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How Does International Crude Price Affect China's Carbon Emission?

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Abstract

This study extends the standard STIRPAT model by introducing an energy price factor and uses the extended STIRPAT model to examine the effect of international crude oil prices on China's carbon emission, This paper applies Ridge regression to conduct empirical analysis. The study finds that changes in international crude prices have a significantly positive impact on China's carbon emission. A 1 percent increase in international crude oil price leads to a 0.12 percent increase in China's carbon emission This finding remains unchanged even after a set of control variables are included in the analysis and survives all the rigidity tests.

Keywords: Crude price, China, Carbon emission.

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1. Introduction

Climate change is an environmental issue that the whole human society is struggling to solve. According to the IPCC 2019 special report on global warming, global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate. In order to achieve the 1.5°C target by the end of this century, the human society needs to reduce global carbon emission by 50% by 2030 and by 100% by 2050. As increasing carbon emission is the chief contributor of global warming, cutting carbon emission is an unavoidable path to a net zero world.

In order to reduce carbon emission, more and more countries have announced their targets on carbon neutral and low-carbon transition. By the end of 2021, the combined carbon emission by countries that have announced carbon neutral pledges accounted for around 90% of world's total carbon emission. More and more companies have announced net zero strategies. By the end of last June, over 3000 companies have announced strategies of net zero operation and production, more than 6 times of the number of companies that have announced net zero strategies in 2019.

China authorities also announced a set of targets on decarbonization, including both short term targets and long term targets. In the 14th Five Year Plan, China aims to reduce the energy intensity of GDP by 13.5% and carbon emission per unit of GDP by 18% in 2020-2025. China also plans to peak its carbon emission by 2030 and achieve carbon neutrality by 2060. In order to achieve these targets on carbon reduction, we needs to have a comprehensive understanding about all factors that have been affecting the changes of China's carbon emission.

The structure of this paper is as follows: section 2 reviews literatures; section 3 lists key assumptions; section 4 introduces research methodology; section 5 describes data; section 6 reports empirical results. Section 7 summarizes key findings.

2. Literature review

Many studies have examined the factors that drive changes in a region's carbon emission. Over the last thirty years, a lot of researchers have investigated the relationship between income and carbon emission. Grossman and Krueger (1991) pioneeringly proposed the inverse U shape relationship between economic growth and environment pollution. Shafik (1994) and Wagner (2008) found that carbon emission per capita rose monotonously with per capita income, and there was no inflection point. Galeotti, et al. (2006) find that there exists an inverse U shape relationship between carbon emission and per capita income, but the inflection points they proposed vary significantly.

Over the last fifteen years, Chinese researchers have paid quite a lot of efforts to understand those key drivers of China's carbon emission. Lin Boqiang et al. (2010) finds that increases in China's per capita GDP, urbanization rates and energy intensity all leads to increasing carbon emission in the 1978-2008 period. Wu Zhenxin (2021) finds that a one percent decrease in China's industry's share in GDP can help lower per capita carbon emission by 0.32%. Lu Wanbo (2013) finds that energy intensity and energy mix have forecasting capability in China's carbon emission. Zhang Lei (2003) finds that diversification of energy consumption mix can help reduce China's carbon emission.

Recently, some researchers started to investigate the influence of a set of different social factors on China's carbon emission. They concluded that social factors also play a role in China's carbon emission. For instance, Li Kai and Qi Shaozhou (2011) finds that foreign trades increases China's carbon emission and carbon intensity. They concludes that international trade has a negative impact on China's environment. Gao Xinwei and Zhu Yuan (2021) finds that improvement in the efficiency of research and development reduces carbon emission. Liu Chuanjiang (2021) finds that human capital accumulation can help boost carbon emission. Zhang Banruo and Li Zijie (2021) finds that access to high-speed-railway can reduce local carbon emission.

But only a small stream of studies examines the relationship between crude oil prices and carbon emission. Some of them document a negative relationship between oil price and a region's carbon emission. For example, Blazquez et al. (2017) finds that international oil price has a significantly negative impacts on Spain's carbon emission. Wong, Chia and Chang (2013) find that crude oil price has a negative impact on the carbon emission of OECD countries. Malik et al. (2020) finds that oil price has a negative influence on the carbon emission of Pakistan. Some of them find no obvious connections between oil price and a region's carbon emission. For example, He and Richard (2010) finds that oil price has no significant impact on Canada's carbon emission.

However, little research has been done to understand how international crude oil prices affect China's carbon emission. Existing research related to this topic seems to be segmented into two parts: one part of research studies the relationship between international crude oil prices and Chinese energy prices. The other part of research studies how domestic energy prices impact domestic carbon emission. However, as domestic fossil fuel markets are still partly regulated by NDRC, domestic energy prices fail to respond to changes in international energy prices in a timely way. In addition, China's market positions of different fossil fuels in the world are quite different, indicating that different types of international energy prices could have different types of impacts on China's carbon emission.

This paper has three contributions to existing literature. First, it extends the standard STIRPAT model by introducing an energy price factor, allowing researchers to examine the effects of energy prices on environmental indicators. Secondly, to the best of my knowledge, it is the first study that have been done to understand the influence of international crude oil prices on China's carbon emission. Thirdly, its findings that international oil price has a significantly positive effect on China's carbon emission through the channel of oil-coal substitution has an important policy implication for Chinese energy policy makers. It shows how important that energy price signals are in carbon emission. This is exactly a point that has been missed by both academic researchers and policy makers.

3. Key assumptions

This paper raises one new assumption on factors that have been contributing to China's carbon emissions. The new assumption is that international crude oil price has a positive impact on China's carbon emission. When international crude oil price increases, China's carbon emission increases; When international crude oil price decreases, China's carbon emission decreases. Changes in international oil prices have an influence on China's carbon emission through two transmission channels, one is the direct substitution channel, the other one is the indirect substitution channel.

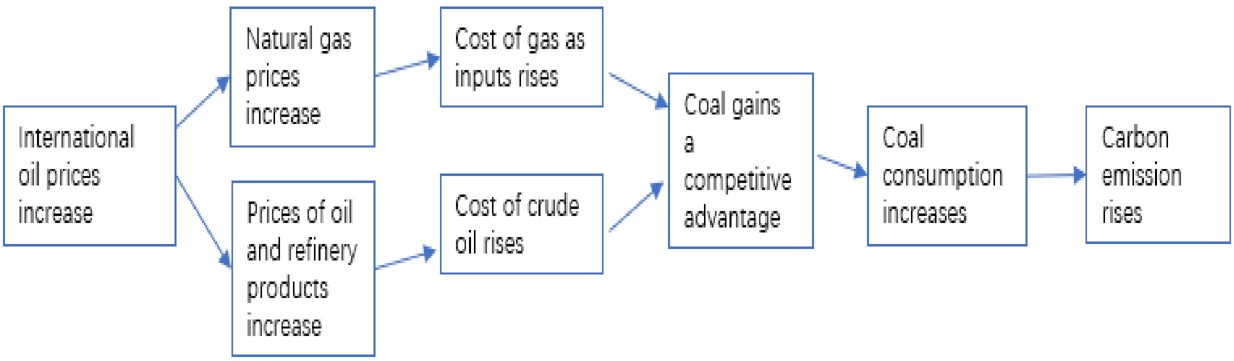

Figure 1: channels through which international oil prices affect China's carbon emission

Direct substitution channel: China is one of the largest oil importation countries in the world, with its oil importation dependency ratio rising to 73% in 2020. When international crude oil price increases, Chinese users in the field of non-combusted sectors, feedstock sectors and petrochemical fields have a higher motivation to switch from crude oil to other fossil fuels like coal and gas. Coal is naturally the best choice for local companies as China has a rich supply of coal at cheap prices. As a consequence of increasing coal use, carbon emission rises.

Indirect substitution channel: Asian gas prices are linked with international crude oil prices. In other words, when international crude oil prices rise, spot market natural gas prices in Asia also trend up; when international crude oil prices go down, spot market natural gas prices in Asia also decrease. One key implication of this linkage is that when internal oil prices and Asian natural gas prices increase, gas' use in industry, power generation and residential sector will be partly replaced by other low-cost fuels like coal. This leads to an increasing carbon emission of these sectors.

Table 1: carbon emission coefficient of different types of fossil fuels

Sources	Coal	Oil	Natural gas
	t (C) /t	t (C) /t	t (C) /t
EIA	0.702	0.478	0.389
IEA	0.756	0.586	0.449
NDRC ERI	0.726	0.583	0.409
average	0.728	0.549	0.415

4. Methodology

Both IPAT model and STIRPAT model are widely used in analyzing the relationship between environmental indicators and driving factors such as population, wealth and technology. This study chooses STIRPAT model as the benchmark model for analysis. The reason for which that this study does not choose IPAT model is that it assumes that each different factor has an equal amount of impact on the environmental indicator investigated. In addition, IPAT model can only examine the impacts of limited number of factors.

A standard STIRPAT model:

$$I_i = aH_i^b A_i^c T_i^d e_i \tag{1}$$

I represents the environmental indicator that the study researches; H, A, T represents population, wealth and technology respectively; b, c, d represents the index of H, A, T respectively; e is model error term; I means that the observation is from different years. When a=b=c=d=1 STIRPAT model is equal to IPAT model.

In this study, China's carbon emission is the environmental indicator that we wanted to investigate further. As energy price may affect carbon emission by fossil substitution in different industries, I include a price factor into the standard STIRPAT model. The extended STIRPAT model is listed as below:

$$I_i = aH_i^b A_i^c T_i^d P_i^f e_i \tag{2}$$

Taking logs on both sides gives us equation (3):

$$Ln^I = \alpha + bLn^H + cLn^A + dLn^T + fLn^P + \epsilon_i \tag{3}$$

Specifically, I represent annual carbon emission in China, denoted by CO_2; H represents China's population size at the end of each year, denoted by pop; A represents China's economic size, denoted by GDP; T represents China's technology of turning energy into economic output. I use primary energy consumption to measure T, and use pe to denote it in this paper. P represents international oil prices, measured by the nominal levels of Brent spot oil prices. I use OP to denote Brent spot oil price. Therefore, the benchmark equation for empirical test in this paper is:

$$Ln^{CO2} = \alpha + bLn^{pop} + cLn^{gdp} + dLn^{pe} + fLn^{OP} + \epsilon_i \qquad (4)$$

Table 2 describes each of these variables in details.

5. Data description

Table 3 reports description statistics of each variable. The sample period is 1978 to 2019. The years before 1978 is excluded, mainly because the country's economy was hardly hit by the Great Cultural Revolution. Data in 2020 and 2021 are also excluded from this sample, because of the outbreak and spread of Covid-19 starting in January 2020. The pandemic not only causes a significant shock to the oil market, it also suppresses the growth of the economy. Thus, observations before 1978 and those after 2019 are treated as outliers in China's economic system and energy market.

During this sample period, average annual carbon emission in China was 4690 mn tones, while average Brent spot oil price was USD 63 per barrel. The skewness of carbon emission and oil price are both larger than zero, suggesting that the distributions have a long tail in the right side. The kurtosis of carbon emission and oil price are both negative, indicating that the distributions of these two variables are flatter than normal distribution. Primary energy consumption reveals similar pattern.

Table 2: Data description

		Variables	**Data**	**Code**	**Unit**	**Frequency**	**Data process**	**Source**	**Sample period**
Dependent variable	environmental indicator	carbon emission	CO2 emission from energy use	CO2	mn tonnes	annual	take log	NBS	1978-2019
Independent variables	population	population	population size	pop	10,000	annual	take log	NBS	1978-2019
	wealth	economic size	GDP	gdp	100 mn,CNY	annual	take log，$2019	NBS	1978-2019
	technology	primary energy consumption	primary energy use	pe	EJ	annual	take log	NBS	1978-2019
	energy price	oil prices	Brent oil spot price	OP	USD per barrel nominal	annual		bp	1978-2019

Table 3: Description statistics

	CO2	OP	pe	gdp	pop
observations	43	43	43	43	43
mean	4690.6	63	60.7	198028	122032
sd	3009	31.8	41.7	264746	13461
median	3236.1	55.7	40.3	45236	125274
trimmed	4509.8	60.5	57.2	148439	122822
mad	2484.9	31.6	32.2	61110	14524
min	1418.5	19.9	16.7	3593	96259
max	9825.8	126.5	141.7	890305	140005
range	8407.3	106.5	125.1	886712	43746
skew	0.5	0.6	0.6	1.3	-0.4
kurtosis	-1.4	-1	-1.2	0.4	-1.2
se	464.3	4.9	6.4	40851	2077

Source: WIND

6. Empirical results

6.1 Ridge regression analysis

Table 4 shows that the correlation coefficient between GDP and pe is 0.95, the correlation coefficient between pop and pe is 0.88, and the correlation coefficient between pop and gdp is 0.76. These large correlation coefficients among variables suggest the existence of multicollinearity, which leads to unreliable estimates from OLS regressions. Consequently, we use Ridge regression rather than OLS to conduct the empirical analysis of the extended STIRPAT model.

Table 4: Correlation

	CO2	OP	pe	gdp	pop
CO2	1				
OP	0.42	1			
pe	0.99	0.39	1		
gdp	0.92	0.34	0.95	1	
pop	0.89	0.08	0.88	0.76	1

Table 5 reports the Ridge regression results. In all of these five regressions, international oil price plays a statistically significant role in explaining the changes in China's carbon emission. International oil price affects China's carbon emission in a positive way. In other words, a 1% increases in international oil price leads to an increase of around 0.12% in China's carbon emission. This is driven by the substitution of coal and crude oil in certain industrial sectors. Specifically, when crude oil price increases, Chinese industrial users of crude oil have a stronger motivation to switch to coal, which is a relatively cheaper but carbon intensive fuel.

As the use of coal rises, total carbon emission in a specific year also trends up. This finding is different from the relationship between oil price and a region's carbon emission from available literatures. Existing literatures document a negative relationship between oil price and a region's carbon emission as already reviewed in previous section.

Table 5: Brent oil prices and China's carbon emission

	(1)	(2)	(3)	(4)	(5)
$\ln^{gdp}$					0.0103
					(0.45)
$\ln^{pop}$		0.8714***		0.5498***	0.5776
		(1.97)		(1.86)	(1.49)
$\ln^{pe}$			0.8936***	0.8453***	0.7939***
			(76.34)	(22.54)	(16.57)
OP	0.0121*	0.0043***	0.0009*	0.0011***	0.0012***
	(6.32)	(5.89)	(4.69)	(5.18)	(5.29)
Control years	Y	Y	Y	Y	Y
Adj.R^2	0.57	0.94	0.93	0.95	0.97

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) is OLS regression; Regression (2)-(5) are ridge regressions. The dependent variables in all regressions are $\ln^{CO2}$

6.2 Control other variables

6.2.1 Control economic variables

Environmental Kuznet hypothesis holds that there is a negative U-shape relationship between a region's economic development level and its carbon emission. That is, the extent to which GDP has an influence on carbon emission falls gradually as GDP rises. Therefore, this study introduces the square of $\ln^{gdp}$ in order to see whether inclusion of this factor will change the relationship between international oil price and China's carbon emission.

Existing literature shows that improvement in economic structure will have an influence on carbon emission. Economic structure refers to the share of industry in GDP or the share of secondary industry in GDP. Industrial sectors and secondary sector are mainly composed of energy intensive fields. Theoretically speaking, a decrease in the share of either secondary industry in GDP or the share of industrial sectors in GDP, may help lead to less carbon emission in the economy. Therefore, this paper controls the impacts of economic structure on China's carbon emission.

Table 6 reports empirical results. The fourth column of table 6 shows that the square of economic size is not a significant variable. It also shows that controlling economic size does not change the estimated relationship between international oil price and China's carbon emission. The estimated coefficient of international oil price is still a significantly positive number, without any noticeable change in its

size. This evidence indicates that the explanation power of oil price remains strong even after controlling the impacts of the square of the economic size.
The fifth column and the sixth column of table 6 shows that the economic structure is a statistically significant variable in forecasting China's carbon emission. Improvement in economic structure can help reduce carbon emission in China. Meanwhile, the estimated coefficient of international oil price is 0.11 in both regressions, suggesting that controlling the economic structure does not change the relationship between international oil price and China carbon emission.

Table 6: Control the square of GDP and economic structure

	(1)	(2)	(3)	(4)	(5)	(6)
ln^{gdp}				0.0413*	0.0619**	0.0637**
				(2.46)	(2.93)	(3.27)
ln^{pop}				0.5787	0.0033	0.0636
				(1.59)	(0.36)	(0.17)
ln^{pe}				0.7801***	0.7673***	0.7553***
				(16.06)	(17.49)	(17.11)
OP	0.0031***	0.0110***	0.0100***	0.0013***	0.0011***	0.0011***
	(5.34)	(6.53)	(6.23)	(5.52)	(4.33)	(4.53)
$(ln^{gdp})^2$	0.0142***			-0.0011		
	(23.47)			(1.57)		
industry_share			0.0182**			0.3369*
			(4.15)			(1.99)
second_share		0.0018***			0.3817*	
		(4.35)			(2.19)	
Control years	是	是	是	是	是	是
Adj. R^2	0.98	0.69	0.73	0.91	0.95	0.96

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) is OLS regression; Regression (2)-(6) are ridge regressions. The dependent variables in all regressions are ln^{CO2}

6.2.2 Control the structure of energy consumption

The structure of energy consumption is relevant for carbon emission. If the share of low carbon energy consumption in total energy use is relatively small, the amount of carbon emission from the same amount of energy use is smaller. This is because the consumption of low carbon energy (eg. hydro, wind power, solar power, geothermal power and biomass) produces much less emission, compared to that of fossil fuels. Therefore, this study also takes into account of the impact of energy consumption structure. I use two variables to measure the change in China's energy consumption structure, one is "nff_share" (i.e. the share of non-fossil fuel in total primary energy consumption); the other one is "power_mix" (i.e. the share of coal-fired power generation in total power generation).

The data source of the former variable is China's Energy Statistics (2021 version). The data source of the later variable is bp World Energy Statistical Review (2021 version).

Table 7: control the structure of energy consumption

	(1)	**(2)**	**(3)**
$\ln^{gdp}$	0.0103	0.0481***	0.0321*
	(0.45)	(3.37)	(2.32)
$\ln^{pop}$	0.5776	0.2718	0.3044
	(1.49)	(1.09)	(1.18)
$\ln^{pe}$	0.7939***	0.8121***	0.8759***
	(16.57)	(25.25)	(28.31)
OP	0.0012***	0.0007***	0.0005***
	(5.29)	(3.78)	(3.12)
nff_share		-1.1961***	
		(4.88)	
power_mix			0.5317***
			(5.91)
Control years	Y	Y	Y
Adjusted R^2	0.95	0.97	0.97

Note: Numbers in ( ) are t values of the estimates. *,**,*** represents significance at 10%,5% and 1% levels. Regression (1)-(3) are ridge regressions. The dependent variables in all regressions are $\ln^{CO2}$

According to the second column of table 7, the share of non-fossil fuel in primary energy consumption has a statistically significant negative effect on China's carbon emission. A 1% increase in the nff_share leads to a 1.2% decrease in carbon emission. This is consistent with theoretical analysis. According to the third column of table 7, the share of coal fired power generation in total power generation has a statistically significant and positive effect on China's carbon emission. A 1% increase in the power_mix leads to a 0.53% increase in carbon emission. This mainly reflects the carbon intensive characteristics of coal-fired power generation.

The estimated coefficients of international oil price in both regression 2 and regression 3 in table 7 shows that controlling the effects of energy use structure does not change the previous conclusion. Despite the fact that the coefficients of oil prices are now smaller compared to the benchmark regression, both coefficients are still statistically significant and positive, which is same as before. These evidence supports the view that the forecasting capability of international crude oil prices cannot be completely diluted by information contained in China's energy consumption structure.

6.2.3 Control urbanization rates

Existing literature finds that urbanization rates help explain carbon emission. Increasing urbanization rates means a greater portion of the whole population is moving to and living in urban areas. In the period of 1978-2019, China's urbanization rate rose from less than 18% to 61%, with urban population expanding from 172 mn to 848 mn in 2019. This has led to steadily increasing demand for energy in urban areas, which boosts carbon emission. Thus, this paper controls the change in urbanization rate. The data source is the official website of NBS.

Table 8 summarizes key empirical results. According to the first column and the third column of table 8, we can see that an increasing urbanization rate does help boost carbon emission. This is consistent with the findings in Zhang Tengfei (2016), but is in exactly the opposition of Li Xiangmei (2014).

After controlling urbanization rates, the size of the coefficient of oil price remained unchanged, and the sign is still significantly positive. It says that the information contained in urbanization rates is not completely overlapped with that of international oil prices.

Table 8: control urbanizations

	(1)	(2)	(3)
$\ln^{gdp}$		0.0103	0.0351*
		(0.45)	(1.72)
$\ln^{pop}$		0.5776	0.6712*
		(1.49)	(2.01)
$\ln^{pe}$		0.7939***	0.8222***
		(16.57)	(17.78)
OP	0.0034***	0.0012***	0.0012***
	(5.59)	(5.29)	(5.51)
urbanization	0.0384***		0.0047*
	(21.69)		(2.12)
Control years	Y	Y	Y
Adj. R^2	0.93	0.95	0.98

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) is OLS regression; Regression (2)-(3) are ridge regressions. The dependent variables in all regressions are $\ln^{CO2}$

6.2.4 Control other energy prices

This study also takes into account of the prices of other fossil fuels, including international gas prices, Chinese coal prices and international coal prices. In order to better measure the impacts of international gas prices, this study adopts three gas price series as control variables, including NBP gas price, Henry Hub gas price, and Japan imported LNG price. In order to fully capture the impacts of coal prices on China's carbon emission, this study adopts four coal price indices, which are northwestern Europe steam coal prices, Japan imported steam coal prices, the U.S.

Appalachia steam coal prices and China's Qinhuangdao port steam coal prices. Energy prices for 1985-2019 is from bp World Energy Statistical Review (2021 version). Energy prices for 1978-1984 is from the pink sheet of World Bank. Table 9 reports variable descriptions. Table 10 reports description statistics of these control variables.

Table 11 reports empirical results. According to column 1, column 2 and column 3, the coefficients of international coal prices are not significant at all, indicating that international coal prices may not be the key drivers of China's carbon emission. During the period of 1978-2019, imported coal only accounts for less than 10% of China's annual coal consumption. Domestic production can meet the majority of domestic demand. This could be the key reason why international coal prices has no significant influence on China's carbon emission. According to the fourth column of table 11, domestic coal price is not a significant variable either. This could be a consequence of the fact that Chinese coal market is still tightly regulated by Chinese authorities and coal prices in domestic market could not reflect market dynamics in time. These numbers tell us that neither international coal prices nor domestic coal prices have any capability to forecast China's carbon emission.

Noticeably, in all these regressions in table 11, the coefficient of crude oil prices are still positive and significant. In addition, the size of the estimates does not change significantly. It shows that the influence of international oil price on China's carbon emission is independent of the trends of other fuel prices.

Table 9: description of other energy prices

Variable name	Data series	Code	Unit	Frequency	Source	Sample period
International coal prices	Northwestern coal price	coal_eu	usd/ton	year	bp,World Bank	1978-2019
	Japan imported coal	coal_japan	usd/ton	year	bp,World Bank	1978-2019
	U.S. Appalachia coal price	coal_us	usd/ton	year	bp,World Bank	1978-2019
Domestic coal prices	Qinhuangdao steam coal prices	coal_china	usd/ton	year	bp,World Bank	1978-2019
International gas prices	NBP gas	nbp	usd/mmbtu	year	bp,World Bank	1978-2019
	Henry Hub gas	hh	usd/mmbtu	year	bp,World Bank	1978-2019
	Japan imported LNG	lng_japan	usd/mmbtu	year	bp,World Bank	1978-2019

Table 10: descriptive statistics of other energy prices

	coal_eu	coal_us	coal_japan	coal_china	nbp	hh	lng_japan
n	42	42	42	42	42	42	42
mean	56.08	44.17	66.43	54.86	4.35	3.29	6.57
sd	26.38	21.34	30.07	28.28	2.68	1.88	3.94
median	43.54	32.46	50.74	41.43	3.3	2.68	5.14
trimmed	52.28	41.81	62.89	51.06	4.01	2.99	5.87
mad	17.37	13.81	18.14	15.34	2.09	1.36	2.57
min	28.79	20.5	34.58	27.15	1.5	0.91	3.04
max	147.67	117.42	136.21	127.27	10.79	8.85	16.75
range	118.88	96.92	101.63	100.12	9.3	7.94	13.71
skew	1.44	1.15	0.91	1.01	0.9	1.42	1.3
kurtosis	1.91	1.2	-0.56	-0.36	-0.36	1.54	0.6
se	4.07	3.29	4.64	4.36	0.41	0.29	0.61

Table 11: Control other energy prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln^{gdp}	0.0069	0.0183	0.0177	0.0036	0.0072	0.0007	0.0021
	(1.05)	(0.94)	(1.17)	(0.23)	(0.45)	(0.05)	(0.13)
ln^{pop}	0.6251***	0.4313	0.6477***	0.6487***	0.6411**	0.4651**	0.6669**
	(3.61)	(1.53)	(3.61)	(3.81)	(3.27)	(2.93)	(4.01)
ln^{pe}	0.8075***	0.7987***	0.7752***	0.8387***	0.7922***	0.8487***	0.8386***
	(21.64)	(18.67)	(21.63)	(22.35)	(19.82)	(25.97)	(22.77)
OP	0.0007**	0.0010***	0.0008***	0.0005***	0.0010***	0.0006***	0.0011***
	(2.95)	(4.65)	(3.42)	(1.87)	(2.78)	(3.69)	(3.99)
coal_eu	0.0004						
	(1.27)						
coal_japan		-0.0003					
		(1.04)					
coal_us			0.0004				
			(0.91)				
coal_china				0.01			
				(0.37)			
nbp					0.0049		
					(1.22)		
hh						0.0071**	
						(3.27)	
lng_japan							0.0025
							(0.97)
Control years	Y	Y	Y	Y	Y	Y	Y
Adj.R^2	0.93	0.95	0.93	0.94	0.95	0.98	0.97

Note: Numbers in () are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1)-(7) are ridge regressions. The dependent variables in all regressions are ln^{CO2}

6.3 Robustness tests

In this section, I run a series of robustness tests. First, I change the measurement of independent variable, using carbon emission per capita and carbon intensity to replace carbon emission. I find that changes in international crude oil prices can lead to changes in carbon emission per capita and changes in carbon intensity in the same direction. Secondly, I split the sample period into two sub-period: 1978-1998 and 1999-2019. I find that international oil prices have forecasting capability in both periods. Thirdly, I use the real oil prices to replace nominal oil prices in the regression. I find that the conclusion remains unchanged.

6.3.1 Different measurements of carbon emission

Existing literature often use three indicators to measure a region's carbon emission. They are the total volume of carbon emission, carbon emission per capita, and carbon intensity. Specifically, the carbon emission per capita is defined as the total volume of carbon emission divided by total population; carbon intensity is defined as the total volume of carbon emission divided by GDP.

For robustness test, I use carbon emission per capita and carbon intensity to be the dependent variable, and use GDP per capita, primary energy consumption per capita, international oil prices and other control variables as independent variables. Table 12 and table 13 reports key results. Despite a slightly smaller size of estimates, international oil prices still show statistically significant power in explaining changes in carbon intensity and carbon emission per capita.

Table 12: use carbon emission per capita to measure carbon emission

	(1)	**(2)**	**(3)**	**(4)**
ln_gdp_percapita		0.3003***		-0.0004
		(20.19)		(0.03)
ln_pe_percapita			0.8773***	0.8756***
			(71.23)	(18.02)
OP	0.0111*	0.0031***	0.0010*	0.0011*
	(6.59)	(5.44)	(5.21)	(4.84)
controls	Y	Y	Y	Y
Adj.R^2	0.59	0.87	0.94	0.94

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) is OLS regression; Regression (2)-(4)are ridge regressions. The dependent variables in all regressions are Ln_CO2_percapita

Table 13: use carbon intensity to measure carbon emission

	(1)	(2)	(3)	(4)
log_gdp_percapita		-0.0354***		-0.0766***
		(9.21)		(6.50)
log_pe_percapita			0.1854***	0.0312
			(15.39)	(0.92)
OP	0.0018*	0.0011***	0.0013***	0.0009***
	(2.60)	(5.51)	(5.67)	(4.98)
controls	Y	Y	Y	Y
Adj. R^2	0.27	0.82	0.93	0.93

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) and regression (2) are OLS regression; Regression (3)-(4) are ridge regressions. The dependent variables in all regressions are carbon intensity.

6.3.2 Split into two sub-sample periods

Before 1998, the prices of domestic oil products were set directly by Chinese authorities. Moreover, the prices usually remained unchanged for a long time. Thus, the connection between international oil prices and domestic oil products before 1998 may not be as strong as that in the period after 1998. Starting from June 1998, the prices of domestic oil products have been linked with the average prices of international crude oil indices and have been updated on a monthly basis. Therefore, I split the dataset into two subsets, composed of the sample period of 1978-1998 and the period of 1999- 2019 and examine the impacts of international oil prices on China’s carbon emission in two periods respectively.

Table 14 reports key findings. In both sub-periods, the coefficients of international oil prices are both statistically significant and positive, suggesting that international oil prices still have explanatory power in other periods.

Table 14: split into two samples

	1978-1998	1978-1998	1999-2019	1999-2019
	(1)	(2)	(3)	(4)
ln^{gdp}		0.0211		0.0452
		(1.25)		(1.61)
ln^{pop}		0.1615		0.1852
		(0.59)		(1.35)
ln^{pe}		0.8530***		0.7078***
		(16.39)		(8.46)
OP	0.0137**	0.0012*	0.0093*	0.0005**
	(3.04)	(2.36)	(4.82)	(3.22)
controls	Y	Y	Y	Y
Adj.R^2	0.35	0.95	0.51	0.94

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1) and regression (3) are OLS regression; Regression (2) and regression (4) are ridge regressions. The dependent variables in all regressions are ln^{CO2}.

6.3.3 Measurement of different oil prices

In the previous section, I use Brent spot oil nominal price to measure international oil price. In this section, I conduct similar empirical analysis using different measurements of international oil prices, including Brent spot oil real price, WTI, and Dubai. These alternative oil price data come from bp's World Energy Statistical Review (2021 version).

Table 15, table 16 and table 17 report key findings. According to table 15, we can see that changing nominal oil price to real oil prices (in USD 2019) does not change the main finding. Table 16 shows that replacing Brent spot oil price with WTI futures prices does not change the main finding. Table 17 shows that changing Brent spot oil price to Dubai oil price has no impact on the main finding. Results in these three tables indicate that the impact of international oil price on China's carbon emission does not change as the measurement of oil price changes.

Table 15: real crude oil prices to measure oil price

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
ln^{gdp}					0.0146
					(0.54)
ln^{pop}		0.6388***		0.4586	0.5247
		(13.74)		(1.45)	(1.24)
ln^{pe}			0.8864***	0.8246***	0.8556***
			(57.49)	(20.21)	(15.68)
OP_real	0.0135***	0.0049***	0.0010***	0.0012***	0.0012***
	(8.39)	(5.88)	(3.76)	(4.34)	(4.09)
controls	Y	Y	Y	Y	Y
Adj.R^2	0.71	0.92	0.91	0.92	0.93

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1)-(3) are OLS regression; Regression (4)-(5) are ridge regressions. The dependent variables in all regressions are ln^{CO2}.

Table 16: use WTI to measure oil prices

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
log_gdp					-0.0067
					(0.26)
log_pop		0.6411***		0.4886	0.4722
		(13.87)		(1.71)	(1.21)
log_pe			0.8806***	0.8162***	0.8372***
			(63.06)	(22.09)	(16.25)
wti	0.0152***	0.0056***	0.0013***	0.0015***	0.0015***
	(8.34)	(5.92)	(4.68)	(5.29)	(4.95)
controls	Y	Y	Y	Y	Y
Adj.R^2	0.71	0.91	0.91	0.92	0.96

Note: Numbers in () are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1)-(3) are OLS regression; Regression (4)-(5) are ridge regressions. The dependent variables in all regressions are ln^{CO2}.

Table 17: use Dubai spot crude prices to measure oil prices

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
ln^{gdp}					-0.0021
					(0.13)
ln^{pop}		0.0454***		0.4616***	0.4923**
		(22.83)		(3.42)	(2.24)
ln^{pe}			0.9231***	0.8338***	0.8332***
			(111.87)	(31.44)	(20.51)
OP_Dubai	0.0176***	0.0071***	0.0005***	0.0011***	0.0011***
	(7.49)	(9.19)	(2.51)	(4.49)	(4.61)
controls		Y	Y	Y	Y
Adj. R^2	0.57	0.94	0.96	0.98	0.98

Note: Numbers in ( ) are t values of the estimates. *, **, *** represents significance at 10%, 5% and 1% levels. Regression (1)-(3) are OLS regression; Regression (4)-(5) are ridge regressions. The dependent variables in all regressions are lnCO2.

7. Conclusions

This study extends the standard STIRPAT model by introducing an energy price factor and uses the extended STIRPAT model to examine the effects of international crude oil prices on China's carbon emission. This paper uses Ridge regression to conduct empirical analysis. The study finds that changes in international crude prices have a significantly positive impact on China's carbon emission. A one percent increase in international crude oil price leads to a 0.12 percent increase in China's carbon emission. This finding remains unchanged when a set of control variables are included in the analysis and survives all the robustness tests.

This finding provides an important reference for Chinese policy makers. As China announced its pledge to achieve carbon neutral by 2060, fully understanding how to decarbonize its carbon intensive economy will be of importance. This paper provides a different angle for policy makers. It tells us that energy prices and relative cost of different fuels should also be considered in energy policy making in the future.

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