Public-Private Partnerships Investment in Energy as New Determinant of CO2 Emissions: The Role of Technological Innovations in China

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Abstract: This paper explores the relationship between 'public-private partnerships investment in energy sector and carbon emissions' considering the vital role of technological innovations in carbon emissions function for China. In doing so, we apply bootstrapping autoregressive distributed lag modeling (BARDL) for examining the cointegration between carbon emissions and its determinants. The empirical results reveal that public-private partnerships investment in energy impedes environmental quality by increasing carbon emissions. On contrary, technological innovations have negative effect on carbon emissions. The relationship between economic growth and carbon emissions is inverted-U shaped i.e. environmental Kuznets curve hypothesis. Exports are positively linked with carbon emissions. Foreign direct investment impedes environmental quality by stimulating CO_2 emissions. The empirical findings provide new insights for policy makers to direct public-private partnerships investment in energy for the betterment of environmental quality in China.

Keywords: Public-Private Partnerships Investment, Energy, CO_2 Emissions, Technological Innovation, China

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I. Introduction

At present, climate change has been one of the biggest challenges to achieve global sustainable development (World Bank, 2000). Global warming will do harm such as reducing biodiversity, decreasing world food production, rising sea levels and increasing morbidity and mortality from diseases. The main cause of these irreversible disasters is the huge amount of carbon dioxide, or greenhouse gas, produced by burning fossil fuels such as oil and coal and destroying ecosystems such as forests. Inappropriate actions of human beings have caused a large number of greenhouse gases that have high transmittance to visible light of solar radiation on one hand, and on other, are highly absorbent to the long-wave radiation emitted from the earth, and can strongly absorb infrared radiation from the ground, leading to the rise of the temperature of earth and finally, global climate change.

One of the most important sources of greenhouse gas is people's extensive use of fossil fuels. Therefore, the transition in energy production source choice is underway and phenomena have got much interest from researchers, policymakers, and business worldwide. At the G20 Summit held in Hangzhou, China in 2016, the Chinese government played a leading role in the implementation of the Paris Agreement on climate change, which gave full play to its sense of responsibility and mission in tackling global climate change and realizing global sustainable development. In addition, the G20 green finance research group initiated by China has submitted the *G20 Green Finance Synthesis Report* to the G20 Hangzhou summit, for the first time that green finance has been included in the G20 agenda. After the signing of the Paris Agreement, most countries in the world have reached a more consistent consensus on developing a low-carbon economy and addressing the issue of climate warming. To this end, in its 13th Five-year Plan, the Chinese government promised to achieve the low-carbon development goal of reducing carbon intensity by 60-65% by 2030 as compared with 2005.

Capital is an essential foundation for the economy in the process of low-carbon transformation (Fulton and Capalino, 2014), and low-carbon investment is an extremely important part of it (McCollum et al. 2013). In the whole stage of economic development, the transition from extensive economic development model to low-carbon economic model is a complex and systematic problem, but it is mainly studied in two key aspects: one is how to produce clean and renewable energy, and the other is how to improve energy efficiency. Both share the goal of substantially reducing investments in energy-intensive industries that cause heavy pollution while expanding low-carbon investments. The transition in energy production sources choice is underway and phenomena have got great interest of researchers, policy makers and businesses worldwide. However, the continuous increase in energy demand and limited resources of the government has influenced policymakers to engage local communities and private sector actors to play their role in sustainable energy production. Newcomb et al. (2013) believed that decentralization of energy production with the engagement of private actors can work as a triggering factor for achieving renewable energy future. Energy efficiency, cost savings, increased capacity, and market reforms are some of the motivation behind decentralization of energy production mix (Goldthau, 2014). Similarly, Buso and Stenge (2018) stressed the importance of public-private partnerships as a policy response to climate change. In doing so, transformation via decentralization of energy production can also contribute toward environmental quality and sustainability.

The alarming signal on climate change from the Kyoto Convention has influenced China to shift its energy production from traditional sources to alternate sustainable energy sources (Ritchie and Roser 2019). The economic slowdown and recent trade war with the US have shown that no country even China has unlimited resources to finance all of its projects. Hence, the mission to transform energy production and limited resources gives rise to the importance of public-private partnerships in renewable energy projects. Partnerships pool complement capability, assets and resources of different players to create collaboration for not only energy projects but also for a sustainable environment. There is yet no consensus on the concept of public-private partnerships (shortly, PPP). According to the United Nations Development Program, PPP refers to the form of cooperation among governments, for-profit enterprises and non-profit organizations based on a project, through which cooperative parties can achieve more favorable results than expected by acting alone. Specifically, PPP refers to the establishment of a long-term cooperative partnership between the public and private sectors to provide public goods and services through formal agreements, during which the resources of non-public sectors should be involved in the provision of public goods and services to realize the functions of government public sectors and bring benefits to private sectors. That is, the public sector and the private sector learn from each other and share risks and benefits. In a broad sense, PPP covers a wide range of applications, from simple short-term management contracts to long-term contracts, including capital, planning, construction, operation, maintenance, and divestiture. Therefore, the management model in the broad scope of PPP includes various specific forms, such as build-operate-transfer (BOT), private finance initiative (PFI), and reconstruct-operate-transfer (ROT). Through such cooperation and management process, investment and profit demands of private sectors can be partially met on one hand; on other hand, public goods and services can be provided efficiently for society to make the limited resources play a greater role.

The PPP mode strongly recommended by the Chinese government now-a-days is exactly the deepening privatization of public services, of which an essential feature is being project-based. These projects cover environmental protection, municipal administration, transportation and other fields with a long cycle and currently huge investment. Because of the scale of these projects, Special Purpose Vehicle (SPV) enterprises are called for, that is, enterprises financed by government and social capital with the aim of running projects together. The government could also opt out of SPV while instead grant franchises to private capital to set up SPV enterprises. To promote the purpose of mastering and achieving public service, management and decision-making power of the projects shall be set in accordance with the proportion of contribution from government sectors. Both financing and investment of PPP projects have the characteristics of the long operating cycle, generally 20 to 30 years, high upfront costs and high investment risks. All these factors make the financing of PPP projects often only applicable to large public service projects, and low-carbon investment often has similar characteristics. The transportation, construction, energy and other fields in the low-carbon investment are also covered by PPP projects.

The empirical evidence is very limited which justify the linkage between public-private partnerships and carbon emissions. For example, Richter (2012) indicated that no single factor can provide resources to fulfill the dream of a renewable energy future. The importance of renewable energy for energy demand and environmental sustainability is well documented but, the role that can be played through public-private partnerships for sustainable energy and environment future is scant in academic research. None of the studies has explored the role of public-private partnerships in energy sector toward carbon emissions in existing energy literature. In doing so, we propose a public-private partnerships investment in energy sector as a new determinant of carbon emissions. This study adds in existing literature by folds: (i), This paper introduces public-private partnerships investment in energy sector as a new determinant in carbon emissions function. Technological innovations as well as economic growth and exports are added in carbon emissions function. (ii), We apply Kim and Perron (2009) unit root test which accommodates single unknown structural break stems in the series for examining order of the variables. (iii), The bootstrapping autoregressive distributed lag modeling (BARDL) is applied for investigating the cointegration between carbon emissions and its determinants. (iv), The causality analysis is conducted by applying innovative accounting approach (variance decomposition analysis and impulse response function). We find that all the variables have long run cointegration. Further, public-private partnerships investment in energy adds to carbon emissions. On contrary, technological innovations lowers carbon emissions and improve environmental quality. The environmental Kuznets curve hypothesis is valid. Exports have positive effect on carbon emissions. Foreign direct investment impedes environmental quality by increasing carbon emissions. Economic growth and foreign direct investment cause public-private partnerships investment in energy sector. The unidirectional causality is found running from carbon emissions to economic growth. Economic growth and carbon emissions cause foreign direct investment.

The rest of the paper is structured as follows: Section-II reviews the existing studies of public-private partnerships investment in energy-emissions nexus and technological innovations-emissions nexus. Section-III elaborates the theoretical framework and data collection. Methodological framework is detailed in Section-IV. Section-V describes empirical results and relevant discussions. Conclusion and policy implications are drawn in Section-VI.

II. Review of Literature

This paper investigates the relationship between public-private partnerships investment in energy and CO_2 emissions by considering role of technological innovations in China. This leads us to divide existing literature review into two portions: (i), Public-private partnerships investment in energy-emissions nexus and (ii), Technological innovations and CO_2 emissions relationship.

II.I Public-Private Partnerships Investment in Energy-Emissions Nexus

Studies investigating the relationship between public-private partnerships investment in energy and carbon emissions are not directly available in existing literature. Therefore, we find few studies investigated the effect of energy innovations investment on carbon emissions using time-series and panel data sets for individual country and group of countries. For example, Alvarez-Herranz et al. (2017a) used public budget for energy as measure of public investment in energy sector for energy innovations for case of OECD countries for the period of 1990-2014 by applying the empirical model employing the framework of finite inverted V-lag distribution[1]. Their empirical results unveiled that energy innovations have negative effect on carbon emissions which in resulting, improves environmental quality. Alvarez-Herranz et

[1]Hamouri (2014) examined the relationship between investment in industrial sector and carbon emissions and noted that industrial investment impedes environmental quality by increasing CO_2 emissions.

al. (2017b) investigated the presence of EKC hypothesis by considering renewable energy consumption and public budget for energy research & development expenses and reported that renewable energy consumption lowers carbon emissions. Their empirical results also indicated that a rise in public budget for energy research & development expenses leads to improve environmental quality by declining CO_2 emissions. Similarly, Ganda (2018) examined the effect of green energy investment on carbon emissions in the case of OECD countries for the period of 2000-2014. They noted that investment in green energy i.e. renewable energy not only increases energy efficiency but also declines environmental degradation by lowering carbon emissions.

Shahbaz et al. (2018) examined the determinants of carbon emissions for French economy by applying bootstrapped ARDL cointegration approach. They used research & development as measure of pubic energy investment. Their results indicated that public investment in energy leads to introduce energy efficient technology which in resulting, improves environmental quality by lowering carbon emissions. The causality analysis reveals the presence of unidirectional causality running from public investment in energy sector to carbon emissions. Similarly, Waqih et al. (2019) used foreign direct investment as measure of private investment to examine the relationship between private investment and carbon emissions using data for SAARC region. They found that private invest is accompanied with carbon emissions and after threshold level of investment, carbon emissions start to decline i.e. inverted-U relationship between the variables. Ganda (2019) examined the effect of innovation and technological investment on environmental degradation using data for OECD countries for the period of 2000-2014. They applied the Generalized Method of Moments approach and reported that innovation and technology investment reduce carbon emissions to improve environmental quality. Their empirical results further indicated that although effect of innovation and technological investment on carbon emissions is not unique but OECD countries can reduce carbon emissions via innovation and technological investments. Balsalobre-Lorente et al. (2109a) examined the environmental Kuznets curve hypothesis for OECD countries for the period of 1995-2016 by considering the vital role of public energy investment i.e. public budget for energy sector. They validated the presence of EKC hypothesis. Their empirical analysis indicated that public investment in energy sector is positively linked with environmental quality. Later, Balsalobre-Lorente et al. (2019b) confirmed the empirical findings reported by Balsalobre-Lorente et al. (2019a) in the case of OECD countries for the period of 1990-2012.

II.II Technological Innovations-Emissions Nexus

Research on the relationship between technological innovations and carbon emissions has been a hot topic, mainly divided into two categories: the positive impact of technological innovations on reducing carbon emissions, and the positive impact of technological innovations on promoting the development of new energy. On the one hand, technological innovations have a positive impact on reducing carbon emissions, such as increasing technology investment and R&D investment can effectively reduce carbon emissions. Technological investments and environmental policies have led to reduce CO_2 emissions for improving environmental quality in host nations. The existing literature provides numerous studies investigating the relationship between technological innovations and carbon emissions but provided conflicting empirical findings. For instance, Sun et al. (2008) examined the association between patents technology and carbon emissions using Chinese provincial panel data by applying the cluster approach. They find that technological innovations play a vital role in reducing CO_2 emissions. Their empirical analysis further indicated that Eastern region is stronger in adopting innovations and environmental technologies compared to rest regions of China. Similarly, Nesta et al. (2014) reported that renewable energy policies have a positive impact on development of green technological innovations in OECD countries. Applying the pre-sample mean count-data econometric approach, they further noted that renewable energy policies are suitable tool to improve environmental quality by fostering green innovation rather than competition which encourages low-quality green innovations. Kahouli (2018) employed the GMM empirical approach to examine the association between R&D investments and CO_2 emissions in a panel of Mediterranean economies for the period of 1990-2016. The empirical findings showed that R&D investment has a significant negative impact on CO_2 emissions and also found the unidirectional causality running from R&D investments to CO_2 emissions. This empirical finding strongly supports that environmental policies are significantly control environmental degradation by focusing on energy-efficient technologies.

Similarly, Fernández et al. (2018) applied OLS approach to examine the impact of R&D expenditures on CO_2 emissions for USA, European Union (EU) and China, spanning the period of 1994-2013. Their results reported that R&D expenditures have a positive impact on reduction of CO_2 emissions in US and EU. On contrary, R&D expenditures has an increasing effect on carbon emissions in China. Their empirical analysis suggests policymakers to boost R&D expenditures in particularly private and public for promoting innovation and innovations are the appropriate tools in the reduction of climate change.

Kocak and Ulucak (2019) investigated the linkage between R&D expenditures and CO_2 emissions in 19 OECD countries, spanning the period of 2003-2015. Their study employed three different methods such as STIRPAT, OLS and GMM empirical approaches. They found that R&D expenditures have a significant and positive impact on reduction of CO_2 emissions. Their empirical analysis recommends a strong requirement for regulations in energy R&D investment to minimize energy intensity, fossil fuel energy consumption and CO_2 emissions. Apergis et al. (2013) applied threshold autoregressive model to study relationship between international financial reporting standards, R&D expenditures and carbon emissions for European manufacturing firms i.e. UK, France and Germany for the period of 1998-2011. They found that R&D expenditures improve environmental quality by lowering carbon emissions. Their empirical results suggest the government to focus on renewable energy sources, energy saving policies, and new green technologies for greater reductions in carbon emissions. Cho and Sohn (2018) examined the effect of green R&D investment and green patent applications on CO_2 emissions in Italy, United Kingdom, France and Germany, spanning the period of 2004-2012. They reported that CO_2 emissions and R&D investment have a small impact on changing green patent applications. Their empirical results highlighted that the effectively minimizing fossil fuel energy related carbon emissions can only possible by promoting green technologies.

On the other hand, technological innovation also has a positive impact on promoting the development of new energy. It is mainly discussed that technological innovations can promote the development of new energy, thereby reducing carbon emissions and improving environmental quality. For instance, Meliciani (2000) applied the Poisson and Binomial distribution empirical techniques to investigate the relationship between investment, research & development, and patents in a panel of 27 nations, spanning the period of 1973-1993. The empirical results indicated that investments have a positive impact on technological change and R&D investment is more important for effectively generating patents for the betterment of environmental quality. By applying generalized OLS approach, Lantz and Feng (2006) examined the impact of income, population and technology on carbon emissions in the case of Canada, spanning the period of 1970-2000. They reported that income and population increase CO_2 emissions while technological development reduces CO_2 emissions. Their empirical results indicated that technological change and economic structure will help to reduce carbon emissions. Lee and Min (2015) also confirmed that green research & development expenditures reduce CO_2 emissions while performance of financial development has a positive impact on green research & development activities. Sohag et al.

(2015) examined the relationship between technological innovations, energy use, trade openness and economic growth in the case of Malaysian economy for the period of 1985-2012 by applying the ARDL bounds testing approach to cointegration. Their empirical results showed that technological innovations have led to reduce energy use which increases energy efficiency and hence, CO_2 emissions are reduced. They further highlighted that the larger-scale substitution of older technologies with new energy efficient technologies, should be possible only by implementing public-private investments and public-private investments should promote innovations in renewable and energy efficient technologies. Shahbaz et al. (2018) examined the relationship between financial development, foreign direct investment, energy consumption and energy innovations, their impact on CO_2 emissions in France, spanning the period of 1955-2016. They found that increasing in energy innovations has a negative impact on CO_2 emissions and similarly, financial development also leads to decline in CO_2 emissions. Their empirical results further indicated that more investments on energy innovations can improve environmental quality by reducing CO_2 emissions. Similarly, a study by Chen and Lie (2018) examined the impact of technological innovations and renewable energy consumption on environmental-energy-growth nexus in a panel of 30 nations by applying panel Fisher Johannsen cointegration and Quantile regression approaches. Their empirical findings noted that technological innovations have a significant and negative impact on CO_2 emissions. They highlighted that high production of CO_2 emissions nations need to invest more money in innovative energy technology by reduction of CO_2 emissions. Jin et al. (2017) examined the relationship between technology and CO_2 emissions in the case of Malaysian economy for the period of 1971-2013 by applying ARDL and VECM empirical approaches. Their empirical findings indicated that technology innovations and CO_2 emissions are negatively linked and technological innovations cause CO_2 emissions. A study by Weixian and Fang (2010) studied the impact of technological advancements on CO_2 emissions in China, spanning the period of 1997-2007. Their results indicated that research & development, and technology, lead to decreasing CO_2 emissions. A study by Lin and Wang (2015) examined the impact of technical efficiency and technological progress on CO_2 emissions in the case of China, spanning the period of 2000-2011. Their empirical evidence indicated that total factor CO_2 emissions performance is high in the case of Eastern and Northeastern regions but low in the case of Western and Central regions. The Eastern and Western regions have the considerable potential for minimizing carbon emissions. Further, they noted that technological innovations and low carbon investments are important for reduction of carbon emissions. Alvarez-Herranz et al. (2017a) examined the impact of energy innovations on air pollution in the case of 17 OECD economies during 1990-2012. Their empirical findings suggested that developing nations should promote renewable energy supply and their need to increase public budget on innovations for achieving a reduction in greenhouse gases and once nations reach a developed stage, they have to continue increasing their energy regulation without delay. Álvarez-Herránz et al. (2017b) studied the impact of energy innovation on greenhouse gas emissions in a panel of 28 OECD nations, spanning the period of 1990-2014. They confirmed that energy innovations have a considerable positive impact on reduction of greenhouse gas emissions i.e. energy innovations have a significant positive impact on environmental quality. Their empirical results highlighted that energy policies should concentrate on innovations to reduce energy intensity and social costs for the improvement of environmental quality. Mensah et al. (2018) examined the association between innovations and CO_2 emissions in a panel of 28 OECD nations during 1990-2014. They found that economic growth has a positive impact on carbon emissions while R&D investments have a positive effect on the improvement of environmental quality. They also reported that innovations play a vital role in decreasing carbon emissions. Their empirical analysis suggests that innovations are necessary for reduction of carbon emissions.

By contrast, Irandoust (2018) studied the nexus between innovations and renewable energy in the case of the four nations namely Norway, Finland, Denmark and Sweden, respectively, spanning the period of 1975-2012. His empirical findings confirmed the unidirectional causality running from technological innovations to renewable energy in Norway and Denmark and renewable energy causes technological innovations in the case of Finland and Sweden. They further noted that technological innovations have played effective role in renewable energy consumption. Jin et al. (2017) examined the impact of technological progress in energy sector on CO_2 emissions in the case of China, spanning the period of 1995-2012. Their empirical results confirmed that technological progress in energy sector has a significant and positive impact on reduction of CO_2 emissions and energy efficiency can significantly reduce CO_2 emissions. They suggested, based on empirical results, that for achieving low carbon emissions, government should increase investments in energy research and also improve energy efficiency. Popp (2002) examined the impact of energy prices on innovation in US economy for the period of 1970-1994. This study considered supply-side and demand-side factors for new innovation activity by increasing new innovations. The empirical findings reported that energy prices have a considerable positive impact on innovation which suggested that the growth of new technological innovations can control environmental pollution in the long-run. Zhang et al. (2018) reported that CO_2 emissions intensity decreases from 84.63% to 67.86% by 2030 but when renewable energy sources have a considerable contribution to reduction of CO_2 emissions in China. Lin and Wang (2014) highlighted that high-level CO_2 emissions countries need to concentration on technological innovations and also need to focus on low-carbon investment. Indeed, the utilization of technological innovations is more helpful to reducing rely non-renewable(s) and also reducing CO_2 emissions. Li et al. (2017) investigated the impact of technological processes on CO_2 emissions in the case of China during 1997-2014. Their empirical results reported that urbanization, energy consumption, and population have a positive impact on CO_2 emissions and FDI has a significant negative impact on CO_2 emissions, while technological processes reduce CO_2 emissions. Similar empirical result also reported by Zhou et al. (2017) in China, spanning the period of 2004-2014. Ma and Liu (2018) examined the relationship between intra and inter regional technological innovations transfer on carbon emissions in China, spanning the period 2006-2010. Their findings reported that energy and environmental technologies have a significant but positive impact on reduction of CO_2 emissions which suggested that governments should pay more attention towards energy saving technology development, new energy and application for reduction of carbon emissions.

In existing literature some studies have examined the relationship between patents and green technologies, for example Kwon et al. (2017) highlighted that an increase in carbon emissions leads to an increase in green patent applications. Indeed, several nations have tried to reduce carbon emissions and energy consumption via research and development (R&D) investment. Weina et al. (2015) as well as Wang et al. (2015) showed that population and economic growth increase lead to an increase in carbon emissions, whereas the progress of technology controls the reduction of carbon emissions. Wang et al. (2012) point out that an increase in research and development (R&D) output leads to a reduction of carbon emissions via science and technology. Fernández et al. (2018) documented that R&D expenditure has a positive effect on CO_2 emissions in China.

III. Theoretical Framework and Data Collection

This study investigates the relationship between public-private partnerships investment in energy and carbon emissions considering vital role of technological innovations, economic growth, exports and foreign direct investment in carbon emissions function for China. It is argued by Buso and Stenge (2018) that public-private partnership is not only necessary for domestic output via investment but also important for climate change in the country. They further noted that transformation via decentralization of energy production through public-private partnership investment in energy sector may also impact environmental quality by affecting carbon emissions. Technological innovations may affect environmental quality by introducing energy innovations and energy efficient technology (Tang and Tan 2013, Shahbaz et al. 2018). Economic growth affects carbon emissions via scale and technique effects (Shahbaz et al. 2017, 2019). This study also examines whether the relationship between economic growth and carbon emissions is U-shaped or an inverted U-shaped. We therefore include a squared term of real GDP per capita into carbon emissions function. Exports may affect environmental quality positively or negatively depend on production technology applies for domestic production and hence, to increase exports in international market (Bosupeng, 2016). Foreign direct investment affects environmental quality via economic activity positively or negatively. This relationship between foreign direct investment and carbon emissions depends on technology foreign investors apply for domestic production. Further, linkage between foreign direct investment and environmental quality also depends on relationship between foreign direct investment and economic growth (Shahbaz et al. 2015). Based on such arguments, we model the general carbon emissions function as following:

$$C_t = f(I_t, P_t, Y_t, Y_t^2, E_i, F_t) \tag{1}$$

where $C_t, I_i, P_t, Y_t, Y_t^2, E_t$, F_t and ε_t are carbon emissions, public-private partnerships investment in energy, patents applications proxy for technological innovations, real GDP and squared of real GDP, exports, and FDI inflows. We have transformed all the variables into natural-log for applying a log-linear specification rather than linear specification for empirical analysis. It is argued by Shahbaz et al. (2012a, b) that log-linear specification provides more reliable and consistent results which later confirmed by Raghutla et al. (2018a, b). The log-linear specification of carbon emissions function is modeled as following:

$$\ln C_t = \alpha_0 + \alpha_1 \ln I_t + \alpha_2 \ln P_t + \alpha_3 \ln Y_t + \alpha_4 \ln Y_t^2 + \alpha_5 \ln E_t + \alpha_6 \ln F_t + \varepsilon_t \tag{2}$$

where, $\ln$ is natural-log and ε_t is error term assumed having normal distribution. We expect $\alpha_1 > 0$ if technological innovations are not environment friendly otherwise $\alpha_1 < 0$. Public-private partnerships investment in energy improves environmental quality if $\alpha_2 < 0$ otherwise environmental quality is impeded with an increase in public-private partnerships investment in energy. The relationship between economic growth and carbon emissions is inverted U-shaped if $\alpha_3 > 0$ and $\alpha_4 < 0$, otherwise, it is U-shaped if $\alpha_3 < 0$ and $\alpha_4 > 0$. The inverted U-shaped association indicates the presence of environment Kuznets curve hypothesis (see, Shahbaz et al. 2018). Exports increase carbon emissions and impedes environmental quality if $\alpha_5 > 0$ otherwise $\alpha_5 < 0$. The relationship between foreign direct investment and carbon emissions is negative if $\alpha_6 < 0$ otherwise foreign direct investment impedes environmental quality.

We use time series data for the period of 1984-2018. The data on carbon emissions (metric tons), public-private partnerships investment in energy (constant LCU), patents applications (resident and non-resident), real GDP (constant LCU), real exports (constant LCU), real FDI (constant LCU) is collected from World Development Indicators (CD-ROM, 2019). We use total population for converting all the variables into per capita units. To overcome the issue of small sample-size, we applied quadratic match-sum method to transform annual data into quarter frequency. This approach adjusts seasonal variations in the data while converting data from low to high frequency and reduces the point-to-point changes in data (Sbia et al. 2014, Shahbaz et al. 2017). This method is also preferred to traditional methods due to its more accuracy (Shahbaz et al. 2016, 2017).

IV. Methodological Framework

IV.I ADF Unit Root and Structural Break ADF Test

To check the stationary properties of the variables, our study applies traditional ADF unit root test developed by Dickey and Fuller (1981). The empirical findings of ADF unit root test may be ambiguous due to ignorance of structural breaks occurring in the series (Shahbaz et al. 2018). This issue is solved by applying advanced ADF unit root test (developed by Kim and Perron 2009). Considering the single unknown structural break is very crucial as a unit root test ignores the structural single unknown structural break that can produce the partial estimates. For example, Augmented Dickey-Fuller (ADF) test ignores the existence of nonlinearity and structural breaks in the chosen series that could potentially trigger unit root problems. The empirical unit root tests can be accepting null hypothesis but it should be false and vice versa, because of their low strength of explanation and present unclear outcomes. In such situation, advanced ADF unit root test is an appropriate test related to traditional ADF unit root test. This solves the nonlinearity problem with single unknown structural break and offers coherent and reliable empirical outcomes. The present research is following Leybourne et al. (1998a) empirical origins including the calculation of Enders and Lee (2012) test statistics, which is, in fact, t-ratio of ϕ is the ordinary least squares regression:

$$\hat{\varepsilon}_t = d(t) + \phi_1 \hat{\varepsilon}_{t-1} + v_t \tag{3}$$

Here $d(t)$ is a function of t, v_t is a stationary disruption with variance σ^2. Therefore, here one point to note is that ε_t is weakly dependent and it is presumed that the original value is fixed. Estimates can be made with equation-3 and to examine the null hypothesis of a unit root, for example $(\phi_1 = 1)$ if $d(t)$ functional model is known. We don't notice $d(t)$ form, though this, any testing might be difficult in that situation for $\phi_1 = 1$ if $d(t)$ is mis-specified. However, the method selected in this research is based on hypothesis that using the Fourier expansion, it is feasible to approximate $d(t)$.

$$d_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\prod kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\prod kt}{T}\right), n \leq T/2 \tag{4}$$

If the amount of cumulative frequencies in the estimate is *n,* then *k* shows a particular frequency, the number of observations is offered by T. We don't have a nonlinear trend in this situation for all the values of $\alpha_k = \beta_k = 0$. Therefore, the specification of Leybourne et al. (1998b) becomes a unique case. For a number of quality reasons, it is not advisable to use a large value of n. We'll show this phenomenon, the primary issue, however, is that it can lead to an over-fitting problem. A number of notable studies, for example, Gallant (1981), Davies (1977), Gallant and Souza (1991), and Bierens (1997), empirically demonstrate that with a small number of frequency variables, while using the Fourier approximation, we can often capture the vital properties of an unknown functional form smooth break. Moreover, as the evolution of the nonlinear trend to be gradual is essential, therefore, *n* should be low. The test equation can finally be provided in the form below:

$$\Delta\hat{\varepsilon}_t = \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\prod kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\prod tk}{T}\right) + \phi_1 \hat{\varepsilon}_{t-1} + \sum_{i-1}^{p} \varphi_k \Delta\hat{\varepsilon}_{t-1} + v_t \tag{5}$$

It is common practice to increase the lag value of the dependent variables in testing equation-5 to account for any stationary dynamics $\hat{\varepsilon}_t$. In Kim and Perron unit root test, a significant problem to look at is whether a small amount of frequency elements could replicate the kinds of breaks that are frequently observed in economic data. To keep an eye on this aspect, we began with a Fourier approximation using a single frequency element to represent the single frequency chosen for approximation by *k*, amplitude and displacement of determinist term's sinusoidal element is evaluated by α_k and β_k. We can therefore allow various smooth breaks with a single frequency $k = 1$.

H0: Unit Root (Linear non-stationary)
H1: Nonlinear stationary (Nonlinear and stationary around smooth breaks)

We will use critical values of smooth structural break unit root test to examine hypothesis against the critical values.

IV.II Bootstrapping ARDL Bounds Testing Approach to Cointegration

We consider the bootstrapping ARDL (BARDL) cointegration technique lately developed by McNown et al. (2018) to evaluate the cointegration relationship between the variables. This methodology has main advantage is that it addresses the problem of weak size as well as power properties encountered in the traditional ARDL method introduced by Pesaran and Shin (1999). In addition, to boost the power of the F-test and t-test, this technique is supportive of integrating a new test and adds to the traditional ARDL bounds testing method.
To confirm the presence of cointegration relationship between the variable, therefore, three tests are required, if not performed by Pesaran et al. (2001) ARDL approach to cointegration. There are two conditions for Pesaran et al. (2001) to identify cointegration relationship, the coefficients of the lagged explanatory variables and the error-correction coefficients are must be statistically significant (Pesaran et al. 2001). The first condition, however, only applies if the lagged dependent variable is statistically significant in the term of error correction, indeed, only if the lagged explanatory variables are statistically significant is the second situation. At this juncture, Pesaran et al. (2001) propose that the critical bounds, for example upper and lower bounds shall be used in the second situation, however, there are no bound tests or critical bounds in the first situation. In the first case, where the error-correction coefficients are statistically significant, the study can be applied when all the sample

variables are stationary at first order i.e. integrated of order 1. Nevertheless, here an important issue to consider is that traditional unit root tests may be problematic because of their low explanatory and power properties (Goh et al. 2017). The bootstrapping ARDL (BARDL) test of McNown et al. (2018) model can solve this problem by using the new statistics. The critical values of bootstrapping model have a larger size and power properties as shown by the simulations of Monte Carlo.

$$C_t = \sum_{i=1}^{p} \alpha_i C_{i-1} + \sum_{r=0}^{q} \beta_r X_{t-r} + \sum_{z=0}^{r} \alpha_z Z_{t-z} + \sum_{i=1}^{s} \gamma_1 D_{t,h} + \mu_t \qquad (6)$$

where i, r, z and h stands the lags (i = 1, 2,…..s; r = 0,1,2,…..p; z = 0,1,2,…..q; h = 0,1, 2,…..g and *t* represent the time), C_t is the response variable in the model, and X_t and Z_t are the explanatory variables. $D_{t,h}$ is the dummy variable, β and α represent the coefficients of lagged explanatory variables, and Υ is the coefficient of dummy variable. μ_t represents the error-term with zero mean and finite variance. Based on this model, therefore, we have written in an error-correction equation is as follows:

$$\Delta C_t = \phi C_{t-1} + \gamma X_{t-1} + \psi Z_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta C_{t-1} + \sum_{r=1}^{q-1} \beta_i \Delta X_{t-1} + \sum_{z=1}^{r-1} \alpha_z \Delta Z_{t-z}$$
$$+ \sum_{i=1}^{s} \gamma_i D_{t,h} + \varepsilon_t \qquad (7)$$

$\phi = \sum_{i=1}^{p} \alpha_i , \gamma \sum_{r=0}^{q} \beta_r$ and $\psi \sum_{z=0}^{r} \alpha_z$, at this point, α_i, β_r, α_z, and Υ_1 stand for the function related with equation-7. Taking vector auto-regression levels into its error-correction equation, the derivation of equation-7 from equation-6 is estimated. Whereas equation-6 can be estimated by using the constant term (C) inthe unconditional model that can be specified as:

$$\Delta C_t = \bar{Y} + \bar{\phi} C_{t-t} + \bar{\gamma} X_{t-1} + \bar{\psi} Z_{t-1} + \sum_{i=1}^{p-1} \bar{\alpha}_i \Delta C_{i-1} + \sum_{r=1}^{q-1} \bar{\beta}_r \Delta X_{t-r} + \sum_{z=1}^{r-1} \bar{\alpha}_z \Delta Z_{t-z} + \sum_{i=1}^{s} \bar{\gamma}_1 D_{t,h} + \bar{\varepsilon}_t \quad (8)$$

It needs that all three null hypotheses be rejected to verify the cointegration between the variables c_t, X_t, and, Z_t.

The hypothesis can be as follows:

i). F1 test based on all relevant terms of error correction (H_0: $\phi = \gamma = \psi = 0$ against H_1: any of ϕ, γ, ψ are different from zero).

ii). F2 test based on all of the explanatory variable's terms (H_0: $\gamma = \psi = 0$ against H_1: either γ or ψ is different from zero).

iii). t-test based on the lagged dependent variable (H_0: $\phi = 0$ against H_1: ϕ is different from zero).

One point to note here is that the traditional ARDL approach generates only the critical values of the bounds test for F1 and t-tests. However, F2 test statistics for the lagged explanatory variables are ignored. Using the bootstrapping approach ARDL suggested by McNown et al. (2018) can provide critical values for all three tests. At the same time, in our effort to deliver the empirically robust outcomes, we used the critical values tabulated by McNown et al. (2018) in this research.

V. Empirical Results and their Discussion

The descriptive statistics and pair-wise correlation are presented in Table-1. The reported descriptive statistics show that carbon emissions are less volatile compared to public-private partnerships investment in energy sector. The volatility in technological innovations is more compared to volatility occurs in foreign direct investment inflows. Exports contain more volatility compared to volatility stemming in economic growth. We find that volatility in technological innovations is higher compared to volatility occurring in carbon emissions, to public-private partnerships investment in energy sector, economic growth, exports and foreign direct investment. The Jarque-Bera test statistic validates the normal distribution of data of all the variables.

Table-1: Descriptive Statistics and Pair-wise Correlations

Variables	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
Mean	0.3254	0.0187	-2.4100	2.4098	2.0010	1.4788
Median	0.2618	0.0758	-2.4767	2.3983	2.0009	1.5678
Maximum	0.5154	0.4497	-1.6758	2.7553	2.3429	1.8336

Minimum	0.1320	-1.2306	-2.9688	2.0415	1.4580	0.7019
Std. Dev.	0.1293	0.2795	0.4272	0.2148	0.2912	0.3310
Skewness	0.2848	-1.6892	0.2322	0.0085	-0.3749	-1.0681
Kurtosis	1.5043	6.9564	1.6312	1.7145	1.7845	2.7098
Jarque-Bera	0.1942	1.5789	1.2187	0.9639	1.1898	0.2711
Probability	0.6945	0.1901	0.2257	0.8067	0.2108	0.9018
$\ln C_t$	1.0000					
$\ln I_t$	0.1025	1.0000				
$\ln P_t$	-0.0429	0.1231	1.0000			
$\ln Y_t$	0.5583	0.0676	0.1586	1.0000		
$\ln E_t$	0.3741	-0.3343	-0.0453	0.3699	1.0000	
$\ln F_t$	0.2149	-0.0399	0.2329	0.4842	0.4843	1.0000

The pair-wise correlation analysis shows positive correlation between public-private partnerships investment in energy sector and carbon emissions. Technological innovations are inversely correlated with carbon emissions. The correlation of economic growth, exports and foreign direct investment with carbon emissions is positive. Technological innovations and economic growth are positively correlated with public-private partnerships investment in energy sector. The correlation between exports (foreign direct investment) and carbon emissions is negative. Exports are also negatively correlated with technological innovations but economic growth and foreign direct investment are positively linked with technological innovations. The correlation between exports (foreign direct investment) and economic growth is positive. A positive correlation exists between exports and foreign direct investment.

Table-2: Unit Root Analysis

Variables	Traditional ADF Test		Structural Break ADF Test		
	T-Statistic	P. value	T-Statistic	P. value	Break Year
$\ln C_t$	-2.9383(2)	0.1953	-4.1380(2)	0.2935	2001_{QI}
$\ln I_t$	-2.1006(4)	0.5301	-4.2090(5)	0.2132	1999_{QI}
$\ln P_t$	-3.1492(1)	0.0993	-3.9912(5)	0.3767	2001_{QI}
$\ln Y_t$	-2.4553(4)	0.3498	-3.8777(9)	0.5853	1994_{QII}
$\ln E_t$	-0.4574(4)	0.9844	-2.2593(9)	0.9901	2012_{QII}
$\ln F_t$	-1.6409(4)	0.7715	-3.2026(5)	0.7101	1991_{QI}
$\Delta \ln C_t$	-6.7005(5)*	0.0001	-5.0288(1)**	0.0308	2001_{QI}
$\Delta \ln I_t$	-6.1425(2)*	0.0000	-7.2502(1)*	0.0001	1985_{QII}

$\Delta \ln P_t$	-5.1386(1)*	0.0002	-7.1196(11)*	0.0000	1997_{QI}
$\Delta \ln Y_t$	-3.4582(4)**	0.0482	-8.7090(9)*	0.0000	1987_{QI}
$\Delta \ln E_t$	-4.7055(4)*	0.0011	-6.4799(0)*	0.0000	1987_{QI}
$\Delta \ln F_t$	-4.0214(4)*	0.0102	-5.7239(7)*	0.0000	2010_{QI}
Note: * shows significance at 1%. () shows lag length based on AIC.					

The first step is to examine the stationary properties of the variables to be used for empirical analysis. In doing so, we have applied traditional ADF unit root test developed by Dickey and Fuller (1981). The empirical results are reported in Table-2 and we find that carbon emissions, public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment contain unit root problem at level with intercept and time trend. After first differencing, we noted that all the variables are found stationary. The empirical findings of ADF unit root test may be ambiguous due to ignorance of structural breaks occurring in the series (Shahbaz et al. 2018). This issue is solved by applying advanced ADF unit root test (developed by Kim and Perron, 2009) accommodating structural single unknown structural break in the series. Based on empirical results provided by structural break ADF unit root test, once again, we confirm the presence of unit root but all the variables are stationary at I(1) in the presence of structural breaks in the series. This shows the robustness of unit root analysis that carbon emissions, public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment are integrated at I(1). The breaks are present for the year of 2001_{QI}, 1999_{QI}, 1994_{QII}, 2012_{QII} and 1991_{QI} for carbon emissions, public-private partnerships investment in energy sector, technological innovations, economic growth, exports, and foreign direct investment. These structural breaks may be consequence of the structural reforms namely environmental policies, implementation of PPP model, technological reforms, economic reforms, trade liberalization, and foreign direct investment, respectively. 2001_{QI} is the period when the structural break of carbon emissions occurred. The factors contributing to the structural change of carbon emissions are complex, and energy price is one of the most important factors affecting carbon emissions. From 1997 to 2003, China’s coal market gradually transferred to marketization with a gradual opening up of coal prices, and a pattern dominated by market pricing was formed. However, reform of electric power system was relatively lagging, as the price of electric power was still determined by government, and the price of electric coal was still subject to the policy of price limit, forming a “double-track system” of price between “planned coal” and “market coal”. In 1999, China's industrial structure started being transformed to be carbon-intensive. Starting from January 1, 2002, the Chinese government announced to cancel the guiding price of electric coal, which made China's economy as well as energy consumption grow rapidly. However, the low energy efficiency led to a slow rate of carbon intensity decline. Therefore, 2001_{QI} becomes the structural breakpoint of China's carbon emissions.

Table-3: Bootstrapped ARDL Cointegration Analysis

Bootstrapped ARDL Cointegration Approach						Diagnostic Tests			
Estimated Models	Lag Length	Break Year	F_{PSS}	T_{DV}	T_{IV}	$\overline{R}^2$	$Q-stat$	$LM(2)$	JB
$C_t = f(I_t, P_t, Y_t, Y_t^2, X_t, F_t)$	6, 5, 6, 6, 5, 6, 6	2001_{QI}	11.1251*	-3.2092**	-4.2704*	0.7309	4.1081	2.715	0.9212
$I_t = f(C_t, P_t, Y_t, Y_t^2, X_t, F_t)$	6, 6, 5, 6, 5, 6, 5	1999_{QI}	12.1918*	-11.8518*	-4.8615*	0.6163	5.1505	2.4163	0.8787
$P_t = f(C_t, I_t, Y_t, Y_t^2, X_t, F_t)$	6, 6, 5, 5, 6, 6, 6	2001_{QI}	9.1060*	-9.2897*	-3.0515**	0.7952	6.1640	2.2252	0.7606
$Y_t = f(C_t, I_t, P_t, Y_t^2, X_t, F_t)$	6, 5, 6, 5, 5, 6, 5	1994_{QII}	1.6051	-1.1010	-1.6090	0.2209	5.0712	0.4056	0.8703
$Y_t^2 = f(C_t, I_t, P_t, Y_t, X_t, F_t)$	6, 6, 5, 5, 6, 5, 6	1994_{QII}	1.1900	-0.9099	-1.1911	0.2322	5.0120	0.5036	0.8456
$X_t = f(C_t, I_t, P_t, Y_t, Y_t^2, F_t)$	6, 6, 5, 5, 5, 6, 6	2012_{QII}	11.2161*	-8.9141*	-4.8605*	0.6657	5.2010	2.9590	0.8809
$F_t = f(C_t, I_t, P_t, Y_t, Y_t^2, X_t)$	6, 6, 6, 5, 6, 6, 6	1991_{QI}	10.9011*	-9.8765*	-3.2314**	0.7865	6.9081	5.4908	0.9123

Note: The asterisks * and ** show significance at 1% and 5%levels respectively. The Akaike Information Criterion (AIC) decides the optimal lag length. F_{PSS} is the F-statistic based on the asymptotic critical bounds that is generated from the use of bootstrap method. T_{DV} is the t-statistic for the dependent variable and T_{IV} is the t-statistic for the independent variables, LM is the Langrage Multiplier test and followed by JB for the Jarque-Bera test.

Next step is to examine the cointegration relationship between carbon emissions and its determinants, after confirming that our variables are integrated at order of I(1). Therefore, we have applied the bootstrapping auto-regressive distributive lagged modeling (BARDL), to confirm whether long-run cointegration equilibrium exists or not between the variables. The BARDL bounds testing approach works better than traditional ARDL model documented by Shahbaz et al. (2018). This approach considers the joint F-test on all lagged level variables, t-test on the lagged level of dependent variable and t-test (new test) on lagged level of the regressors, which will help with respect to cointegration equilibrium between the sample variables. This reveals that the bootstrapping ARDL test is better than the basic ARDL bounds testing approach for examining cointegration between the variables. The lag length selection is necessary while applying the BARDL bounds testing approach to determine cointegration between the variables. The inappropriate lag length selection produces misleading empirical results. For appropriate lag order of the variables, we find Akaike Information Criteria (AIC) suitable due to its superior power properties (Lütkepohl 2006). The lag length selection of the variables is shown in column 2 of Table-3.

In the present of bootstrapping ARDL cointegration background, t-value and F-value have bootstrapped for investigating long-run cointegration relationship among the variables. The empirical findings are reported in Table-3. These bootstrapping statistics such as t-test and F-test, both the lagged level of dependent variable rejects the null hypothesis where public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment are treated as independent variables. Moreover, t-test on the lagged explanatory variables also accepts the alternative hypothesis. This suggests that the joint F-test, t-test on the lagged dependent while t-test on the lagged independent variables confirm the presence of long-run equilibrium cointegration relationship among variables at the 1% and 5% levels, respectively.

This study also estimated other models where public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment are employed as dependent variables. The study fails to achieve considerable findings for the joint F-test, t-test on the lagged dependent and t-test on the lagged independent variables, therefore we treated economic growth (real GDP and square of real GDP) as dependent variable. This leads to acceptance of null hypothesis and confirms no long-run cointegration relationship. Overall, we find the presence of five cointegrating vectors between carbon emissions and its determinants. Our empirical findings establish the presence of a long-run equilibrium cointegration relationship between the variables for the period of 1984-2018[2]. We have also explained diagnostic analysis which reveals the acceptance of the null hypothesis by Q-stat. This suggests that all the variables have a similar populace given by the standard variance analysis which, affirms the normal distribution of data. This empirical finding is consistent with empirical results reported by Jarque-Bera normality test (see Table-1). The empirical results also show the absence of serial correlation in the models which further indicates that each variable has an independent observation (Pesaran et al. 2001).

Table-4: Long Run Analysis

Dependent Variable = $\ln C_t$				
Variables	Coefficient	Std. Error	T. Statistic	Prob. Value
Constant	6.4897*	0.5298	12.2472	0.0000

[2] The empirical results reported in Table-A (see Appendix) indicate that economic growth and foreign direct investment cause public-private partnerships investment in energy sector. The causality is confirmed running from carbon emissions to economic growth but similar is not true from opposite side. Exports are caused by carbon emissions and economic growth. Economic growth and carbon emissions cause foreign direct investment.

$\ln I_t$	0.2225*	0.0467	4.7552	0.0000
$\ln P_t$	-0.1477*	0.0354	-4.1659	0.0001
$\ln Y_t$	6.4952*	0.4673	13.8982	0.0000
$\ln Y_t^2$	-1.3802*	0.0925	-14.9168	0.0000
$\ln E_t$	0.4909*	0.0394	12.4465	0.0000
$\ln F_t$	0.0476*	0.0173	2.7483	0.0068
D_t	-0.0184***	0.0110	-1.6683	0.0976
R^2	0.9683			
$Adj-R^2$	0.9574			
Durbin-Watson	2.0197			
Stability Analysis				
Test	F-statistic	P. value		
χ^2_{NORMAL}	0.4151	0.2210		
χ^2_{SERIAL}	0.8804	0.7060		
χ^2_{ARCH}	0.4080	0.2510		
χ^2_{Hetero}	0.2050	0.8615		
χ^2_{RESET}	1.1907	0.1104		
CUSUM	Stable			
CUSUMsq	Stable			
Note: * and *** show significance at 1% and 10% levels respectively.				

The presence of cointegration between the variables leads us for examining long-run and short-run effect of public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment on carbon emissions. The long-run empirical analysis is reported in Table-4. We find that public-private partnerships investment in energy sector has positive and significant effect on carbon emissions. A 1% increase in public-private partnerships investment in energy sector increases CO_2 emissions by 0.2225%, keeping other things constant. The relationship between technological innovations and carbon emissions is negative and significant at 1%. This shows that technological innovations improve environmental quality by lowering carbon emissions. Keeping all else same, a 1% increase in technological innovations reduces carbon emissions by 0.1477%. This empirical evidence is in line with studies of the existing literature such as Dinda (2004), Brock and Taylor (2005), Lantz and Feng (2006), Tang and Tan (2013), Fei et al. (2014). Linear and nonlinear terms of real GDP per capita (economic growth) have positive and negative effect on carbon emissions. This shows the presence of an inverted U-shaped association between economic growth and CO_2 emissions confirming environmental Kuznets curve hypothesis in China. This empirical result is consistent with studies in existing literature such as Esteve and Tamarit (2012) for Spain, Fosten et al. (2012) for UK, Sephton and Mann (2013) for Spain and Tiwari et al. (2013) for India, Shahbaz et al. (2017a) and, Iwata et al. (2010) & Can and Gozgor (2017) for French economy. Exports have positive and significant impact on carbon emissions. This reveals that exports impede environmental quality by increasing carbon emissions. A 1% increase in exports increases carbon emissions by 0.4909% by keeping other things same. Foreign direct investment increases environmental degradation by increasing carbon emissions. A 0.0476% increase in carbon emissions is led by 1% increase in foreign direct investment, all else is same. This empirical evidence is similar to Tang and Tan (2015) for Vietnam, Chandran and Tang (2013) and Baek (2016) for ASEAN-5 countries, Sbia et al. (2014) for the Middle Eastern countries, Shahbaz et al. (2015) for France, Lau et al. (2014) and Hitam and Borhan (2012) for Malaysia, Ren et al. (2014) for China, and Abdouli and Hammami (2017) for the MENA economies. The dummy variable has negative and statistically significant effect on carbon emissions. This confirms that transformation of Chinese economy from high carbon intensive to low-carbon intensive has improved environmental quality by lowering carbon emissions. The stability analysis confirms the normal distribution of error term. The absence of serial correlation and autoregressive conditional heteroscedasticity is also confirmed in the model. There is no white heteroscedasticity and model is well designed confirmed by Ramsey reset test statistics. In long-run model is 96.83% of carbon emissions is explained public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment and rest is by error term. The Durbin-Watson test statistic also confirms the absence of autocorrelation in the model. All long-run estimates are reliable (stable) validated by CUSUM and CUSUM_{SQ} tests.

Table-5: Short Run Analysis

Dependent Variable = $\Delta \ln C_t$				
Variables	Coefficient	Std. Error	T. Statistic	Prob. Value
Constant	-0.0031	0.0009	-3.2410	0.0015
$\Delta \ln I_t$	-0.0324***	0.0184	-1.7565	0.0814
$\Delta \ln P_t$	0.0043*	0.0015	2.7118	0.0076
$\Delta \ln Y_t$	0.8444**	0.3855	2.1899	0.0303
$\Delta \ln Y_t^2$	1.7322	37.6472	0.0460	0.9634
$\Delta \ln E_t$	0.0969*	0.0245	3.9550	0.0001
$\Delta \ln F_t$	-0.0062	0.0121	-0.5183	0.6051
D_t	0.0229*	0.0040	5.7313	0.0000

ECM_{t-1}	-0.0952*	0.0082	-11.6097	0.0000
R^2	0.5210			
$Adj-R^2$	0.4915			
Durbin-Watson	1.9718			
Stability Analysis				
Test	F-statistic	P. value		
χ^2_{NORMAL}	0.2051	0.2516		
χ^2_{SERIAL}	0.8505	0.7102		
χ^2_{ARCH}	0.4989	0.2313		
χ^2_{Hetero}	0.3051	0.8301		
χ^2_{RESET}	0.9017	0.2403		
CUSUM	Stable			
CUSUMsq	Stable			
Note: *, ** and *** show significance at 1%, 5% and 10% levels respectively.				

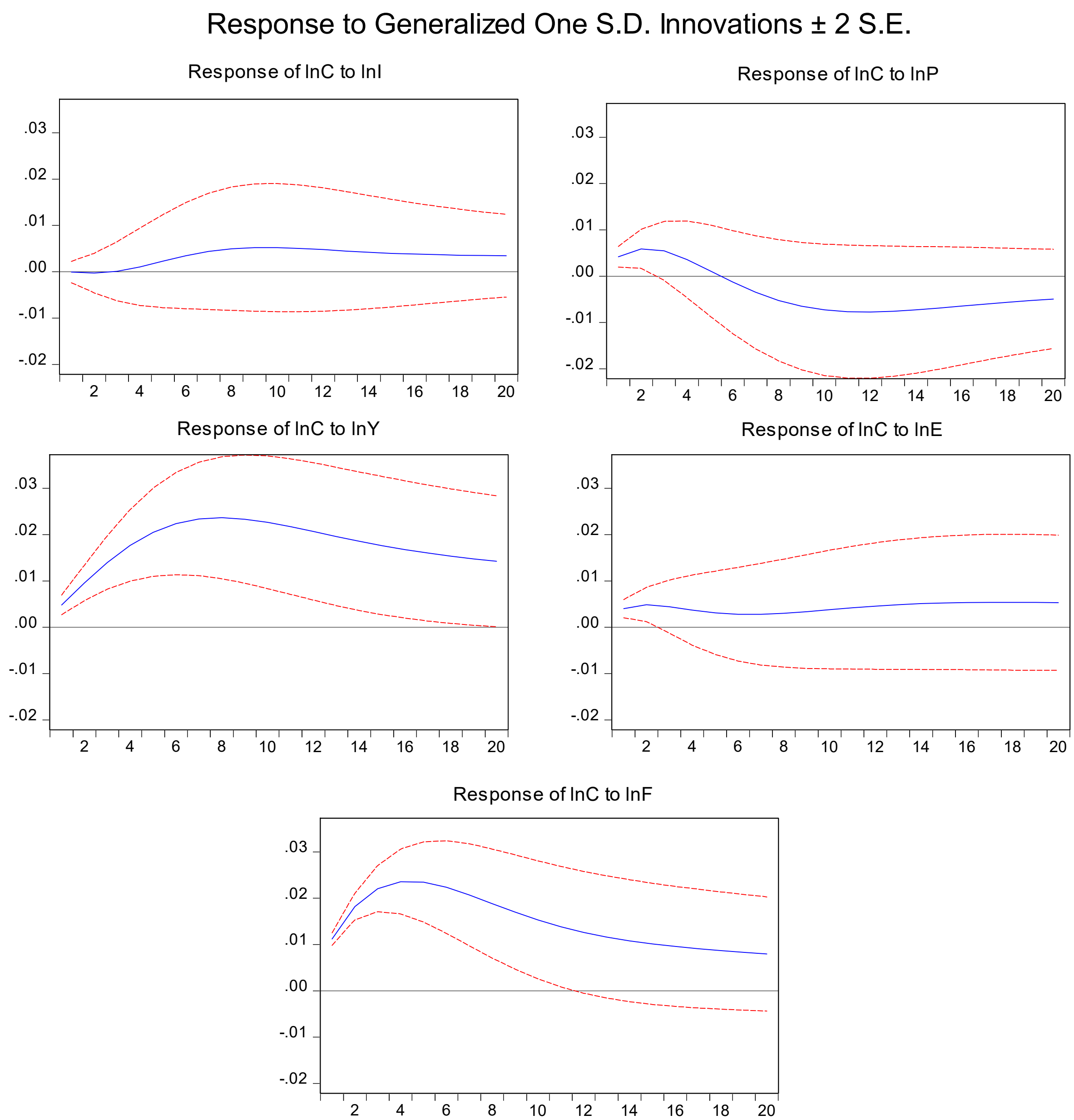
The short-run results are reported in Table-5. We note that public-private partnerships investment in energy sector has negative impact on carbon emissions (significant at 10%). Technological innovations are positively linked with carbon emissions. The relationship between economic growth and carbon emissions presents invalidation of environmental Kuznets curve hypothesis. Exports significantly contribute to carbon emissions. Foreign direct investment has negative but insignificant effect on CO_2 emissions. The dummy variable significantly contributes to environmental degradation. The coefficient of the lagged error term, ECM_{t-1} shows speed of adjustment, is significant at the 1% level. This indicates that any deviation in the short-run from the long-run path is corrected by about 9.52% each quarter. The negative sign confirms the established long-run relation (Banerjee et al.1998). Table-5 also reports the stability analysis. We find the absence of autoregressive conditional heteroscedasticity and serial correlation. The existence of white heteroscedasticity is not confirmed and model is empirically well-designed. We also noted that CUSUM and CUSUMsq tests are statistically stable and confirm the reliability of empirical analysis.

The results of variance decomposition such as carbon emissions, public-private partnerships investment in energy, technological innovations, economic growth, exports and foreign direct investment are reported in Table-A (See Appendix). We find that innovation shocks stem public-private partnerships investment in energy sector contributes to carbon emissions is very minimal i.e. 0.3228%. Technological innovations contribute to carbon emissions by 1.6365% by its innovation shocks. Innovative shocks in economic growth contribute to carbon emissions is 1.3404%. The contribution of exports in CO_2 emissions is 1.7090%. A 0.4472% of carbon emissions is contributed by innovative shocks stemming in foreign direct investment. A major portion of carbon emissions i.e. 94.5437% is explained by its innovative shocks occurring in carbon emissions. Similarly, carbon emissions contribution to public-private partnerships investment in energy sector is negligible i.e. 0.7899. A 85.1668% contribution in public-private partnerships investment in energy sector is contributed by its innovative shocks. Technological innovations explain public-private partnerships investment in energy sector by 6.3336%. Foreign direct investment, economic growth and exports contribute to carbon emissions by 1.5892%, 2.3350% and 3.7852% respectively. Public-private partnerships investment in energy sector, exports and carbon emissions explain technological innovations by 2.7939%, 5.0802% and 9.9759% respectively. Technological innovations itself contribute i.e. 54.3583% by its own innovative shocks. Innovative shocks stem in economic growth (foreign direct investment) explain technological innovations by 15.2873 (12.5040%). This shows that economic growth and foreign direct investment play effective role in improving technological innovations.

Technological innovations, foreign direct investment, exports and public-private partnerships investment in energy sector, explain economic growth by 0.5713%, 0.9931%, 2.8528% and 2.8545% respectively. A major contribution i.e. 65.9256% to economic growth is contributed via innovative shocks stem in economic growth. Carbon emissions contribute to economic growth significantly by 26.8025%. A 31.8515% portion of exports is contributed by its own innovation shocks. Economic growth explains exports by 21.9789% by its innovative shocks. Innovative shocks stem in carbon emissions contribute to exports by 40.9797%. Technological innovations, foreign direct investment and public-private partnerships investment in energy sector explain exports by 0.1291%, 1.7781% and 3.2824% respectively. This reveals that economic growth and carbon emissions contribute to exports significantly. The contribution of exports and public-private partnerships investment in energy sector to foreign direct investment is 2.6970% and 3.8489% respectively. A significant contribution to foreign direct investment is by economic growth which is 47.1969%. A 12.1999% portion of foreign direct investment is contributed by carbon emissions. Innovative shocks stem in technological innovations explain foreign direct investment is by 7.7460%. We find that economic growth and carbon emissions contribute to foreign direct investment significantly. A 26.3111% of foreign direct investment is contributed by its own innovative shocks.

We have further applied the impulse response function for examining the response of dependent variable due to changes/shocks stem in independent variable. This empirical evidence of impulse response function is shown in Figure-1. We find that carbon emissions respond positively after 3rd time-horizon due to standard forecast error stems in public-private partnerships investment in energy sector. The response of carbon emissions initially positive and then turn into negative (till 20^{th} time horizon) due to standard forecast error occurring in technological innovations. Economic growth affect carbon emissions positively till 6^{th} time horizon and then carbon emissions are negatively affected by economic growth after 9^{th} time horizon. This reveals that carbon emissions are accompanied with economic growth initially and start to decline with further economic growth (rise in real GDP per capita) which confirms the presence of an inverted U-shaped relationship between economic growth and carbon emissions. Our empirical evidence confirmed the established relationship between the variables and validated the existence of environmental Kuznets curve. The response of carbon emissions due to standard forecast error in exports is positive. Carbon emissions respond positively due to changes occur in foreign direct investment. This empirical evidence confirms established effect of public-private partnerships investment in energy sector, technological innovations, economic growth, exports and foreign direct investment on carbon emissions (see Table-4).

Figure-1: Impulse Response Function



VI. Conclusion and Policy Implications

This paper focused on China, (in doing this), we commitment to deal with public-private partnerships investment in energy and carbon emissions issue related to technological innovations, which will more helpful for economy. Therefore, we investigated the relationship between public private partnerships investment in energy and carbon emissions considering vital role of technological innovations, economic growth, exports and foreign direct investment in carbon emissions function for the China economy, spanning the period of 1984-2018. We applied traditional ADF and structural break ADF unit root tests in order to verify the order of integration of the variables. The presence of cointegration relationship between carbon emissions and its determinants is investigated by applying the bootstrapping autoregressive distributed lag modeling (BARDL) approach to cointegration. Further, we estimated the long-run and short-run analysis and innovative accounting approach i.e. variance decomposition techniques and impulse response function.

Based on empirical findings, we find the presence of long-run cointegration relationship between carbon emissions and its determinants. Moreover, public-private partnerships investment in energy has positive effect on carbon emissions i.e. impedes environmental quality by increasing CO_2 emissions. Contrarily, technological innovations improve environmental quality by declining carbon emissions. The relationship between economic growth and carbon emissions is an inverted U-shaped i.e. environmental Kuznets curve hypothesis. The relationship between exports and carbon emissions is positive. Foreign direct investment increases carbon emissions and lowers environmental quality. The empirical analysis reveals the presence of unidirectional causality running from economic growth and foreign direct investment to public-private partnerships investment in energy sector. Economic growth is cause of carbon emissions. Carbon emissions and economic growth cause exports. The causality is also found running from economic growth and carbon emissions to foreign direct investment.

Based on the above conclusions, this paper proposes relevant policy implications as follows: first, improve the carbon trading market for PPP climate finance, and accelerate the research and establishment of a national unified carbon emissions permit market system based on existing environmental exchanges across China; guide pilot provinces and cities to establish their own carbon emissions permit allocation schemes and trading mechanisms, and establish regional carbon emissions trading platforms by cooperating with provincial and municipal economic and information commissions, energy conservation and emissions reduction groups and other functional departments; thus, China's carbon trading pricing power can be formed as soon as possible to promote the development of low-carbon industry; second, actively promote the research and development of low-carbon technologies, which are the key factors in China's transition to a low-carbon economy; develop technologies for clean development and utilization of coal energy and for carbon dioxide capture and storage; develop a circular economy, build a circular system for all industries, and vigorously promote the recycling of industrial and household waste; third, pay attention to the positive role of foreign direct investment on carbon emissions reduction; as foreign direct investment in China is facing the huge pressure of carbon emissions, the local government should increase the intensity of energy conservation and emissions reduction work, improve the regulations about carbon emissions intensity, set threshold of carbon emissions to foreign companies to put an end to the entrance of foreign direct investment with high pollution, emissions and energy consumption; fourth, attach importance to the positive role of economic development in carbon emissions reduction; view the carbon emissions in economic growth from the perspective of long-term development instead of adopting the short-term behavior of "switching off electricity" to reduce carbon emissions; give full play to "carbon emissions reduction" effect of EKC mechanism to realize China's low-carbon transformation in the process of economic development.

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Table-A: Variance Decomposition Analysis

Variance Decomposition of $\ln C_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	99.4489	0.1476	0.0658	0.0163	0.0012	0.3200
10	98.2888	0.4734	0.3397	0.1877	0.0560	0.6542
15	97.0726	0.4322	0.8333	0.6928	0.4903	0.4785
20	94.5437	0.3228	1.6365	1.3404	1.7090	0.4472
Variance Decomposition of $\ln I_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	0.0421	99.9578	0.0000	0.0000	0.0000	0.0000
5	0.0136	96.1325	2.6086	0.1797	0.5945	0.4709
10	0.1492	91.9977	4.1488	1.4082	1.1263	1.1694
15	0.4012	86.8857	6.0368	2.2773	3.2210	1.1776
20	0.7899	85.1668	6.3336	2.3350	3.7852	1.5892
Variance Decomposition of $\ln P_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	0.2466	1.4012	98.3520	0.0000	0.0000	0.0000
5	0.3507	3.4795	91.7115	3.5842	0.5230	0.3508
10	3.5752	3.8685	71.9788	12.8293	2.2945	5.4534
15	7.2776	3.1761	59.1346	14.4465	4.1675	11.7973
20	9.9759	2.7939	54.3583	15.2873	5.0802	12.5040
Variance Decomposition of $\ln Y_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	16.1080	0.0569	2.4980	81.3368	0.0000	0.0000
5	20.29906	0.3360	1.2117	77.3386	0.0958	0.7186
10	23.78756	1.5493	0.7725	71.8880	0.6166	1.3859
15	25.86302	2.4747	0.6411	68.1279	1.6277	1.2654
20	26.8025	2.8545	0.5713	65.9256	2.8528	0.9931
Variance Decomposition of $\ln E_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	18.8725	5.9595	0.0045	13.8501	61.3131	0.0000
5	34.2425	1.5828	0.0444	14.6456	48.8523	0.6321
10	43.1863	2.6674	0.0290	14.6537	37.6680	1.7954
15	43.8763	3.2232	0.0419	17.6474	33.2877	1.9232
20	40.9797	3.2824	0.1291	21.9789	31.8515	1.7781

Variance Decomposition of $\ln F_t$						
Period	$\ln C_t$	$\ln I_t$	$\ln P_t$	$\ln Y_t$	$\ln E_t$	$\ln F_t$
1	6.8311	0.0354	7.6922	12.3128	8.7437	64.3845
5	10.6500	0.5362	1.7760	29.1611	2.5154	55.3609
10	11.8369	2.7385	4.4627	42.5348	1.1370	37.2898
15	12.1270	3.6178	7.4875	46.1399	1.7299	28.8975
20	12.1999	3.8489	7.7460	47.1969	2.6970	26.3111