Development of Digital Financial Inclusion in China's Regional Economy: Evidence from Panel Threshold Models

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Abstract: This study aims to investigate the effect of digital financial inclusion and air pollution on economic growth for 31 Chinese provinces between 2003 and 2022 using Panel Threshold Auto-Regressive (PTAR) and Panel Smooth Transition Auto-Regression (PSTAR) models. The results show that there is a nonlinear link between digital financial inclusion and economic growth in China. For PTAR, the LnDFII thresholds are 4.264 (i.e., DFII = 71.094), and for PSTAR are 4.563 (i.e., DFII = 95.871). Below these thresholds, digital financial inclusion significantly boosts economic growth by 0.061 and 0.063 in the PTAR and PSTAR models, respectively. However, above these thresholds, the positive impact diminishes, with coefficients dropping to 0.015 and 0.004 in the PTAR and PSTAR models, respectively. Additionally, both models indicate that digital financial inclusion positively affects reducing air pollution, thereby potentially fostering economic growth. Hence, authorities should strategically implement digital technologies and strengthen collaborative efforts at the regional level to maximize these benefits.

Keywords: Digital Financial Inclusion, Regional Economy, Panel threshold model

Introduction

Digital financial inclusion influences consumption, income, and development inequality. For instance, Liu *et al.* (2021) and Li *et al.* (2020) conclude that digital finance has a significant role in promoting household consumption and, consequently, economic growth. Moreover, inclusive digital finance changes the consumption patterns of residents by boosting their income, enhancing convenience, and improving mobility, especially in rural regions (Yu *et al.*, 2022). In other studies, Yu & Wang (2021) and Xu *et al.* (2023) proved the effectiveness of digital finance in alleviating regional development disparities and bridging the income gaps between urban and rural areas. All these are confirmed by our results, which show that digital financial inclusion has a positive and significant impact on economic growth in China.

To explain further, when we talk about digital financial inclusion, we are referring to the extent to which individuals and industries in a given area can benefit from digital financial services like mobile banking, online payments, or digital lending. Regional economy, on the other hand, relates to the overall economic development and expansion within a specific geographic area.

According to a report by the China Financial Inclusion Institute (CAFI) (2018), digital financial inclusion (DFI) has impressive penetration rates, enabling a large portion of previously unbanked or underbanked activities to easily access financial services by time or space. Over the past decade, DFI has experienced rapid growth with the phenomenal growth of digital technology, especially financial technology (FinTech), and the popularity of mobile communications and smartphones in China.

Another report from the Peking University Digital Finance Institute (PKU-DFII) showed that the median Digital Financial Inclusion Index (DFII) across Chinese provinces (Feng *et al.*, 2019) increased from 33.6 in 2011 to 294.3 in 2011–2018. This is where wireless fifth-generation networks, cloud computing and data storage centres, and other large-scale infrastructure initiatives are driven by China's rapid digitization (Cheng *et al.*, 2021). Due to their large energy consumption, these infrastructure projects significantly worsen air pollution (Dong *et al.*, 2021).

Although economic growth, industrial structure, energy consumption patterns, and environmental policies are considered important factors affecting China's air quality, the digital economy boom can be regarded as a new mechanism to reconstruct China's economic and environmental development (Guo *et al.*, 2021; Yang *et al.*, 2022b; Zeraibi, Jahangir *et al.*, 2023; Jiang *et al.*, 2022; Ren *et al.*, 2023). Moreover, the air pollution level in China showed a decreasing tendency from 2003 to 2022, which is consistent with the country's dropping sulphur dioxide (SO2) and particulate matter ($PM_{2.5}$) per 10 Km^2 (see Figure 1). Furthermore, the digital economy grew quickly, and the value added to China's digital economy expanded from 9.5 to 50.2 trillion yuan (from about 1.31 trillion U.S. dollars to 7.25 trillion U.S. dollars)

http://doi.org/10.18080/jtde.v12n1.838

between 2011 and 2022. Thus, air pollution levels and the digital economy are related in this country.

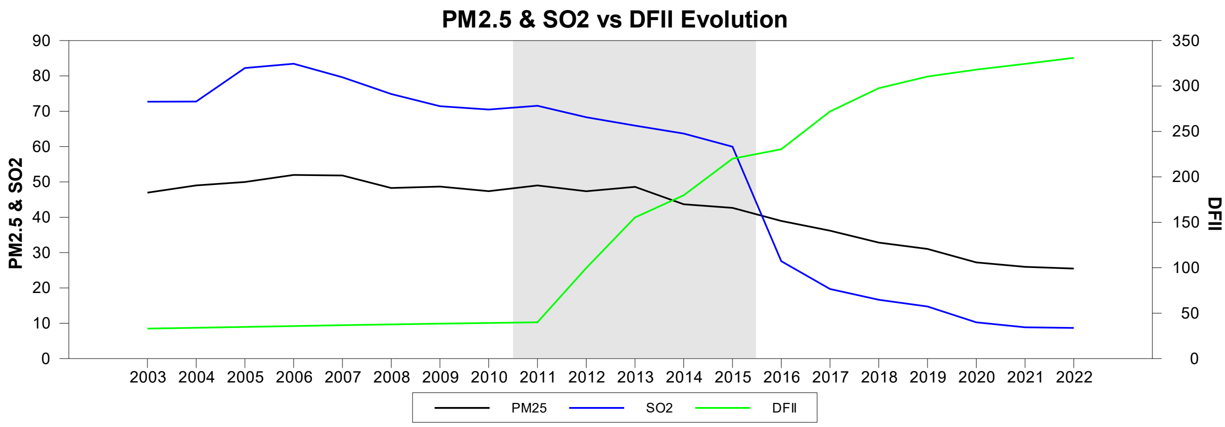

Figure 1. Evolution of DFII and the indexes of air pollution in China (per year)

In particular, existing literature shows that the digital economy can reduce environmental pollution by promoting economic growth (Higon *et al.*, 2017; Li *et al.*, 2021; Jahanger *et al.*, 2022). In addition, digital economy development can lead to the effective reallocation of economic resources among different economic sectors, thereby affecting environmental quality.

With this in mind, it is important to examine how China's digital economy affects economic growth. To evaluate this impact on province-level air pollution in China, this study employed panel threshold models for 31 Chinese provinces from 2003 to 2022. It is possible that this research can have unknown disruptions to China's future efforts to reduce pollution. This is the precise research issue that this study looked into: how do environmental factors (air pollution, sulphur dioxide, and nitrogen oxide) relate to China's regional economy when digital financial inclusion improves from lower to higher levels?

Our analysis has two main contributions. Firstly, we investigate the nonlinear impacts of digital financial inclusion on economic growth in China using dynamic panel threshold models (PTAR and PSTAR). We find that digital financial inclusion has a modest yet significant positive effect on growth below certain threshold levels. These findings contribute to the understanding of how digital financial inclusion can stimulate economic growth in different regional contexts (Yu *et al.*, 2022; Ben Abdallah *et al.*, 2023). Secondly, the study also examines the co-effects of a mix of environmental factors (SO_2, NOX, and $PM_{2.5}$) on digital finance inclusion in China. It concludes that digital financial inclusion contributes positively to reducing air pollution (Liu *et al.*, 2021; Li *et al.*, 2020). This aspect of the research is particularly important as it links financial inclusion with environmental sustainability, offering insights into how digital financial tools can support broader socio-economic goals, including environmental protection.

The remaining sections of the essay are structured as follows: The pertinent literature is briefly reviewed in the second section. The data and methodology used in this investigation are described in the third section. The empirical analysis and discussion are presented in the fourth section. The research is concluded in the fifth section, which also addresses the consequences for policy and identifies potential future research areas.

Theoretical Overview and Hypothesis Development

As soon as the notion of digital financial inclusion was proposed in China, a large number of theoretical and empirical studies were carried out to determine its impact on economic growth. According to most researchers, the development of digital financial inclusion promotes economic expansion. For example, Lv *et al.* (2021) and Yang *et al.* (2022a) revealed that digital financial inclusion significantly promotes economic growth, but there are also slight regional differences in spatial correlation and promotion effects.

Another study by Ma & Jiang (2024) explores the impact of DFI on the investment efficiency of small and medium-sized enterprises (SMEs) in China from 2011 to 2020. They find strong evidence that the development of DFI improves the investment efficiency of underinvested SMEs. However, this effect is not observed for overinvested SMEs. In addition, they show that the positive impact of DFI on underinvestment is more pronounced among SMEs with weaker financial conditions or weaker industry competitiveness.

Other scholars (He *et al.*, 2021; Yang *et al.*, 2022a) believe that regional economic growth and digital financial inclusion have a non-linear relationship with the existence of a threshold effect. Above a certain threshold of development, the positive impact of digital financial inclusion on economic growth can be reinforced.

In addition, Zhan (2018) proved that inclusive digital finance improves the quality of economic growth but would have a negative effect on the level of economic growth. Thus, this relationship exhibits a U-shaped and an inverted-U-shaped relationship, respectively.

On the other hand, the impact of digital financial inclusion on the environment has not been thoroughly studied. The per-capita gross domestic product (GDP) has an inverted U-shaped relationship with environmental pollution, which is called the Environmental Kuznets Curve (EKC) (Grossman & Kruege, 1995). EKC believes that economic growth usually leads to an increase in environmental pollution, but, after the introduction of effective environmental controls, additional economic growth will reduce environmental costs (Dong *et al.*, 2018; Zhang *et al.*, 2020; Fang *et al.*, 2021).

In addition, as regional economic growth momentum increases, China's political leaders can limit the flow of resources to polluting companies, prudently guide capital flows to green industries, and increase corporate enthusiasm for green technologies (Ding *et al.*, 2022). This can solve an issue with digital finance inclusion and achieve a sustainable economy. In the same era, the findings of Song & Majeed (2023) confirm that digital financial inclusion, ICT, and GDP are critical to promoting short- and long-term renewable energy production. Green investment, environmental governance, and carbon emissions also have a significant positive impact on long-term renewable energy production.

Thus, the following hypotheses are put forth in this study:

H1: A combined policy of environmental protection (NOX, SO2, and PM2.5) and digital financial inclusion have a corroborated positive effect on regional economic improvement.

H2: The level of air pollution has an impact on how the expansion of digital financial inclusion moves regional economic growth.

H3: The extent of air pollution and GRP co-movement depends on the level of progress in digitalized financial inclusion.

H4: The DFII at lower and higher levels impacts GRP differently.

By taking into account the studies mentioned above on the effects of environmental legislation, regional economic growth, and digital financial inclusion, the framework depicted in Figure 2 can be obtained.

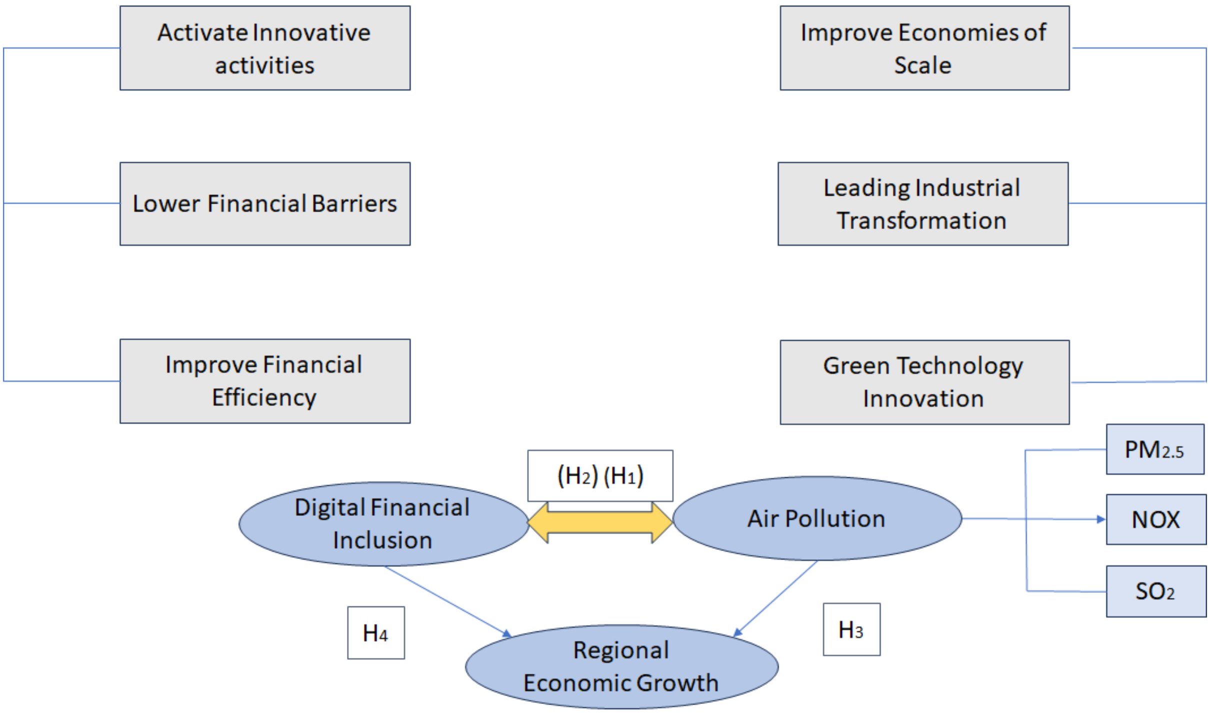

Figure 2. Theoretical framework

http://doi.org/10.18080/jtde.v12n1.838

Empirical Methodology

The purpose of this study is to examine the impact of DFII on GRP per province using threshold panel data models. According to Ding *et al.* (2022), our model is presented as follows:

$$lnGRP_{it} = \beta_0 + \beta_1 lnPOP_{it} + \beta_2 lnGFCF_{it} + \beta_3 lnEII_{it} + \beta_4 lnDFII_{it} + \beta_5 lnSO2_{it} + \beta_6 lnNOX_{it} + \beta_7 lnPM2.5_{it} + \lambda_i + \varepsilon_{it} \quad (1)$$

where ε_{it} is the related error term and λ_i is the unobserved effect, representing the individual effect. The subscript $i = 1, \dots, N$ refers to the individual measurement, and the subscript $t = 1, \dots, T$ refers to the time measurement. "ln" refers to natural logarithms. The definition of attributes and the sources are presented in Table 1.

Table 1. Definition of variables

Variable	Designation	Source	References
GRP	Gross Regional Product (100 million Yuan)	NBS	Ding *et al.* (2022), Li *et al.* (2022)
POP	Resident Population (year-end) (10000 persons)	NBS	Kalai *et al.* (2024)
GFCF	Gross Fixed Capital Formation (% of GDP)	NBS	Chen *et al.* (2022), Kalai *et al.* (2024)
EII	Energy Industrial Investment (100 million Yuan)	NBS	Zahoor *et al.* (2022), Li & Li (2020)
DFII	Digital Financial Inclusion Index	PKU-DFII	Ding *et al.* (2022), Ahmad *et al.* (2021), Yang *et al.* (2022)
SO2	Sulphur Dioxide Emission in Waste Gas (10000 tons)	NBS	Zeraibi, Jahanger *et al.* (2023), Lou *et al.* (2021), Ramakrishnan *et al.* (2016)
NOX	Nitrogen Oxide Emission in Waste Gas (10000 tons)	NBS	Ramakrishnan *et al.* (2016)
PM2.5	Atmospheric particulate matter that has a diameter of less than 2.5 µm	TAP Data	Bildirici & Çoban Kayıkçı (2024), Qi *et al.* (2022)

Notes: NBS represents the National Bank Statistics; PKU-DFII indicates the Peking University Digital Finance Institute; and TAP Data represents the Tracking Air Pollution Data.

This study highlights the importance of considering the determinants of the non-linear relationship between digital financial inclusion and regional economic growth across Chinese provinces. By assessing macroeconomic factors (air pollution, capital investment, energy industry, and human capital), we can summarize our approach in Figure 3.

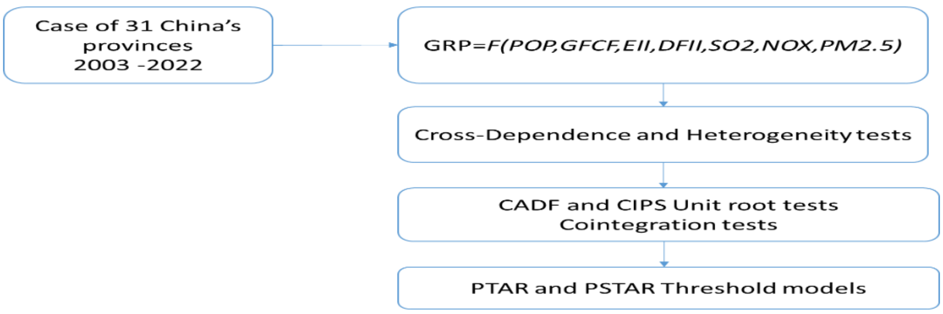

Figure 3. Methodological framework

As the purpose of this research is to detect the existence of structural non-linearity in the GRP-DFII link, we will also seek to determine whether thresholds are characterizing the relationship between DFII and GRP in 31 Chinese provinces between 2003 and 2022. The Panel Threshold Auto-Regressive (PTAR) model was established by Hansen (1999). Using this model, the endogenous variable y_{it} depends on several different non-dynamic relationships. Consequently, the process $y_{it}, t \in Z, i \in Z$ (Equation 1) satisfies a two-regime PTAR model only if:

$$y_{it} = \mu_i + \sum_{j=1}^{p} \rho_j \, y_{\mathrm{it-j}} + \beta_1' X_{it} + \beta_2' X_{it} I(q_{it} > c) + \varepsilon_{it} \tag{2}$$

where μ_i is the vector of individual fixed coefficients, ρ_j is the autoregressive coefficients of the process y_{it} , $I(q_{it} > c)$ denotes the indicator function concerning the transition variable q_{it} and the threshold parameter c, $X_{it} = \left(X_{it}^1, \dots, X_{it}^k\right)$ is the matrix of k exogenous variables that do not contain lagged explanatory variables, $\beta = (\beta_1, \dots, \beta_k)$ and $\varepsilon_{it} \sim N(0, \sigma^2)$.

For their part, González *et al.* (2005) proposed to reinforce the PTAR model by creating a model called PSTAR. The purpose of this model is to move from a fast transition approach to a smooth transition approach in the case of time series. Thus, the process $y_{it}, t \in Z, i \in Z$, conforms to a two-regime PSTAR model (Equation 3) if and only if:

$$y_{it} = \mu_i + \sum_{j=1}^{p} \rho_j \, y_{\mathrm{it-j}} + \beta_1' X_{it} + \beta_2' X_{it} G(q_{it}; \gamma, c) + \varepsilon_{it} \tag{3}$$

where $G(q_{it}; \gamma, c)$ signifies the transition function for the transition variable q_{it}, the threshold parameter c, and the smoothing coefficient γ.

As a preliminary step, it is crucial to estimate the PSTAR model and check for linearity, specifically the existence of a statistically significant regime-switching effect. González *et al.* (2017) outlined a procedure to test the null hypothesis of linearity (H_0: $\beta_2{}' = 0$, equivalent to H_0: $\gamma = 0$) in the context of a PSTAR model. It is possible to apply the Wald, Fisher, and LR tests, where the corresponding statistics for each (specified in Equation 4) are as follows:

$$LM_w = \frac{TN(RSS_0 - RSS_1)}{RSS_0};\; LM_F = \frac{TN(RSS_0 - RSS_1)/K}{RSS_0/(TN - N - K)};\; LR = -2[log(RSS_0) - log(RSS_1)] \tag{4}$$

where RSS_0 and RSS_1 are the panel residual sum of squares. Under the null hypothesis, the Wald LM_w, LR statistics are calculated according to a chi-squared distribution with K degrees of freedom, representing the number of variables; and the LM_F statistics follow a chi-squared distribution.

Empirical Results

In what follows, we show the relative descriptive statistics of the different variables changed into a logarithm (see Table 2). By using the Jarque & Bera (1987) normality test and the Born & Breitung (2016) serial autocorrelation test, the null hypothesis of these two tests is rejected.

Table 2. Retrieval of the various descriptive statistics of the series

	GRP	POP	EII	GFCF	DFII	SO2	NOX	PM2.5
Observation	620	620	620	620	620	620	620	620
Mean	9.29	8.10	6.23	8.88	4.56	3.27	3.81	3.63
Median	9.42	8.24	6.38	8.98	4.84	3.70	3.91	3.62
SD	1.19	0.85	0.98	1.23	1.06	1.54	0.89	0.46
Min	5.22	5.60	2.30	4.89	2.43	-2.31	1.22	2.14
Maxi	11.76	9.44	8.22	11.05	5.98	5.29	5.21	4.72
Skewness	-0.62	-0.97	-0.80	-0.53	-0.27	-1.42	-0.83	0.09
Kurtosis	3.33	3.52	4.00	2.92	1.54	4.95	3.43	2.54
JB test	43.06	105.60	93.91	29.48	62.74	307.30	76.09	6.34
JB Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04
BB test	983.86	18.32	141.98	327.97	305.73	105.34	108.57	106.64
BB Prob	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: JB refers to the Jarque & Bera (1987) normality test. BB refers to Born & Breitung (2016). SD represents the standard deviation. All variables are in natural logs.

The "LnGRP" variable shows an overall mean of 9.292 with a standard deviation of 1.192. The form of the supply is extended to the left because the skewness statistic equals -0.623 < 0. All values are bounded between 5.225 and 11.768, with a strong concentration around 9.429.

For the "LnDFII" variable, the series has an average of 4.568 with a large standard deviation of 1.068. The 620 observations ranged between 2.431 and 5.984, with a strong concentration around 4.849. The distribution is asymmetric spread on the left since the skewness is equal to -0.275, and once again it is leptokurtic, where the kurtosis = 1.542 > 0.

Following globalization, cross-sectional dependence may be within and among nations as well as regional economies (De Hoyos & Sarafidis, 2006; Bilgili *et al.*, 2017; Dong *et al.*, 2018; Shahbaz *et al.*, 2018). In addition, the unit root and panel cointegration tests are greatly skewed if the cross-sectional dependence is not taken into account (O'Connell, 1998; Atasoy, 2017; Pesaran, 2021).

Table 3. Cross-dependence and heterogeneity tests

Tests	Value	Probability	Decision
Friedman (1937)	220.054	0.000	Dependence
Breusch & Pagan (1980)	1666	0.000	Dependence
Frees (1995); (2004)	6.492	0.000	Dependence
Pesaran (2004)	35.74	0.000	Dependence
Pesaran (2006)	34.631	0.000	Dependence
Pesaran *et al.* (2008)	53.97	0.000	Dependence
Pesaran (2015)	25.335	0.000	Dependence
Pesaran & Yamagata (2008)	11.372 15.334	0.000 0.000	Heterogeneity

Therefore, the tests suggested by Friedman (1937), Breusch & Pagan (1980), Frees (1995), Pesaran (2004), Pesaran (2006), Peseran (2015), and Pesaran *et al.* (2008) are used to test cross-sectional dependence. These tests were crucial in identifying how frequently shocks occurred in the cross-sectional portion of the data set. Regarding Table 3, the result indicates a breakdown to reject the cross-sectional independent null hypothesis. In addition, the second panel in Table 3 tests the hypothesis of homogeneity proposed by Pesaran & Yamagata (2008). The results of the homogeneity test reveal that the two statistics indicate statistically significant probability values at the 1% level, leading us to accept the alternative hypothesis of heterogeneous coefficients.

Due to the presence of cross-sectional dependency and heterogeneity, we employ Pesaran (2003) and Pesaran (2007) second-generation unit root tests. Table 4 shows that all series show the presence of unit roots in level (rejection H0). As a result, we can assume that all of the series are integrated into order 1. As a result, we must investigate the cointegration relationship between variables using the first-generation tests of Kao (1999), Pedroni (2004), and Westerlund (2007), as well as a second-generation test of Persyn & Westerlund (2008). See Table 5.

Table 4. Results of the second generation of unit root test

	GRP	POP	GFCF	EII	DFII	SO2	NOX	PM2.5
Pesaran (2003)								
				Panel A: In level				
C	-2.19***	-2.20***	-2.94***	-2.03*	-2.67***	-2.27***	-1.66	-2.75***
C & T	-2.16	-1.64	-2.73***	-2.70**	-2.77***	-2.89***	-1.98	-3.18***
Decision	NS	NS	S	S	S	S	NS	S
				Panel B: In first difference				
C	-2.38***	-1.89	-2.71***	-3.15***	-3.20***	-3.25***	-2.64***	-3.66***
C & T	-2.66**	-2.31	-2.86***	-3.10***	-3.26***	-3.65***	-3.45***	-3.68***
Decision	S	NS	S	S	S	S	S	S
Pesaran (2007)								
				Panel A: In level				
C	-2.02	-2.04	-2.83***	-2.35***	-4.35***	-2.40***	-1.52	-2.90***
C & T	-2.16	-0.99	-2.42	-2.98***	-4.39***	-3.23***	-2.25	-3.28***
Decision	NS	NS	NS	S	S	S	S	S
				Panel B: In first difference				
C	-3.29***	-2.65***	-3.36***	-4.08***	-5.19***	-4.35***	-2.85***	-4.55***
C & T	-3.48***	-3.24***	-3.52***	-4.11***	-5.28***	-4.88***	-3.48***	-4.49***
Decision	S	S	S	S	S	S	S	S

Notes: ***, **, * represent the significance at 1%, 5%, and 10%; C: Constant; T: Trend; NS: Non-Stationary; S: Stationary; All variables are in natural logs.

Table 5. Results of cointegration tests

	Tests	Value		p-value		Decision
First generation	Kao (1999)	-2.895		0.00		Cointegration
	Pedroni (2004)	-4.192		0.00		Cointegration
	Westerlund (2007)	-2.012		0.02		Cointegration
Second generation	**Persyn & Westerlund (2008)**	**Value**	**Z-value**	**p-value**	**Robust p-value**	**Decision**
	G_t	-4.29	-5.98	0.00	0.00	Cointegration
	G_a	-5.07	3.22	0.99	0.00	Cointegration
	P_t	-18.96	-8.23	0.00	0.00	Cointegration
	P_a	-6.73	0.24	0.59	0.01	Cointegration

http://doi.org/10.18080/jtde.v12n1.838

Table 6. Test for the presence of LNDFII threshold effects in the PTAR model

Hypothesis	Threshold	F-test	p-value	Confidence Interval	RSS	Residual variance
H_0: No threshold	4.264	85.279	0.000	[4.239–4.292]	1.585	0.002

Notes: Test the null of no threshold against the alternative of one threshold. The threshold is obtained by minimizing the residual sum of squares (RSS).

The next step consists of estimating our model using the PTAR and PSTAR approaches. We obtained the number of Lags equal to “1” (either $\chi^2(2) = 1280.94$), which means both models can be performed in Lag 1. We move to use the PTAR(1) model. Therefore, we begin by testing the linearity hypothesis on the link between LnDFII and LnGRP variables. Using the 1000 bootstrap procedure, the results of Table 6 show that the null hypothesis of no threshold is rejected at the 1% level, and there is one threshold obtained equal to LnDFII = 4.264 (i.e., DFII = 71.094).

Our focus will shift towards examining the correlation between the DFII and the GRP within the varying LnDFII systems listed in Table 7. During the initial phase (LnDFII ≤ 4.264), there is a significant impact at the 5% level, so this result has a favourable impact on economic growth. The magnitude and direction of the DFII coefficient are dependent on the level of DFII in this low-LnDFII area, where the elasticity of DFII on economic growth is notably positive (0.061). A 1% rise in DFII leads to a 0.061% surge in regional economic growth, which further results in a 0.049% reduction in $PM_{2.5}$ emissions. The empirical and theoretical research (Cao *et al.*, 2021; Ding *et al.*, 2022) supports the estimated nonlinear relationship between digital financial inclusion and economic growth. This indicates that economic growth is stimulated when DFII falls below a particular threshold.

Table 7. PTAR(1) regression output

Variables	Regime 1: $LnDFII_{it-1} \leq 4.264$		Regime 2: $LnDFII_{it-1} > 4.264$	
	Coefficient	t-statistic	Coefficient	t-statistic
$LnGRP_{it-1}$	0.731	21.465***	0.859	32.615***
$LnPOP_{it}$	0.092	1.429	0.105	1.370
$LnGFCF_{it}$	0.160	6.867***	0.019	1.405
$LnEII_{it}$	-0.040	-3.608***	0.005	2.608***
$LnDFII_{it}$	0.061	3.475***	0.015	2.296**
$LnSO_{2it}$	0.008	0.953	-0.004	-2.651***
$LnNOX_{it}$	0.014	0.601	-0.043	-2.322**
$LnPM_{2.5it}$	-0.049	-2.186**	-0.030	-2.478**

Note: *** and ** show the significance at 1% and 5% levels, respectively.

In the second regime (LnDFII > 4.264), its slight growth-enhancing effect is quite positive (0.015%). Due to this increase, the reduction of SO_2, NOX, and $PM_{2.5}$ has a positive impact on GRP. Statistically, this discount boosts economic growth by 0.004%, 0.043%, and 0.030%, respectively.

The PTAR model may struggle with accurately identifying and estimating threshold values, leading to potential misspecification issues, while the PSTAR model alleviates this concern by allowing for continuous transition functions. For this reason, we move on to estimate the PSTAR model.

We start by carrying out the linearity test, which allows us to define the number of thresholds. Table 8 displays the results of the Wald LM_w test, Fisher LM_F test, and LR test. The p-values show that there is a single threshold with a 1% probability for a logistic PSTAR model (m = 1). This implies that the DFII-GRP relationship is non-linear.

Table 8. PSTAR(1) linearity tests

	H0: r=0 vs H1: r=1		H0: r=1 vs H1: r=2	
Tests	**t-Statistic**	**Probability**	**t-Statistic**	**Probability**
Wald (LM_w)	70.565	0.000	5.807	0.098
Fisher (LM_F)	9.327	0.000	1.067	0.092
Likelihood Ratio (LR)	74.914	0.000	6.360	0.111

Table 9. Test for the existence of DFII threshold effects

Order	Threshold ($\hat{c}$)	Parameter of transition ($\hat{\gamma}$)	RSS	AIC	BIC
m=1; r=1	4.563	4.816	1.465	-5.890	-5.761

The results of Table 9 suggest that the estimated threshold is equal to 4.563 and the transition parameter γ is equal to 4.816. In addition, the minimum values of RSS, AIC, and BIC are touched for values equal to 1.465, -5.890, and -5.761, respectively.

For the PSTAR model, the results indicate the existence of two separate regimes. As shown in Table 10, the threshold value for the LnDFII variable is equal to 4.563. Statistically, the first regime shows that the variables LnPOP, LnGFCF, and LnDFII have a positive and significant impact on the variable LnGRP, with elasticities of 0.14, 0.158, and 0.063, respectively. However, both LnEII and $LnPM_{2.5}$ have a negative and significant effect on the variable LnGRP, with elasticities of -0.03 and -0.043, respectively. For the second regime, all the variables have a significant effect on LnGRP, while the variable LnPOP does not have a significant effect. The variables LnGFCF, LnEII, LnDFII, and LnNOX have a positive effect of 0.127, 0.025, 0.004, and 0.037, respectively, while the variables $LnSO_2$ and $LnPM_{2.5}$ have a slightly negative effect.

The DFII can help small enterprises and people living in rural areas by easing their financial constraints. For provinces linked to the economy, digital financial inclusion can create spillover effects in terms of technological innovation and the inter-regional economy, encouraging the continued improvement of the industrial structure. These developments stimulate economic development in other regions through the flow of factors of production (Liu *et al.*, 2023).

http://doi.org/10.18080/jtde.v12n1.838

Table 10. PSTAR(1) regression

Variables	Regime 1: $LnDFII_{it-1} \leq 4.563$		Regime 2: $LnDFII_{it-1} > 4.563$	
	Coefficient	t-statistic	Coefficient	t-statistic
$LnGRP_{it-1}$	0.720	22.303***	0.105	3.965***
$LnPOP_{it}$	0.140	2.063**	0.006	0.310
$LnGFCF_{it}$	0.158	7.123***	0.127	5.946***
$LnEII_{it}$	-0.030	-2.658***	0.025	1.980**
$LnDFII_{it}$	0.063	4.231***	0.004	2.280**
$LnSO2_{it}$	-0.0002	-0.028	-0.006	-2.629***
$LnNOX_{it}$	-0.004	-0.212	0.037	-1.922**
$LnPM2.5_{it}$	-0.043	-1.835**	-0.001	-2.132**

Note: ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

In China, digital financial inclusion promoted through platforms has played a crucial role in promoting financial prosperity. These mobile payment solutions transform transactions by enabling electronic payments through smartphones, reducing dependence on cash, and increasing financial efficiency. Furthermore, digital financial inclusion can help reduce pollution in China by promoting a shift toward more sustainable and environmentally friendly business and industrial practices. It can encourage investment in clean technologies and green business practices by providing wider access to financial services, especially to rural populations and small businesses.

Due to the development of the digital economy, concentrations of $PM_{2.5}$, industrial wastewater discharges, and industrial emissions of sulphur dioxide, soot, and dust have fallen significantly. Moreover, the constructive effects of the digital economy on the decline of environmental pollution are more pronounced in central and western China. Hypotheses (**H2**) and (**H3**) have therefore been validated based on these data.

Moreover, the primary method by which the digital economy reduces pollutant emissions is through the promotion of industrial restructuring and advances in eco-friendly technology. Furthermore, the digital economy's ability to reduce pollution depends on the threshold level of economic development. As a result, conjecture (**H1**) has been confirmed. Further analysis of this threshold effect reveals that the more developed an economy is, the greater the reduction in emissions will be (Guo *et al.*, 2023).

The transition function is defined as a mathematical function that determines how the relationship between two variables changes when a threshold variable exceeds a certain threshold value. Thus, and regarding Figure 4, the estimated value of the smoothing parameter, equal to $\hat{\gamma}$ = 4.816, is assumed to be low and suggests that the switch of transition from the first regime to the second is smooth.

http://doi.org/10.18080/jtde.v12n1.838

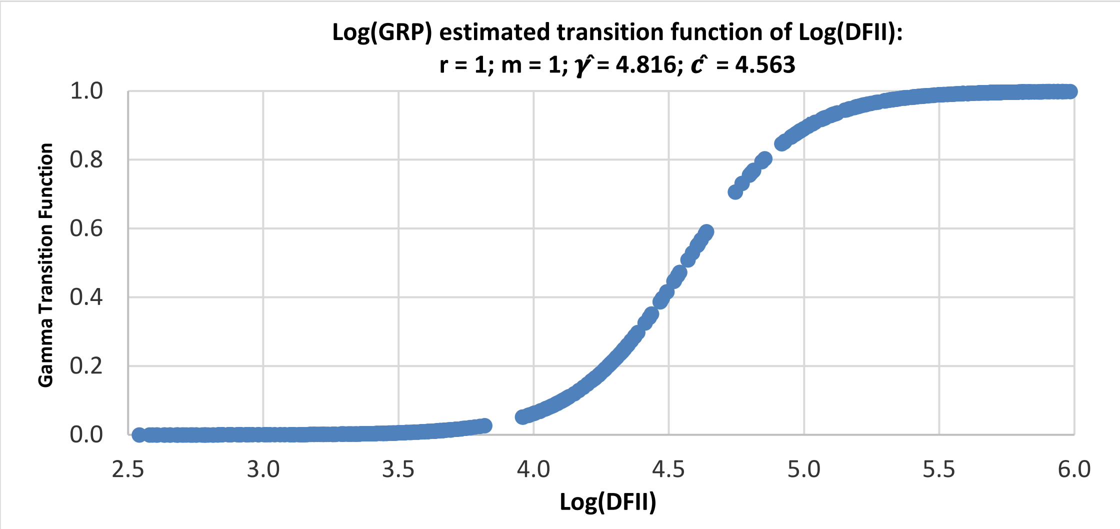

Figure 4. Log (GRP) estimated transition function of Log (DFII)

Consequently, it is possible to conclude that the LnDFII variable and LnGRP support the idea of a non-linear association. However, when digital financial inclusion increases beyond this threshold value, the relationship between the two variables becomes much stronger.

After constructing the PSTAR model, we can conclude that digital finance has a positive impact on the level of air pollution and economic growth. Moreover, the findings confirm the non-linearity between DFII and GRP in China's provinces. As a result, hypothesis ($\mathbf{H_4}$) is supported.

Conclusion and Policy Implications

For China, the creation of a digital economy is essential to achieving high-quality development, and the digital financial sector is an excellent tool for a new financial development model that is of considerable importance. To examine the impact of digital financial inclusion and air pollution on economic growth, this study uses provincial panel data from 2003 to 2022 and conducts empirical analysis based on existing theory and literature. According to the results, there are two thresholds for digital financial inclusion, with respective values of 4.264 for the PTAR model and 4.563 for the PSTAR model, and both regimes have a positive and significant marginal impact on regional growth. However, the impact is weaker in the second regime. Furthermore, the PTAR and PSTAR models demonstrate that reducing air pollution through digital financial inclusion has a crucial effect on regional economic growth.

In terms of digital financial inclusion, the following policy recommendations aim to facilitate access to financial services through digital channels. Firstly, governments need to strengthen the overall infrastructure for the digital financial system to ensure inclusiveness, put in place a sound organizational management framework, and increase the performance and effectiveness of digital finance in supporting the real economy. Secondly, to foster the positive impact of digital financial inclusion on economic growth, it is imperative for the authorities to judiciously implement digital technologies and bolster regional collaboration.

Therefore, to encourage financial institutions to expand their digital financial services and reduce transaction costs in underdeveloped areas, public authorities should provide financial support and develop infrastructure. In addition, financial institutions should introduce innovative financial services into the developed regions of the East to encourage local economic growth and innovation. Fourthly, financial regulators should utilize digital technology to learn from advanced experiences and expedite the establishment of regulatory guidelines for the inclusive digital financial sector. This will increase the flexibility, inventiveness, and effectiveness of supervision.

Moreover, the argument assumes that digital financial inclusion can represent a fundamental cause, namely financial prosperity (Zhao & Jiao, 2024). Indeed, where an increase in financial prosperity is related to an increase in digital financial inclusion, a reduction progressively in environmental pollution follows. Therefore, conclusions in favour of promoting digital financial inclusion as a pollution control measure are considered untenable. By addressing the root causes of financial wellbeing, policymakers have the potential to achieve dual benefits: improving digital financial inclusion and reducing pollution. Therefore, the focus should shift from promoting digital financial inclusion alone to implementing measures that comprehensively improve overall financial wellbeing, thereby indirectly addressing environmental issues.

There were limitations to this research, which should be taken into account in other studies. There are some limitations in using PTAR (panel threshold autoregressive) and PSTAR (panel smooth transition autoregression) models to examine the impact of digital financial inclusion on regional economic growth in China. First, while these models allow for non-linear relationships and threshold effects, they may require specifying threshold levels *a priori*, which can be difficult and subjective. Furthermore, using combined regional data in panel models might not take into account differences within regions and hide important differences in how digital financial inclusion affects economic growth in various regions.

In addition, the connection between digital financial inclusion and environmental pollution has its limitations. While digital financial inclusion has the potential to reduce pollution by financing green initiatives, comprehensive data on the scale and effectiveness of such initiatives may be lacking, making it difficult to accurately quantify their impact. Furthermore, it can be hard to determine what causes what when it comes to digital financial inclusion and environmental effects. This is because of the long-term nature of environmental changes and the presence of confounding factors. To solve these problems, we need strong methods and data sources.

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