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Financial Agglomeration and Carbon Emissions: Theoretical Analysis and Empirical Evidence from China

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Financial Agglomeration and Carbon Emissions: Theoretical Analysis and Empirical Evidence from China

Xuesong Gu* and Yuhao Qian+

Abstract

This paper establishes a theoretical model to reveal how financial agglomeration influences carbon emission, considering the influence of three driving factors to carbon emission, i.e. urbanization, economic growth and technological progress. Empirically, it quantifies the hypothesis proposed by the theoretical analysis using China's provincial panel data during the year 2005-2016. Our empirical results show that financial agglomeration promotes carbon emissions, but the positive correlation is mitigated by urbanisation, economic growth and technological progress. In addition, as the data of 29 provinces in China are grouped into three regions, it is found that East China generates more carbon emissions as becoming increasingly urbanized and no long-term equilibrium relationship exists between carbon emissions and explanatory variables in West China. These findings can help policymakers in China and other developing countries regulate the development of the financial industry, especially, regarding its agglomeration in response to the aggravating greenhouse gas effects in the globe.

Keywords: Financial agglomeration, Carbon emissions, Urbanization, Economic growth, Technological progress

JEL Classification: Q5

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1. Introduction

Climate change and global warming are the greatest threats to lives and the future on Earth (United Nations Climate Change, 2018). Accumulated carbon emissions from the burning of fossil fuels and other human-induced greenhouse gas emissions exacerbated the global warming (IPCC, 2007). There are apparent climate changes globally, such as the increasing frequency of extreme weather events, changing precipitation patterns, enhancing storm intensity, and a rising sea level. The changes have significantly influenced the operation of ecosystems, the living of wildlife and the welfare of humans.

China became the second largest economy in the world in 2010 and is also the country that produces the highest amount of carbon emissions, creating 26% of the world's carbon emission in 2015 (International Energy Agency, 2018). Following the path of sustainable development, China promised to reach the peak of its carbon emissions no later than 2030, when the ratio of GDP to carbon dioxide emissions should be 60-65% of the figure in 2005 in the Intended Nationally Determined Contribution (INDC) to United Nations Framework Convention on Climate Change (UNFCCC). Therefore, to control the greenhouse gas emissions and to fulfil China's commitment to the international community and human being, it is important to understand the environment-energy-economy nexus. The branch of literature which concerns carbon emissions in China incorporated not only economic growth (Liu et al., 2015; Wang et al., 2015; Alam et al., 2016), urbanisation (Li & Yao, 2009; Wang et al., 2014; Fang, Wang & Li, 2015), technological progress (Feng, Hubacek & Guan, 2009; Yin, Zheng & Chen, 2015), but also financial development (Jalil & Feridun, 2011; Zhang, 2011). Previously, Gu and He (2012) implemented a study on financial development and carbon emissions with provincial data from 1979 to 2008 in China. Their research findings showed that financial agglomeration has a mixed effect on carbon emissions, as financial agglomeration would offset carbon emissions reduction if it could not stimulate financial growth. However, what is exactly the mixed effect? How does financial agglomeration reduce carbon emissions in developing countries? This paper tries to address these issues.

2. Literature Review

STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model is widely employed in studying drivers of carbon emissions. Based on IPAT identity which does not allow for non-monotonic or non-proportional effects from driving factors, Dietz and Rosa (1994) redeveloped IPAT into STIRPAT to construct a stochastic model. STIRPAT not only is an accounting equation as IPAT but also can be utilised in empirical analyses. Besides, since it allows alteration and transformation of variables (York, Rosa & Dietz, 2003), STIRPAT is commonly used to evaluate both linear and non-linear relationships between carbon emissions and its driving factors, among which the most extensively studied are urbanization (Dai & Liu, 2011; Shahbaz, Chaudhary & Ozturk, 2017), economic growth (Xu et al., 2016; Yeh & Liao, 2017) , technological progress (Li et al., 2017).

Financial agglomeration's promoting effects on contributing factors to carbon emission, namely urbanization, economic growth, and technological progress, have been extensively studied. First, financial agglomeration effectively promoted urbanization. Some related studies verified the existence of Environmental Kuznets Curve (EKC) hypothesis (Martínez-Zarzoso & Maruotti, 2011; Wang et al., 2015; Xu, Dong & Yang, 2018) and a number of other studies found a positive association between urbanization and carbon emission over countries of different economic levels (Al-mulali et al., 2012; Liddle, 2015; Li & Lin, 2015; Dogan & Seker, 2016; Wang, Chen & Kubota, 2016; Wu et al., 2016). Second, financial agglomeration was conducive to economic growth (Zhang & Cheng, 2009). The non-linear relationship between economic growth and carbon emission, namely, the environmental Kuznets curve (EKC), has been discovered by many researchers (Ahmad et al., 2016; Gill, Viswanathan & Hassan, 2018; Li, Zhang & Ma, 2015; Ulucak & Bilgili, 2018). Third, financial agglomeration stimulates technological progress by optimizing the regional financial industry layout, gathering and overflowing the capital, and dispersing the appropriate financial investment risk (Huang et al., 2015). Technical impact on carbon emission is a well-researched topic as well. Adopting the extended STIRPAT model (Yang et al., 2018), Malmquist CO2 emission performance index (MCPI) (Zhou, Ang & Han, 2010), and environmental Kuznets curve theory (Yin, Zheng & Chen, 2015), research showed that the carbon emissions performance of countries as a whole is improved by technological progress. Acemoglu et al. (2012), considering environmental constraints and limited resources, divided inputs into two sectors which are "dirty" and "clean" machines, and found that it is optimal to redirect technological progress to clean technologies immediately.

Given the existing literature, we find two issues to be addressed. Firstly, although some scholars noted the complexity of the relationship between financial agglomeration and carbon emission, no theoretical attempt has been made to study the influential mechanisms of financial agglomeration on carbon emission. Secondly, despite many studies on the relationships between financial agglomeration and driving factors to carbon emission, there is no empirical research revealing the impact mechanism of financial agglomeration on carbon emission from the aspect of drivers to carbon emission.

The contributions of this paper are twofold. First, we establish a theoretical model in the field of environmental economics. The STIRPAT model is expanded by including financial agglomeration, the interactions of financial agglomeration and urbanization, the interaction of financial agglomeration and technological progress, and the interaction of financial agglomeration and economic growth into the model. Second, although a few papers dealt with the nexus of financial agglomeration and carbon emission, none has studied the complex mechanism empirically. To test the existence of the relationship between financial agglomeration and carbon emission and analyse the complex relationship, we employ the cross-section fixed effects model, following the co-integration indicated in panel cointegration tests and panel vector error correction models.

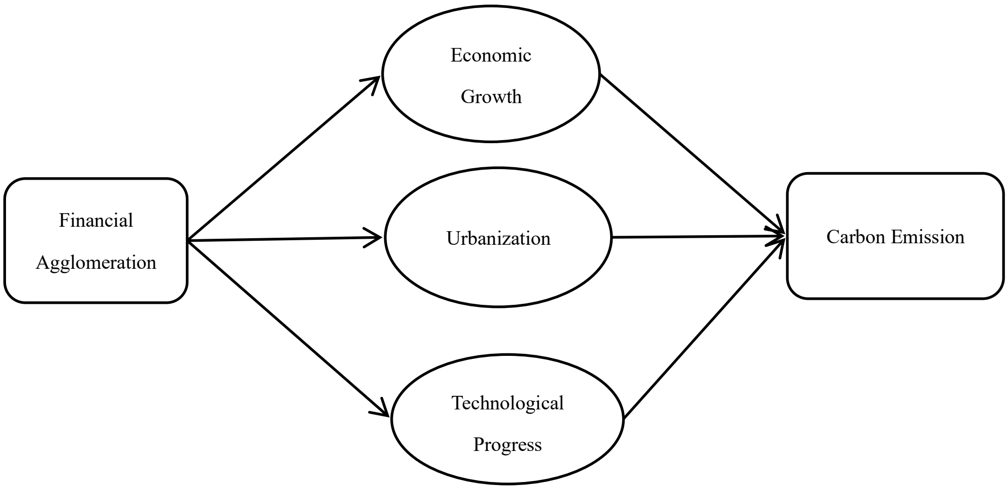
The rest of the paper is organised as follows. Section 3 focuses on the methodology and model. Section 4 carries out an empirical study and demonstrates the main findings, and Section 5 is a discussion. Finally, Section 6 concludes the article.

3. Research Methods and Data Sources

3.1 Theoretical Model and Related Assumptions

Following Yuan et al. (2019), this paper defines financial agglomeration as the optimization and reorganization of financial industry along with its related industries, giving rise to the establishment of capital, information, innovation and market centers in a specific region through the flow of elements. According to the above literature review, this paper argues that financial agglomeration affects carbon emissions through economic growth, urbanization and technological progress. The development of financial agglomeration promotes concentration of capital, which directly finance the growth of the real economy. The concentration of resources that is brought about by financial agglomeration attracts workers to relocate to local areas. The percentage of workers living in urban areas grows, and urbanization is improved. High-tech industry is known for high capital intensity, flows of information and levels of innovation. Capital, information and innovation centers in a specific region because of financial agglomeration.

Figure 1: Relationship diagram of financial agglomeration and carbon emission



As we can see from Figure 1, financial agglomeration reduces carbon emission indirectly through economic growth, urbanization and technological progress. Based on the Kuznets curve theory, carbon emission drops as the economy grows after a threshold. Technological progress, especially in the environmental area, improves the carbon emission performance. Urbanization reduces the area of vegetation and increases energy consumption. Urbanization causes increases in carbon emission. Following assumptions are made in the paper:

- Hypothesis I: Financial agglomeration reduces carbon emission. The reduction effect is mitigated by urbanization.
- Hypothesis II: Financial agglomeration reduces carbon emission. The reduction effect is enhanced by technological progress.
- Hypothesis III: Financial agglomeration reduces carbon emission. The reduction effect is enhanced by economic growth.

3.2 Constructing the Model

The Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, derived from Influence, Population, Affluence, and Technology (IPAT) model (Dietz & Rosa, 1994), is widely used to describe the effects of human activities on the environment. The environmental impact (I) is anatomised into three main contributing factors: population size (P), affluence (A) and the environmentally-inefficient technology level or the impact per unit of economic activity (T). STIRPAT model can be shown as the following equation:

$$I_{it} = \alpha_i P_{it}^b A_{it}^c T_{it}^d e_{it} \tag{15}$$

In this model, the parameter α is the constant term, and b, c and d are parameters of P, A and T respectively. The variable e represents the random error term. The subscript i ($i = 1, 2, \ldots, T$) refers to time periods. By taking the logarithms form of both sides of Eq.15, this paper estimates the new equation in a linear specification.

$$ln\, I_{it} = ln\alpha_i + blnP_{it} + clnA_{it} + dlnT_{it} + e_{it} \tag{16}$$

Among studies that expanded the STIRPAT model, the research of Xiong and Qi (2018) and Khan, Saleem & Fatima (2018) incorporated the financial sector's influence on carbon emission into the STIRPAT framework. In this paper, to explore financial agglomeration's influential mechanisms on carbon emissions, we add interactions into the models:

Model I:

$$ln(C_{it}) = \delta + \delta_1\, ln(F_{it}) \cdot \ln(\theta_{it}) + \delta_2\, ln(F_{it}) \cdot \ln(Y_{it}) + \delta_3\, ln(F_{it}) \cdot \ln(T_{it}) + \delta_4 \ln(F_{it}) + \delta_5 \ln(\theta_{it}) + \delta_6\, ln(Y_{it}) + \delta_7\, ln(T_{it}) + \delta_8 \ln(P_{it}) + \delta_9 M_{it} + \mu_{it} + \xi_{it} \tag{17}$$

where C_{it} means carbon emissions in economy i during period t, F_{it} means financial agglomeration in economy i during period t, θ_{it} means urbanization in economy i during period t, Y_{it} means economic growth in economy i during period t, T_{it} means technological progress in economy i during period t, $ln(F_{it}) \cdot \ln(\theta_{it})$ means the interaction of financial agglomeration and urbanization, $ln(F_{it}) \cdot \ln(Y_{it})$ means the interaction of financial agglomeration and economic growth, $ln(F_{it}) \cdot \ln(T_{it})$ means the interaction of financial agglomeration and technological progress, M_{it} means other macroeconomic variables influencing carbon emissions, α, β, and γ are constants, μ_{it} is fixed effects or random effects, and ξ_{it} is the stochastic error.

Furthermore, to improve the stability of the empirical results, three models incorporating, respectively, the interaction of financial agglomeration and urbanization, the interaction of financial agglomeration and economic growth, as well as the interaction of financial agglomeration and technological progress are given as follows.

Model II:

$$ln(C_{it}) = \alpha + \alpha_1\, ln(F_{it}) \cdot \ln(\theta_{it}) + \alpha_2 \ln(F_{it}) + \alpha_3 \ln(\theta_{it}) + \delta_8 \ln(P_{it}) + \alpha_6 M_{it} + \mu_{it} + \xi_{it}$$
(18)

Model III:

$ln(C_{it}) = \beta + \beta_1\, ln(F_{it}) \cdot \ln(Y_{it}) + \beta_2 \ln(F_{it}) + \beta_3 \ln(Y_{it}) + \delta_8 \ln(P_{it}) + \beta_6 M_{it} + \mu_{it} + \xi_{it}$
(19)

<u>Model IV:</u>
$ln(C_{it}) = \gamma + \gamma_1\, ln(F_{it}) \cdot \ln(T_{it}) + \gamma_2 \ln(F_{it}) + \gamma_3 \ln(T_{it}) + \delta_8 \ln(P_{it}) + \gamma_6 M_{it} + \mu_{it} + \xi_{it}$
(20)

3.3 Variables

Under the STIRPAT framework, we use total carbon emission as the dependent variable to denote total environmental impact (I) (Sadorsky, 2014; Salim & Shafiei, 2014; Zhang, Yu & Chen, 2017).

The independent variables are selected not only for their commonness in literature and the availability of data, but also based on the STIRPAT framework. Since according to our theoretical analysis financial agglomeration is predicted to decrease carbon emission via urbanization (θ), which is denoted as the ratio of urban population to total population in our paper, we measure the impact of demographic factors with urbanization. Affluence is defined as GDP per capita (Y). Following Ramanathan (2000), Hu & Wang (2006), and Wu et al. (2017), we adopt DEA-based Malmquist productivity index to evaluate energy efficiency, which measures technological progress in the STIRPAT model (Fan et al., 2006; Rafiq, Salim & Nielsen, 2016; Lin et al., 2017; Shahbaz, Chaudhary & Ozturk, 2017). In this paper, we measure the level of financial agglomeration with location entropy in the 29 provinces in China (Jiacheng, Yujie & Nan, 2018). Location entropy measures the distribution of specific factors in a region, reflecting the specialized level of a specific industry. The formula is $LQ_{ij} = (q_{ij}/q_i)/(q_{kj}/q_k)$ where q_{ij} means j industry's output value, quantity or other related indicators in i region and is measured by the added value of the financial industry in i region in this paper; q_j means the related indicators of all industries in i region and is measured by GDP in i region, q_{kj} means j industry's output value, quantity or other related indicators in all the regions studied and is measured by the added value of the financial industry in China, q_k means the related indicators of all industries in all the regions studied and is measured by GDP in China. The description of these variables is listed in Table 1.

Table 1: Description of variables

	Symbol	Variable	Definition
Dependent variable	CO_2	total carbon emission	carbon emissions from fossil fuels
Explanatory variables	F	financial agglomeration	location entropy of the financial industry
	θ	urbanization	the share of the urban population in the total population
	Y	economic growth	GDP per capita at 2005 constant price
	T	technological progress	DEA-based Malmquist productivity index

Note: Data sources, China Statistical Yearbooks, the 29 studied provinces' Statistical Yearbooks.

3.4 Descriptive Statistics

Because of too much missing data in Tibet and Qinghai Province, we drop the two provinces in our empirical study. The paper acquires a panel dataset of 29 provinces (Appendix A) from 2005 to 2016 according to data accessibility. This paper investigates the influential mechanisms and then proposes policy suggestions for China and other developing countries. The summary statistics of variables are shown in Table 2.

The correlation matrix for dependent and independent variables is presented in Table 3. It is shown that correlation coefficients between $ln\ (CO_2)$ and explanatory variables and between explanatory variables are all well below 0.7 except for those between interactions and between interactions and their interacting variables. In addition, all variance inflation factors (VIF) are smaller than 5. It is not very likely for there to be multicollinearity in our models.

Table 2: Descriptive statistics of variables

Variable	Mean	Std. Dev.	Max	Min
$ln\ (CO_2)$	1.068	0.729	11.565	7.370
$ln\ (F)$	-0.113	0.423	1.284	-1.659
$ln\ (\theta)$	-0.676	0.258	-0.110	-1.314
$ln\ (Y)$	9.701	0.465	10.849	8.528
$ln\ (T)$	0.112	0.059	0.141	-0.159
$ln\ (F) \cdot ln\ (\theta)$	0.137	0.244	1.050	-0.392
$ln\ (F) \cdot ln\ (Y)$	-0.993	4.246	13.775	-15.885
$ln\ (F) \cdot ln\ (T)$	-0.002	0.024	0.092	-0.123

Note: All the variables are taken in the logarithm form.

Table 3: Correlation matrix

Variable	$ln\ (CO_2)$	$ln\ (F)$	$ln\ (\theta)$	$ln\ (Y)$	$ln\ (T)$	$ln\ (F) \cdot ln\ (\theta)$	$ln\ (F) \cdot ln\ (Y)$	$ln\ (F) \cdot ln\ (T)$
$ln\ (CO_2)$	1							
$ln\ (F)$	-0.205	1						
$ln\ (\theta)$	0.017	0.554	1					
$ln\ (Y)$	0.144	0.551	0.912	1				
$ln\ (T)$	0.001	-0.035	-0.062	-0.057	1			
$ln\ (P)$	0.684	-0.309	-0.220	-0.096	0.044			
$ln\ (F) \cdot ln\ (\theta)$	0.081	-0.879	-0.444	-0.392	0.027	1		
$ln\ (F) \cdot ln\ (Y)$	-0.220	0.999	0.562	0.561	-0.035	-0.856	1	
$ln\ (F) \cdot ln\ (T)$	-0.006	0.131	0.081	0.076	-0.291	-0.149	0.128	1.000
VIF	—	1.04	1.00	1.02	1.00	1.01	1.05	1.00

4. Results and discussion

The primary objective of our empirical analysis is to test and specify the long-term equilibrium relationship between carbon emissions and explanatory variables in China. Our analysis includes four steps which are panel unit root tests, panel cointegration tests, and panel data models. The empirical results are shown as follows.

4.1 Panel unit root tests

To identify the stationary properties of relevant variables, panel unit root tests must be implemented first in panel data analysis. We adopt two panel unit root tests, namely, Levin. Lin & Chu (LLC) test and Im. Pesaran and Shin W (IPS) test to enhance the robustness of the results. The LLC test considers the heterogeneity of various sections but is not fairly effective for small samples due to ineliminable serial correlations. By contrast, the IPS test not only considers heterogeneity among sections but also eliminates serial correlations, therefore having a strong ability to test small samples. The null hypothesis of the aforementioned two panel unit root tests is that there exist unit roots, and the alternative hypothesis is that no unit root exists in the series.

Table 4 shows the results of the panel unit root tests for each variable. It can be seen that the first differences of all variables are statistically significant under LLC and IPS test. It is reasonable to assume that all the variables in first difference form are stationary. Therefore, we believe that each variable is integrated of order one, i.e. $I(1)$.

Table 4: Results of panel unit root tests

Variable	LLC test		IPS test	
	Level	1st difference	Level	1st difference
$ln\ (CO_2)$	-9.381 ***	-7.863 ***	-3.785 ***	-3.278 ***
$ln\ (F)$	-7.370 ***	-10.064 ***	-1.954 **	-6.446 ***
$ln\ (\theta)$	-5.124 ***	-9.237 ***	2.763	-5.656 ***
$ln\ (Y)$	-7.657 ***	-9.616 ***	-2.336 ***	-4.432 ***
$ln\ (T)$	-14.594 ***	-16.111 ***	-7.755 ***	-9.302 ***
$ln\ (F) \cdot ln\ (\theta)$	-5.978 ***	-9.949 ***	0.989	-6.610 ***
$ln\ (F) \cdot ln\ (Y)$	-8.282 ***	-11.206 ***	-2.478 ***	-6.715 ***
$ln\ (F) \cdot ln\ (T)$	-13.512 ***	-16.395 ***	-7.267 ***	-9.514 ***

Note: LLC test: Levin, Lin and Chu test. IPS test: Im, Pesaran and Shin test. The null hypotheses of LLC test and IPS test are unit root. *, ** and *** represents significance at the 10%, 5% and 1% level respectively.

4.2 Panel cointegration tests

Based on the results that all variables were cointegrated of order one, we examine the cointegration relationship among variables of interest as a next step. Three panel cointegration tests are commonly used in the panel cointegration analysis: the Johansen, Kao, and Pedroni tests. Combined with former studies, the Kao test is utilised to estimate the long-run relationship between carbon dioxide emissions and explanatory variables.

There is a cointegration relationship under the null hypothesis but no cointegration relationship under the alternative hypothesis. This paper primarily draws conclusions on the Kao Panel Cointegration Test statistics (shown in Table 5) that the nullity of non-cointegration of the variables is rejected at the 10% significance level. It can be seen from Table 5 that the panel statistics for China reject the null hypothesis of no cointegration.

Table 5: Kao Panel Cointegration Test

	Whole China	East China	Middle China	West China
$\ln(F)$	-1.923 **	-2.211 **	-2.397 ***	-0.429
$\ln(\theta)$	-2.504***	-2.951 ***	0.083	-0.747
$\ln(Y)$	-0.390 *	-1.341 **	-1.447 *	0.243
$\ln(T)$	-1.953 **	-2.290 **	-1.338 *	-0.447
$\ln(F) \cdot \ln(\theta)$	-2.609 **	-3.099 ***	-1.905 **	-0.960
$\ln(F) \cdot \ln(Y)$	-1.282 *	-2.440 ***	-1.430 *	0.071
$\ln(F) \cdot \ln(T)$	-2.476 ***	-2.838 ***	-1.655 **	-0.587

Note: *, ** and *** represents significant at the 10%, 5% and 1% level respectively. The null hypothesis is no cointegration for panel data. N = 319.

4.3 Panel vector error correction models

Following Pesaran (1990) a panel vector error correction model is estimated to infer the causal dynamics:

$$\begin{aligned}\Delta \ln(X)_{it} = \xi_{Xj} &+ \sum_{k=1}^{q} \alpha_{X1ik} \Delta \ln(CO_2)_{it-k} + \sum_{k=1}^{q} \alpha_{X2ik} \Delta \ln(F)_{it-k} \\ &+ \sum_{k=1}^{q} \alpha_{X3ik} \Delta \ln(\theta)_{it-k} + \sum_{k=1}^{q} \alpha_{X4ik} \Delta \ln(Y)_{it-k} \\ &+ \sum_{k=1}^{q} \alpha_{X5ik} \Delta \ln(T)_{it-k} + \sum_{k=1}^{q} \alpha_{X6ik} \Delta \ln(F)_{it-k} \cdot \ln(\theta))_{it-k} \\ &+ \sum_{k=1}^{q} \alpha_{X7ik} \Delta \ln(F)_{it-k} \cdot \ln(Y)_{it-k} + \sum_{k=1}^{q} \alpha_{X8ik} \Delta \ln(F)_{it-k} \cdot \ln(Y)_{it-k} \\ &+ \lambda_{Xi} \varepsilon_{Xt-1} + u_{Xit}, \\ X &= \{CO_2, F, \theta, Y, T\} \qquad (21)\end{aligned}$$

$$
\begin{aligned}
\Delta\, ln(F)_{it} \cdot l\,n(Z) \\
&= \xi_{Zj} + \sum_{k=1}^{q} \alpha_{Z1ik} \Delta \ln\, (CO_2)_{it-k} + \sum_{k=1}^{q} \alpha_{Z2ik} \Delta \ln\, (F)_{it-k} \\
&+ \sum_{k=1}^{q} \alpha_{Z3ik} \Delta \ln\, (\theta)_{it-k} + \sum_{k=1}^{q} \alpha_{Z4ik} \Delta \ln\, (Y)_{it-k} \\
&+ \sum_{k=1}^{q} \alpha_{Z5ik} \Delta \ln (T)_{it-k} + \sum_{k=1}^{q} \alpha_{Z6ik} \Delta \ln\, (F)_{it-k} \cdot \ln(\theta)_{it-k} \\
&+ \sum_{k=1}^{q} \alpha_{Z7ik} \Delta \ln\, (F)_{it-k} \cdot \ln(Y)_{it-k} + \sum_{k=1}^{q} \alpha_{Z8ik} \Delta \ln\, (F)_{it-k} \cdot \ln(Y)_{it-k} \\
&+ \lambda_{Zi} \varepsilon_{Zt-1} + u_{Zit} \\
& \qquad Z = \{ F, \theta, Y, T \} \qquad (22)
\end{aligned}
$$

where Δ means the first-difference operator; k means the lag length based on likelihood ratio tests; ε means the error correction term; λ means the error correction parameters and u means the serially uncorrelated error term. Short-term causality is decided by the statistical significance of the partial F-statistics for the corresponding right-hand side variables.

Table 6 reports the estimation for the error correction parameters, as this paper only aims to test the null hypothesis of no cointegration in panel data. In China, financial agglomeration responds to deviations from long-run equilibrium, adjusting towards the long-run equilibrium. Thus, financial agglomeration promotes carbon emission both in the short and long term. Also, there are adjustments towards the long-term equilibrium in the interaction of financial agglomeration and urbanization, the interaction of financial agglomeration and economic growth and the interaction of financial agglomeration and technological progress. In other words, in the short and long run, urbanization, economic growth and technological progress generate a negative influence of financial agglomeration on carbon emission.

Table 6: Panel vector error correction model

	Whole China	East China	Middle China	West China
$\Delta ln\ (F)$	-0.524***	-0.511***	-0.595**	0.213
$\Delta ln\ (\theta)$	-0.591***	-0.55***	-0.422	1.080
$\Delta ln\ (Y)$	-0.318***	-0.416***	-0.185	-0.311
$\Delta ln\ (T)$	-0.495***	-0.540***	-0.496**	-0.023
$\Delta ln\ (F) \cdot ln\ (\theta)$	-0.553***	-0.580***	-0.608**	-0.681
$\Delta ln\ (F) \cdot ln\ (Y)$	-0.414***	-0.455***	-0.256	0.447

$\Delta ln\ (F) \cdot ln\ (T)$	-0.486***	-0.410***	-0.483**	-0.208

Note: The table reports the estimation of the error correction parameters λ in Eq.21 and Eq.22, as we only aim to test the null hypothesis of no cointegration in the panel data. * (**) (***): Significant at the 10 (5) (1) % level.

4.4 Panel data models

Confirmed by results from the unit root tests and the cointegration tests that there will be no spurious regression, this paper calculates the F-statistics and implements the Hausman test. The results of Hausman tests reject the null hypothesis of random effect. Therefore, we adopt a panel fixed effects model to estimate the effects of financial agglomeration on carbon emissions. The fixed effect μ_i captures the observed and unobserved characteristics of provinces in China, such as infrastructure development (Démurger, 2001), income levels (Xie & Zhou, 2014), resource endowment, geographical features, culture and population sizes (Tian et al., 2017). The empirical results are reported in Table 7, which presents the results of the whole China.

According to Table 7, financial agglomeration positively increases carbon emissions when controlling for other factors in China, with positive coefficients insignificant in Models I and III. The results are consistent with those in previous studies, showing that China's financial agglomeration acts as a driver for carbon emission increase (Gu & He, 2012). The agglomeration of the financial industry attracts sufficiently many market participants which are necessary for the success of emerging economics, such as China. When influences of other factors (technological progress, urbanization and economic growth) are excluded from the analysis, the rising number of market participants induces carbon emission (Gehrig, 2000).

Urbanization enhanced financial agglomeration's impetus on carbon emissions in the whole China. The result rejects Hypothesis I, with the interaction coefficients of financial agglomeration and urbanization exceeding those of financial agglomeration and significant at 0.05 level in Model I and Model II. According to Poumanyvong and Kaneko (2010), urbanization increases energy use and thereby carbon emission in middle income countries, such as China, and its positive impacts on carbon emission are the most pronounced in the middle-income group among all the other income groups.

Economic growth impedes financial agglomeration's positive influence on carbon emissions in China. The result completely accepts Hypothesis II. The interaction coefficient of financial agglomeration and economic growth is negative and statistically significant at 0.1 and 0.05 level. According to Ma and Stern (2008), China's economic development has surpassed the turning point from 2005 to 2016 in the Environmental Kuznets Curve (EKC). The findings agree with our empirical results. As China becomes increasingly industrialized, the economy has been transforming from being energy-intensive to being knowledge-intensive.

The empirical results about influence of technological progress on the relationship between financial agglomeration and carbon emissions partly accept Hypothesis III in Model I and Model IV, the coefficients for financial agglomeration are positive with t-statistics significant at the 0.05 level, while the interaction coefficients of financial agglomeration and technological progress are negative but insignificant in China. The result shows that, although unstably, technological progress lessens the positive influence of financial agglomeration on carbon emissions. The instability might be caused by the heterogeneity of technological progress's influence on carbon emissions. Technological progress in industries with high energy efficiency curbs carbon emissions, but that in industries with low energy efficiency produces the greenhouse gas (Li & Lin, 2016).

Table 7: Panel fixed effects model

	Variable	Model I	Model II	Model III	Model IV
		Coefficient	Coefficient	Coefficient	Coefficient
China	$ln\ (F)$	0.086	0.351***	0.029	0.267**
	$ln\ (F) \cdot ln\ (\theta)$	1.344***	0.483**	—	—
	$ln\ (F) \cdot ln\ (Y)$	-0.691***	—	-0.204*	—
	$ln\ (F) \cdot ln\ (T)$	-0.103	—	—	-0.531
	Hausman test	54.300***	20.632***	40.035	7.650*
	R^2	0.972	0.9655	0.9619	0.9135
East China	$ln\ (F)$	0.190*	0.149	-0.237	0.371
	$ln\ (F) \cdot ln\ (\theta)$	1.968***	-0.094	—	—
	$ln\ (F) \cdot ln\ (Y)$	-0.924***	—	-0.525***	—
	$ln\ (F) \cdot ln\ (T)$	-0.031	—	—	-0.293
	Hausman test	24.618***	8.805**	13.072***	18.336***
	R^2	0.994	0.989	0.983	0.963
Middle	$ln\ (F)$	-4.875***	0.510***	-0.749***	0.552***

China	$ln\,(F) \cdot ln\,(\theta)$	-4.811**	--0.790***	—	—
	$ln\,(F) \cdot ln\,(Y)$	-0.518	—	-0.782***	—
	$ln\,(F) \cdot ln\,(T)$	0.850	—	—	-0.262
	Hausman test	—	8.592**	6.482**	9.388***
	R^2	0.965	0.955	0.958	0.910
	$ln\,(F)$	-1.120	-0.895	0.760***	-0.264
	$ln\,(F) \cdot ln\,(\theta)$	-0.500	-0.710	—	
West China	$ln\,(F) \cdot ln\,(Y)$	-0.363	—	0.610***	
	$ln\,(F) \cdot ln\,(T)$	0.112	—	—	-0.923
	Hausman test	7.627	15.189***	36.668***	0.126
	R^2	0.284	0.212	-0.030	0.560

Note: The table presents the estimates of Model I (Eq.17), Model II (Eq.18), Model III (Eq.19), Model IV (Eq.20) via the panel fixed effects model. This paper cannot perform Hausman test on the Model III in Middle China, as the number of explanatory variables exceeds that of sections and therefore random effect regression cannot be estimated. *, ** and *** represents significant at the 10%, 5% and 1% level respectively.

4.5 A Regional Analysis

Considering the levels of economic development and location factors and following the example of most existing studies, we divide these provinces into three groups: East China, Middle China, and West China. East China is constituted of 14 provinces that are most economically developed and advantageously located in China. There are 9 provinces in West China, which are on the lowest level of economic development and have the least advantaged location conditions in China. The degrees of economic development and location conditions in the 6 provinces of Middle China are between those of East China and West China.

No long-term relationship exists between carbon emission and explanatory variables in West China. In the Kao Panel Cointegration Test, the statistics for West China accept the alternative hypothesis, i.e. there are no cointegration relationships between carbon emissions and explanatory variables. The results may indicate that West China and developing countries with backward location conditions and far less advanced economies should give priority to financial agglomeration, urbanization, economic growth and technological progress, since they may not increase carbon emissions or endanger the environment.

In Middle China, urbanization induces a negative influence of financial agglomeration on carbon emission. It appears that the interaction of financial agglomeration and economic growth is not responsive to adjustments towards long-run equilibrium, indicated by the statistically insignificant error correction term in the panel vector error correction model. In the cross-section fixed effect model, the interaction coefficient of financial agglomeration and urbanization is negative and statistically significant at the 0.05 level while the coefficient of financial agglomeration is positive and statistically significant at the 0.05 level in Model II. In comparison, the enhancement of urbanization on financial agglomeration's impetus on carbon emission in the whole China, urbanization generates a mitigating effect on the positive influence of financial agglomeration on carbon emission in Middle China, accepting hypothesis I. The result may be attributed to the lower income level in Middle China than the average level in the whole China. Urbanization decreases carbon emission in the low-income group (Poumanyvong & Kaneko, 2010).

In East China, explanatory variables are correlated with carbon emission with larger coefficients and higher statistical significance than those in the whole China. The interaction coefficients of financial agglomeration and economic growth are greater and more statistically significant than those of the whole China. As the region with the highest average income among the three regions in China, East China passes through the turning point of carbon emission regarding economic growth on the EKC to a greater extent than other regions in China and the whole China. Also, the interaction coefficient of financial agglomeration and urbanization (1.968) surpasses that of the whole China (1.344) in Model I. The region's high levels of the second industry output value of high energy consumption, built-up area, average vehicle ownership and population density are responsible for the stimulus of urbanization on the positive influence of financial agglomeration on carbon emission.

5. Conclusion and policy implications

This paper deals with the relationship of financial agglomeration and carbon emissions by conducting both theoretical and empirical analysis. Via the expanded STIRPAT model incorporating financial agglomeration, the interaction of financial agglomeration and urbanization, the interaction of financial agglomeration and economic growth and the interaction of financial agglomeration and technological progress, we attain the theoretical results that support the following hypotheses: urbanization generates a negative influence of financial agglomeration on carbon emission; economic growth creates a mitigating effect of financial agglomeration on carbon emission; technological progress induces a reducing impact of financial agglomeration on carbon emission. In the empirical analysis, the unit root tests demonstrate that all variables are integrated of order one, following which Kao panel cointegration tests and panel vector error correction models confirm long-term equilibrium relationships between carbon emissions and explanatory variables. Then, upon processing the provincial panel data of 29 provinces over the period of 2005-2016 via cross-section fixed effects models, the empirical results accept the hypotheses.

The empirical results indicate that financial agglomeration is positively correlated with carbon emissions in China. The empirical results reject Hypothesis I. The interaction coefficients of financial agglomeration and urbanization are greater than the coefficient of financial agglomeration in the whole China. Hypothesis II is accepted by the empirical results. The interaction coefficients of financial agglomeration and economic growth are significantly negative, while the coefficients of financial agglomeration are positive in total sample of China. The empirical results partly accept Hypothesis III. Although the coefficients of technological progress are all negative, they are statistically insignificant. In the regional analysis, in West China there is no long-term cointegration relationship between carbon emission and explanatory variables (financial agglomeration, the interaction of financial agglomeration and urbanization, the interaction of financial agglomeration and economic growth, and the interaction of financial agglomeration and technological progress). In Middle China, Hypothesis I is accepted. The interaction of financial agglomeration and economic growth is negatively correlated with carbon emission. In East China, the coefficients are larger and more statistically significant than that of the whole China in the cross-section fixed effect model. Urbanization promotes the positive influence of financial agglomeration on carbon emission more considerably. Economic growth, greater than the turning point on the EKC to a larger extent, generate a negative effect of financial agglomeration on carbon emission more significantly.

Based on the results of the study, the following policy implications must be pursued in order to improve the environment in China and can be referred to by other developing countries. First, according to the result that urbanization promotes the positive influence of financial agglomeration on carbon emission. Policymakers should direct the agglomerated financial resources to the development of environmentally friendly means of transportation, such as hybrid and electric vehicles. The government should make use of the knowledge spillover brought about by financial agglomeration to create the smart city environment to monitor and control the environmental impacts of carbon emission. Second, to tackle the unstable negative effect of financial agglomeration on carbon emission induced by technological progress, climate finance should be paid more attention to. This will alter the current situation where industries with high and low energy efficiency are supported evenly by channelling more financial resources to more competitive eco-friendly projects as financial agglomeration increases the competition on the capital market. Third, while East China shows a similar pattern in the relationships between carbon emission and financial agglomeration to a more considerable and significant level than the whole China, there is no long-term relationship between them in West China. The degrees of financial agglomeration, urbanization, economic growth and technological progress are significantly lower in West China than other regions in China. To mitigate the regional imbalance, policymakers should encourage urban population to relocate from East China to West China, so as to assuage the negative influence of too densely populated urban areas in East China and to channel human capital to the development of West China.

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Appendix A

Table A1: List of China's Provinces

Beijing	Tianjin	Hebei	Shanxi	Neimeng	Liaoning
Jilin	Heilongjiang	Shanghai	Jiangsu	Zhejiang	Anhui
Fujian	Jiangxi	Shandong	Henan	Hubei	Guangdong
Guangxi	Hainan	Chongqing	Sichuan	Guizhou	Yunnan
Shaanxi	Gansu	Ningxia	Xinjiang	Hong Kong	Macao
Taiwan					