Assessing the impact of digital financial inclusion on PM2.5 concentration: evidence from China

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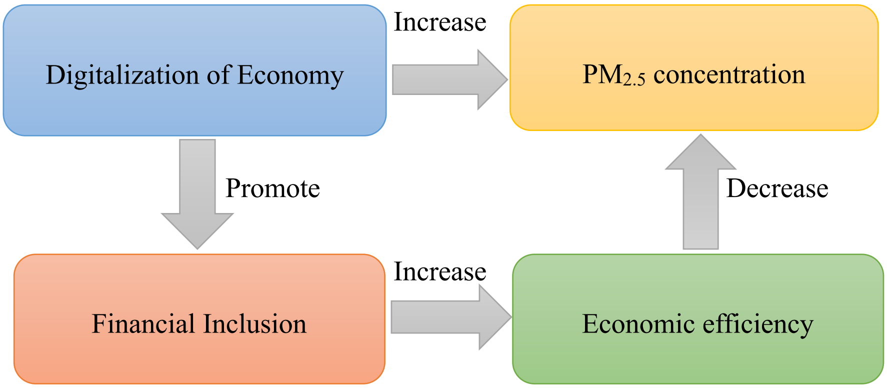
Abstract

Digital finance as a new technology-driven business model shortens the distance between borrowers and lenders. Economic research finds that digital finance promotes economic efficiency by reducing transaction costs, information asymmetry, and inequality. Digital finance is an energy-intensive industry; therefore, increased efficiency in the industry should yield environmental benefits. We examine the externality of digital finance on air pollution. By analyzing data on digital financial inclusion and fine particulate matter concentration in China, we demonstrate using a dynamic panel data model that the development of digital finance damages the environment. However, after incorporating a threshold effect into a kink model, we determine that digital finance reduces pollution when its development exceeds a certain level. The results suggest that a high level of digital finance development not only increases economic growth but also improves air quality; this result provides novel insight into the relationship between economic growth and the environment.

Keywords： Digital finance; $PM_{2.5}$ concentration; GMM; Threshold model

Graphical Abstract



Highlight

The $PM_{2.5}$ concentration in cities of China was analyzed.

An asymmetric impact exist for digital financial inclusion and $PM_{2.5}$.

Dynamic panel threshold model is used to investigate the nonlinear relationship.

Digital financial inclusion show different impacts on $PM_{2.5}$ at high- and low-level phases.

1. Introduction

Digital finance driven by big data is gradually transforming China's financial system by reducing transaction costs and information asymmetry and optimizing capital allocation. The development of digital finance allows individuals in various regions to access financial services more easily and cheaply. A 2020 report by the Institute of Digital Finance of Peking University revealed that the median Digital Inclusive Finance Index for Chinese provinces increased from 33.6 in 2011 to 294.3 in 2018. Furthermore, in recent years, with the help of the Internet, the finance industry has become deeply integrated with other industries. Economic digitalization in China has brought technological innovation to other sectors and boosted total productivity.

However, the rapid digitalization has lead to massive infrastructure projects in China, including the fifth-generation wireless network and cloud computing and data storage centers (Cheng et al. 2021). Such infrastructure projects create severe air pollution because of their intensive energy consumption (Dong et al. 2020). China relies heavily on fossil fuels for its electricity generation. In 2020, according to the National Energy Administration in China, fossil fuels still accounted for 57.7% of China's total energy use, and fossil fuel consumption is significantly and positively related to air pollution (Wang et al. 2014; Zhou et al. 2018; Dong et al. 2021; Ren et al. 2021). As a proxy for air pollution, fine particulate matter ($PM_{2.5}$) has been widely studied in investigations of the impact of air pollution on the economy, human health, and society (Chen and Chen 2021; Sarkodie and Owusu 2021; Yang and Xu 2021).

Concern about $PM_{2.5}$ is growing among the public and researchers. Socioeconomic development, including foreign trade, economic growth, and industrial structures, is a key contributor to $PM_{2.5}$ concentration (Zhu et al. 2018; Yan et al. 2019; Yan et al. 2020). Studies provide evidence that the effects of socioeconomic determinants on $PM_{2.5}$ concentrations in Chinese cities are heterogeneous. Similarly, the degree of digitalization of Chinese cities varies dramatically with their economic development and can be used to explore the impact of digital finance on the environment in developed and developing regions.

Digital finance is an information-driven industry, and its environmental externalities have largely been ignored by the public. Although digital finance can improve the efficiency of resource allocation and reduce $PM_{2.5}$ concentrations, it is an energy-intensive industry that has also been observed to increase $PM_{2.5}$ concentrations (Rickard et al. 2017; Yang and Hamori 2021). This nonlinear relationship warrants further research. This study investigates whether digital financial inclusion can reduce $PM_{2.5}$ concentrations in China by improving economic efficiency. Using a panel data set covering the 283 prefecture-level cities for the period 2011–2018, we employ both a dynamic panel model and a kink model to explore the nonlinear relationship between the digital financial inclusion and $PM_{2.5}$ concentration. Our chosen models address the potential endogeneity problem of bilateral causality between digital finance and $PM_{2.5}$ concentration. Consequently, our estimations confirm the threshold effect, which reveals that the effect of digital finance on $PM_{2.5}$ concentrations is asymmetric.

The four contributions of our analysis can be summarized as follows: First, we explore a neglected issue in the environmental externalities of digital finance in China. Second, we explore the nonlinear effects of digital financial inclusion on $PM_{2.5}$ by using a dynamic panel threshold model; we demonstrate that the digital finance can improve environmental performance when it exceeds a certain level. We employ city-level data from China to investigate whether the relationship between air pollution and digital finance is an inverted U-shaped across all cities. Third, digital financial inclusion has a significant and positive impact at the 1% significance level on $PM_{2.5}$ in the dynamic panel model. After consideration of the heterogeneous effects caused by regional differences, air pollution tends to decrease in developed regions and increase in developing regions as digital financial inclusion grows. Finally, we incorporate the threshold effect into the dynamic panel model, which reveals nonlinear effects.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the relevant literature. Section 3 describes the data and methodology employed in this study. Section 4 provides the empirical analysis and discussion. Section 5 concludes this research, discusses the policy implications, and indicates future research directions.

2. Literature review

Most studies on the impact of digital finance characterize it positively. For example, Sarma and Paris (2011) report that financial inclusion boosts economic development, alleviates income inequality, and narrows regional gaps. Ozili (2018) suggests that big data can increase financial inclusion. Li et al. (2020) observe that digital financial inclusion can promote recurrent consumption among households in China. In finance, studies indicate that mobile payments, Internet finance, and other big data–based financial services can diversify the banking industry (Cortina Lorente and Schmukler 2018), improve financial decisions (Beck et al. 2018), and increase the efficiency of financial markets (Zhong and Jiang 2021). Financial exclusion in rural areas of China has been significantly reduced because of the expansion of digital finance, which brings new technology to spur economic growth in such areas (Yu et al. 2020). However, the side effects of digital financial inclusion on the environment remain unexplored.

Previous studies report an inverted U-shaped relationship between gross domestic product (GDP) per capita and environmental pollution; this relationship is also termed the environmental Kuznets curve (EKC; Grossman and Kruege 1995). According to the EKC, economic growth generally increases environmental pollution, but, after effective environmental regulations are implemented, further economic growth incurs lower environmental costs. The trade-off between economic development and $PM_{2.5}$ pollution can be regarded as a form of "coupling," a term from physics. Although researchers investigate means for decoupling $PM_{2.5}$ concentration and economic growth (Dong et al. 2019; Zhang et al. 2020; Fang and Yu 2021), little attention has been paid to the nonlinear relationship between digital finance and $PM_{2.5}$ concentration (Rickard et al. 2017).

The EKC is unconfirmed on a global scale, possibly because of the varied outcomes obtained by developed and developing economies (Stern and van Dijk 2017). Cheng et al. (2017) confirm the EKC in China on the basis of a sample of 285 Chinese cities; they find that, in most cities, pollution increases with economic growth. However, the relationship digital finance and $PM_{2.5}$ concentration remains unclear. Digital finance is an energy-intensive industry that can cause severe air pollution because of the current reliance on fossil fuel in China's energy mix. However, improvement in economic efficiency due to digital finance can reduce environmental pollution and increase economic growth. Because the industrial structure and economic development of China's cities vary, this study also utilizes variations of the decoupling chain behind digital financial inclusion and $PM_{2.5}$ concentrations.

The socioeconomic determinants of China's $PM_{2.5}$ concentrations attract extensive research attention (Stern and Zha 2016; Zhu et al. 2019; Zhou et al. 2018). However, no studies consider the issue dynamically at the city level. Moreover, no studies incorporate the threshold effect into models of the causal relationship between digital financial inclusion and $PM_{2.5}$ concentration. Although several papers present panel threshold models of the nonlinear effects of economic factors on $PM_{2.5}$ concentrations (Ouyang et al. 2019; Ren et al. 2019; Xie and Sun 2020; Cheng et al. 2020), they focus on environmental regulation and foreign direct investment and ignore the dynamic impacts of financial inclusion, especially digital financial inclusion. Because such estimations using threshold models are static, we employ the first-difference generalized method of moments (GMM) estimator proposed by Seo and Shin (2016) to create a dynamic panel threshold model in which both threshold variables and regressors can be endogenous. As a result, we clarify the decoupling chain behind digital financial inclusion and $PM_{2.5}$ concentration.

Other factors can influence $PM_{2.5}$ concentration as well; for example, Jiang et al. (2018) reveal that socioeconomic factors can explain over 40% of the variance in $PM_{2.5}$ emissions. Human activity, population density, and traffic intensity also increase $PM_{2.5}$ concentrations (Cheng et al. 2017; Wang et al. 2017). In contrast to Jiang et al. (2018), Yang et al. (2018) and Liu et al. (2020) contend that natural factors such as ecological and atmospheric characteristics are more dominant than any socioeconomic factors. We provide another perspective on the relationship between digital finance and the environment, challenging traditional views on the sources of air pollution. Our findings suggest that technological innovation eventually improves the environment; however, the turning point varies by region with the level of economic development.

3. Data and methodology

3.1. Data

This study investigates the impact of digital financial inclusion on $PM_{2.5}$ concentrations by using a panel of China's 283 prefecture-level cities from the period of 2011–2018. Data on $PM_{2.5}$ concentration, GDP per capita, and the proportion of secondary industry and electricity consumption at the city level are from the Chinese Research Data Services Platform. Digital Inclusive Finance Index data are taken from the Institute of Digital Finance of Peking University (Guo et al. 2016).

All series are transformed into in the natural logarithmic form before empirical analysis. After logarithmic transformation, the standard deviations of $PM_{2.5}$ concentration and the Digital Inclusive Finance Index are the same (0.51), implying similar movement patterns on the second moment. The largest standard deviation is 1.20 for electricity consumption, followed by 0.69 for GDP per capita, indicating considerable variation in industry structures and household income.

Insert Table 1

Table 2 reports the correlation coefficients of all variables. Almost all correlations are significant at the 5% level. Moreover, most correlations are positive. The Digital Inclusive Finance Index is positively correlated with $PM_{2.5}$ concentration, GDP per capita, and electricity consumption, suggesting that digital financial inclusion provides additional economic growth at the cost of greater electricity consumption and air pollution. Only the correlation between the Digital Inclusive Finance Index and the proportion of secondary industry is negative, confirming that digital finance is a part of the tertiary sector of the economy.

Insert Table 2

3.2. Econometric model

This study applies two panel data models with fixed effects to examine the impact of the financial inclusion on $PM_{2.5}$ concentration. The first one is a dynamic panel data model that can determine the influence of the past by adding the lagged values of dependent variables to the right-hand side of the regression equation. A dynamic panel data model allows for the estimation of the effects of past dependent variables on the current ones. Arellano and Bond (1991) propose a GMM estimator without the assumption of strict exogeneity for explanatory variables. Arellano–Bond estimation adopts all available lags for the dependent variables as instruments for the first-difference equation, elevating individual effects. We propose the following dynamic panel data specifications, including $PM_{2.5}$ mass concentration as the dependent variable:

$$\ln PM2.5_{it} = \beta_0 + \ln PM2.5_{it-1}\beta_1 + \ln INDEX_{it}\beta_2 + \ln PCGDP_{it}\beta_3 + \ln SI_{it}\beta_4 + \ln ELEC_{it}\beta_5 + \alpha_i + \varepsilon_{it},\ i = 1,\ldots,N, t = 1,\ldots,T, \quad (1)$$

where $PM2.5_{it}$ denotes the $PM_{2.5}$ mass concentration for city i and year t, $INDEX_{it}$ is the

Digital Inclusive Finance Index, $PCGDP_{it}$ is GDP per capita, SI_{it} is the proportion of secondary industry, $ELEC_{it}$ is electricity consumption, and α_i is a city-specific effect. ε_{it} is a zero-mean idiosyncratic random disturbance. Because α_i is assumed to follow a stochastic process, we must consider the correlation between the individual effects and explanatory variables. To deal with this problem, we take the first difference of (1) as follows:

$$\Delta \ln PM2.5_{it} = \Delta \ln PM2.5_{it-1}\beta_1 + \Delta \ln INDEX_{it}\beta_2 + \Delta \ln PCGDP_{it}\,\beta_3 + \Delta \ln SI_{it}\beta_4 + \Delta \ln ELEC_{it}\beta_5 + \Delta\varepsilon_{it}, \qquad (2)$$

where Δ is the first-difference operator. This model allows for endogeneity, which is the correlation between explanatory variables and the error term. To avoid ordinary least-squares (OLS) estimator bias, we apply the Arellano and Bond (1991) GMM to the dynamic panel data model.

The aforementioned dynamic panel data model assumes a linear relationship between regressors and dependent variables. A popular method of accounting for nonlinearity in a model is to add a threshold effect. Hansen (1999) proposes a static panel threshold model with a strong exogeneity assumption. Seo and Shin (2016) present a dynamic, extended version of Hansen's model that allows both regressors and the threshold effect to be endogenous. Considering the possibility of nonlinear asymmetry, we extend (1) to our framework with the threshold effect as follows:

$$\ln PM2.5_{it} = \beta_0 + \ln PM2.5_{it-1}\beta_1 + \ln INDEX_{it}\beta_2 + \ln PCGDP_{it}\,\beta_3 + \ln SI_{it}\beta_4 + \ln ELEC_{it}\beta_5 + \ln INDEX_{it}\delta\,\mathbf{1}\{\ln INDEX_{it} \geq \gamma\} + \alpha_i + \varepsilon_{it}, \qquad i = 1, \dots, N, t = 1, \dots, T, \qquad (3)$$

where $\mathbf{1}\{\cdot\}$ is an indicator function, $\ln INDEX_{it}$ is the threshold variable, and γ is the threshold parameter, which can be considered a change point. In this model, according to the value of Peking University Digital Inclusive Finance Index, the influence of digital financial inclusion on $PM_{2.5}$ mass concentration differs. Seo and Shin (2016) generalize the Arellano and Bond (1991) first-differenced GMM (FD-GMM) estimation into a method that can be applied to our dynamic panel threshold model. Because both regressors and threshold variables are assumed to be endogenous, the FD-GMM approach can overcome the main limitation of modeling dynamic panels with the threshold effect and endogeneity. First, we remove the individual effect α_i by taking the first difference as follows:

$$\Delta\ln PM2.5_{it} = \Delta\ln PM2.5_{it-1}\beta_1 + \Delta\ln INDEX_{it}\beta_2 + \Delta\ln PCGDP_{it}\,\beta_3 + \Delta\ln SI_{it}\beta_4 + \Delta\ln ELEC_{it}\beta_5 + (\ln INDEX_{it}\,\mathbf{1}\{\ln INDEX_{it} \geq \gamma\} - \ln INDEX_{it-1}\,\mathbf{1}\{\ln INDEX_{it-1} \geq \gamma\})\delta + \Delta\varepsilon_{it}, \quad (4)$$

where Δ is the first-difference operator. $\beta = (\beta_1,\ \beta_2,\ \beta_3,\ \beta_4,\ \beta_5)'$, and $\Delta x_{it} = (\Delta PM2.5_{it-1}$, $\Delta\ln INDEX_{it}$, $\Delta\ln PCGDP_{it}$, $\Delta\ln SI_{it}$, $\Delta\ln ELEC_{it})'$. The following describes the GMM method used by Seo and Shin (2016) to estimate the unknown parameters $\theta = (\beta',\ \delta,\ \gamma)'$. Because the OLS estimator in (4) is biased because of the correlation between the transformed regressors and error terms, we set an l-dimensional vector of instrument variables $(z'_{it_0}, \dots, z'_{iT})'$ for $2 \leq t_0 \leq T$ such that either

$$\mathrm{E}\left(z'_{it_0}\Delta\varepsilon_{it_0}, \dots, z'_{iT}\Delta\varepsilon_{iT}\right)' = 0,$$

or $\mathrm{E}(\Delta\varepsilon_{it}|z_{it}) = 0$, for each $t = t_0, \dots, T$.

Next, we consider the following sample moment:

$$\bar{g}_n(\theta) = \bar{g}_{1n} - \bar{g}_{2n}(\gamma)(\beta',\ \delta)' = \frac{1}{N}\sum_{i=1}^{N} g_{1i} - \frac{1}{N}\sum_{i=1}^{N} g_{2i}(\gamma)(\beta',\ \delta)',$$

where

$$g_{1i} = \begin{pmatrix} z_{it_0}\,\Delta\ln PM2.5_{it_0} \\ \vdots \\ z_{iT}\,\Delta\ln PM2.5_{iT} \end{pmatrix}, g_{2i}(\gamma) = \begin{pmatrix} z_{it_0}\left(\Delta x'_{it_0},\ X'_{it_0}\mathbf{1}_{it_0}(\gamma)\right) \\ \vdots \\ z_{iT}\left(\Delta x'_{iT},\ X'_{iT}\mathbf{1}_{iT}(\gamma)\right) \end{pmatrix}$$

with $X_{it} = \begin{pmatrix} \ln INDEX_{it} \\ \ln INDEX_{it-1} \end{pmatrix}$ and $\mathbf{1}_{it}(\gamma) = \begin{pmatrix} \mathbf{1}\{\ln INDEX_{it} \geq \gamma\} \\ -\mathbf{1}\{\ln INDEX_{it-1} \geq \gamma\} \end{pmatrix}$. Then, the GMM estimator, $\hat{\theta}$ can be produced by minimizing the following criterion function with a weight matrix $\boldsymbol{W_n}$,

$$\bar{J}_n = \bar{g}_n(\theta)'\boldsymbol{W_n}\bar{g}_n(\theta).$$

For a given γ, the model becomes linear model. The GMM estimator of β and δ can be obtained by the grid search algorithm as follows:

$$\left(\hat{\beta}(\gamma)', \hat{\delta}(\gamma)\right)' = \left(\bar{g}_{2n}(\gamma)'\boldsymbol{W_n}\bar{g}_{2n}(\gamma)\right)^{-1}\bar{g}_{2n}(\gamma)'\boldsymbol{W_n}\bar{g}_{1n}.$$

For the weight matrix, either $\boldsymbol{W_n} = \boldsymbol{I_l}$ or

$$\boldsymbol{W_n} = \begin{pmatrix} \frac{2}{N}\sum_{i=1}^{N} z_{it_0}z_{it_0}' & \frac{-1}{N}\sum_{i=1}^{N} z_{it_0}z_{it_0+1}' & 0 & \cdots \\ \frac{-1}{N}\sum_{i=1}^{N} z_{it_0}z_{it_0+1}' & \frac{2}{N}\sum_{i=1}^{N} z_{it_0+1}z_{it_0+1}' & \ddots & \ddots \\ 0 & \ddots & \ddots & \frac{-1}{N}\sum_{i=1}^{N} z_{iT-1}z_{iT}' \\ \vdots & \ddots & \frac{-1}{N}\sum_{i=1}^{N} z_{iT-1}z_{iT}' & \frac{2}{N}\sum_{i=1}^{N} z_{iT}z_{iT}' \end{pmatrix}^{-1}.$$

This can be updated to

$$\boldsymbol{W_n} = \left(\frac{1}{N}\sum_{i=1}^{N} \hat{g}_i\hat{g}_i' - \frac{1}{N^2}\sum_{i=1}^{N} \hat{g}_i\hat{g}_i'\right)^{-1},$$

where $\hat{g}_i = \left(\widehat{\Delta\varepsilon}_{it_0}z_{it_0}', \dots, \widehat{\Delta\varepsilon}_{iT}z_{iT}'\right)'$.

Seo et al. (2019) extend the dynamic panel threshold model to a kink model in which one regressor element is the threshold variable. In this case, the discontinuity of a regression function means the presence of a kink, not a jump. Therefore, (3) can be transformed into the following kink model:

$$\ln PM2.5_{it} = \beta_0 + \ln PM2.5_{it-1}\beta_1 + \ln INDEX_{it}\beta_2 + \ln PCGDP_{it}\,\beta_3 + \ln SI_{it}\beta_4 + \ln ELEC_{it}\beta_5 + \kappa\,(\ln INDEX_{it} - \gamma)\,\mathbf{1}\{\ln INDEX_{it} \geq \gamma\} + \alpha_i + \varepsilon_{it}, \quad i = 1, \dots, N, t = 1, \dots, T, \tag{5}$$

If the explanatory variables of the indicator function include the constant term, the first element of δ equals $-\gamma\kappa$. In the following empirical analysis, we examine the influence of the financial inclusion on $PM_{2.5}$ concentration with a kink model and employ FD-GMM estimation.

4. Empirical analysis

In this section, we first consider the empirical results provided by the dynamic panel model, which are given in Table 3. In Model 1, the interactions between $PM_{2.5}$ concentration and the dependent variables are significant at the 1% level, with coefficients of 0.146, −0.251, 0.554, and 0.0535, respectively. The results indicate that a 1% increase in digital financial inclusion, the proportion of secondary industry, or electricity consumption increases $PM_{2.5}$ concentrations by 0.146%, 0.554%, and 0.0535%, respectively. By contrast, a 1% increase in GDP per capita reduces concentrations by 0.251%, corroborating the findings of Zhou et al. (2018).

On the basis of geography and economic development, we divide the sample into three subsamples for the eastern region, central region, and western region. The eastern region is considered a developed region, the central region is considered a developing region, and the western region is considered an undeveloped region. The empirical results of Models 2–4 are provided in Table 3. Surprisingly, the positive associations between digital financial inclusion and $PM_{2.5}$ concentration and between electricity consumption and $PM_{2.5}$ concentration disappear in Model 2. In other words, in the eastern region, digital finance and electricity consumption are not drivers of $PM_{2.5}$ concentration. The results of Models 3 and 4 are similar to those of Model 1. These results corroborate the findings of Ouyang et al. (2019) that a high level of economic development is negatively correlated with $PM_{2.5}$ concentration and a low level of economic development is positively correlated with $PM_{2.5}$ concentration.

Insert Table 3

The results from the three regions are dissimilar, indicating that economic development plays a large role in determining the relationship between digital financial inclusion and $PM_{2.5}$ concentration. We examine the threshold effect of digital financial inclusion because reflects not only the degree of air pollution but also the degree of economic development. Unlike the dynamic panel data model, the kink model considers the nonlinear asymmetry of dynamic panels. The threshold model can split the individual observations into classes based on the value of an observed variable. The effect of this observation variable on the dependent variable can vary from class to class.

We present the estimations of the dynamic panel threshold model in Table 4. Similar to the results in Table 3, the analysis results indicate that the lagged dependent variable has a positive effect on $PM_{2.5}$ concentration. Electricity consumption and the proportion of secondary industry positively affect $PM_{2.5}$ concentration, whereas GDP per capita negatively affects it. In Model 1, digital financial inclusion causes the threshold variable with one threshold value (γ) to split the Digital Inclusive Finance Index into two asymmetric phases: a low-digitalization phase and a high-digitalization phase. Digital financial inclusion has a significant and negative effect on $PM_{2.5}$

concentration in the high- digitalization phase: A 1% increase in digital financial inclusion causes a 0.5934% decrease in $PM_{2.5}$ concentration.

Models 2–4 (Table 4) examine whether regional development affects the empirical results of the kink model. Compared with the entire sample, the developed and undeveloped regions exhibited similar threshold effects, with coefficients of −0.8176 and −0.7919 at the 1% significance level; these indicate that a 1% increase in digital financial inclusion causes a 0.8176% and 0.7919% decrease in $PM_{2.5}$ concentration in the eastern and western regions, respectively. The coefficient of the threshold effect in the central region is −1.6530 at the 1% significance level, a value considerably higher than those for the eastern and western regions. The main reason for this may be that environmentally unsound industries in China are mainly located in the central region, in which digital financial inclusion can improve industrial efficiency and reduce air pollution.

Insert Table 4

5. Discussion

Through empirical analysis observe a significant correlation between digital financial inclusion and $PM_{2.5}$ concentration. The novel Digital Inclusive Finance Index reflects the digitalization of the economy at the city level and can be used to examine the effect of digitalization on air pollution. Our empirical results indicate that the impacts of digital financial inclusion on $PM_{2.5}$ concentration in China differ by region. We observe no significant effect in the eastern region and a significant, positive relationship in the central and western regions. A possible explanation for this observation is a nonlinear relationship between digital financial inclusion and $PM_{2.5}$ concentration.

By incorporating the threshold effect into our study, we identify an inverse relationship between digital financial inclusion and $PM_{2.5}$ concentration in areas with high digitalization at the 1% significance level. The central region exhibits the highest reduction in $PM_{2.5}$ concentration when digital financial inclusion peaks. This result implies an asymmetric relationship between digital financial inclusion and $PM_{2.5}$ concentration. The nonlinear relationship between digital financial inclusion and $PM_{2.5}$ concentration exhibits consequent positive correlations at the national level. By contrast, the eastern region exhibits no such correlation. Consistent with the EKC, this result implies that a high level of economic development may help to mitigate air pollution (Nigatu 2015; Hao and Liu 2016; Wang et al. 2017; Luo et al. 2018). In this case, economic development along with the continuing expansion of digital financial inclusion helps to reduce $PM_{2.5}$ concentration in the eastern region.

We observe a significant negative correlation between GDP per capita and $PM_{2.5}$ concentration. This result is contrary to that of Ji et al. (2018); on the basis of data from 30 Organisation for Economic Co-operation and Development (OECD) member countries, they argue that GDP per capita grows linearly with $PM_{2.5}$ concentration. However, our sample comprises data on developed, developing, and undeveloped cities in China; the OECD countries examined by Ji et al. (2018) are generally more developed. Digital financial inclusion, as an essential component of economic growth, is also affected by GDP per capita, which, at high levels, causes the relationship between digital financial inclusion and PM2.5 concentration to become negative (Ouyang et al. 2019). Therefore, our findings remain consistent with the EKC.

The positive effects of electricity consumption and the proportion of the secondary industry on $PM_{2.5}$ concentration we observe are logical; with the rapid industrialization of China, the proportion of secondary industry has increased along with electricity consumption. (Hao and Liu 2016; Wang et al. 2017). Because the proportions that the service and industry sectors constitute within the overall economy are always changing, digital finance consumes more energy than other industries and thus has nonlinear effects on $PM_{2.5}$ concentration. Our findings provide evidence of an inverted U-shaped relationship between digital financial inclusion and air pollution, demonstrating that digital financial inclusion is positively correlated with $PM_{2.5}$ concentration at a low level of digitalization level; the relationship reverses at a high level of digitalization. This finding indicates that the rapid growth of digital financial inclusion improves economic efficiency, which offsets energy consumption in the early stages of digitalization. Pollutant emissions are growing along with digitalization in China, implying that the degree of digitalization has not yet exceeded the threshold. Economic efficiency must increase before air pollution can be mitigated through digital financial inclusion.

6. Conclusions and policy implications

This paper examines the nonlinear effect of digital financial inclusion on $PM_{2.5}$ concentration in

283 cities in China from 2011 to 2018 by employing a dynamic threshold model. We further divide these 283 cities into three regions based on the cities' location and degree of economic development. We present three main findings. First, the correlation of digital financial inclusion with $PM_{2.5}$ concentration still exists in the Central region and Western region while gradually disappear in the Eastern region. Second, significant negative correlations occur across all three regions when digital financial inclusion serves as a threshold variable, suggesting that the development of digital finance helps to mitigate air pollution. Third, an relationship between digital financial inclusion and air pollution is nonlinear and asymmetric because digital finance improves economic efficiency, which can eventually reverse the effects of digital finance on air pollution.

Our findings have the following policy implications. First, we provide direct evidence of the asymmetric nonlinear relationship between digital financial inclusion and air pollution. Certain cities in eastern China have already reached the threshold level of digitalization; therefore, stricter environmental protection policies and regulations, rather than further economic development, are needed to achieve lower the $PM_{2.5}$ concentration in these cities. Second, unlike the eastern region, the central region can benefit through the expansion of digital financial inclusion, which can reduce $PM_{2.5}$ concentrations; policies promoting digital financial inclusion could be of both economic and environmental benefit. Lastly, beyond digital financial inclusion and economic growth, migration policies should be relaxed to allow more people to move into the eastern region to promote further economic growth and reduce $PM_{2.5}$ concentration.

Our study has several limitations. We ignore the effect of environmental regulation on $PM_{2.5}$ concentration. Specifically, we do not consider the new Environmental Law, which came into effect on January 1, 2015, in our analysis. Although the new law is much stricter than previous laws, enforcement across cities varies. For example, the local environmental regulations in Shanghai are much stricter than the 2015 law requires, whereas cities in the western region effectively adhere to no environmental regulations at all, making evaluation of the law's impact difficult. Therefore, more specific data are required to explore this issue.

Our study provides pioneering results on the externalities of digital finance. Future studies can proceed in at least three directions. Frist, digital finance can be a general idea, which can be specified into different categories; thus, provide more concrete and meaningful findings not only for environmental issue but also for social problem (He et al., 2016). Second, since digital financial inclusion and $PM_{2.5}$ concentrations may have bi-directional associations, a causal route should be explored in terms of spatiality, time-scales, and dimensions (Hao and Liu, 2016; Yang, 2021; Yang and Hamori, 2021). Finally, given the complex interaction between digital finance, economic growth, and air pollution, the mechanism of the complex interaction between digital finance, economic growth, and air pollution should be investigated more specifically to capture the landscape on the EKC hypothesis or other possibilities (Sinha and Bhattacharya, 2016; Sinha and Bhattacharya, 2017; Ouyang et al., 2019).

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Most of the basic data are publicly available, mainly from the National Bureau of Statistics of China, the official website, http://www.stats.gov.cn/, and the Wind and IFind financial databases. Other data are calculated by authors, and the calculation method is shown in the text of this paper.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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None

Authors' contributions

Lu Yang: Resources, Validation, Writing-original draft, Writing - review & editing.

LuLu Wang: Investigation, Writing-original draft.

Xiaohang Ren: Conceptualization, Methodology, Software, Writing-original draft, Formal analysis.

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Table 1: Data Summary

VarName	Obs	Mean	St.D	Min	Median	Max
lnPM2.5	2264	3.49	0.51	0.878269	3.533782	4.459912
lnINDEX	2264	4.94	0.51	2.834389	5.078045	5.713676
lnPCGDP	2251	10.57	0.69	7.635538	10.56189	15.27122
lnSI	2264	3.84	0.24	2.704711	3.873282	4.492449
lnELEC	2264	13.39	1.20	9.315421	13.38211	17.49943

Note: This table displays some summary statistics of dependent variables and explanatory variables.

Table 2: Correlation Matrix

	lnPM2.5	lnINDEX	lnPCGDP	lnSI	lnELEC
lnPM2.5		0.14*	0.06*	0.10*	0.33*
lnINDEX	0.13*		0.28*	-0.27*	0.48*
lnPCGDP	0.02	0.22*		0.25*	0.54*
lnSI	0.15*	-0.21*	0.24*		0.01
lnELEC	0.31*	0.40*	0.52*	0.06*	

Note: Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation

* $p<0.05$

Table 3. Results of the dynamic panel data model.

VARIABLES	(1) Total lPM25	(2) Eastern lPM25	(3) Central lPM25	(4) Western lPM25
L.lPM25	0.349***	0.835***	0.384***	0.277***
	(0.0341)	(0.0387)	(0.0502)	(0.0443)
lnINDEX	0.146***	0.0670	0.201***	0.0986***
	(0.0242)	(0.0472)	(0.0405)	(0.0376)
lnPCGDP	-0.251***	-0.119***	-0.238***	-0.301***
	(0.0139)	(0.0254)	(0.0202)	(0.0229)
lnSI	0.554***	0.925***	1.123***	0.0709
	(0.0889)	(0.195)	(0.172)	(0.114)
lnELEC	0.0535***	0.0146	0.0703***	0.122***
	(0.0120)	(0.0221)	(0.0169)	(0.0193)
Constant	1.368***	-2.190**	-1.532*	3.132***
	(0.496)	(1.027)	(0.903)	(0.613)
Observations	1,968	593	546	829
Number of id	283	85	78	120

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Results of the dynamic panel threshold data model.

	(1)	(2)	(3)	(4)
	Total	Eastern	Central	Western
VARIABLES	lPM25	lPM25	lPM25	lPM25
L.lPM25	0.2730***	0.2490***	0.3310***	0.3553***
	(0.0187)	(0.0124)	(0.0236)	(0.0155)
lnINDEX	0.3521***	0.6597***	0.2902***	0.5581***
	(0.0515)	(0.1360)	(0.0147)	(0.2124)
lnPCGDP	-0.2664***	-0.2429***	-0.2836***	-0.3506***
	(0.0127)	(0.0102)	(0.0175)	(0.0209)
lnSI	0.1328***	0.0676	0.6587***	0.0765
	(0.0108)	(0.0815)	(0.0841)	(0.0653)
lnELEC	0.0033	0.0755***	0.3490***	0.1509***
	(0.0165)	(0.0113)	(0.0211)	(0.0125)
kink_slope	-0.5934***	-0.8176***	-1.6530***	-0.7919***
	(0.0366)	(0.1240)	(0.0923)	(0.2024)
r	4.8189***	4.7547***	5.1235***	4.6092***
	(0.0374)	(0.0442)	(0.0102)	(0.0724)
Observations	1,968	593	546	829
Number of id	283	85	78	120

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1