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RESEARCH ARTICLE

Revisit causal nexus between financial development and environmental quality in China: a structural shift panel data analysis

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Abstract
Climate change is a challenge for all of humanity. Should financial be environmentally responsible? This paper uses the Toda–Yamamoto test and the extended Fourier Toda–Yamamoto test re-examine the relationship between financial development and environmental quality in 31 provinces and municipalities in China during the period 2000–2018. We find that financial development in certain regions has effectively reduced the concentration of PM2.5, which indicates that it has a significantly positive effect on environmental quality, though with regional differences. After considering structural shifts, the relationship between financial development and environmental improvement is found to be significant in more regions, indicating that China has undergone structural shifts in these aspects. The aforementioned conclusions are also supported by further robustness tests. China can consequently utilize the positive impact of finance for advocating carbon emission reduction and improving environment quality, therefore contributing to the response to global climate change.

Keywords Financial development · Environmental quality · Structural shifts · Panel Fourier Toda–Yamamoto causality test

Introduction

Climate change is a global problem that humanity is currently facing. The carbon dioxide emissions from across the globe have caused the volume of greenhouse gases to soar, posing a substantial threat to living systems. In this context, countries around the world made global environmental agreements to cut greenhouse gas emissions. Some of these agreements are the United Nations Framework Convention on Climate Change, which became effective in 1994, the Kyoto Protocol, which became effective in 2005, and the Paris Agreement, which was signed in 2015. As a major country in the world, China has also taken its share of responsibilities. At the general debate of the 75th Session of the United Nations General Assembly on 22 September 2020, President Xi Jinping announced that China would scale up its NDCs by adopting highly vigorous policies and measures, strive to reduce CO_2 emissions before 2030, and achieve carbon neutrality before 2060. China is taking pragmatic actions, such as incorporating the response to climate change into national economic and social development plans and increasing green finance support, towards these goals. As of the end of 2021, China's balance of green loans amounted to RMB15.9 trillion. China has issued a total of

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approximately RMB1.1 trillion of green bonds, with roughly RMB800 billion outstanding, making it world's second-biggest green bond market.

By optimizing the allocation of social resources, financial development can have a significant impact on environmental development. For example, it drives economic growth, raises energy consumption, and increases carbon dioxide emissions by promoting enterprise production and investment and household consumption. At the same time, it promotes the advancement of technology and its uses, which effectively reduces the unit energy consumption of economic growth and emissions and facilitates daily energy saving. China is attaching great significance to the role of financial development in promoting energy conservation and emission reduction, especially for financial institutions such as banks, which evaluate the environmental costs and benefits of enterprises or projects when issuing credits. They also encourage different green financial products.

Whether financial development improved environmental quality in China, existing research on China has failed to give a unified perspective on this problem. The main reason is the lack of effective handling of differences in China's economic growth and structural shifts. On the one hand, China's vast territory and the large economic gaps between different regions create regional differences in the relationship between financial development and the environment. On the other hand, as a major developing country, China has experienced tremendous economic and financial growth as well as major changes in its energy consumption structure (Jiang et al. 2022), which will inevitably affect the relation between the two. A panel causality approach can be used to examine both cross-area interrelations and country-specific heterogeneity. Furthermore, the Toda–Yamamoto causality test, based on the extended Fourier function, can well handle the influence of structural shifts and has no requirements for the stability characteristics of the data, which are quite suitable for processing the data of this paper. Thus, we employed the panel Fourier Toda–Yamamoto (PFTY) causality test to explore the relationship between financial development and environmental quality on China's inter-provincial panel data. The results can provide additional information for political support of science and academic purposes.

Literature review

Three representative conclusions have been reached in the existing studies on the mechanism of financial development affecting environmental quality. The first is that financial development has negatively affected environmental quality. Energy consumption, which is the main determinant of environmental quality, is also the main channel through which finance has an impact on environmental quality. Sadorsky (2010) listed three channels through which financial development promotes economic growth and consequently leads to greater energy consumption: (1) it helps consumers purchase durable goods more easily, which in turn increases energy consumption; (2) it reduces financing costs and facilitates the expansion of production for companies, which increases energy consumption; (3) it provides a mechanism for risk diversification, boosting the confidence in the economy of both consumers and manufacturers and promoting wealth concentration, hence the buying of more energy-intensive commodities. Liu and Wen (2019) found that the easier access to financial credit leads to a favouring of heavy assets and heavy pollution industries, which lead to a misallocation of resources, have also increased the environmental costs of economic growth.

The second conclusion is that financial development has improved environmental quality. This view suggests that financial development can help companies obtain energy-friendly technologies more easily by offering capital with lower costs, thereby reducing energy consumption. Yu and Chen (2011) found that financial development can have multiple impacts on environmental quality in terms of capital, technology, income, and regulation. For example, green credit can accelerate the closing down of outdated production facilities, thus making their production activities more environment-friendly. A study by Cole et al. (2005) finds that financial development can help companies ease restrictions resulting from a capital budget and achieve economy of scale through financing. This leads to a reduction in resource waste and pollution in production. In their study, Kumbaroğlu et al. (2008) found that faster technological upgrades and iteration usually reduce pollution emissions significantly in countries with a developed financial system. Claessens and Feijen (2007) also found that financial institutions can reduce investment costs related to environmental protection projects, thereby helping improve environmental quality. Shahbaz et al. (2013a) observed that financial development improves environmental quality through carbon trading. It also encourages companies to improve their corporate image and facilitate financing by emission reduction.

The third conclusion that can be drawn from studies is that financial development has nonlinear effects on environmental quality. Yan et al. (2016) built an endogenous growth model that included financial development, innovation, and carbon dioxide emissions. They found an inverted U-shaped relationship between financial development and carbon dioxide intensity. The higher the level of financial development, the higher the level of technologies, they found, and thus the lower the carbon dioxide intensity. Moreover, the higher the level of financial development, the higher the economic growth rate, which led to greater energy consumption and carbon dioxide emissions. Financial development leads to an increase in carbon dioxide intensity when the emission reduction effect it causes is less than the increase in carbon emissions; conversely, it will lead to a decrease in carbon dioxide intensity.

Empirical tests on the impacts of financial development on environmental quality have also come to three different conclusions. The first is that financial development has improved environmental quality. Tamazian et al. (2009) empirical study on the BRIC countries from 1992 to 2004 found that more developed finance leads to a higher environmental quality. Tamazian and Rao (2010) conducted a study among 24 countries going through economic transitions. A complete banking system and developed capital market, they found, are all conducive to reducing per capita carbon dioxide emissions. Jalil and Feridun (2011) explored the relationship between China's financial development and carbon dioxide emissions from 1953 to 2006. Their results show that financial development can help reduce carbon dioxide emissions. Shahbaz et al. (2013b) ran co-integration tests on Malaysian data from 1971 to 2011 and found a long-term equilibrium relationship between financial development and carbon dioxide emissions. The authors concluded that financial development is conducive to reducing carbon dioxide emissions. Omri et al. (2015) studied 12 countries in the Middle East and North Africa from 1990 to 2011. Their results show high-level financial development stimulated technological innovation, which in turn facilitated a reduction in pollutant emissions and improved environmental quality. Bekhet et al. (2017) conducted a study on countries around the Persian Gulf by using data from the period 1980–2011 and found that financial development in the region effectively promoted energy saving. Jahanger et al. (2022)reported that financial development reduced the ecological footprint in the Asian countries between 1990 and 2016. Furthermore, Doğan et al. (2022) first investigated the moderating role of an environmental tax on renewable and non-renewable energy consumption, natural resources rent, and CO_2 emissions. They found that environmental taxes effectively reduced emissions for G7 countries from 1994 to 2014.

The second conclusion that can be drawn from empirical tests is that financial development has caused the deterioration of environmental quality. Brännlund et al. (2007) study found that the production technologies have advanced with the financial development, and this has expanded the production scale of companies and led to an eventual increase in pollutant emissions, which have a negative impact on environmental quality. Sadorsky (2010) analysed the panel data of 22 countries from 1990 to 2006 and concluded that developing financial markets have raised consumers' demands for energy, and the increase in energy demand has led to increased air pollutant emissions. This indicates that financial development may have a negative impact on environmental quality. Zhang (2011) found a positive correlation between China's financial development and carbon emissions. Shahzad et al. (2017) studied data from Pakistan for the period 1971–2011 and found that financial development has increased carbon dioxide emissions both in the short and long term. Dong et al. (2020) identified the current situation of China's credit resources, which favour heavy pollution industries by using capital market data. Their study proved that the allocation ratio of credit resources is highly correlated with pollution emissions. Wen and Liu (2019) demonstrated that environmental pollution is aggravated by investing credit resources in heavily polluting industries. Usman and Balsalobre also reported that financial development drove environmental pollution from 1990 to 2019 in newly industrialized countries (Usman and Balsalobre-Lorente 2022). Balsalobre-Lorente et al. (2022) indicated high FDI to be the culprit for increasing environmental degradation in the PIIGS economies from 1990 to 2019.

The third argument that can be drawn from empirical studies is that there is no significant relationship between financial development and environmental quality or the relationship is nonlinear. Ozturk and Acaravci (2013) studied data from Turkey between 1960 and 2007 and found that the long-term impacts of financial development on per capita carbon emissions are not significant. Yan et al. (2016) conducted empirical tests for 30 provinces in China by using data from 1997 to 2021 and found an inverted U-shaped relationship between financial development and carbon dioxide intensity.

Two primary mechanisms of financial development act on environmental quality: (1) financial development drives economic growth, leading to higher energy consumption and a consequent deterioration in environmental quality; (2) financial development promotes technological advancements, thus cutting unit energy consumption and improving environmental quality. These two mechanisms act concurrently in economic activities, and the overall effect changes depend on the relative strength of the two. As a developing country, China has gone through different stages of economic development. Furthermore, great differences exist in the relationship between its financial development and environmental quality both in terms of space and time as a result of its vast territory. The challenge facing existing literature is located in identifying these characteristics and changes and exploring the relationship between the two more accurately. The panel causality test, which is commonly used today, is based on the overall causality test. If one sample shows nonsignificant causality, the overall causality will be concluded to be nonsignificant. In reality, some samples tend to present a causal relationship while others show no causality at all. If there are structural shifts in the data, tests should be made while taking these factors into account. Moreover, no significant non-same order integration and the co-integration relationship between time-series data exists. This consequently fails to meet the conditions of the traditional Granger causality test. The Toda–Yamamoto causality test, which is based on the extended Fourier function, can better handle the influence of structural shifts and has no requirements on the stability characteristics of the data, which are quite suitable for processing data in this paper. Therefore, this study intends to adopt the Toda–Yamamoto causality test based on the extended Fourier function (Toda and Yamamoto 1995; Nazlioglu et al. 2016) to test the impacts of financial development on environmental quality by using data from 31 provinces and cities in China from 2000 to 2018.

Introduction of methodology

In the last two decades, China's financial development and environmental quality have undergone tremendous changes, while the measurement of environmental quality only began in 1998. The data processed in this paper have therefore a complex structure and are drawn from limited time. Toda and Yamamoto's new method, developed by improving the Granger causality test, can directly apply Wald on level data to test the causality. This can be done irrespective of whether the variables are stable and whether there is a co-integration relationship between them (the Toda–Yamamoto method) (Toda and Yamamoto 1995). To deal with possible structural shifts in the data, Nazlioglu et al. (2016) used the Fourier function in the causality test. This paper intends to integrate the Fourier function into the Toda–Yamamoto method, thus handling possible structural shifts. The detailed description of the process is as follows:

The P-order vector autoregressive model of the Granger causality test (Granger 1969) is:

$$y_t = \alpha + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t \tag{1}$$

where y_t is the vector of dependent variables, α is the vector of intercept, β is the coefficient matrix, and ε_t is the vector of white noise residual.

y_t assumes that there is no structural shift, while the intercept term α does not change with time. Recent studies, however, have indicated the growing importance of structural shifts in causal analysis. Ventosa-Santaulària and Vera-Valdés (2008) found in their study that the test of series with no causality will also reject the hypothesis that there is no causality when there are structural shifts in data generation. Enders and Jones (2016) further found through Monte Carlo simulation that the results obtained by the Granger causality test may be wrong, especially when structural shifts are not considered or are not properly handled. However, controlling structural shifts and analysing their causes in the VAR model are quite complicated, because structural shifts in one variable will also lead to changes in other variables. Determining whether this change is caused by exogenous influence or is endogenously generated is often difficult analysing the structural shift of one variable in the VAR model. The structural shift of one variable having a lagging effect on other variables would make it even more complicated. The influence of the change of the variable y_1 at t on other variables would only show at $t+j$ as a consequence. All these restrictions have posed prominent challenges to the traditional method of modelling structural shifts by using dummy variables in the VAR framework. Enders and Jones (2016) used Fourier approximation to extend the standard Granger causality model in Eq. (1) to overcome these difficulties and simplify the forms and number of structural shifts and the estimation of dates in the VAR model.

The standard Granger causality analysis requires testing of unit roots and co-integration. If the difference of the variables in the VAR model is stable or a co-integration relationship exists, the Wald test will not follow the standard distribution. Its distribution parameters will be determined by the characteristics of the tested data as well (Toda and Yamamoto 1995; Dolado and Lütkepohl 1996). Toda and Yamamoto used the (p + d)-lag expanded VAR model to perform the Granger causality estimation on horizontal data, where d is the maximum number of differences. This step effectively overcomes the dependence of the estimation method on data stability and co-integration. In their method, they relaxed the assumption that the intercept term is fixed and set it as a function that changes with time, creating a VAR$(P+d)$ model as follows:

$$y_t = \alpha(t) + \beta_1 y_{t-1} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{2}$$

where α(t) is a function of time and denotes the structural shifts of y_t. The α(t) function adopts the form of a Fourier function to approximate the structural shifts of the intercept term (Nazlioglu et al. 2016), which relaxes the prerequisite requirements on the time, frequency, and form of structural shifts.

$$\alpha(t) \cong \alpha_0 + \sum_{k=1}^{n} \alpha_{1k}\, sin(\frac{2\pi kt}{T}) + \sum_{k=1}^{n} \alpha_{2k} cos(\frac{2\pi kt}{T}) \tag{3}$$

where n denotes the frequency and α_{1k} and α_{2k} denote the amplitude and displacement of the frequency, respectively. By substituting F. (3) in F. (2), a new causality test equation is obtained:

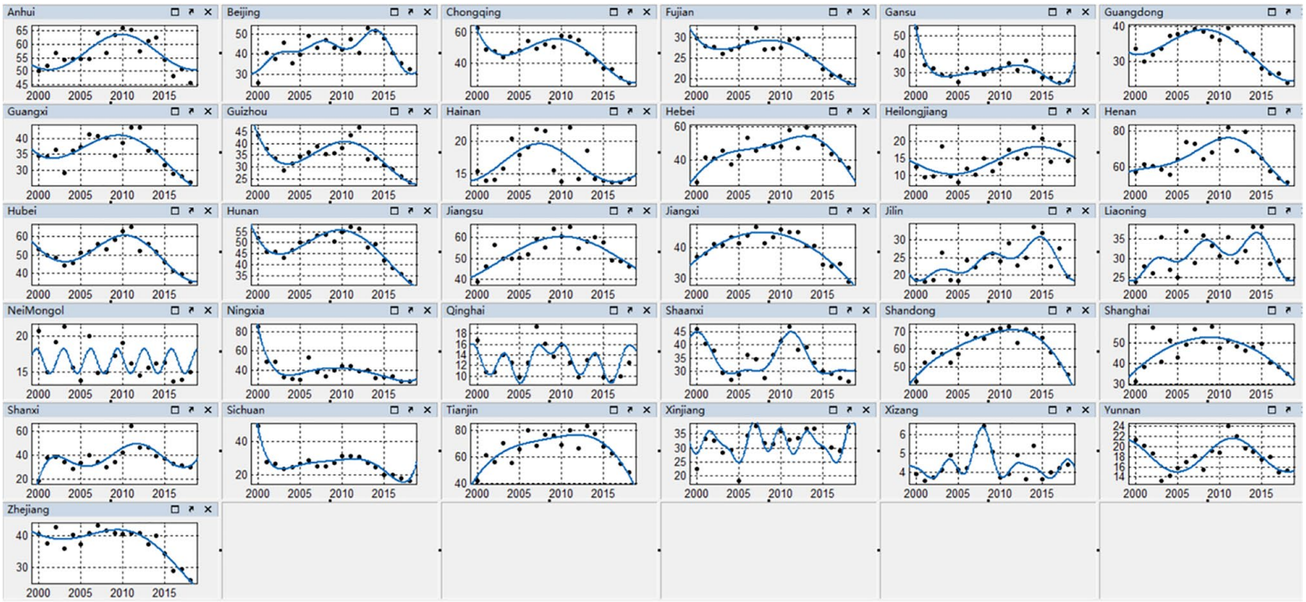

Fig. 1 Environmental quality (PM) and its Fourier fitting curve

$$y_t = \alpha_0 + \sum_{k=1}^{n} \alpha_{1k} sin(\frac{2\pi kt}{T}) + \sum_{k=1}^{n} \alpha_{2k} cos(\frac{2\pi kt}{T}) + \beta_1 y_{t-1} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{4}$$

In the above formula, the translation of the intercept term is used instead of the time-dependent coefficient to express the structural shift. This aims at reducing the estimated coefficient and ensuring a sufficient degree of freedom. The degree of freedom will experience a significant fall if the Fourier function is used while considering the possible time-dependent characteristics of the regression coefficient of the lag term. For example, we estimated a VAR model containing a third-order lag (p), three Fourier cumulative frequencies (n, which means six Fourier series should be created, three for the sine function, and the other three for the cosine function) for three endogenous variables (K). In this case, 54 (2n×p×K) time-dependent

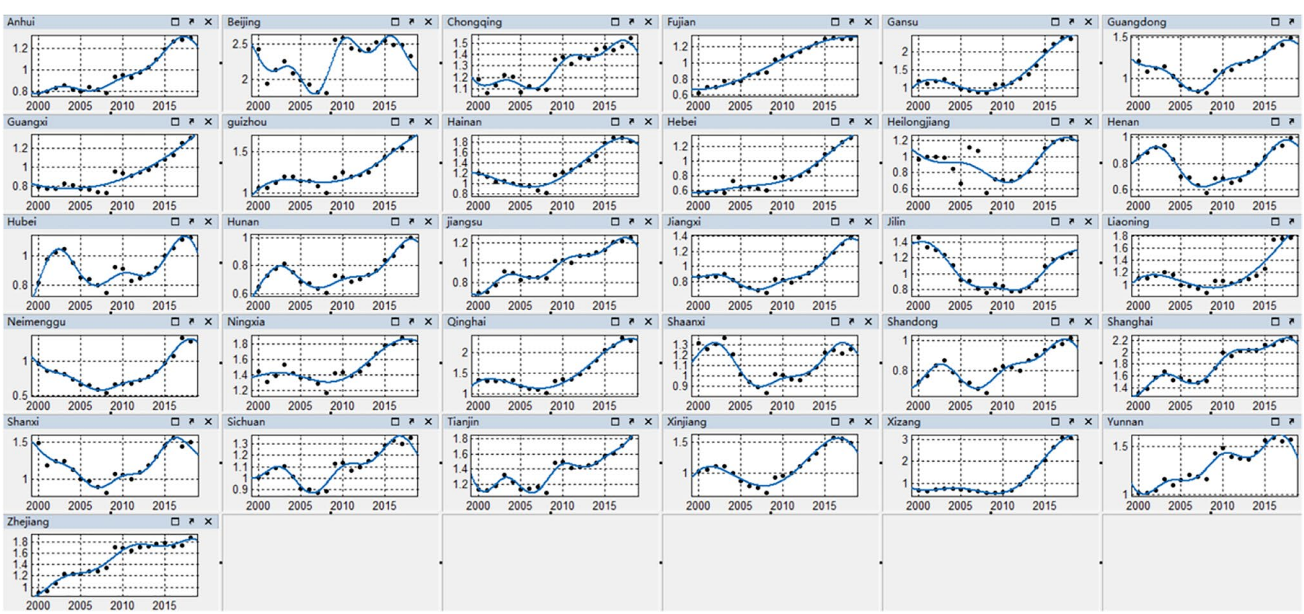

Fig. 2 Financial development (FD) and its Fourier fitting curve

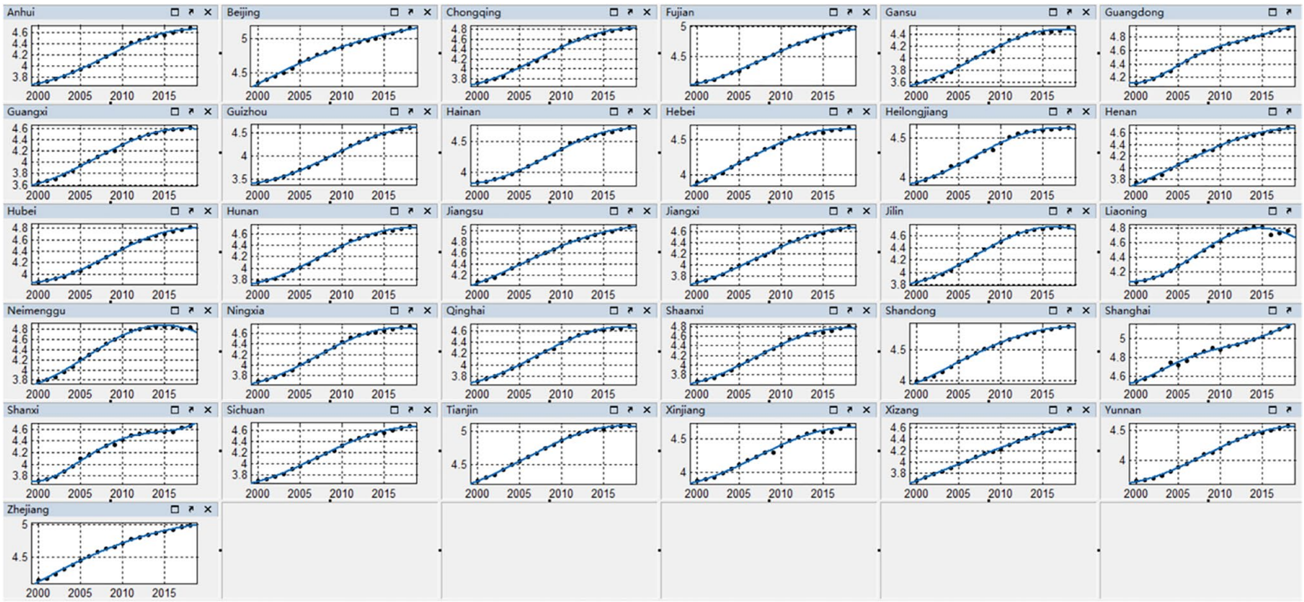

Fig. 3 GDP per capita and its Fourier fitting curve

parameters should be used to estimate the VAR model, significantly limiting the degrees of freedom. We learn from the practice of Enders and Jones (2016) in the unit root test, assuming a structural shift in the intercept term.

The priority for Eq. (4) is to test the existence of the nonlinear term (e.g. the trigonometric function component). The method proposed in the two studies by Becker et al. (2004) and Becker et al. (2006) can be used to perform the F test on the coefficients at a given frequency: $\alpha_{1k}=\alpha_{2k}=0$ (k = 1,…,n). In the case where the original hypothesis with a coefficient of zero is rejected, the existence of a structural shift is indicated, and the Fourier function should be included in the VAR model proposed by Toda and Yamamoto.

We should then determine the value of the frequency n and the lag order p in the cumulative Fourier function in Eq. (4). AIC and SIC criteria are the commonly used methods for determining the optimal lag order in causality analysis and can also be used to determine the above frequency and lag order of the Fourier function. The Fourier frequency is specifically set to n^{max}, whereas the number of lags is set to p^{max}. The optimal n and p will then be selected according to the size of the information criterion value.

The three variables involved in this study are financial development (FD), economic growth (EG), and environmental quality (PM). Environmental quality is measured by PM2.5, and the causality test equations are built as follows:

$$PM_t = \alpha_{1,1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \alpha_{1,2k} cos\left(\frac{2\pi kt}{T}\right) + \sum_{j=1}^{p+d} \beta_{1,1j} PM_{t-j} + \sum_{j=1}^{p+d} \beta_{1,2j} FD_{t-j} + \sum_{j=1}^{p+d} \beta_{1,3j} EG_{t-j} + \varepsilon_{1,t}$$

$$FD_t = \alpha_{2,0} + \sum_{k=1}^{n} \alpha_{2,1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \alpha_{2,2k} cos\left(\frac{2\pi kt}{T}\right) + \sum_{j=1}^{p+d} \beta_{2,1j} PM_{t-j} + \sum_{j=1}^{p+d} \beta_{2,2j} FD_{t-j} + \sum_{j=1}^{p+d} \beta_{2,3j} EG_{t-j} \varepsilon_{2,t} \tag{5}$$

Table 1 Statistical characteristics and correlation test of variables

Variable	*pm*	*fd*	*loggdp*
Mean	36.41	1.16	10.06
N	589	589	589
p50	35.6	1.09	10.18
max	85.5	3.08	11.85
min	3.5	0.53	7.89
sd	16.78	0.42	0.86
Variance	281.56	0.18	0.73
cv	0.46	0.36	0.09
Kurtosis	2.68	5.41	2.19
Skewness	0.28	1.38	-0.24
Jarque–Bera	10.33	330.4	21.89
Probability	0.01	0.00	0.00
Correlation matrix			
pm	1.00		
fd	-0.14	1.00	
loggdp	0.15	0.44	1.00

Table 2 Results of unit root tests for environmental quality (PM)

Region	PM			DPM		
	ADF	ZA	EL	ADF	ZA	EL
Anhui	−1.463	−4.805	−5.962***	−5.736***	−6.179***	−7.9***
Beijing	−2.914	−6.681***	−3.872	−7.015***	−8.088***	−6.001***
Chongqing	−1.245	−6.765***	−6.94***	−4.990***	−4.655	−3.281
Fujian	−1.389	−3.993	−5.642***	−4.760***	−5.957***	−4.138**
Gansu	−5.796***	−7.363***	−3.266	−6.680***	−8.334***	−3.961
Guangdong	−0.723	−3.592	−5.139***	−5.574***	−5.991***	−9.015***
Guangxi	−1.423	−4.127	−5.488***	−4.830***	−5.256***	−5.034***
Guizhou	−1.571	−4.231	−5.575***	−3.736**	−6.324***	−5.552***
Hainan	−3.155	−6.712***	−1.429	−6.751***	−7.077***	−6.689***
Hebei	−2.487	−7.253***	−3.66	−7.296***	−7.893***	−3.822
Henan	−3.943**	−5.366**	−4.422**	−5.736***	−7.171***	−7.976***
Heilongjiang	−1.237	−4.107	−5.31***	−4.830***	−5.387**	−4.713**
Hubei	−0.693	−4.312	−4.18*	−4.327**	−7.447***	−1.519
Hunan	−0.458	−5.532**	−6.166***	−4.7***	−6.237***	−9.821***
Jilin	−2.13	−3.921	−5.81***	−6.154***	−5.03*	−6.376***
Jiangsu	−1.028	−4.747	−2.671	−6.051***	−6.026***	−3.896
Jiangxi	−3.452*	−5.989***	−4.578**	−5.785***	−7.578***	−6.571***
Liaoning	−3.616**	−6.031***	−8.235***	−6.862***	−6.626***	−4.983***
NeiMongol	−5.140***	−9.251***	−4.875**	−5.766***	−7.01***	−4.845**
Ningxia	−5.597***	−6.797***	−6.087***	−6.058***	−8.696***	−4.262*
Qinghai	−3.126	−4.297	−5.147***	−4.327**	−8.34***	−7.616***
Shandong	−2.059	−3.537	−4.645**	−3.584*	−5.339**	−4.691**
Shanxi	−0.883	−3.516	−4.139*	−4.553***	−5.899***	−5.824***
Shaanxi	−3.465*	−5.359**	−5.601***	−7.998***	−10.686***	−8.538***
Shanghai	−2.641	−7.674***	−4.843**	−4.737***	−5.893***	−4.449**
Sichuan	−4.597***	−4.805	−2.737	−7.959***	−8.094***	−3.087
Tianjin	−2.401	−3.434	−6.591***	−8.474***	−9.218***	−9.569***
Xizang	−4.098**	−5.669**	−3.755	−5.109***	−5.863***	−5.239***
Xinjiang	−3.144	−6.031***	−5.626***	−5.468***	−4.811	−5.031***
Yunnan	−2.058	−3.589	−5.578***	−4.359**	−6.053***	−5.245***
Zhejiang	−1.43	−2.763	−3.888	−8.156***	−8.623***	−3.302

$$
\begin{aligned}
EG_t = \alpha_{3,0} &+ \sum_{k=1}^{n} \alpha_{3,1k} sin\left(\frac{2\pi kt}{T}\right) \\
&+ \sum_{k=1}^{n} \alpha_{3,2k} cos\left(\frac{2\pi kt}{T}\right) + \sum_{j=1}^{p+d} \beta_{3,1j} PM_{t-j} \\
&+ \sum_{j=1}^{p+d} \beta_{3,2j} FD_{t-j} + \sum_{j=1}^{p+d} \beta_{3,3j} EG_{t-j} + \epsilon_{3,t}
\end{aligned}
$$

A non-null Wald test is conducted in the Toda–Yamamoto test equations above for the regression coefficients of the first p-order lag of the explanatory variable to determine the existence of causality. At this time, the p regression coefficient is an approximation $\chi 2$ distribution with a degree of freedom of p. A joint test is needed for $\beta_{1,2j}=0(\mathrm{j}=1,\ldots,\mathrm{p})$ if this paper hopes to test whether FD has an impact on environmental quality.

The Wald statistic may not follow the asymptotic chi-square distribution as it may depend on the frequency parameter k in the Fourier function. To solve the aforementioned problem of statistical distribution, Becker et al. (2004) found that bootstrap sampling can be used to obtain the bootstrap distribution of the Wald statistic of the coefficient. Recent literature on Granger causality tests attaches importance to data robustness features such as unit roots and co-integration and increasingly using bootstrap distributions to improve the ability of small sample testing

Table 3 Results of unit root tests for financial development (FD)

Region	FD			DFD		
	ADF	ZA	EL	ADF	ZA	EL
Anhui	−1.34	−3.415	−7.621***	−4.055**	−5.24**	−4.699**
Beijing	−2.99	−7.534***	−3.976	−4.361**	−5.714***	−5.575***
Chongqing	−3.113	−5.665***	−4.728**	−4.587***	−5.085**	−5.498***
Fujian	−1.939	−3.496	−4.804**	−4.48***	−6.396***	−5.951***
Gansu	−0.867	−2.55	−4.007	−2.385	−3.633	−3.898
Guangdong	−1.688	−5.648***	−4.756**	−4.08**	−5.772***	−5.892***
Guangxi	−1.328	−3.04	−5.016***	−4.526***	−4.928*	−6.277***
Guizhou	−0.802	−2.862	−6.758***	−3.575*	−6.777***	−4.147*
Hainan	−2.082	−3.712	−3.84	−3.229	−5.456**	−7.355***
Hebei	−1.186	−3.748	−6.409***	−5.171***	−5.725***	−3.444
Henan	−1.953	−4.134	−3.676	−4.7***	−6.162***	−2.977
Heilongjiang	−0.33	−3.046	−5.838***	−3.3*	−4.805	−6.084***
Hubei	−1.308	−3.601	−3.962	−3.913**	−3.968	−3.727
Hunan	−0.502	−2.999	−4.593**	−3.506*	−4.94*	−6.707***
Jilin	−2.815	−4.781	−3.527	−4.155**	−6.097***	−3.866
Jiangsu	−0.251	−2.25	−4.03	−4.149**	−4.957*	−5.799***
Jiangxi	−0.595	−2.268	−3.355	−3.396*	−4.269	−5.17***
Liaoning	−0.77	−2.905	−4.137*	−3.848**	−4.076	−3.682
NeiMongol	−0.888	−2.56	−4.712**	−5.02***	−5.701**	−4.507**
Ningxia	−1.847	−3.87	−5.363***	−4.345**	−5.989***	−6.274***
Qinghai	−1.193	−3.578	−4.131*	−3.606**	−4.845*	−6.652***
Shandong	−1.044	−3.601	−4.759**	−3.095	−3.968	−5.045***
Shanxi	−1.341	−3.878	−4.536**	−3.395*	−4.653	−5.283***
Shaanxi	−1.991	−5.528	−4.091*	−3.331*	−4.369	−4.174*
Shanghai	−2.3	−3.272	−3.779	−4.793***	−6.016***	−3.935
Sichuan	−1.517	−4.256	−4.458**	−3.268*	−3.692	−4.981***
Tianjin	−2.377	−4.061	−4.536**	−4.521***	−4.888*	−4.724**
Xizang	−1.201	−3.255	−5.439***	−2.626	−4.675	−3.791
Xinjiang	−0.152	−3.818	−3.206	−1.433	−1.414	−6.067***
Yunnan	−3.114	−5.84***	−3.648	−4.015**	−4.648	−4.003
Zhejiang	−2.151	−5.694***	−6.656***	−3.888**	−4.065	−5.762***

(Mantalos 2000; Hatemi-J 2002; Hacker and Hatemi-J 2006; Balcilar et al. 2010). This paper also used the residual bootstrap sampling method proposed by Efron (1979) to this end to solve the bootstrap distribution of the Wald statistic.

Result analysis

The data referenced in this paper provide information about the FD and air quality of 31 provinces, municipalities, and autonomous regions in China from 2000 to 2018.[1] The FD of each region is measured by calculating the ratio of the loan balance to GDP; the loan balance and GDP numbers are released by the National Bureau of Statistics of China and the provincial statistics bureaus. The air quality indicators of each province take the average PM2.5 concentration data after the satellite-monitored climate data provided by the atmospheric composition analysis team of Dalhousie University being processed by raster processing and matching the vector maps of 286 prefecture-level cities (Van Donkelaar et al. 2019; Hammer et al. 2020). The main control variable, which is the per capita GDP data, is extracted from the statistical yearbooks of each province.

During the years 2000–2018, the macroeconomic finance and energy consumption patterns have undergone major changes. However, it is quite challenging to define in which specific form and at what time the changes occurred. Fourier approximation, since it can accurately analyse the periodic fluctuations of time series, has become a common

[1] The data for 2019 and 2020 are affected by the epidemic; hence, the analysis sample only includes data before 2018.

Table 4 Results of unit root test for GDP per capita

Region	LogGDP			d.loggdp		
	ADF	ZA	EL	ADF	ZA	EL
Anhui	−0.343	−5.513**	−5.904***	−2.71	−4.846*	−9.08***
Beijing	−1.132	−6.5***	−1.349	−3.72**	−4.001	−6.123***
Chongqing	0.328	−3.349	−5.344***	−2.822	−4.35	−4.635**
Fujian	−0.864	−3.803	−5.592***	−2.641	−4.009	−5.826***
Gansu	0.125	−3.944	−2.667	−2.781	−3.607	−2.58
Guangdong	−0.09	−5.226**	−5.841***	−3.218	−3.932	−4.421*
Guangxi	0.407	−4.961*	−3.106	−3.15	−3.997	−6.246***
Guizhou	−1.157	−3.363	−4.765**	−1.929	−5.258*	−1.782
Hainan	−0.801	−5.845***	−6.582***	−2.456	−4.897	−1.568
Hebei	0.354	−4.502	−2.924	−3.172	−3.773	−8.798***
Henan	0.141	−5.142**	−4.376**	−3.470*	−4.852*	−3.628
Heilongjiang	0.098	−3.854	−6.833***	−3.438*	−5.024**	−6.158***
Hubei	−0.86	−3.708	−5.402***	−2.119	−4.581	−3.375
Hunan	0.506	−5.238**	−6.368***	−2.311	−2.652	−3.095
Jilin	0.613	−4.723	−7.17***	−2.974	−4.799	−7.378***
Jiangsu	0.238	−5.475**	−5.968***	−2.777	−4.586	−3.034
Jiangxi	1.546	−4.779	−6.138***	−1.801	−3.851	−4.004
Liaoning	0.064	−3.386	−3.983	−2.748	−3.209	−4.702**
NeiMongol	1.099	−2.553	−6.458***	−2.999	−4.409	−9.176***
Ningxia	0.575	−6.834***	−7.413***	−2.262	−4.008	−8.526***
Qinghai	1	−4.059	−5.618***	−2.34	−4.1	−5.462***
Shandong	0.332	−5.231**	−7.295***	−2.161	−2.78	−5.577***
Shanxi	0.974	−2.803	−2.446	−3.344*	−6.142***	−9.338***
Shaanxi	−2.482	−3.995	−5.778***	−4.561***	−5.568**	−5.321***
Shanghai	−0.393	−3.448	−5.016***	−3.449*	−3.845	−5.766***
Sichuan	−0.186	−4.629	−6.002***	−2.941	−4.077	−5.476***
Tianjin	1.73	−4.219	−5.555***	−2.801	−4.706	−4.183*
Xizang	−0.758	−4.033	−4.207*	−3.469*	−4.3	−3.723
Xinjiang	−0.267	−3.257	−5.181***	−3.179	−4.019	−5.311***
Yunnan	−0.849	−4.851*	−4.019	−2.648	−3.745	−6.881***
Zhejiang	−0.119	−3.002	−4.071*	−4.275**	−5.644***	−2.391

ADF, augmented Dickey and Fuller (1979) unit root test; *ZA*, Zivot and Andrews (1992) ADF unit root test with a break; *EL*, Enders and Lee (2012b) ADF unit root test with Fourier approximation. ADF test includes constant and trend terms. ZA and EL tests include a structural shift in the constant and trend terms. The critical values for ADF test are −4.38 (1%), −3.6 (5%), and −3.24 (10%). The critical values for ZA are −5.57 (1%), −5.08 (5%), and −4.82 (10%) (see Table 4 in Zivot and Andrews, 1992). The critical values for EL are −4.95 (1%), −4.35 (5%), and −4.05 (10%) for $k=1$ (see Table 1a in Enders and Lee, 2012). ***, **, and * denote statistically significance at the 1%, 5%, and 10% levels, respectively

method for determining the existence of structural shifts in a time series. Figures 1, 2, and 3 show the trends of PM2.5, FD index and logarithmic index of per capita GDP, and their Fourier fitting curves. The Fourier approximation goodness of fit of the three variable indices appears to have reached a high level,[2] indicating that the index variables of all provinces and municipalities have undergone structural shifts within the analysis interval.

The first step of Toda–Yamamoto causality analysis constitutes the study of the unit root properties of variables to determine the highest order integral (d) in the VAR system. To this end, we adopted a set of unit root tests: Dickey and Fuller's ADF test (1979), Zivot and Andrews's ADF test with a breakpoint (1992) (ZA), and Enders and Lee's Fourier ADF test (2012) (EL). The

[2] By setting different fitting parameters, the goodness of fit of the fitting curve to the index reaches over 0.5.

Table 5 Causality test between financial development (FD) and environment quality (PM)

Region	H0:FD does not cause PM						HO:pm does not cause fd					
	TY		FTY				TY		FTY			
	W	Pboot	W	Pboot	F_F	pval	W	Pboot	W	Pboot	F_F	pval
Anhui	2.25	0.39	0.47	0.79	1.78	0.39	2.43	0.36	2.02	0.5	0.82	0.62
Beijing	0.06	0.8	2.88	0.41	11.55	0.08	0.02	0.89	0.16	0.93	0.23	0.9
Chongqing	1.19	0.33	21.1	0.08	34.92	0.03	0.09	0.78	26.2	0.08	30.5	0.03
Fujian	0.7	0.73	0.74	0.73	0.38	0.82	1.53	0.5	0.38	0.83	0.48	0.76
Gansu	0.06	0.8	2.63	0.43	0.81	0.62	0.06	0.82	0.55	0.79	0.49	0.75
Guangdong	6.51	0.12	20.7	0.08	30.78	0.03	1.4	0.52	12.4	0.15	10.4	0.09
Guangxi	24.08	0.01	9.73	0.17	0.41	0.8	0.78	0.69	0.08	0.96	7.99	0.11
Guizhou	14.89	0.02	23.8	0.08	14.59	0.07	1.96	0.41	0.76	0.73	4.33	0.2
Hainan	2.25	0.18	24.7	0.08	17.21	0.06	0	0.97	0.54	0.79	0.77	0.63
Hebei	0.2	0.67	8.65	0.19	10.59	0.09	1.62	0.22	2.34	0.46	1.62	0.42
Henan	0.01	0.91	2.55	0.44	3.85	0.22	0.7	0.44	21.8	0.09	4.22	0.2
Heilongjiang	0.01	0.95	0.19	0.92	4.36	0.2	2.07	0.19	18.3	0.11	7.25	0.13
Hubei	0.68	0.71	0.14	0.72	1.32	0.36	3.09	0.29	2.84	0.16	3.17	0.1
Hunan	0.01	0.93	0.01	1	2.32	0.32	0.03	0.87	4.26	0.31	2.55	0.3
Jilin	1.53	0.5	0.27	0.88	2.94	0.27	0.24	0.88	1.08	0.63	1.21	0.5
Jiangsu	0.1	0.77	2.37	0.45	5.77	0.15	3.22	0.09	3.61	0.35	4.77	0.18
Jiangxi	1.87	0.22	1.53	0.57	0.93	0.58	1.72	0.22	0.16	0.92	11.8	0.08
Liaoning	0.8	0.39	1.35	0.6	1.06	0.54	0.5	0.49	0.18	0.91	6.41	0.14
NeiMongol	0.06	0.82	1.37	0.58	0.87	0.6	1.09	0.31	1.43	0.59	2.37	0.32
Ningxia	13.4	0.03	2.71	0.43	2.83	0.28	1.44	0.52	28.8	0.07	15.6	0.06
Qinghai	2.18	0.16	2.18	0.47	6.93	0.13	0.74	0.4	1.61	0.57	1.24	0.49
Shandong	1.84	0.46	0.03	0.99	3.49	0.24	0.34	0.83	9.54	0.2	15.2	0.06
Shanxi	0.11	0.74	1.58	0.56	2.74	0.29	0.94	0.37	24.6	0.08	25.9	0.04
Shaanxi	2.08	0.17	0.24	0.88	0.98	0.56	0.18	0.69	1.5	0.58	6.72	0.13
Shanghai	0.91	0.39	1.97	0.51	1.57	0.43	1.35	0.28	4.34	0.32	1.41	0.46
Sichuan	3.73	0.08	7.78	0.21	21.4	0.05	1.28	0.29	1	0.68	1.7	0.4
Tianjin	1.3	0.27	0.38	0.85	1.43	0.45	2.37	0.17	0.39	0.84	30.9	0.03
Xizang	2.13	0.41	7.25	0.21	1.56	0.43	2.13	0.41	27.6	0.07	208	0.01
Xinjiang	5.24	0.16	0.57	0.77	0.97	0.57	0.9	0.65	2.21	0.5	10	0.09
Yunnan	1.03	0.62	3.68	0.35	14.61	0.07	0.49	0.78	0.55	0.78	1.13	0.52
Zhejiang	0	0.97	0.55	0.79	3.96	0.21	0.68	0.44	146	0.01	95.7	0.01

outcomes indicate that although the test results of all variables cannot reject the original hypothesis of a unit root, the tests for first-order difference variables all reject the original hypothesis of a unit root. Therefore, in the VAR(p + d) model, the maximum order of the variable (d) is 1. After considering structural shifts, the ZA and EL unit test results show that several sample provinces and cities have structural shifts in the analysis interval.

The second step is to analyse the causal relationship by using the VAR model containing three variables. Tables 1, 2, 3, 4, 5, 6, 7 show the results of causality analysis for Toda–Yamamoto (TY) and Fourier Toda–Yamamoto (TY). Before performing causality analysis and reasoning, the significance of the Fourier term in all estimated VAR models was tested with the help of the F test. Nearly one-third of the sample test results rejected the original hypothesis of no Fourier term, thereby highlighting the importance of considering smooth structure transfer in the test.

Table 5 shows the causality between FD and PM. The Toda–Yamamoto test indicates that there is a one-way causality that FD affects PM in Guangxi, Guizhou, Ningxia, and Sichuan and that PM affects FD in Jiangsu. Furthermore, after using the Fourier function to handle

Table 6 Causality test between economic growth (EG) and environmental quality (PM)

Region	HO:EG does not cause PM						HO:PM does not cause EG					
	TY		FTY				TY		FTY			pval
	W	Pboot	W	Pboot	F_F	pval	W	Pboot	W	Pboot	F_F	
Anhui	4.47	0.19	1.94	0.49	1.78	0.39	5.57	0.14	1.3	0.6	17.83	0.05
Beijing	0	0.97	0.82	0.72	11.55	0.08	1.1	0.32	2.9	0.4	1.53	0.43
Chongqing	1.24	0.28	47.5	0.04	34.92	0.03	0.02	0.89	9.6	0.17	19.87	0.05
Fujian	3.22	0.28	0	1	0.38	0.82	2.6	0.33	1.5	0.58	1.96	0.37
Gansu	0.04	0.83	0.02	0.99	0.81	0.62	0.33	0.57	0.8	0.72	4.69	0.18
Guangdong	14.39	0.03	11.9	0.14	30.78	0.03	2.06	0.39	1.3	0.61	1.68	0.41
Guangxi	55.11	0	0.82	0.71	0.41	0.8	0.98	0.63	0.3	0.88	1.41	0.46
Guizhou	7.31	0.09	33.3	0.06	14.59	0.07	0.79	0.7	3.1	0.4	9.39	0.1
Hainan	0.02	0.88	5.84	0.26	17.21	0.06	0.04	0.85	7.6	0.22	8.58	0.11
Hebei	0.03	0.87	5.49	0.27	10.59	0.09	0.7	0.41	6	0.25	4.88	0.18
Henan	0.16	0.69	2.4	0.47	3.85	0.22	0.37	0.56	7.4	0.22	7.88	0.12
Heilongjiang	1.61	0.22	0.55	0.78	4.36	0.2	1.1	0.33	5.3	0.27	4.78	0.18
Hubei	5.15	0.15	0.02	0.9	1.32	0.36	1.67	0.47	0.1	0.84	4.81	0.04
Hunan	0.07	0.81	0.04	0.98	2.32	0.32	0.02	0.88	2.7	0.44	4.66	0.18
Jilin	0.78	0.7	0.76	0.75	2.94	0.27	0.23	0.91	2.6	0.44	3.63	0.23
Jiangsu	2.77	0.13	6.59	0.23	5.77	0.15	0.23	0.66	13	0.14	7.57	0.12
Jiangxi	0.64	0.44	1.38	0.59	0.93	0.58	3.38	0.08	0.1	0.94	2.8	0.28
Liaoning	0.26	0.62	4.66	0.29	1.06	0.54	0.18	0.69	13	0.13	9	0.1
NeiMongol	1.76	0.21	0.62	0.76	0.87	0.6	0.12	0.74	30	0.07	43.34	0.02
Ningxia	1.93	0.43	2.1	0.49	2.83	0.28	0.57	0.76	3.8	0.33	17.07	0.06
Qinghai	0.25	0.62	1.85	0.53	6.93	0.13	0.1	0.76	2.4	0.45	4.77	0.18
Shandong	2.42	0.35	0.54	0.77	3.49	0.24	3.1	0.28	2.4	0.47	9.05	0.1
Shanxi	1.43	0.27	0.51	0.8	2.74	0.29	0	0.99	34	0.05	44.58	0.02
Shaanxi	0.65	0.45	0.25	0.88	0.98	0.56	1.26	0.28	1.2	0.62	0.13	0.96
Shanghai	2.17	0.17	1.96	0.52	1.57	0.43	0.72	0.4	0.3	0.87	1.04	0.55
Sichuan	0.01	0.94	7.22	0.2	21.4	0.05	0.07	0.81	5.3	0.28	7.51	0.12
Tianjin	2.06	0.2	0.77	0.71	1.43	0.45	2.42	0.15	2.2	0.49	1.21	0.5
Xizang	1.55	0.5	2.93	0.4	1.56	0.43	3.81	0.23	9.5	0.18	20.47	0.05
Xinjiang	18.36	0.02	0.82	0.72	0.97	0.57	1.69	0.47	0.4	0.83	2.39	0.32
Yunnan	2.89	0.31	5.39	0.28	14.61	0.07	1.32	0.55	0.3	0.85	1.02	0.55
Zhejiang	3.55	0.08	0.41	0.83	3.96	0.21	0.57	0.46	2.8	0.42	1.02	0.55

structural shifts, a one-way causality that FD affects PM is found in Guizhou, Guangdong, and Hainan, a one-way causality that PM affects FD is found in Ningxia, Tibet, Shanxi, Henan, and Zhejiang, and a two-way causality between FD and PM is found in Chongqing. In general, once the Fourier function is introduced to handle possible structural shifts, a significant relationship between financial development and environmental quality starts to appear in more samples.

Table 6 shows the causality between EG and PM. From the Toda–Yamamoto test, we learn that there is a one-way causality that EG affects PM in Guizhou, Xinjiang, Guangdong, Guangxi, and Zhejiang, and a one-way causality that PM affects EG in Jiangsu. After the introduction of Fourier functions, a one-way causality that EG affects PM is observed in Chongqing and Guizhou, and a one-way causality that PM affects EG in Shanxi and Inner Mongolia.

Table 7 reports the causality between FD and EG. The Toda–Yamamoto test indicates that there is a one-way causality that EG affects FD in Inner Mongolia, Henan, Hebei, Gansu, and Hunan, and a one-way causality that FD affects EG in Tibet, Anhui, and Xinjiang. Following the introduction of the Fourier function, a one-way

Table 7 Causality test between financial development (FD) and environment quality (PM)

Region	HO:EG does not cause FD						HO:FD does not cause EG					
	TY		FTY				TY		FTY			
	W	Pboot	W	Pboot	F_F	pval	W	Pboot	W	Pboot	F_F	pval
Anhui	1	0.63	0.68	0.75	0.82	0.62	10.4	0.05	47.1	0.04	17.8	0.05
Beijing	3.37	0.1	0.32	0.85	0.23	0.9	1.76	0.23	1.6	0.57	1.53	0.43
Chongqing	0.08	0.78	6.81	0.24	30.51	0.03	2.96	0.11	23.5	0.08	19.9	0.05
Fujian	0.51	0.77	0.59	0.78	0.48	0.76	5.06	0.16	2.45	0.46	1.96	0.37
Gansu	3.72	0.09	0.2	0.91	0.49	0.75	0.15	0.7	10.2	0.18	4.69	0.18
Guangdong	0.31	0.86	4.35	0.32	10.43	0.09	7.31	0.1	5.03	0.28	1.68	0.41
Guangxi	1.67	0.48	2.42	0.45	7.99	0.11	0.51	0.78	0.27	0.88	1.41	0.46
Guizhou	1.67	0.5	12.1	0.14	4.33	0.2	2.51	0.35	5.72	0.23	9.39	0.1
Hainan	0.85	0.39	0.64	0.77	0.77	0.63	0.11	0.73	12.3	0.13	8.58	0.11
Hebei	7.12	0.02	0.5	0.79	1.62	0.42	3.06	0.11	14.5	0.13	4.88	0.18
Henan	8.65	0.01	4.14	0.33	4.22	0.2	0.96	0.37	4.59	0.31	7.88	0.12
Heilongjiang	0.62	0.47	5.05	0.28	7.25	0.13	0.24	0.63	4.16	0.31	4.78	0.18
Hubei	2.78	0.33	0.57	0.49	3.17	0.1	4.65	0.18	2.87	0.14	4.81	0.04
Hunan	4.85	0.05	1.11	0.64	2.55	0.3	2.67	0.14	1.43	0.59	4.66	0.18
Jilin	0.91	0.65	0.41	0.83	1.21	0.5	3.69	0.24	9.1	0.17	3.63	0.23
Jiangsu	0.32	0.59	0.96	0.67	4.77	0.18	2.73	0.13	23.5	0.09	7.57	0.12
Jiangxi	2.01	0.19	3.29	0.39	11.75	0.08	2.73	0.13	0.09	0.95	2.8	0.28
Liaoning	0.14	0.72	10.4	0.16	6.41	0.14	0.01	0.91	12	0.19	9	0.1
NeiMongol	7.31	0.02	0.82	0.73	2.37	0.32	0.07	0.8	81.7	0.03	43.3	0.02
Ningxia	2.96	0.3	6.37	0.25	15.61	0.06	2.29	0.39	13	0.14	17.1	0.06
Qinghai	2.01	0.19	0.47	0.81	1.24	0.49	1.5	0.24	2.86	0.4	4.77	0.18
Shandong	2.14	0.41	10.1	0.2	15.23	0.06	4.9	0.15	42.3	0.05	9.05	0.1
Shanxi	1.23	0.3	12.7	0.12	25.93	0.04	0.97	0.36	30.2	0.06	44.6	0.02
Shaanxi	0.93	0.36	1.76	0.55	6.72	0.13	0.48	0.52	0.07	0.97	0.13	0.96
Shanghai	0.26	0.62	0.29	0.89	1.41	0.46	0.88	0.38	0.13	0.94	1.04	0.55
Sichuan	0.52	0.48	2.78	0.4	1.7	0.4	1.42	0.25	8.57	0.19	7.51	0.12
Tianjin	0.51	0.5	16.6	0.11	30.89	0.03	1.37	0.26	0.6	0.76	1.21	0.5
Xizang	0.39	0.81	17.7	0.11	208.1	0.01	10.8	0.05	26.6	0.07	20.5	0.05
Xinjiang	1.38	0.56	2.59	0.42	10.02	0.09	19	0.01	3.39	0.35	2.39	0.32
Yunnan	0.85	0.66	0.01	1	1.13	0.52	3.12	0.26	3.46	0.35	1.02	0.55
Zhejiang	0.01	0.92	5.67	0.28	95.74	0.01	0.39	0.55	2.1	0.48	1.02	0.55

causality that FD affects EG is found in Shanxi, Inner Mongolia, Tibet, Chongqing, Anhui, Shandong, and Jiangsu. It is apparent that after taking into account the structural shifts in the time-series data, the significant impacts of financial development on EG can be observed in more provinces and cities.

Causality between the three is in general found in two-third of the samples. The results of the Toda–Yamamoto test further support the three one-way causal relationships of EG that promote FD, economic growth affecting environmental quality, and FD affecting environmental quality. Three one-way causal relationships are found after introducing Fourier to handle structural shifts: financial development affects EG, environmental quality affects EG, and environmental quality affects FD. One of the most prominent examples of this is Chongqing. In the general Toda–Yamamoto test, the relationship between FD, environmental quality, and EG is not significant. However, after introducing the Fourier function, significant relationships that FD affects EG, EG affects environmental quality, and FD and environmental quality affect each other are found.

The three variables of FD, EG, and environmental quality are quite strongly correlated. As a result, the third

Table 8 Causality test statistics

Region	fd-pm		eg-pm		eg-fd	
	TY	FTY	TY	FTY	TY	FTY
Beijing						
Tianjin						
Hebei					→	
Shanxi		←		←		←
Nei Mongol				←	→	←
Liaoning						
Jilin						
Heilongjiang						
Shanghai						
Jiangsu	←					←
Zhejiang		←	→			
Anhui					←	←
Fujian						
Jiangxi			←			
Shandong						←
Henan		←			→	
Hubei						
Hunan					→	
Guangdong		→	→			
Guangxi	→		→			
Hainan		→				
Chongqing		↔		→		←
Sichuan	→					
Guizhou	→	→	→	→		
Yunnan						
Xizang		←			←	←
Shaanxi						
Gansu					→	
Qinghai						
Ningxia	→	←				
Xinjiang			→		←	

variable often affects the causality test between each pair of them. At the same time, cross-sectional correlation is an important feature of cross-regional analysis, as in the flow of economic factors. A strong interaction thus exists between the EG of different regions. Pesaran (2006) found that the cross-sectional dependence between individual samples should be controlled. He identified that ignoring this will lead to a large number of deviations and scale distortions. The cross-sectional correlation is controlled to test the causality between two variables to further explore the relationship between FD, EG, and environmental quality.

Three causality models, namely FD-PM, GDP-PM, and FD-GDP, were built based on the hypothesis of this

Table 9 Results of cross-section correlation test

	FD-PM		FD-EG		EG-PM	
	statistics	*p*-value	statistics	*p*-value	statistics	*p*-value
LM	1558	0	4756	0	2258	0
CD_{LM}	25.63	0	65.07	0	37.87	0
CD	23.523	0	76.219	0	33.066	0
LM_{adj}	81.73	0	329.7	0	133.1	0

Table 10 Results of panel causality test

Panel A	H0:FD does not cause PM					H0:PM does not cause FD				
	Wald	Bootstrap critical values			*p*-val	Wald	Bootstrap critical values			*p*-val
		10%	5%	1%			10%	5%	1%	
Anhui	0.688	6.469	9.516	16.833	0.722	2.408	5.94	8.723	21.47	0.364
Beijing	0.343	6.399	9.487	18.089	0.848	0.652	6.483	9.266	14.86	0.71
Chongqing	1.099	3.277	5.375	9.698	0.304	3.208	3.252	5.096	8.351	0.102
Fujian	0.513	3.147	5.107	10.549	0.495	1.843	3.278	5.215	10.56	0.202
Gansu	0.402	3.153	4.624	9.03	0.511	0.742	3.37	5.396	9.819	0.401
Guangdong	0.578	3.575	5.326	10.975	0.488	0.53	3.574	5.099	9.879	0.504
Guangxi	0.01	3.502	5.407	10.663	0.924	6.036	3.391	5.207	8.159	0.032
Guizhou	2.094	3.394	4.716	8.353	0.181	0.563	3.774	5.714	11.46	0.47
Hainan	2.436	3.129	4.701	9.921	0.134	0.528	3.338	5.2	8.599	0.47
Hebei	0.324	3.036	5.177	8.867	0.568	0.107	3.702	5.641	10.68	0.757
Henan	17.02	6.13	8.9	18.066	0.013	0.66	6.574	8.911	16.58	0.729
Heilongjiang	2.406	3.632	5.15	9.989	0.164	0.782	3.647	5.449	9.548	0.379
Hubei	1.207	3.126	4.452	8.291	0.299	1.107	3.084	4.773	9.922	0.3
Hunan	1.079	3.119	4.448	9.111	0.301	0.002	3.558	4.66	8.579	0.96
Jilin	3.094	5.949	8.253	17.658	0.28	3.305	6.571	9.566	21.66	0.252
Jiangsu	0.146	3.203	4.528	8.539	0.704	0.069	3.566	4.737	9.694	0.823
Jiangxi	0.666	3.532	5.091	10.608	0.44	3.489	3.212	4.486	9.944	0.09
Liaoning	0.253	3.353	5.267	11.579	0.624	1.425	3.108	4.937	9.563	0.24
NeiMongol	0.899	6.118	9.841	21.334	0.651	9.717	7.294	10.05	21.33	0.053
Ningxia	18.07	6.191	9.455	21.093	0.015	3.035	6.133	9.126	17.48	0.297
Qinghai	0.025	3.154	4.707	9.951	0.874	2.698	3.085	5.253	11.5	0.114
Shandong	2.62	6.804	9.822	18.515	0.358	0.317	6.838	9.717	20.26	0.863
Shanxi	0.547	3.105	5.019	9.217	0.464	0.122	3.483	5.219	8.612	0.718
Shaanxi	4.986	6.321	9.459	17.125	0.164	4.599	6.37	8.613	17.86	0.175
Shanghai	11.65	7.067	10.12	23.174	0.04	5.739	6.216	8.671	18.56	0.12
Sichuan	5.857	3.201	4.611	8.883	0.027	0.075	3.26	5.008	10.04	0.799
Tianjin	0.07	6.705	10.82	19.695	0.975	0.468	6.761	9.816	19.54	0.789
Xizang	0.174	6.677	9.794	21.947	0.926	6.412	6.168	9.025	20.51	0.094
Xinjiang	0.001	3.14	4.879	11.564	0.975	4.352	3.233	4.996	9.427	0.062
Yunnan	0.856	6.729	9.263	16.061	0.662	3.584	6.802	10.03	23.38	0.233
Zhejiang	1.053	6.324	9.681	15.167	0.613	0.696	6.386	9.009	19.81	0.718
Panel B	H0:gdp does not cause FD					H0:FD does not cause gdp				
	Wald	Bootstrap critical values			*p*-val	Wald	Bootstrap critical values			*p*-val
		10%	5%	1%			10%	5%	1%	
Anhui	1.475	6.306	8.821	18.904	0.522	31.54	6.534	8.339	15.8	0.002
Beijing	0.067	6.802	9.899	18.773	0.967	3.499	5.989	8.936	17.88	0.222
Chongqing	1.408	6.505	9.804	17.815	0.541	4.046	6.711	9.366	19.19	0.203
Fujian	0.616	6.419	9.625	18.539	0.735	3.943	6.403	8.794	15.96	0.2
Gansu	0.036	3.146	4.904	9.87	0.836	4.349	3.179	4.669	10.64	0.06
Guangdong	1.913	6.375	9.903	17.962	0.427	34.8	6.252	8.858	19.41	0.002
Guangxi	6.828	6.34	9.29	16.626	0.088	4.71	6.812	9.485	19.27	0.176
Guizhou	4.208	6.279	8.689	14.807	0.182	10.62	6.82	9.941	20.52	0.044
Hainan	0.029	3.07	5.064	10.077	0.884	7.516	3.435	5.44	10.81	0.026
Hebei	0.487	3.098	4.627	11.133	0.501	4.539	3.33	4.815	10.96	0.054
Henan	0.24	3.066	4.469	9.005	0.621	1.872	3.212	4.89	9.736	0.195
Heilongjiang	2.082	6.329	9.232	17.436	0.408	18.72	7.154	9.935	19.87	0.011
Hubei	6.427	6.489	10.05	20.378	0.102	12.7	7.013	10.85	21.9	0.037
Hunan	0.522	3.224	5.351	10.388	0.501	1.634	3.529	5.249	10.68	0.236
Jilin	5.539	6.516	10.18	17.489	0.137	1.569	6.734	9.791	20.78	0.512
Jiangsu	2.451	6.028	9.017	16.612	0.337	10.84	6.963	10.85	24.57	0.051
Jiangxi	0.116	3.448	5.598	11.165	0.748	0.337	3.116	5.261	9.764	0.516

Table 10 (continued)

Liaoning	3.614	6.097	9.592	18.101	0.209	0.129	6.418	9.439	18.33	0.943
NeiMongol	0.422	6.659	8.889	16.568	0.827	0.139	5.9	8.671	17.37	0.952
Ningxia	0.01	3.259	4.941	12.567	0.924	5.692	3.107	4.56	8.708	0.028
Qinghai	0.604	6.573	9.42	19.991	0.742	5.98	6.49	9.104	16.45	0.119
Shandong	0.952	7.072	10.48	20.308	0.641	18.13	7.336	10.53	22.58	0.024
Shanxi	2.948	5.937	9.402	19.17	0.288	0.463	6.313	8.354	15.07	0.782
Shaanxi	1.96	6.888	9.076	20.941	0.435	0.906	5.843	9.132	17.58	0.624
Shanghai	8.54	6.037	8.452	16.064	0.047	2.777	6.524	9.492	17.88	0.286
Sichuan	8.492	6.615	8.909	16.903	0.055	4.901	6.43	9.176	25.42	0.152
Tianjin	0.536	5.598	8.392	16.914	0.764	3.173	6.849	9.99	19.56	0.275
Xizang	1.065	6.844	10.77	21.681	0.585	21.36	6.623	9.764	16.8	0.003
Xinjiang	1.279	6.401	9.007	21.322	0.559	32.29	6.846	9.605	19.67	0.003
Yunnan	5.298	6.346	9.061	18.995	0.127	5.838	6.258	8.757	20.42	0.113
Zhejiang	5.895	6.697	9.645	16.12	0.126	1.157	6.584	9.485	18.13	0.585
Panel C	H0:gdp does not cause PM					H0:PM does not cause gdp				
	Wald	Bootstrap critical values			*p*-val	Wald	Bootstrap critical values			*p*-val
		10%	5%	1%			10%	5%	1%	
Anhui	3.754	6.314	9.674	18.039	0.222	0.153	6.711	10.2	22.89	0.93
Beijing	0	3.179	4.414	8.115	0.992	0.241	3.64	5.401	10.85	0.623
Chongqing	0.59	3.223	4.916	9.89	0.47	0.64	3.297	4.886	9.411	0.464
Fujian	0.056	3.252	4.663	8.137	0.825	0.003	3.21	4.493	9.526	0.964
Gansu	2.163	6.813	9.375	20.262	0.397	1.928	6.313	8.935	17.12	0.436
Guangdong	1.555	6.408	9.113	21.689	0.497	4.809	6.518	9.267	19.2	0.158
Guangxi	1.972	6.483	8.976	16.543	0.419	1.089	6.44	9.811	18.71	0.603
Guizhou	0.278	6.282	9.459	21.418	0.862	8.932	6.105	8.288	17.83	0.047
Hainan	0.584	3.25	4.878	11.492	0.464	1.671	3.01	4.899	10.57	0.202
Hebei	0.266	3.09	4.605	9.013	0.623	1.044	3.269	4.814	9.31	0.332
Henan	0.385	3.231	5.112	8.679	0.55	0.023	3.825	5.83	11.8	0.883
Heilongjiang	0.029	3.407	6.057	11.123	0.873	1.505	3.211	5.213	8.734	0.268
Hubei	2.402	3.291	5.413	11.783	0.153	5.803	3.059	5.1	9.032	0.037
Hunan	5.44	6.275	8.611	17.525	0.133	0.607	6.735	10.5	20.47	0.775
Jilin	1.382	3.557	5.11	11.125	0.273	0.535	3.237	5.111	10.77	0.484
Jiangsu	0.433	2.932	4.735	8.232	0.51	0.006	3.103	4.728	10.94	0.919
Jiangxi	0.003	3.28	4.77	8.327	0.956	4.695	3.388	4.655	10.91	0.05
Liaoning	2.568	6.509	8.975	20.16	0.332	6.304	6.289	9.628	17.51	0.099
NeiMongol	0.387	3.274	5.29	10.198	0.525	0.231	3.615	5.389	9.532	0.661
Ningxia	4.87	6.54	8.934	16.849	0.167	1.535	6.853	10.4	18.57	0.5
Qinghai	0.055	3.27	4.612	9.254	0.835	0.893	3.439	5.009	9.216	0.404
Shandong	5.561	3.391	5.092	9.88	0.041	0.153	3.205	4.468	8.26	0.689
Shanxi	1.702	6.972	9.859	18.746	0.469	1.239	7.271	10.92	24.35	0.557
Shaanxi	8.594	6.832	10.51	23.457	0.069	1.17	6.703	9.691	22.21	0.569
Shanghai	0.642	3.197	4.868	8.944	0.439	0	3.459	4.668	9.204	0.994
Sichuan	2.034	3.638	5.39	11.591	0.19	2.259	3.571	5.598	10.36	0.183
Tianjin	1.037	3.245	4.925	9.684	0.344	12.72	3.324	4.535	8.611	0.002
Xizang	0	3.399	5.077	11.064	0.985	2.755	3.344	5.204	9.984	0.127
Xinjiang	0.775	3.324	5.043	9.617	0.397	0.55	3.436	5.092	9.524	0.482
Yunnan	0.016	3.528	4.995	9.91	0.896	1.542	3.374	5.252	10.42	0.237
Zhejiang	1.323	5.86	9.016	19.895	0.552	5.806	6.387	9.974	16.83	0.121

The optimal combination of lags from 1 to 4 is selected according to the Schwarz-Bayesian criterion to estimate the seemingly uncorrelated regression (SUR) model. Based on the simulation of 10,000 samples, the significant critical values of the parameters at 10%, 5%, and 1% are shown paper for the three indices of per capita GDP, FD, and air quality (PM), respectively, to perform the Granger causality test. The test results of the three models in the cross-section correlation test (Tables 8, 9, 10) all rejected the original hypothesis that the cross-sections are not correlated.

A one-way causality that FD affects PM is found by controlling the cross-sectional correlation (Konya 2006) in Henan, Ningxia, Shanghai, and Sichuan; a one-way causality that PM affects FDG in Guangxi, Jiangxi, Inner Mongolia, Tibet, and Xinjiang; a one-way causality that GDP affects FD in Guangxi, Shanghai and Sichuan; a one-way causality that FD affects GDP in Anhui, Gansu, and other 13 provinces; a one-way causality that GDP affects PM in Shandong and Shaanxi, and a one-way causality that PM affects GDP in Guizhou, Hubei, Jiangxi, Liaoning, and Tianjin. These results are clearly not completely consistent with the results of the Toda–Yamamoto test and the Fourier Toda–Yamamoto test, which suggests a strong cross-sectional correlation between samples and a correlation between variables. However, the results also prove that the multiple causal relationships still exist between FD, EG, and environmental quality. This finding shows the robustness and reliability of the conclusion of previous analysis.

Conclusions and suggestions

This paper used panel data from 31 provinces and municipalities in China for the period 2000–2018 to explore the relationship between financial development and environmental quality. Additionally, the Toda–Yamamoto causality test and Fourier's extended Toda–Yamamoto causality test were used to handle regional differences in financial development and environmental quality changes and the possible structural shifts in time. We found that financial development has a significant influence on environmental quality with regional differences and that the structural shifts over time in some provinces and municipalities have also affected the relationship between financial development and environmental quality. Moreover, the cross-sectional correlation is further controlled to test the key robustness of the causality between the two variables. The results support the above conclusion. These conclusions are an important supplement to studies on the treatment of structural changes and the investigation of regional differences.

Based on the aforementioned conclusions, we believe that China should prioritize the role of financial development in reducing carbon emission. Financial development can not only directly promote the growth of a low-carbon economy but also indirectly drive low-carbon development through channels such as technological innovations. Bank credit should be tilted towards the green economy and low-carbon economy to this end, and greater support should be given to environment-friendly and energy-saving enterprises, facilitating China's economic restructuring and upgrading through financial support and achieving carbon peak and carbon neutralization.

In this study that we focus only on the causal links among FD, PM, and GDP three variables, in fact, there are several variables that might affect PM in our research such as inward FDI (foreign direct investment), technical innovation, regional tree planting acres and government regulation policy, … and so on. This is the limitation of our study and future study can incorporate those variables into the model. Our research model did give us some clear links among FD, PM, and GDP and we believe this model can be used in other region study such as the states of the USA, Latin American countries, African countries, and Asian countries. Future study will be in this direction.

Author contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Yiguo Chen, Peng Luo, Teng Tong, and Jing Wang. The first draft of the manuscript was written by Yiguo Chen and all authors commented on previous versions of the manuscript. Tsangyao Chang revised it critically for important intellectual content. All authors read and approved the final manuscript.

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Data availability The data can be available upon request.

Declarations

Ethics approval and consent to participate We declare that we have no human participants, human data, or human tissues.

Consent for publication N/A.

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