic development, and make the regional "cakes" bigger; they should further adopt a wide variety of measures to stimulate regional residents' consumption and increase residents' income levels; they should work hard to facilitate regional urbanization and break regional urban and rural areas and barriers to promote the integrated development of urban and rural areas. On that basis, the inhibitory effect of FinTech development on income inequality can be fully brought into play by creating a good external environment for regional FinTech development.

One limitation of our study is the use of inter-provincial panel data and the small sample size used for analysis, which warrants further consideration in future research. Additionally, given the expansive nature of FinTech and the multitude of keywords potentially associated with it, some important keywords may have been missed in our analysis; future research should thus aim to explore this topic in greater detail. Specifically, future researchers should consider expanding the scope of the study to include micro-level data, particularly in rural areas, given the critical role that income inequality in rural areas plays in overall social welfare improvement.

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Author contributions

Conceptualization, Kefu Liu and Yunping Hao; methodology, Kefu Liu and Yunping Hao; software, Yuhang Ge; validation, Yuhang Ge, Weiwei Mu, and Yunping Hao; formal analysis, Weiwei Mu; Investigation, Yuhang Ge; resources, Kefu Liu; data curation, Yuhang Ge; writing–original draft preparation, Kefu Liu; writing–review and editing, Yunping Hao; visualization, Weiwei Mu and Yuhang Ge; supervision, Weiwei Mu; project administration, Kefu Liu; funding acquisition, Yuhang Ge. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

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