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Are Chinese Green Transport Policies Effective? A New Perspective from Direct Pollution Rebound Effect, and Empirical Evidence From the Road Transport Sector

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Academic Editors: Liexun Yang, Peng Zhou, Ning Zhang and Marc A. Rosen
Received: 26 December 2016; Accepted: 11 March 2017; Published: 15 March 2017

Abstract: Air pollution has become a serious challenge in China. Emissions from motor vehicles have been found to be one main sources of air pollution. Although the Chinese government has undertaken numerous green policies to mitigate harmful emissions from road transport sector, it is still uncertain for both policy makers and researchers to know whether the policies are effective in the short and long terms. We propose a new concept of "pollution rebound effect" (PRE) to estimate the effectiveness of green traffic policies. We estimate direct air PRE as a measure of the effectiveness of the policies of reducing air pollution from the transport sector based on time-series data from the period 1986–2014. We find that the short-term direct air PRE is -0.4105, and the corresponding long-run PRE is -0.246. The negative results indicate that the direct air PRE does not exist in the road passenger transport sector in China, both in the short term and in the long term during the period 1986–2014. This implies that the Chinese green transport policies are effective in terms of harmful emissions reduction in the transport sector. This research, to the best of our knowledge, is the first attempt to quantify the effectiveness of the green transport policies in the transitional period that China is currently undergoing.

Keywords: direct rebound effect; air pollution; road passenger transport; policy effectiveness

1. Introduction

China is facing a serious environment problems, especially air pollution resulting from the rapid economic growth. According to one study by the World Bank, 12 of the 20 most polluted cities in the world are located in China [1]. This ranking is based on ambient concentrations of particulate matter less than 10 μm in diameter. The ambient concentration of $PM_{2.5}$ in China is the most polluted in the world based on the report of the World Bank [2] (see Figure 1). The State of Environment (SOE) Report of 2016 states that: "Among the 338 prefecture- level cities, there are eighty percent whose air quality exceed the standard [3]." Serious air pollution has severe effects on human health, increasing the risk of lung cancer, respiratory and cardiovascular diseases [4–8], which also increases the residents' medical cost [9–13]. Now more attention has been paid to air quality, putting pressure on the Chinese government to introduce scientific and feasible policies to balance economic development and environmental problems.

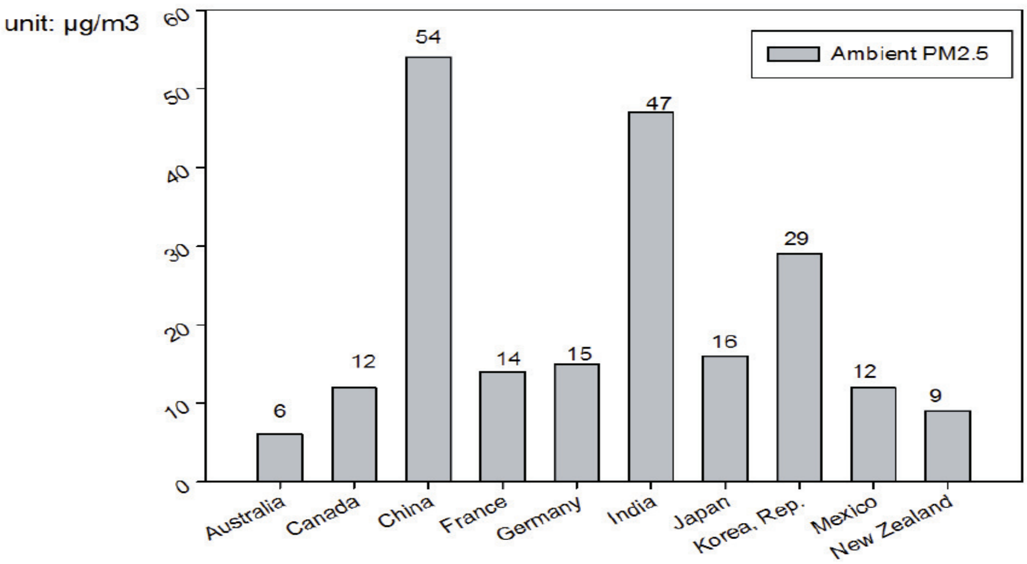

Figure 1. Concentration of ambient $PM_{2.5}$ in different countries, 2013 [2].

To control and decrease air pollution, it is necessary to figure out the main sources of air pollution. According to the "China Vehicle Environmental Management Annual Report, 2016", motor vehicles are one of the main sources of air pollution in China [14]. The transport sector is a major area that policymakers should pay more attention to. The last decade witnessed a dramatic increase in the travel demand of Chinese residents. China's passenger turnover has risen from 1746.67 billion passenger-kilometers (pkm) in 2005 to 3009.74 billion pkm in 2014 [15] (see Figure 2), resulting in serious polluted air emissions. The total vehicle emissions in China reached 45.32 million tons in 2015. Specifically, the emissions of CO, HC, NO_x and PM from vehicles were 34.61, 4.30, 5.85 and 0.56 million tons, respectively [14]. The transport sector has been a major field of harmful emissions reduction [9,16,17].

The Chinese government has implemented several laws and policies to deal with the serious air pollution. The law "Prevention and Control of Air Pollution" was introduced in 1987 by the National People's Congress and its Standing Committee. A wide range of regulations, decisions, orders and quality standards have been issued. For example, the State Council promulgated the "Atmospheric Pollution Prevention Action Plan" in 2013. In 2004, the mandatory fuel economy standard for passenger vehicles was launched and the first, second and third phases were implemented in 2005, 2008 and 2010, respectively. In some megacities (e.g., Beijing, Shanghai and Guangzhou), regulatory policies imposed on vehicle usage, as well as car ownership. The Chinese government has also introduced various policies to encourage and popularize the research and development of new energy vehicles, like tax preferential policy, technology innovation policy and financial subsidy policy.

Due to the efforts of the Chinese government, the environment quality has been improved. However, China's environment protection is still lagging behind its economic and social development. Environmental capacity has been reached, or we have reached a ceiling that prevents further improvement [3]. To accurately understand the actual effect of these policies, a measure of rebound effect (RE) is necessary, which can provide useful information about the effectiveness of the policies for the policymakers.

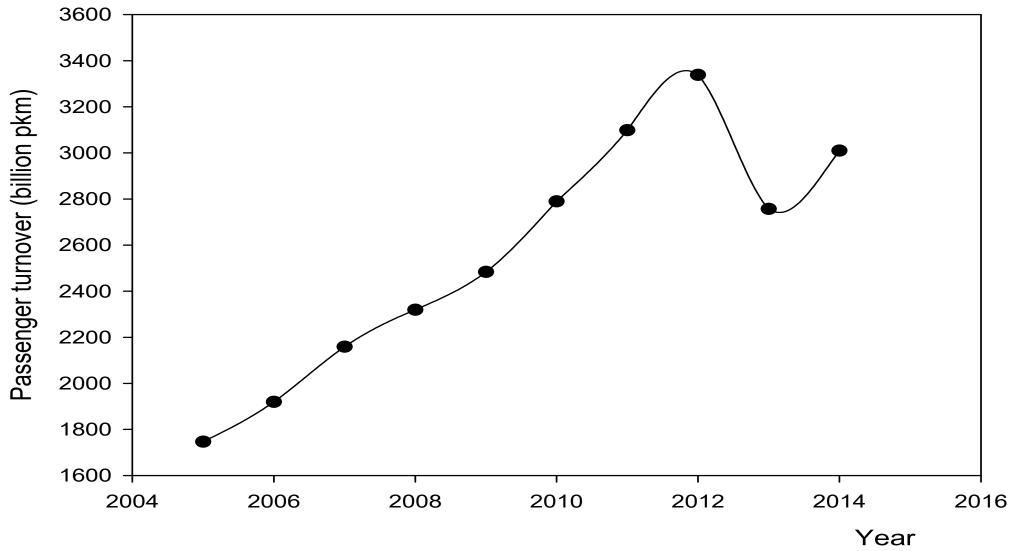

Figure 2. Passenger turnover in China, 2005-2014 [15].

The rebound effect is initially proposed by Jevons [18]. It is generally acknowledged that when technological progress causes an increase in efficiency by 1%, a reduction in energy consumption obtaining the same products by 1% is expected, whereas the actual reduction may be below 1%. Studies have identified three main types of rebound effects (RE): direct rebound effect, indirect rebound effect and macro-level rebound effect [19–22].

Direct rebound effect is limited to a single energy service or a single sector. With the improvement of energy efficiency, energy consumption is not reduced to the expected level in theory because of the decline in the cost of energy product or energy service and the increase in consumers' energy demand. The issue of pollution rebound effect (PRE) in the transport sector also relates to the improvement in energy efficiency. The government encourages an improvement in the energy efficiency of vehicles to reduce harmful emissions and save energy from the travel. However, fuel-efficient vehicles make energy services cheaper, thereby encouraging the increased consumption of those services. For instance, consumers may choose to drive farther and/or more often following the purchase of a fuel-efficient vehicle because the operating cost per kilometer has fallen. This may offset some savings because of fuel efficiency improvement. So there will be a rebound effect of the fuel consumption, which results in the harmful emissions also appearing in a rebound effect. Indirect rebound effect measures the reallocation of energy savings to spending on other goods and services that also require energy. The macro-level rebound effect refers to the impact of energy efficiency improvement on the entire economy. This paper focuses on the direct air pollution rebound effect from the transport sector.

Based on the definition of rebound effect in energy consumption, we firstly define the pollution rebound effect (PRE), namely,

$$PRE = \frac{Forecasted Emission Reductions - Achieved Emission Reductions}{Forecasted Emission Reductions} \quad (1)$$

According to the magnitude, PRE can be classified into five categories, which represent different policy effects (see Table 1). When the size of PRE is greater than 0, it means that the pollution rebound effect exists. $0 < PRE < 1$ means that the policies are partially effective, not fully achieving the goal of pollution emission reductions. PRE=1 means that the policies are completely ineffective and $PRE > 1$ is the worst, implying that the policies not only do not decrease harmful emissions, but in fact are increasing the emissions. When the size of PRE is less than 0 or equal to 0, it indicates that the pollution rebound effect does not exist. PRE = 0 means that the policies are effective, which fully achieve the goal of emission reductions. PRE < 0 is the best for the policymakers, it means the actual reductions are more than the planned reductions.

Table 1. Categories of PRE based on the size.

Size	Existence	Policy Implication
PRE > 1	Yes	Negative effect
PRE = 1	Yes	Completely ineffective
0 < PRE < 1	Yes	Partially ineffective
PRE = 0	No	Fully effective
PRE < 0	No	Positive effect

Some studies have examined the rebound effect in the transport sector, but most focus on the fuel consumption. Sorrell et al. provide a review of studies that include transportation and energy in general [23]. They report that, for personal automotive transport, in OECD countries, the mean value of the long-run direct rebound effect is likely to be less than 30% and may be closer to 10% for transport. Through examining motor vehicle transportation in the US, Small and Van Dender estimate the short and long-run rebound effect of 4.5% and 22.2%, respectively [24]. Barla et al. present estimates of the rebound effect for the Canadian light-duty vehicle fleet. Their results imply a rebound effect of 8% in the short term and a little less than 20% in the long term [25]. Using panel data on U.S. states, Hymel and Small confirm the earlier finding of a rebound effect that declines in magnitude with income, but they also find an upward shift in its magnitude of about 0.025 during the years 2003–2009 [26]. Some studies also estimate the direct rebound effect for passenger transport in China [27,28]. Although all the current studies conclude that the rebound effect exists in fuel consumption for the transport sector, the range of the magnitude is very different. For example, Wang et al. estimate the direct rebound effect for passenger transport in urban China, finding that the average rebound effect for passenger transport by urban households is around 96% [27]. Zhang et al. reveal that the short-term and long-term direct rebound effects of the whole country are 25.53% and 26.56% on average, respectively [28]. Furthermore, we can not find any study on the pollution rebound effect of China.

In summary, it is necessary to explore whether the direct air pollution rebound effect exists in the road passenger transport in China. To the best of our knowledge, this paper is the first attempt in the current literature to evaluate the direct air pollution rebound effect. The results can provide useful information for policy makers to understand the effectiveness of the green policies, which aim to reduce harmful emissions of transport sector.

The remainder of this paper is structured as follows. Section 2 introduces the methods used to estimate the rebound effect of air pollution as well as data definitions. Section 3 presents the empirical results and detailed discussions. Finally, Section 4 summarizes our results and offers some policy implications.

2. Methods and Data

In this paper we explore the existence of direct air pollution rebound effect for the road passenger transport sector in China during 1986–2014. To estimate the direct air pollution rebound effect, we firstly need to calculate the emissions reduction from the transport sector based on the definition of PRE (see Equation (1)). Here, we have an assumption that the emission factor remains unchanged and the emission factor refers to harmful gases emissions from unit energy consumption of vehicles. The details are provided in Section 2.1. So we can directly calculate the fuel consumption reduction. According the analysis, we find that we can estimate the fuel rebound effect, which is equal to the PRE. Following the definition introduced by Berkhout et al. [19] and Khazzoom [29], we can calculate the rebound effect according to the elasticity of fuel consumption with respect to fuel efficiency. In this paper, we use the elasticity of vehicle kilometers (VKM) with respect to fuel price as a proxy.

2.1. The Direct Air Pollution Rebound Effect

Like the estimation in the literature by Chen and He [11], we calculate the air pollutant emissions of transport by the following equation:

$$H_i = F_m \times A_{m,i} \tag{2}$$

where H refers to the traffic-related harmful gases emissions, F the consumption of the fuel from transport, A the emission factor; m, i refer to the fuel type and pollutant type, respectively.

In the last 30 years, the technology of vehicles has not undergone revolutionary innovation; they still mainly burn fuel. The emissions still have a strong relationship with fuel consumption. So in this paper we suppose the emission factor remains unchanged. When the fuel consumption has a rebound effect, then the air pollution rebound effect will occur. The two are equal. However, we can notice that according to Equation (2), the emission factor also influences emissions. Here, we assume that emission factors are constant to simplify the study. The assumption is reasonable during the sample period. However, further study can be conducted to take into account the emission factor.

According to the definition of rebound effect mentioned by other studies [19,29], the estimation can be calculated by the following equation:

$$RE = \eta_E(F) + 1 \tag{3}$$

where RE is the rebound effect; F is the consumption of fuel; E is fuel efficiency; $\eta_E(F)$ refers to the elasticity of fuel consumption with respect to fuel efficiency.

Following the previous study by Odeck and Johansen [30], the relationship between the elasticity of fuel consumption with respect to fuel efficiency and elasticity of vehicles kilometers traveled (VKM) demand with respect to fuel price is as follows:

$$\eta_E(F) = -\eta_P(VKM) - 1 \tag{4}$$

where $\eta_P(VKM)$ is the elasticity of VKM demand with respect to fuel price. Combining Equations (3) and (4), the negative $\eta_P(VKM)$ is used as a proxy measure for the rebound effect. We adopt the logarithmic model to measure the short-term direct rebound effect for road passenger transport, then we estimate the corresponding long-term direct rebound effect.

2.2. The Elasticity Model

Following most studies in the literature [24,28], we choose the logarithmic equations to investigate the size of elasticity of VKM demand with respect to fuel price. The most common assumption in the literature is that fuel price and income are the only explanatory variables for VKM demand [31–33]. However, considering that the number of vehicles explains some degree of the demand for travel, in this paper we choose price level, income level and vehicle stock as the determinants for passenger travel following the study by Odeck and Johansen [30]. After adding the time-lagged VKM, we take the logarithmic operation to all variables before regression in Equation (5), where VKM_t refers to per capita demands for travel; Y_t is real income per capita; P_t is the real price of fuel; V_t is vehicle stock; VKM_{t-q-1} is the time-lagged VKM; the vector Λ are the parameters to be estimated; and ϵ_t is residuals for VKM demand, at time t. Here, the real income refers to the disposable income in the whole country. We use per capita road passenger turnover to represent the demand for travel. Considering the statistical standard of the road passenger turnover in China, the main statistical respondents are road commercial passenger vehicles, which mainly refer to buses. V refers to the stock of road commercial passenger vehicles. We use the No. 0 diesel price to probe how the price level influences VKM, because the vehicles in road passenger transport in China are heavy and mainly burn diesel [28].

$$\ln VKM_t = \lambda_0 + \lambda_Y \ln Y_t + \lambda_P \ln P_t + \lambda_V \ln V_t + \sum_{q=0}^{n} \lambda_{vkm} \ln VKM_{t-q-1} + \epsilon_t \quad (5)$$

We find that the result of one-ordered lagged lnVKM is not significant through Equation (5), using the time-series data from 1986–2014. Then we use the two-lagged lnVKM, namely, lnVKM_{t-2}. Finally, the VKM demand equation can be written as follows:

$$\ln VKM_t = \lambda_0 + \lambda_Y \ln Y_t + \lambda_P \ln P_t + \lambda_V \ln V_t + \lambda_{vkm} \ln VKM_{t-2} + \epsilon_t \quad (6)$$

where the meaning of the variables and parameters are the same as in Equation (5). In this way, $-\lambda_P$ and $-\frac{\lambda_P}{1-\lambda_{vkm}}$ are the size of short-term and long-term direct air pollution rebound effect for road passenger transport in China [34].

2.3. Data

By collecting the time-series data from 1986 to 2014, we explore the existence of the direct air pollution rebound effect for road passenger transport in China and estimate the magnitudes of short-term and long-term direct rebound effects. The utilized data are all the annual average data. The National Bureau of Statistics of the People's Republic of China, which has collected official statistics on Chinese society (http://www.stats.gov.cn/), provides macroeconomic data, such as disposable income, population, vehicle stock and road passenger turnover. Diesel price data is obtained from "Price Yearbook of China" [35] and "Price Statistical Yearbook of China" [36]. Variables that required conversion to their per capita forms are divided by the total annual population. Descriptive statistics of all variables are shown in Table 2, including the logarithmic forms of vehicles kilometers traveled per capita, the disposable income per capita, diesel price and vehicle stock.

Table 2. Descriptive statistics of the variables in China, 1986–2014.

Variable	lnVKM	lnY	lnP	lnV
Minimum	2.2656	2.7330	3.0336	4.9571
Maximum	3.1348	4.3126	3.9354	6.6426
Mean	2.7032	3.5524	3.4951	5.6985
Std. Dev.	0.2558	0.4790	0.2901	0.5849
Skewness	−0.1121	−0.1432	0.0843	0.0350
Kurtosis	1.8700	1.9057	1.8197	1.3909
Observations	29	29	29	29

3. Empirical Results and Discussions

3.1. Unit Root Test and Cointegration Test

A specific issue regarding the data's stationarity properties must be considered using time-series data. If two time-dependent variables follow a common trend that cause them to move in the same direction, it is possible to observe a significant correlation between them, even if there is no "true" association. This potential problem with time-series data can lead to a spurious regression. To avoid the mistake resulting from spurious regression problems, all the variables are checked for their stationarity properties. We employ both the Dickey and Fuller test and the Phillips and Perron test to determine the presence of a unit root. Table 3 presents the tests for the stationarity of the variables.

As is shown, all the variables are nonstationary at various levels because the results of the DF test and PP test cannot reject the null hypothesis at the 10% significance level. Then we test the stationarity of the first order difference of each variable, and the DF and PP tests indicate that the first differences exceed the critical value for all the variables, which indicates that all the variables are stationary in first differences, i.e., all the series are I(1). These results allow us to conduct the cointegration test to estimate whether a long-term equilibrium relationship exists among these variables, which is presented in Table 4. According to the Johansen test, the results of the trace statistic and the max statistic both imply that cointegration relationship is not rejected at the 5% significance level, which means the existence of one long-run relationship. Hence, we can conclude that the long-run relationship does exist among vehicles in terms of kilometers traveled per capita, the disposable income per capita, diesel price and vehicle stock.

Table 3. DF and PP test for the presence of unit root in level and differenced variables.

Variable	DF Test	1% Critical Value	5% Critical Value	10% Critical Value
$lnVKM$	−1.576	−3.730	−2.992	−2.626
lnP	−0.681	−3.730	−2.992	−2.626
lnY	−0.994	−3.730	−2.992	−2.626
lnV	−1.293	−3.730	−2.992	−2.626
$\Delta lnVKM$	−5.190 ***	−3.736	−2.994	−2.628
ΔlnP	−5.545 ***	−3.736	−2.994	−2.628
ΔlnY	−2.800 *	−3.736	−2.994	−2.628
ΔlnV	−4.117 ***	−3.736	−2.994	−2.628
Variable	**PP Test**	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
$lnVKM$	−1.643	−3.730	−2.992	−2.626
lnP	−0.667	−3.730	−2.992	−2.626
lnY	−0.791	−3.730	−2.992	−2.626
lnV	−1.376	−3.730	−2.992	−2.626
$\Delta lnVKM$	−5.193 ***	−3.736	−2.994	−2.628
ΔlnP	−5.611 ***	−3.736	−2.994	−2.628
ΔlnY	−2.919 *	−3.736	−2.994	−2.628
ΔlnV	−4.117 ***	−3.736	−2.994	−2.628

Notes: All variables are $I(1)$. *** indicates the significance at 1% level. * indicates the significance at 10% level. $\Delta lnVKM$ denotes the first-order difference of $lnVKM$, with the similar meaning to other variables.

Table 4. Results of Johansen test for cointegration.

Rank	LL	Trace Statistic	5% Critical Value	Max Statistic	5% Critical Value
0	192.45	64.93	54.64	36.37	30.33
1	210.64	28.56	34.55	16.23	23.78
2	218.75	12.33	18.17	7.95	16.87
3	224.92	4.38	3.74	4.38	3.74

3.2. Rebound Effect Estimation

Since the variables are found to be cointegrated, we develop logarithmic regression model to estimate the coefficients according to Equation (6), which is reported in Table 5. The adjusted R-squared value is relatively high. The estimated coefficients are statistically significant. We can identify the following findings.

Table 5. OLS estimation of the logarithmic regression model.

Dependent Variable	$lnVKM_t$			
Explanatory Variables	**Coefficient**	**SE**	***t*-Statistic**	***p* Value**
lnP_t	0.4105	0.1793	2.29	0.032 **
lnY_t	0.6023	0.2119	2.84	0.009 ***
lnV_t	0.0644	0.0248	2.60	0.016 **
$lnVKM_{t-2}$	−0.6690	0.3462	−1.93	0.066 *
λ_0	0.5375	0.3074	1.75	0.094 *
Adjusted R-squared	0.96			

Notes: *, **, *** denote the significance at 10%, 5% and 1% level, respectively.

First, from the direct meaning of estimated coefficients, the static elasticities of travel demand (VKM) with respect to fuel price, income and vehicle stock are 0.4105, 0.6023 and 0.0644, respectively. The elasticity of fuel price and vehicle stock are significant at the 5% significance level. The result of income is significant at the 1% level. These results imply that an increase in the fuel price of 10% would increase travel demand per capita by 4.105%; an increase of disposable income per capita of 10% would cause an increase in travel distance per capita of 6.023%; and the travel demand per capita would increase 0.644% if vehicle stock increases by 10%. The magnitude of income elasticity is close to the previous studies. For instance, Zhang et al., based on data of 30 provinces from 2003 to 2012, estimate that the elasticity of passenger kilometers with respect to gross domestic product per capita (PGDP) is 0.7907 in whole China [28]. The result of vehicle stock is relatively smaller than the income and fuel price. One reason for this may be that in this model we mainly use the road commercial passenger vehicles. Although the stock has increased during the last 30 years, the growth rate of population in China is much bigger than that of vehicle stock.

Our attention is drawn to a striking difference: most studies have negative price elasticities [25,28,30], which means that when the fuel prices increase, the travel demand will decrease. However, our result is different from these results, which is reasonable in this paper. We mainly study the road passenger transport, and use road passenger turnover per capita as the proxy. The model we applied is based on the time-series data. China has experienced a dramatic increase in the last 30 years. The growth rate of diesel price is largely smaller than the residents' travel demand. So from the result of this model, we find that when the diesel price increases, the travel demand also increases.

Second, this paper mostly concerns the existence of an air pollution rebound effect for the road passenger transport sector. From the results of Table 5 and Equations (3) and (4), the short-term PRE can be estimated as -0.4105. This negative estimation means that the direct air pollution rebound effect does not exist in the road passenger transport sector for the whole of China in the short-term during 1986–2014 based on the Table 1. The harmful emissions reduction is more than 1% in the short-term when the fuel efficiency of vehicles improves by 1% based on the unchanged emission factors. This result implies that the policies that control air pollution from the transport sector are effective. The policies not only achieve the initial emissions reduction goal, but also exceed expectations.

In addition, we can calculate the long-term PRE according to the equation: $-\frac{\lambda_P}{1-\lambda_{vkm}} = -\frac{0.4105}{1-(-0.669)} = -0.246$. So the corresponding long-run PRE is obtained as -0.246. The negative result also implies that direct PRE does not exist in the long-term during 1986–2014. However, the long-run PRE is smaller than the short-term, which means the effect of harmful emissions reduction declines more than in the short-term. This result puts forward a new doubt about whether the PRE will occur for a long time. Considering the existence of direct energy rebound effect for transport sector in developed countries [25,30,37], it is necessary to study this problem further in the future.

4. Conclusions

This study, to the best of our knowledge, is the first attempt to explore whether there is direct air pollution rebound effect for road passenger transport in China, based on time-series data from the period 1986–2014. Our empirical results indicate that direct PRE does not exist in the road passenger transport sector for the whole of China during 1986–2014. The policies, which aim to reduce harmful emissions of the transport sector, not only fully achieve the expected benefits, but also exceed the expectations. The results imply that improving the fuel efficiency of vehicles is a useful policy option for decreasing the transport energy use, resulting in the reduction of harmful gas emissions.

Our empirical study shows that the effect of harmful emissions reduction in the long-term declines more than in the short-term during 1986–2014. With China's development, the air pollution of the transport sector in China may experience a rebound effect in the future. The policy makers should consider the possibility of a rebound effect to avoid overestimating harmful emissions reduction achieved by implementing some policies for the transport sector.

Although there is no study on the air pollution rebound effect, there are studies about the energy rebound effect for transport in China. Wang et al. and Zhang et al. both find that there exists a direct energy rebound effect for transport [27,28]. However, their results are very different from each other. Based on the data of 28 provinces during 1994–2009, Wang et al. find that the average rebound effect for passenger transport by urban households is around 96% by employing the LA-AIDS model [27]. Zhang et al. find that the average sizes of short-term and long-term rebound effect are 25.53% and 26.56% in the whole country through a dynamic panel data model, based on the data of 30 provinces during 2003–2012 [28]. According to the two studies of the Chinese transport sector, we find that the study by Wang et al. [27] indicates that the majority of the expected reduction in transport energy consumption from efficiency improvement could be offset, whereas the study by Zhang et al. [28] finds that a partial direct rebound effect exists in the whole of China. This difference may be on account of the different methods and observations. This prompts us to conduct further research to estimate the different regions of China and use the panel data to get more observations.

Furthermore, as for the future work, further research can be conducted to combine the gasoline and diesel together, and consider more factors influencing travel demand to downsize related bias as much as possible.

Acknowledgments: The authors would like to thank Yang Sheng, Chen Su-Mei, Xu Feng, Liu Li, Ou Jia-Jia, Wei Wei, and all other colleagues from both China Agricultural University and JiNan University, for all their warm helps, constructive suggestions and pertinent comments. This project is supported by the National Natural Science Foundation of China (Grant Nos. 71273261 and 71573258).

Author Contributions: Ling-Yun He is a full professor of energy economics and environmental policies. Lu-Yi Qiu is a Ph.D. candidate supervised by Ling-Yun He. The authors contribute equally in the project.

Conflicts of Interest: The authors declare no conflict of interest.

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