TECHMIND RESEARCH
ISSN: 2292-1648

International Journal of Management Excellence
Volume 16 No.3 April 2021

The impact of green fiscal policy on green technology investment: Evidence from China

Prince Asare Vitenu-Sackey[1*], Stephen Oppong[2] & Isaac Akpemah Bathuure[3]
School of Finance and Economics[1,3]/School of Management[2], Jiangsu University, No 301 Xuefu Road, Zhenjiang, 212013, Jiangsu Province, P. R. China
pavsackey@gmail.com[1]
[*]Corresponding author

Abstract - *Our objective is to investigate the impact of green fiscal policy on green technology investment in China. We employed some econometric techniques as our strategy for the empirical analysis. We used a quantile regression with the lad method in our long-run estimations. The results suggest that green fiscal policy has a heterogeneous impact on green technology investment total factor productivity considering the kind of proxy and magnitude of the coefficients. However, we observed that environmental tax as a proxy measure of green fiscal policy positively impacts green technology investment total factor productivity while environmental expenditure negatively does. Our findings imply that when green technology investment total factor productivity is on the ascendency, increasing the existing energy consumption structure could decrease green technology investment total factor productivity. In other words, provinces with a higher level of green technology investment total factor productivity should ensure a reduction in their existing energy consumption structure to promote green technology investment. Also, we conclude that green technology investment progress is opposed by increasing research and development, gross domestic product, and existing energy consumption structure through environmental expenditure. To sustain green technology investment progress, environmental taxes be increased substantially to deter polluters by adopting green technologies.*

Jel Classification: *C50, H20, O39, Q58*

Keywords: *Green technology investment; Green technology total factor productivity; Green technology efficiency; Green fiscal policy; Environmental tax and expenditure*

1. INTRODUCTION

In pursuit of green economic development, numerous countries have cultivated various policies characterized by domestic strategies. Notably, the renewable energy sector development through investments has achieved great stride in the war against greenhouse gas emissions in recent times (Chang et al., 2019)[5]. Efforts channeled toward reducing greenhouse gas emissions stem from the backdrop of achieving sustainable development "green economy" (He et al., 2019)[15]. A green economy reflects high environmental quality through environmental protection from high non-renewable energy demands – from an ecological perspective. Also, a green economy reflects stabilizing growth and adjusting economic structure in the process of development. Ultimately, a green economy has low pollution, low emissions, and low energy consumption (He et al., 2019)[15].

Recently, many developed countries have earmarked funds in pursuit of a green economy. The United States of America enacted an act in 2009 dubbed the "recovery and reinvestment act" – the act saw the birth of a US$ 5 billion from which US$1.4 billion was appropriated for green investment – specifically renewable energy investment (He et al., 2019)[16]. More so, in 2013, the European Union also provided 10.5 billion Euros for green technology investments in the region. In the same spirit, Japan aimed to reduce carbon emissions and strategize with different initiatives (Gu & Shi, 2012)[14]. The Chinese government devised numerous strategies, such as the 12th and 13th Five-Year plan to achieve economic and social development. Invariably, achieving green economic growth is one of the Chinese government's priorities through initiatives in new energy industries – photovoltaic and wind power, etc.

One of the challenges surrounding the implementation of green investment is financing. This menace stalls the implementation of transformational green policies. But for China, some initiatives have been rolled out to resolve the financial constraints, such as green credit provided by financial institutions. Meanwhile, it is still considered low since they are in the early stages – even though some green technology investments have been embarked through this initiative (Zeng et al., 2014)[56]. Globally, the renewable energy sectors (green technology) have received swift investment growth targeted at reducing

greenhouse gas emissions. Notably, the Chinese government has devised several green fiscal policies in the quest to increase green technology investments. Some of these green fiscal policies are tax rebates and subsidies - towards renewable energy investment promotions (Chang et al., 2019)[5]. Many investors in China have gained interest in green technology investments due to stringent environmental regulations, fiscal incentive policies, and investment sentiment improvement. In that regard, China has witnessed a significant increase in its renewable energy investment market (green technology). Moreover, enormous economic benefits have cropped up from it, championing the country as a global green technology investment leader (Zeng et al., 2018)[55].
Several empirical studies have illustrated that tax incentives and subsidy policies stimulate green technology investment from the macro context in applying different techniques. A score of studies contends that the availability of funds, higher investment, market stability, and subsidy levels inform the decision processes for green technology adoption (Zhang et al., 2016[57]; Zhang et al., 2017[58]; Li et al., 2018[29]; Ozorhon et al., 2018[36]; Yang et al., 2018)[50]. Other scholars contend that capacity consolidation, low-carbon energy technology progress and integration, legislative development, and feed-in tariffs promote green technology investments (Kim et al., 2015[25]; Kim et al., 2017[26]; Liu et al., 2016[30]; Punda et al., 2017[38]; Conrad & Nøstbakken, 2018[7]; Liang et al., 2019)[28]. Consequently, overheating and free riding of green technology investment subsidies could hinder its efficiency (Instefjord et al., 2016)[22]. According to Mundaca (2017)[33], reducing fossil fuel subsidies could propagate higher employment levels, leading to higher economic gross domestic product per capita. That notwithstanding, in China, the introduction of the green car subsidy initiative has contributed tremendously to the efforts to curb carbon emissions and also lead to the development of the green technology industry (new energy vehicle industry) (Li et al., 2018)[29]. In attracting more foreign direct investment in the green technology industrial sector market, efficiency is eminent based on tax reduction and investment subsidies (Tian, 2018)[46]. Swift development in the fuel cell and solar photovoltaic industries in the United States can be attributed to investment tax credits (Comello & Reichelstein, 2016)[8]. Also, the acceleration in renewable energy capacity and green technology investments are reliant on diversified incentive policies – such as market-based instruments, financial and fiscal incentives, and other support policies (Liu et al., 2019)[31].
Green technology investment efficiency is driven by several micro essential factors for energy production industries. By reducing the responsiveness of investment, most firms are cautious about high energy price uncertainty (Yoon & Ratti, 2011)[51] – because when the prices of energy surges, it negatively investments of manufacturing industries (Sadath & Acharya, 2015)[41]. Economic value differences in green technology industries are determined by rents from market power and capital adjustment in countries like Mexico, the USA, Brazil, and Germany (Dockner et al., 2013[11]; Salas-Fumás et al., 2016[42]; Niesten et al., 2018)[35]. Conversely, industry-specific characteristics and macroeconomic conditions influence green technology investment efficiency (Zeng et al., 2018[55]; Uz, 2018)[48]. Green technology investment volatility stems from public policy uncertainty – thereby, reducing uncertainty is a critical aspect of a green technology investment policy's effectiveness (Barradale, 2010)[2]. In that context, political connections and government subsidies produce an insignificant impact on green technology industries' financial performance (Zhang et al., 2014; Zhang et al., 2015). In essence, investment subsidies channeled toward SMEs potentially promote employment generation, industrial investment, and productivity (Decramer & Vanormelingen, 2016)[10]. More importantly, governments' subsidies stimulate green technology industries to embark on research and development (Neisten et al., 2018[35], Cosconati & Sembenelli, 2016[9]; Yu et al., 2016[52]; Sim, 2018)[43]. In effect, these subsidies ensure the mitigation of carbon emission and reduction in non-renewable energy consumption (Yuyin & Jinxi, 2018)[53]. Carbon taxes and energy taxes are policy instruments that effectively promote green technology investments (Stucki & Woerter, 2016[44]; Zhao et al., 2019)[61]. On the other hand, feed-in tariffs and tradable green certificates could impact green technology industries' income surplus (Jaraitė & Kažukauskas, 2013). In furtherance, Finley et al. (2014)[12], Rao (2016)[40], Álvarez Ayuso et al. (2018)[1], and Chang et al. (2018) suggest that research and development tax credit positively increases research and development expenditure and increases output and knowledge spillover (Finley et al., 2014[12]; Rao, 2016[40]; Álvarez Ayuso et al., 2018[1]; Chang et al., 2018[4]; Hong & Lee, 2016[18]; Neicu et al., 2016[34]; Freitas et al., 2017)[13]. However, Yang et al. (2018)[50] and Rammer et al. (2017)[39] argued that in China, Germany, Austria, and Switzerland, the adoption and development of green technologies could be hindered by subsidy and tax regulation and policies standard, which may affect green technology industries' international competitiveness. Conventionally, green technology adoption, financial channels, imperfect government policies, and investment shortages are the major setbacks of the BRICS countries (Brazil, Russia, India, China, and South Africa) (Hochman & Timilsina, 2017[17]; Zeng et al., 2017)[54].
In recent studies, He et al. (2019)[16] studied 150 renewable energy companies listed on the Chinese stock market in pursuit to understand the non-linear relationship

between green finance (green credit) and green economic development. Their study focused on renewable energy investment and assessed the threshold effects of green credit. In their conclusion, they contended that increasing environmental expenditure to control pollution by adjusting the industry structure could lead to green economic development. Moreover, they understand that green credit affects green economic development in three-folds – promoting successfully, promoting, and restraining. In another study, Chang et al. (2019)[5] opined that green fiscal policies positively and significantly impact green technology investment efficiency (renewable energy technology investment) supported by Wei and Jinglin (2019)[49]. Increasing tax rebates and government subsidies lead to increased total green investment efficiency and pure technical efficiency in China. They further contended that between 2010 and 2017, China's overall green technology investment efficiency galloped and dwindled concurrently but scale efficiency and increased tremendously.

In view of previous studies, the nexus of green fiscal policy and green technology investment has not been studied on the macro-level. In contrast, He et al. (2019)[15] studied the micro-level using a panel threshold regression method. Other studies like Chang et al. (2019)[5] focused on green investment and green economic development using the data envelopment analysis method. Also, He et al. (2019)[16] applied the Richardson model to understand green finance's impact on renewable energy investment through bank credit insurance. Wei and Jinglin (2019)[49] utilized the generalized method of moment (GMM) to evaluate the extent to which environmental fiscal policy affects green credit acquisition. However, we intend to delve into the role of green fiscal policy in green technology investment on the macro-level considering 30 provinces in China. Moreover, we tend to apply the non-linear econometric technique; thus, the quantile regression method to fish out the non-linear relationship between green fiscal policy and green technology investment in China. We present fresh evidence in a quantile approach and disaggregate green technology investment into three dimensions: green technology total factor productivity, the overall investment index, green technology investment progress, and green technology investment efficiency.

We have structured our study as (1) introduction, (2) empirical strategy, (3) empirical finding and discussion, and (4) conclusion.

2. EMPIRICAL STRATEGY

Our objective is to investigate the impact of green fiscal policy on green technology investment in China; therefore, we employed some econometric techniques as our strategy for the empirical analysis. In that regard, we utilized the following techniques:

2.1 Unit Root Test

We performed unit root tests to unravel our data series's stationarity status, particularly the study's selected variables. In the technique, we expect our variables to be stationary at 5% significance levels or less to reject the unit root's null hypothesis, which suggests that evidence of unit root in the variables. If the variables are non-stationary, perhaps further estimations would produce spurious coefficients and invalid outcomes. To ensure stationarity among the variables, we utilized the methods of Levin et al. (2002)[27], Maddala and Wu (1999)[32], and Im et al. (2003)[21].

2.2 Cross-Sectional Dependence Test

We tend to check for cross-sectional dependency among the variables after evidence of no unit root has been substantiated. Cross-sectional dependence suggests that the error terms of the variables have a cross-sectional correlation with the individual panels. Therefore, we used Pesaran (2004)[37] cross-sectional dependence test. At 5% or less significance levels, we expect to reject the assumption that the variables have cross-sectional independence.

2.3 Cointegration Test

At this stage, we tend to check the long-run equilibrium or long-run relationship between the endogenous and exogenous variables. We then use the Kao (1999) cointegration test to perform that function. To reject the null hypothesis that the variables are not cointegrated, we then expect coefficients with significance equal to or less than 5%.

2.4 Correlation Matrix

The correlation matrix reveals two statistical functions; thus, multicollinearity and correlation coefficients. We used the correlation matrix most importantly for checking the presence of multicollinearity in our proposed model. Because it brings about the problem of heteroskedasticity producing invalid coefficients and probabilities. On the other hand, the correlation matrix exhibits the correlation coefficients and signs between the endogenous and exogenous variables. According to Sun et al. (2002)[45], exogenous variables with a correlation coefficient greater than -/+0.70 are assumed to be highly correlated to the endogenous variable. Hence, the problem of multicollinearity could exist in the proposed model.

2.5 Long-Run Estimations With Quantile Regression With A Lad

We relied on the quantile regression with a lad method because we believe it provides a better outcome than the ordinary least square method. The ordinary least square method uses the exogenous variables' average effect on the endogenous variable in a linear model. Meanwhile, the quantile regression method has two advantages over the ordinary least square method. Firstly, the quantile regression estimations' outcome has robust outcomes to the outliers (Buchinsky, 1994). Secondly, according to Coad and Rao (2011)[6], the entire conditional distribution of the endogenous variables can be explained by the quantile regression. However, we assume that the slope parameters differ at various quantiles in the distribution, and at all points of the conditional distribution – the error terms are not identically distributed.

The econometric model of the quantile regression method was developed by Koenker (2005)[20] and Koenker and Bassett (1978)[19] and is as follows:

$$y_{it} = x_{it}\beta_0 + \mu_{\theta it} \; with \; Quant_\theta \; (y_{it}/x_{it}) = x_{it}\beta_0 \quad (1)$$

In equation (1), y represents the endogenous variable, x is a vector of the endogenous variables, β represents the vector of coefficients or parameters to be estimated, $Quant_\theta \; (y_{it}/x_{it})$ represents the Θ^{th} conditional quantile of the endogenous variable (y) given (x) the endogenous variables, μ represents a vector of the residuals.

However, we incorporate our variables into equation (1) above for our empirical analysis. Hence, the empirical model is as follows:

$$(GTI)_{it} = (GFP)_{it}\beta_0 + \mu_{\theta it} \; with \; Quant_\theta \; (GTI_{it}/GFP_{it}) = GFP_{it}\beta_0 \quad (2)$$

In equation (2), GTI represents green technology investment with proxy measures of green total factor productivity (GTFP), green technology investment progress (GEP), and green technology investment efficiency (GEC). GFP represents green fiscal policy with proxy measures of ETAX and EEXP representing environment tax and expenditure as green fiscal policy, i represents the cross-section of 30 provinces, and t represents the study period from 2007 to 2017.

2.6 Variable Description

2.6.1 Endogenous variable

Green Total Factor Productivity GTFP. The input indicators are labor, material capital stock, and energy input. The expected output is GDP, and the undesired output is urban industrial wastewater discharge and sulfur dioxide emissions. The labor force is measured by the sum of employment in urban units and the number of employees in individual and private units. The stock of physical capital is calculated based on social fixed asset investment data using the perpetual inventory method, and GDP is processed on a fixed basis. Use the global reference SBM-ML index to measure green total factor productivity as ML represents the growth rate of green total factor productivity and the growth rate of GTFP represented by the ML index; the index is processed based on 2007.

2.6.2 Green fiscal policy

EEXP is the ratio of fiscal environmental protection expenditure to general fiscal expenditure. This article draws on Wei and Jinglin (2019) practice as they used the proportion of local fiscal, environmental protection expenditure in the regional GDP as the measurement index of EEXP. TAX is tax revenue, which is measured as the proportion of tax revenue with the effect of energy-saving and emission reduction in total tax revenue. Refer to the practice of Zhang Lei and Jiang Yi , and take the proportion of local fiscal domestic value-added tax to local fiscal tax revenue as the proportion of TAX Measure index.

Other control variables: Based on the research of existing scholars, the control variables selected in this article include:

The level of economic development (GDP). GDP per capita indicator is used to reflect various regions' economic development levels. The environmental Kuznets curve hypothesis believes that an "inverted U" relationship between economic development and environmental quality. In the early stage of economic development, the development model is relatively extensive, economic development is more dependent on resource consumption, and environmental costs are high. After the development to a certain stage and the "turning point," as the economy grows, environmental pollution changes from high to low, and environmental quality is improved.

Research and experimental development (R&D) expenditures: the actual expenditures of basic research, applied research, and experimental development in the whole society. It is generally believed that increasing R&D can effectively improve resource utilization efficiency, promote technological progress, and improve pollution control. , Saving governance costs is an important factor in promoting green total factor productivity.

Environmental control (ER): We selected the investment in industrial pollution source treatment to represent the intensity of environmental control. The "Porter Hypothesis" proposes that environmental regulation can effectively promote enterprises' technological innovation improvement and transformation capabilities. When environmental regulation is strengthened, high-polluting enterprises may take the initiative to reduce emissions or withdraw from the market because they cannot meet regulatory requirements. On the other hand, enterprises that may adapt to a new intensity of control may spend additional capital investment, which will increase management costs, and affect technological innovation. Nonetheless, they may pass on external costs by raising prices. Environmental regulations will significantly reduce the effect of improving green productivity and inhibit green total factor productivity.

This article selects panel data of 30 provinces (except Tibet) in Mainland China from 2007 to 2017. The relevant data are from the "China Statistical Yearbook," "China Financial Yearbook," "China Environment

Statistical Yearbook," regional statistical yearbooks, and national statistics. Bureau official website.

3. FINDINGS AND DISCUSSION

3.1 Descriptive statistics

Table 1 presents the descriptive statistics of the variables. We observed from the outcome in table 1 that our data series is not normally distributed. Moreover, we can report mean values of 0.998 for GTFP (standard deviation = 0.0530, 1.010 for GEP (standard deviation = 0.049), 0.988 for GEC (standard deviation = 0.035), 0.201 for ETAX (standard deviation = 0.088), 0.007 for EEXP (standard deviation = 0.005), 21.259 for ER (standard deviation = 19.906), 10.492 for LNGDP (standard deviation = 0.606), 4.839 for LNR_D (standard deviation = 1.623), and 0.601 for ECS (standard deviation = 0.168). So far, ER depicted the highest mean value and standard deviation; thus, 21.259 and 19.906, respectively. This implies that some provinces have stringent environmental regulation policies than others considering the minimum and maximum values of environmental regulation (ER).
In other words, we can report that China's economic growth has been on the backdrop of minimal environmental expenditure backed by stringent environmental regulation policies. Moreover, the descriptive statistics suggest that increased research and development has promoted green technology investment progress and efficiency through environmental tax increment.

Table 1 Descriptive statistics

	GTFP	GEP	GEC	ETAX	EEXP	ER	LNGDP	LNR_D	ECS
Mean	0.998	1.010	0.988	0.201	0.007	21.259	10.492	4.839	0.601
Median	0.994	1.006	0.992	0.173	0.006	15.050	10.523	4.986	0.627
Maximum	1.515	1.450	1.437	0.495	0.036	141.600	12.908	7.759	0.881
Minimum	0.652	0.652	0.688	0.059	0.001	0.400	8.816	-0.756	0.062
Std. Dev.	0.053	0.049	0.035	0.088	0.005	19.906	0.606	1.623	0.168
Skewness	4.700	3.681	4.244	1.348	2.306	2.376	-0.038	-0.660	-0.632
Kurtosis	54.760	49.418	98.728	4.265	10.481	10.866	3.202	3.304	3.238
Jarque-Bera	38053.220	30372.040	126992.200	121.914	1062.048	1161.088	0.642	25.235	22.774
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.725	0.000	0.000
Observations	330	330	330	330	330	330	330	330	330

3.2 Unit Root and Cross-Sectional Dependence Test

The results of the unit root tests and cross-sectional dependence test are presented in Tables 2 and 3. The outcome of the unit root tests suggests that our variables are stationary. Specifically, at 1% and 5% significance levels at the first difference, we reject a unit root's null hypothesis. Moreover, there is evidence of cross-sectional dependence in the variables. In particular, at a 1% significance level, all the variables exhibited cross-sectional dependency.

3.3 Cointegration Test

The results of the Kao cointegration test performed can be found in Table 3. The outcome confirms a long-run relationship between the endogenous and the exogenous variables. Specifically, at a 1% significance level, we reject the null hypothesis of cointegration.

3.4 Correlation Matrix

The correlation matrix outcome is exhibited in table 4. We observed no multicollinearity issue in our model – because no exogenous variable has a coefficient equal to /+0.70 or more with the endogenous variable. However, we observed a positive and significant correlation between ETAX, LNR_D, LNGDP, and GTFP. Meanwhile, ECS, ER, EEXP, and GTFP showed negative correlations, but EEXP and ER are insignificant. On the other hand, GEP and ETAX are positively and significantly correlated, while ECS and GEP are negatively and significantly correlated. In contrast, LNGDP and LNR_D positively and significantly correlate to GEC.

	GTFP	GEP	GEC	ETAX	EEXP	ER	LNGDP	LNR_D	ECS
Level									
LLC	-5.587***	-7.910***	-9.662***	16.076	-5.327***	-5.139***	-43.186***	-8.459***	0.997
IPS	-3.876***	-4.866***	-6.114***	5.982	-3.370***	-2.609**	-15.367***	-1.696**	5.503
ADF	106.883***	116.564***	130.537***	16.280	114.386***	86.616**	220.263***	63.984	27.964
PP	100.196***	128.568***	138.930***	5.399	118.855***	76.283	58.554	60.884	33.359
First difference									
LLC	-15.828***	-20.476***	-18.225***	-13.131***	-16.548***	-13.820***	-6.312***	-32.105***	-15.199***
IPS	-9.787***	-12.364***	-10.898***	-10.617**	-9.411***	-8.347***	-6.247***	-16.073***	-8.665***
ADF	218.458***	255.140***	223.635***	205.729***	205.624***	189.416***	157.722***	332.805***	187.809***
PP	242.165***	260.694***	331.439***	211.630***	243.783***	219.489***	196.647***	544.452***	227.470***
Pesaran CD	30.275***	49.528***	15.235***	64.201***	18.057***	23.115***	65.739***	68.158***	13.911***

Table 2 Unit root test and Cross-sectional dependence tests

Note: *** indicates 1% significance level, ** indicates 5% significance level

Table 3 Kao cointegration test

Kao Residual Cointegration Test					
			t-Statistic	Prob.	Sig.
ADF			-16.600	0.000	***

Note: *** indicate 1% significance level

Table 4 Correlation matrix

Correlation									
Probability	GTFP	GEP	GEC	ETAX	EEXP	ER	LNGDP	LNR_D	ECS
GTFP	1								
GEP	0.689***	1							
GEC	0.512***	-0.262***	1						
ETAX	0.188***	0.139**	0.088	1					
EEXP	-0.078	-0.059	-0.047	0.106*	1				
ER	-0.001	-0.059	0.069	0.097*	-0.317***	1			
LNGDP	0.150**	0.035	0.185***	0.114**	-0.238***	0.291***	1		
LNR_D	0.132**	-0.023	0.235***	0.103*	-0.523***	0.457***	0.643***	1	
ECS	-0.158**	-0.135**	-0.064	0.033	0.078	0.120**	-0.381***	-0.192***	1

Note: *** indicate 1% significance level, ** indicate 5% significance level. * indicate 10% significance level

3.5 Quantile Regression Estimations

In our long-run estimations, we first investigated the impact of green fiscal policy on green technology investment (total factor productivity) as the overall index measure. The outcome of the quantile regression in that regard can be found in Table 5. The results suggest that green fiscal policy has a heterogeneous impact on green technology investment total factor productivity considering the kind of proxy and magnitude of the coefficients. However, we observed that environmental tax as a proxy measure of green fiscal policy positively and significantly impacts green technology investment total factor productivity. Specifically, environmental tax showed a positive relationship with green technology investment total factor productivity from the 20th quantile to the 90th quantile. Conversely, a percentage point increase in environmental tax could lead to increase in green technology investment total factor productivity by 0.055%, 0.066%, 0.074%, 0.072%, 0.078%, 0.079%, 0.110%, and 0.094% at a 1% significance level, correspondingly. On the contrary, we observed that environmental expenditure negatively and significantly associated with green technology investment total factor productivity – in particular, from 10th quantile to the 80th quantile. Specifically, a percentage point increase in environmental expenditure could lead to a decrease in green technology investment total factor productivity by 1.730%, 0.963%, 0.878%, 1.025%, 0.964%, 0.829%, 0.535%, and 0.653% at 1% and 5% significance levels, correspondingly. We observed a significant environmental regulation influence, but the coefficients were near zero considering the relationship between green fiscal policy and green technology investment total factor productivity.

Meanwhile, the gross domestic product showed a positive and significant relationship with green technology investment total factor productivity only in the 90th quantile. In contrast, research and development showed positive and significance in the 30th and 40th quantiles. Furthermore, we observed a negative and significant relationship between energy consumption structure and green technology investment total factor productivity from the 50th quantile to the 90th quantile. This implies that when green technology investment total factor productivity is on the ascendency, increasing the existing energy consumption structure could decrease green technology investment total factor productivity. In other words, provinces with a higher level of green technology investment total factor productivity should ensure a reduction in their existing energy consumption structure to promote green technology investment.

Subsequently, we disaggregated green technology investment total factor productivity into two; thus, green technology investment progress and green technology investment efficiency. The outcome of the quantile regression estimations for the two proxies can be found in Tables 6 and 7. We observed from our findings that from the 10th quantile to 90th quantile, environmental tax and expenditure showed a significant relationship with green technology investment progress – just that environmental tax is positive and environmental expenditure is negative. Similar to environmental expenditure results, we also observed a negative relationship between gross domestic product, research and development, energy consumption structure, and green technology investment progress. Specifically, research and development showed significant relationships from the 10th quantile to the 90th quantile. The gross domestic product showed significant relationships from the 10th quantile to the 30th quantile, and the energy consumption structure showed significant relationships from the 40th quantile to the 90th quantile. The findings imply that green technology investment progress is opposed by increasing research and development, gross domestic product, and existing energy consumption structure through environmental expenditure. Moreover, to sustain green technology investment progress, provinces should increase environmental taxes substantially to deter polluters by adopting green technologies.

In an account of green technology investment efficiency, we observed that environmental tax negatively and significantly impact green technology investment efficiency in the 10th and 20th quantiles but positively and significantly impact green investment efficiency in the 80th and 90th quantiles. In contrast, environmental expenditure positively and significantly impact green technology investment efficiency only in the 30th quantile. On the other hand, energy consumption structure and gross domestic product positively and significantly impact green technology investment efficiency only in the 10th quantile. Research and development positively and significantly impact green technology investment efficiency from the 10th quantile and the 90th quantile. These findings imply that to promote green technology investment efficiency, research and development are eminent and prioritized.

To robustly confirm our findings' outcome, we performed some post-estimation diagnostic tests such as the wald test to check the slope equality in the quantiles, and Ramsey reset test to ascertain the models' stability. Moreover, to confirm the non-linearity of the model. The outcome of these tests can be found in tables 8 and 9. We observed that our models were statistically fit for inference from the results of the diagnostic tests performed. Specifically, the Ramsey Reset test confirmed that our model was non-linear; hence quantile regression method was appropriate for the estimation. Furthermore, the wald tests confirm that the quantiles' slopes were equal by showing chi-square statistics with probabilities less than 0.05 (5%).

Table 5 Quantile estimations for green technology investment – total factor productivity

GTFP	10th	20th	30th	40th	50th	60th	70th	80th	90th
ETAX	0.038	0.055	0.066	0.074	0.072	0.078	0.079	0.110	0.094
	(1.594)	(3.824)***	(5.551)***	(6.452)***	(6.015)***	(6.517)***	(6.408)***	(6.821)***	(3.485)***
EEXP	-1.730	-0.963	-0.878	-1.025	-0.964	-0.829	-0.535	-0.653	0.575
	(-3.487)***	(-3.225)***	(-3.530)***	(-4.309)***	(-3.885)***	(-3.325)***	(-2.098)**	(-1.947)**	(1.026)
ER	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-1.964)**	(-1.904)**	(-1.867)*	(-2.808)**	(-2.802)**	(-2.920)**	(-2.130)**	(-2.588)**	(-2.045)**
LNGDP	-0.005	-0.003	-0.003	-0.001	-0.002	-0.003	-0.001	0.002	0.009
	(-1.003)	(-1.008)	(-1.324)	(-0.270)	(-0.709)	(-1.127)	(-0.356)	(0.636)	(1.702)*
LNR_D	0.000	0.001	0.002	0.002	0.001	0.001	0.000	0.000	0.001
	(0.202)	(1.005)	(2.267)**	(1.816)*	(0.863)	(0.881)	(0.270)	(-0.300)	(0.570)
ECS	0.022	-0.005	-0.008	-0.004	-0.012	-0.013	-0.015	-0.016	-0.044
	(1.609)	(-0.593)	(-1.136)	(-0.690)	(-1.743)*	(-1.903)*	(-2.098)**	(-1.741)*	(-2.857)**
C	1.016	1.009	1.009	0.988	1.011	1.023	1.009	0.985	0.927
	(21.045)***	(34.704)***	(41.685)***	(42.640)***	(41.852)***	(42.152)***	(40.630)***	(30.151)***	(16.991)***
Pseudo R^2	0.421	0.412	0.456	0.489	0.425	0.416	0.498	0.51	0.523

Note: *** indicate 1% significance level, ** indicates 5% significance level,* indicates 10% significance level

Table 6 Quantile estimations for green technology investment progress

GTP	10th	20th	30th	40th	50th	60th	70th	80th	90th
ETAX	0.077	0.070	0.062	0.072	0.071	0.079	0.095	0.106	0.083
	(6.587)***	(6.749)***	(6.489)***	(7.293)***	(7.006)***	(7.891)***	(8.669)***	(7.111)***	(3.782)***

EEXP	-1.152	-1.068	-1.098	-1.135	-1.179	-1.378	-1.562	-1.519	-1.966
	(-4.731)***	(-4.970)***	(-5.507)***	(-5.524)***	(-5.617)***	(-6.635)***	(-6.850)***	(-4.921)***	(-4.303)***
ER	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.382)	(0.609)	(0.179)	(0.758)	(0.582)	(0.098)	(0.549)	(-0.580)	(-0.620)
LNGDP	-0.007	-0.005	-0.004	-0.003	-0.002	-0.002	-0.001	0.001	0.007
	(-2.913)**	(-2.555)**	(-2.138)**	(-1.611)	(-0.883)	(-0.918)	(-0.372)	(0.285)	(1.562)
LNR_D	-0.004	-0.004	-0.004	-0.005	-0.005	-0.006	-0.006	-0.006	-0.009
	(-3.810)***	(-4.763)***	(-4.585)***	(-5.544)***	(-6.207)***	(-6.906)***	(-7.081)***	(-5.284)***	(-5.069)***
ECS	0.008	-0.007	-0.008	-0.014	-0.017	-0.027	-0.033	-0.043	-0.084
	(1.267)	(-1.195)	(-1.507)	(-2.504)**	(-2.982)**	(-4.745)***	(-5.264)***	(-5.099)***	(-6.687)***
C	1.068	1.068	1.060	1.059	1.054	1.066	1.064	1.057	1.052
	(45.047)***	(51.044)***	(54.622)***	(52.957)***	(51.565)***	(52.727)***	(47.896)***	(36.172)***	(23.648)***
Pseudo R^2	0.563	0.596	0.623	0.421	0.496	0.426	0.496	0.514	0.632

Note: *** indicate 1% significance level, ** indicates 5% significance level,* indicates 10% significance level

Table 7 Quantile estimations for green technology investment efficiency

GTE	10th	20th	30th	40th	50th	60th	70th	80th	90th
ETAX	-0.071	-0.046	-0.011	0.000	-0.004	-0.001	0.012	0.027	0.033
	(-4.895)***	(-3.556)***	(-0.951)	(-0.023)	(-0.337)	(-0.144)	(1.260)	(2.977)**	(2.698)**
EEXP	0.080	0.104	0.170	0.068	0.159	0.197	-0.068	-0.115	-0.286
	(0.264)	(0.388)	(0.714)*	(0.315)	(0.733)	(0.957)	(-0.340)	(-0.605)	(-1.114)
ER	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-3.140)**	(-1.885)*	(-2.563)**	(-3.270)***	(-3.449)***	(-3.410)***	(-3.219)***	(-2.325)**	(-2.603)**
LNGDP	0.007	0.002	0.000	0.000	0.002	0.002	0.001	0.001	0.001
	(2.324)**	(0.803)	(0.015)	(0.117)	(1.152)	(0.805)	(0.749)	(0.685)	(0.360)
LNR_D	0.009	0.008	0.007	0.006	0.005	0.004	0.003	0.002	0.002
	(7.686)***	(7.557)***	(7.322)***	(7.014)***	(5.854)***	(4.435)***	(3.197)**	(2.225)**	(2.299)**
ECS	0.015	0.001	0.003	0.006	0.006	0.004	0.007	0.001	0.009
	(1.808)*	(0.196)	(0.419)	(1.075)	(1.020)	(0.714)	(1.356)	(0.275)	(1.221)
C	0.863	0.926	0.951	0.954	0.940	0.959	0.966	0.975	0.978
	(29.299)***	(35.651)***	(40.925)***	(45.325)***	(44.441)***	(47.848)***	(49.963)***	(52.615)***	(39.039)***
Pseudo R^2	0.569	0.632	0.569	0.456	0.536	0.623	0.548	0.632	0.652

Note: *** indicate 1% significance level, ** indicates 5% significance level,* indicates 10% significance level

Table 8 Ramsey reset test

	Ramsey RESET Test	Value	Probability
Model 1	QLR L-statistic	0.893	0.345
	QLR Lambda-statistic	0.892	0.345
Model 2	QLR L-statistic	1.785	0.182
	QLR Lambda-statistic	1.781	0.182
Model 3	QLR L-statistic	0.046	0.125
	QLR Lambda-statistic	0.194	0.125

Table 9 Wald test

	Quantile Slope Equality Test				
		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.	Sig.
Model 1	Wald Test	77.024	18	0.000	***
Model 2	Wald Test	89.519	18	0.000	***
Model 3	Wald Test	53.056	18	0.000	***

Note: *** indicate 1% significance level

4. CONCLUSION

The purpose of our study was to investigate the impact of green fiscal policy on green technology investment in China. Therefore, we employed some econometric techniques as our strategy for the empirical analysis. The data used in the study were collected from the National Bureau of Statistics of China from 2007 to 2017.

The results suggest that green fiscal policy has a heterogeneous impact on green technology investment total factor productivity considering the kind of proxy and magnitude of the coefficients. However, we observed that environmental tax as a proxy measure of green fiscal policy positively and significantly impacts green technology investment total factor productivity in support of Wei and Jinglin (2019)[49], Zhao et al. (2019)[61] and

Stucki and Woerter (2016)[44]. We observed from our findings that from the 10th quantile to 90th quantile, environmental tax and expenditure showed a significant relationship with green technology investment progress – just that environmental tax is positive and environmental expenditure is negative. In an account of green technology investment efficiency, we observed that environmental tax negatively and significantly impact green technology investment efficiency in the 10th and 20th quantiles but positively and significantly impact green investment efficiency in the 80th and 90th quantiles in support with Zhang et al. (2016)[57]. Their study opined that carbon taxes could significantly impact green technology investment efficiency but could not be significant in other ways. In contrast, environmental expenditure positively and significantly impact green technology investment efficiency only in the 30th quantile.

Our findings imply that when green technology investment total factor productivity is on the ascendency, increasing the existing energy consumption structure could decrease green technology investment total factor productivity. In other words, provinces with a higher level of green technology investment total factor productivity should ensure a reduction in their existing energy consumption structure to promote green technology investment. Also, we conclude that green technology investment progress is opposed by increasing research and development, gross domestic product, and existing energy consumption structure through environmental expenditure. Moreover, to sustain green technology investment progress, provinces should increase environmental taxes substantially to deter polluters by adopting green technologies. These findings imply that to promote green technology investment efficiency, research and development are eminent and should be prioritized.

Data availability statement: The data supporting this study can be found at Mendeley Data repository at http://dx.doi.org/10.17632/mj264czxhs.1.

Funding: This study received no specific financial support.

Competing Interests: The authors declare that they have no competing interests. **Acknowledgement:** All authors contributed equally to the conception and design of the study.

5. REFERENCES

[1] Álvarez-Ayuso, I.C., Kao, C., & Romero-Jordánc, D. (2018). Long run effect of public grants and tax credits on R&D investment: a non-stationary panel data approach, Econ. Modell. 75, 93e104.

[2] Barradale, M.J. (2010). Impact of public policy uncertainty on renewable energy investment: wind power and the production tax credit, Energy Policy 38 (2010)7698e7709.

[3] Buchinsky, M. (1994). Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression. *Econometrica*, 62(2), 405-458.

[4] Chang, A.C. (2018). Tax policy endogeneity: evidence from r&d tax credits. *Econ. Innovat. N. Technol.*, 27, 809e833.

[5] Chang, K., Wan, Q., Lou, Q., Chen, Y., & Wang, W. (2019). Green fiscal policy and firms' investment efficiency: New insights into firm-level panel data from the renewable energy industry in China. *Renewable Energy*. https://doi.org/10.1016/j.renene.2019.11.064

[6] Coad A., & Rao R. (2011). The firm-level employment effects of innovations in high-tech US manufacturing industries. *Journal of Evolutionary Economics*, 21(2), 255-283.

[7] Conrad, J.M., & Nøstbakken, L. (2018). Innovation and site quality: implications for the timing of investments in renewable energy. *Energy*, 148 (2018) 1173e1180.

[8] Comello, S., & Reichelstein, S. (2016). The US investment tax credit for solar energy: alternatives to the anticipated 2017 step-down. *Renew. Sustain. Energy Rev*. 55 (2016) 591e602.

[9] Cosconati, M., & Sembenelli, A. (2016). Firm subsidies and the innovation output: what can we learn by looking at multiple investment inputs. *Ital. Econ. J.*, 2, 31e55.

[10] Decramer, S., & Vanormelingen, S. (2016). The effectiveness of investment subsidies: evidence from a regression discontinuity design. *Small Bus. Econ.*, 47, 1007e1032.

[11] Dockner, E.J., Kucsera, D., & Rammerstorfer, M. (2013). Investment, firm value, and risk for a system operator balancing energy grids. *Energy Econ*. 37, 182e192.

[12] Finley, A.R., Lusch, S.J., & Cook, K.A. (2014). The effectiveness of the R&D tax credit: evidence from the alternative simplified credit. *J. Am. Tax. Assoc*. 37, 157e181.

[13] Freitas, I.B., Castellacci, F., Fontana, R., Malerba, F., & Vezzulli, A. (2017). Sectors and the additionality effects of R&D tax credits: a cross-country micro-econometric analysis. *Res. Policy*, 46, 57e72.

[14] Gu, & Shi (2012). Let Green Economy Become the Engine of Steady Growth and Structural Adjustment. www.zyjjw.cn/finance/china/55619.html. (Accessed 22 July 2018).

[15] He, L., Zhang, L., Zhong, Z., Wang, D., & Wang, F. (2019). Green credit, renewable energy investment and green economy development: Empirical analysis based on 150 listed companies of China. *Journal of Cleaner Production*, 208, 363e372. https://doi.org/10.1016/j.jclepro.2018.10.119.

[16] He, L., Liu, R., Zhong, Z., Wang, D., & Xia, Y. (2019). Can green financial development promote

renewable energy investment efficiency- a consideration of bank credit. *Renew. Energy*, 143, 974e984.

[17] Hochman, G., & Timilsina, G.R. (2017). Energy efficiency barriers in commercial and industrial firms in Ukraine: an empirical analysis. *Energy Econ*. 63, 22e30.

[18] Hong, C., & Lee, J.-D. (2016). Macroeconomic effects of R&D tax credits on small and medium enterprises. *Econ. Syst. Res*. 28, 467e481.

[19] Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, 46(1), 33-50.

[20] Koenker R. (2005). *Quantile regression*. Cambridge University Press: New York.

[21] Im, K. S., Pesaran, M. H. & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), 53–74.

[22] Instefjord, N., Nawosah, V., Yang, P. (2016). A contingent claims analysis of optimal investment subsidy. *J. Econ. Dyn. Control*, 73 (2016) 354e372.

[23] Jaraitė, J., & Kažukauskas, A. (2013). The profitability of electricity generating firms and policies promoting renewable energy. *Energy Econ*. 40, 858e865.

[24] Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90(1), 1-144.

[25] Kim, K.-T., Lee, D.J., Park, S.-J., & Zhang, Y., & Sultanov, A. (2015). Measuring the efficiency of the investment for renewable energy in Korea using data envelopment analysis. *Renew. Sustain. Energy Rev*. 47 (2015) 694e702.

[26] Kim, K., Park, H., & Kim, H. (2017). Real options analysis for renewable energy investment decisions in developing countries. *Renew. Sustain. Energy Rev*. 75 (2017) 918e926.

[27] Levin, A., Lin, C.F., Chu, C.S.J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1), 1–24.

[28] Liang, Y., Yu, B., Wang, L. (2019). Costs and benefits of renewable energy development in China power industry. *Renew. Energy*, 131 (2019), 700e712.

[29] Li, Y., Zhang, Q., Liu, B., McLellan, B., Gao, Y., & Tang, Y. (2018). Substitution effect of new energy vehicle credit program and corporate average fuel consumption regulation for green-car subsidy. *Energy*, 152 (2018) 223e236.

[30] Liu, C., Li, N., & Zha, D. (2016). On the impact of fit policies on renewable energy investment: based on the solar power support policies in China's power market. *Renew. Energy*, 94 (2016) 251e267.

[31] Liu, W., Zhang, X., & Feng, S. (2019). Does renewable energy policy work- Evidence from a panel data analysis. *Renew. Energy*, 135 (2019) 635e642.

[32] Maddala, G.S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61(S1), 631-652. DOI/abs/10.1111/1468-0084.0610s1631.

[33] Mundaca, G. (2017). Energy subsidies, public investment and endogenous growth. *Energy Policy*, 110 (2017) 693e709, 580.

[34] Neicu, D., Teirlinck, P., & Kelchtermans, S. (2016). Dipping in the policy mix: do R&D subsidies foster behavioral additionality effects of R&D tax credits. *Econ. Innovat. N. Technol*. 25, 218e239.

[35] Niesten, E., Jolink, A., & Chappin, M. (2018). Investments in the Dutch onshore wind energy industry: a review of investor profiles and the impact of renewable energy subsidies. *Renew. Sustain. Energy Rev*. 81 (2018) 2519e2525.

[36] Ozorhon, B., Batmaz, A., & Caglayan, S. (2018). Generating a framework to facilitate decision making in renewable energy investments. *Renew. Sustain. Energy Rev*. 95, 217e226.

[37] Pesaran, M. H. (2004). General diagnostic tests for cross-section dependence in panels, Cambridge University, Working Paper, No. 0435.

[38] Punda, L., Capuder, T., Pandžić, H., & Delimar, M. (2017). Integration of renewable energy sources in southeast Europe: a review of incentive mechanisms and feasibility of investments. *Renew. Sustain. Energy Rev*. 71, 77e88.

[39] Rammer, C., Gottschalk, S., Peneder, M., Wörter, M., Stucki, T., & Arvanitis, S. (2017). Does energy policy hurt international competitiveness of firms- a comparative study for Germany, Switzerland and Austria. *Energy Policy*, 109, 154e180.

[40] Rao, N. (2016). Do tax credits stimulate r&d spending? the effect of the R&D tax 660 credit in its first decade. *J. Public Econ*. 140, 1e12.

[41] Sadath, A.C., & Acharya, R.H. (2015). Effects of energy price rise on investment: 595 Firm level evidence from Indian manufacturing sector. *Energy Econ*. 49, 516e522.

[42] Salas-Fumás, V., Rosell-Martínez, J., & Delgado-Gómez, J. M. (2016).Capacity, investment and market power in the economic value of energy firms. *Energy Econ*.53, 28e39.

[43] Sim, J. (2018). The economic and environmental values of the R&D investment in a renewable energy sector in South Korea. *J. Clean. Prod. 189*, 297e306.

[44] Stucki, T., & Woerter, M. (2016). Intra-firm diffusion of green energy technologies and the choice of policy instruments. *J. Clean. Prod.* 131, 545e560.

[45] Sun, Q., Tong, W., & Yu, Q. (2002). Determinants of foreign direct investment across China. *Journal of International Money and Finance*, 21(1), 79-113. DOI: https://doi.org/10.1016/S0261-5606(01)00032-8.

[46] Tian, Y. (2018). Optimal policy for attracting fdi: investment cost subsidy versus tax rate reduction. Int. Rev. Econ. Financ. 53, 151e159.

[47] Upreti, G., & Greene, D.L., Duleep, K., & Sawhney, R. (2016). Impacts of the American recovery and reinvestment act and the investment tax credit on the north American non-automotive PEM fuel cell industry. *Int. J. Hydrogen Energy*, 41, 3664e3675.

[48] Uz, D. (2018). Energy efficiency investments in small and medium sized manufacturing firms: the case of California energy crisis. *Energy Econ.* 70(620), 421e428.

[49] Wei, W., & Jinglin, C. (2019). Research on the synergy between green credit and environmental fiscal policy. *Science & Technology Progress and Policy*, 36(12), 21-27.

[50] Yang, Y.-C., Nie, P.-Y., Liu, H.-T., & Shen, M.-H. (2018). On the welfare effects of subsidy game for renewable energy investment: toward a dynamic equilibrium model. *Renew. Energy*, 121, 420e428.

[51] Yoon, K.H., & Ratti, R.A. (2011). Energy price uncertainty, energy intensity and firm investment. *Energy Econ.* 33, 67e78.

[52] Yu, F., Guo, Y., Le-Nguyen, K., Barnes, S.J., & Zhang, W. (2016). The impact of government subsidies and enterprises' R&D investment: a panel data study from renewable energy in China. *Energy Policy*, 89, 106e113.

[53] Yuyin, Y., & Jinxi, L. (2018). The effect of governmental policies of carbon taxes and energy-saving subsidies on enterprise decisions in a two-echelon supply chain. *J. Clean. Prod.* 181, 675e691.

[54] Zeng, S., Liu, Y., Liu, C., & Nan, X. (2017). A review of renewable energy investment in the BRICS countries: history, models, problems and solutions. *Renew. Sustain. Energy Rev.* 74, 860e872.

[55] Zeng, S., Jiang, C., Ma, C., & Su, B. (2018). Investment efficiency of the new energy industry in China. *Energy Econ*. 70, 536e544.

[56] Zeng, M., Liu, X., Li, Y., et al. (2014). Review of renewable energy investment and financing in China: status, mode, issues and countermeasures. Renew. Sustain. Energy Rev. 31 (2), 23e37.

[57] Zhang, M.M., Zhou, P., Zhou, D.Q. (2016). A real options model for renewable energy investment with application to solar photovoltaic power generation in China. *Energy Econ*. 59 (2016) 213e226.

[58] Zhang, M.M., Zhou, D.Q., Zhou, P., Chen, H.T. (2017). Optimal design of subsidy to stimulate renewable energy investments: the case of China. *Renew. Sustain. Energy Rev.*, 71, 873e883.

[59] Zhang, H., Li, L., Zhou, D., & Zhou, P. (2014). Political connections, government subsidies and firm financial performance: evidence from renewable energy manufacturing in China. *Renew. Energy*, 63, 330e336.

[60] Zhang, H., Zheng, Y., Zhou, D., & Zhu, P. (2015). Which subsidy mode improves the financial performance of renewable energy firms? a panel data analysis of wind and solar energy companies between 2009 and 2014. *Sustainability*, 7, 16548e16560.

[61] Zhao, X., Yao, J., Sun, C., & Pan, W. (2019). Impacts of carbon tax and tradable permits on wind power investment in China. *Renew. Energy*, 135, 1386e1399.