atmosphere

Article

Impacts of Urban Rail Transit on On-Road Carbon Emissions: A Structural Equation Modeling Approach

Yifu Ou [1], Ji Zheng [1] and Kyung-Min Nam [1,2,*]

1 Department of Urban Planning and Design, The University of Hong Kong, Pokfulam, Hong Kong SAR, China
2 Centre for Urban Studies and Urban Planning, Faculty of Architecture, The University of Hong Kong, Pokfulam, Hong Kong SAR, China
* Correspondence: kmnam@hku.hk

Abstract: We examine the effects of urban rail transit on on-road carbon emissions in 90 Chinese cities, taking a structural equation modeling approach. Urban rail transit theoretically helps mitigate overall transport-sector emissions by absorbing part of the vehicular traffic demand or by generating traffic-diversion effects. However, its net contribution is obscure, given potential traffic-creation effects, since improved rail access can also incentivize new developments and thus induce additional on-road traffic. In contrast to many existing studies that neglect rail transit's traffic-creation effects, we analyze these opposing effects within a single framework, where primary rail-associated emission channels are explicitly modeled. Our central results show that urban rail density is negatively associated with on-road carbon emissions with a net elasticity of −0.0175, speaking for the dominance of the traffic-diversion effects in China's context. However, mixed evidence exists on the effects of increased urban rail density on vehicle-kilometers traveled and vehicle ownership, with the two opposing effects being relatively balanced. These findings suggest that transport-sector mitigation needs coordination between urban rail development and planning regulations.

Keywords: urban rail transit; carbon emissions; structural equation modeling; traffic diversion; China

check for updates

Citation: Ou, Y.; Zheng, J.; Nam, K.-M. Impacts of Urban Rail Transit on On-Road Carbon Emissions: A Structural Equation Modeling Approach. *Atmosphere* **2022**, *13*, 1783. https://doi.org/10.3390/atmos13111783

Academic Editor: Xinghua Li

Received: 24 September 2022
Accepted: 27 October 2022
Published: 28 October 2022

1. Introduction

The on-road transportation sector has become a primary source of carbon emissions in China, with rapid urbanization and soaring vehicle ownership. In 2019, for example, the transportation sector produced 901 million tonnes of carbon dioxide (CO_2), or 9.1% of China's total carbon emissions, and over 80% (728 million tonnes) of the transport-sector emissions were from on-road traffic [1]. In this context, urban rail transit has received increased attention within China's policy circle as a low-carbon transportation alternative to motorized vehicles [2,3]. In fact, massive urban rail developments are under way throughout China. As of 2021, 50 mainland Chinese cities were operating urban rail systems, with a total service rail length of 9207 km [4].

Although the climate-mitigation potential of urban rail transit is often highlighted, this claim has rarely been tested in an empirical setting due to the limited availability of detailed sectoral carbon emissions data. Recent studies of the rail impacts on on-road traffic, however, seem to provide indirect empirical evidence in support of the claim. For example, urban rail transit is found to significantly reduce traffic congestion, traffic volume, traffic-related air pollution, and automobile energy consumption in the United States [5], Europe [6], and China [7,8]. It may not be far-fetched to associate such evidence with urban rail's carbon-mitigation potential. However, a critical limitation of these studies lies in their sole focus on the rail-to-road mode shift. The framework that treats urban rail as a pure carbon abator is incomplete, since it can also play a catalytic role in attracting jobs and population and thus create a new demand for on-road traffic. Neglecting the latter can lead to substantial overestimation of the mitigation potential.

Against this background, we assess rail-induced net mitigation potential in China's context, considering two opposing forces—traffic-diversion and traffic-creation effects—within a single framework. Our main research questions include: (1) How large is the total effect of urban rail transit on road traffic carbon emissions? (2) What are the main channels through which urban rail transit affects road traffic carbon emissions? (3) How are the total effects distributed by channel? For the analysis, we take a structural equation modeling (SEM) approach, using a 2015 cross-sectional dataset constructed for 90 Chinese cities. SEM has strength in representing multiple causal paths within a single modeling framework—with key mediators incorporated along the paths—and allows a thorough decomposition analysis by path and link. Accordingly, SEM serves our research purpose well, and in particular, is superior to typical regression analyses, assuming only direct paths from a set of regressors to a given response variable.

Our study is distinguished from others in two respects. First, we directly estimate the rail-induced impacts on on-road carbon emissions, using a city-level sectoral emissions dataset. Directly measuring the impacts in terms of emissions has rarely been undertaken due to limited data. Second, we explicitly model multiple causal paths under an SEM framework, incorporating both traffic-diversion and creation dynamics in a parallel manner. This approach helps avoid potential overestimation and thus improves the robustness of estimation results.

The rest of this paper is organized as follows. In Section 2, we review the literature on the road traffic effects of urban rail transit. Detailed explanations of the dataset and methodology are presented in Section 3. Then, we discuss our main results in Section 4 and conclude our study in Section 5.

2. Literature Review

Theoretically, urban rail developments promote a road-to-rail mode shift and aggregate vehicle emissions [9]. However, urban rail's opposing effect may also be argued, since rail-induced economic activities and land developments can serve as an indirect emission intensifier and offset part of the mitigation potential [10]. In fact, urban rail in China has played a catalytic role in initiating land development and reshaping urban forms as anchor projects for land value capture and transit-oriented development (TOD) [11,12]. In other words, urban rail may have both traffic-diversion and traffic-creation effects, and their relative strength would determine urban rail's net impacts on on-road emissions. Accordingly, rail impact studies need to consider these two opposing forces in a parallel manner, and examine multiple rail-road interaction paths, incorporating key mediators, such as socio-demographic conditions and urban form.

Of the two opposing effects, recent quasi-experimental studies focus on the traffic-diversion effects, positing a substitutive rail-road relationship (Table 1). For example, urban rail transit strikes in the United States and Germany significantly increased traffic congestion and nitrogen dioxide (NO_2) concentrations [5,6]. The opening of new metro stations in China is also found to significantly reduce automobile energy consumption [7] and carbon monoxide (CO) concentrations [8]. All these results speak for a rail-to-road mode shift, but their neglect of the traffic-creation effect resulting from the research design may substantially overestimate the rail-induced emission-abatement potential.

Table 1. Literature on vehicle use effects of urban rail transit.

Studies	Region	Study Period	Independent Variables	Dependent Variable	Sign
***Substitution effects**: urban rail transit & vehicle use*					
[5]	US	2003	Urban rail	Traffic congestion	−
[6]	Germany	2002–2011	Urban rail, bus	Traffic volume, NO_2	−
[7]	China	2003–2013	Urban rail	Automobile energy use	−
[8]	China	2013–2015	Urban rail	CO concentration	−
***Mediating effects**: urban rail transit & urban form*					
[13]	US	1973–1993	Urban rail	Polycentricity	+
[14]	US	2000–2014	Urban rail	Population density	+
[15]	China	2000–2010	Urban rail	Polycentricity, density	+
[16]	China	2008–2014	Urban rail	Density	+
***Mediating effects**: urban form & vehicle use*					
[17]	US	1990–1991	Density, diversity, design	Vehicle trips	−
[18]	US	2003	Density	VMT	−
[19]	US	2000–2001	Polycentricity, density	VMT, transportation CO_2	+/−
[20]	China	2000	Density	Vehicle trips	−
[21]	China	2005–2015	Polycentricity, compactness	Residential CO_2	+/−
***Mediating effects**: urban rail transit & socio-demographics*					
[22]	Spain	2000–2010	Urban rail	Population	+
[23]	France	1970–2000	Urban rail	Employment	+
[24]	Denmark	1992–2012	Urban rail	Employment	+
[25]	China	2010–2019	Urban rail	Population, GDP, employment	+
***Mediating effects**: socio-demographics & vehicle use*					
[26]	Italy	1980–1995	GDP	Transportation CO_2	+
[27]	US	2000–2010	Population, income	VMT	+
[28]	China	1995–2012	GDP, population	Transportation CO_2	+
[29]	China	2005–2015	GDP per capita, population	Transportation CO_2	+

Although few studies directly tap into the traffic-creation effects, empirical evidence hints at a set of key mediators bridging such a complementary rail-road relationship. One of the key mediators is urban form, which affects demand for rail services and is at the same time affected by rail-transit accessibility. For example, urban rail has shaped a polycentric urban form in the San Francisco Bay Area and compact, high-density urban environments in the Dallas-Fort Worth metropolitan area [13,14]. Similarly, urban rail transit in China tends to enhance polycentricity and increase population density [15,16]. The connections between urban form and vehicle use are also well documented. So-called "3Ds" [17]—high *density*, land use *diversity*, and enhanced street *design*—are negatively associated with automobile-based trips and vehicle emissions in the United States [18,19] and China [20]. Polycentric and compact urban forms also significantly affect road traffic and carbon emissions [21].

In addition to urban form, various socio-demographic conditions also mediate the rail effects on vehicular traffic. For example, evidence shows that urban rail transit contributes to population and employment growth in Europe [22–24] and gross domestic product (GDP) growth in China [25]. Such population and economic growth necessarily drive-up demand for vehicle use and thus on-road CO_2 emissions [26–29].

Despite the empirical evidence, the vast majority of rail impact studies focus on only one piece of the puzzle—direct traffic-diversion effects—while neglecting those mediator variables and associated "indirect" traffic-creation effects (Figure 1). Such a sole focus on the former can lead to substantial overestimation of urban rail's mitigation potential. Instead, a balanced consideration of the two opposing forces would require an explicit representation of multiple rail-to-road causal paths with key mediator variables incorporated. This study is motivated to fill this gap.

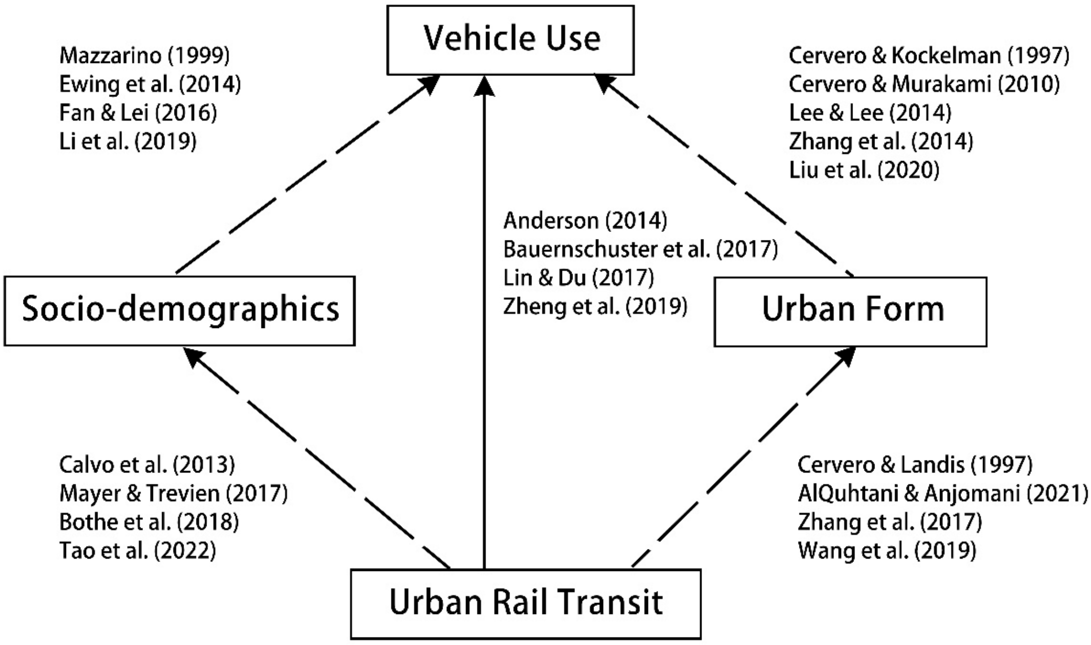

Figure 1. Literature on direct and indirect effects of urban rail transit on vehicle use. Source: Created by the authors [5–8,13–29].

3. Method

3.1. Structural Equation Modeling

We take an SEM approach to assessing the climate-mitigation potential of urban rail transit, and explicitly represent multiple causal paths within a single modeling framework. Our path-analysis design under the SEM framework incorporates key mediators along multiple paths, allowing us to decompose total effects by path and link. In this respect, our approach is superior to typical regression analyses, assuming only direct paths from a set of regressors to a given outcome variable.

Our path diagram consists of nine variables and six rail-to-carbon paths in total (Figure 2). Two variables measuring vehicle use and vehicle stock—vehicle kilometers traveled per vehicle (VKT_PV) and vehicle ownership (VO)—are directly linked to a response variable on-road carbon emissions (R_CO2).We limit our research scope to carbon dioxide, although black carbon—the second largest contributor to climate change—is also partly emitted from diesel-powered vehicles [30,31]. Black carbon, however, has little relevance to this study focusing on on-road passenger trips in China's context, which are dominated by gasoline vehicles. In 2017, for example, diesel vehicles accounted for around 9% of China's total active vehicle stock, and most of them were commercial freight trucks [32]. Urban rail density (MTR_DEN), at the bottom of all six paths, indirectly affects R_CO2 through mediators, such as travel mode choice (MPK_SHR), urban form (POLYCENT, POP_DEN), urban population (POP), and GDP per capita (GDP_PC). Here, POLYCENT and POP_DEN are proxy variables to measure the degree of polycentricity (vs. monocentricity) and compactness (vs. sprawl) at a city level.

Given that rail-network expansions often take a few years, our cross-sectional study reasonably assumes that urban rail services in operation affect mediator variables, but not vice versa. In this respect, we estimate recursive, one-way causal relationships, which are plain to interpret. We also model correlated errors within the recursive feedback structure to control for potential endogeneity arising from omitted variables [33].

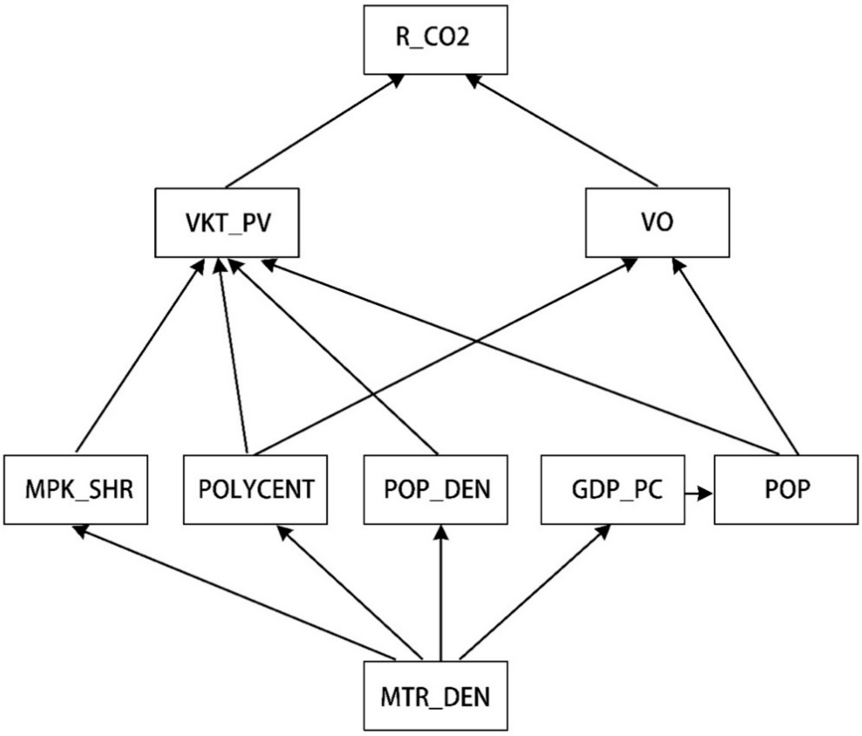

Figure 2. Path diagram. Source: Created by the authors.

3.2. Data

Our 2015 cross-sectional dataset for 90 Chinese prefecture-level cities is constructed from multiple sources, and the descriptive statistics of all variables tested are listed in Table 2 (see Figure 3 for the sample's spatial distribution). Response variable R_CO2 is built on the China City Greenhouse Gases Emissions Dataset (2015) [34]. VKT_PV for each city is computed from traffic volume, road length, and road width data provided in China's Environmental and Urban Construction Statistical Yearbooks [35,36]. The 60″ × 60″ LandScan population grids [37] are used to identify urban centers and measure POLYCENT, and the two urban rail variables (MTR_DEN and MPK_SHR) are extracted from the China Association of Metros [38]. Other built environment and socioeconomic variables, such as POP_DEN, POP, GDP_PC, and VO, are collected and created from two primary sources, China Urban Construction Statistical Yearbook [36] and the CEIC Database [32].

Table 2. Variable list and descriptive statistics.

Variable Name	Variable Description	Obs	Mean	Std. Dev
R_CO2	Carbon emissions from on-road vehicles (10^4 tonnes)	90	3.04×10^2	3.69×10^2
VKT_PV	Vehicle kilometer traveled per vehicle	90	5.23×10	5.03×10
VO	Vehicle ownership (thousand vehicles)	90	9.62×10^5	9.94×10^5
GDP_PC	GDP per capita (RMB)	90	6.18×10^4	2.85×10^4
MTR_DEN	Urban rail line density (km/km^2)	90	4.80×10	1.16×10^2
MPK_SHR	Urban rail passenger kilometers share	90	1.99×10^{-2}	7.65×10^{-2}
POLYCENT	Number of urban centers	90	2.78	2.13
POP_DEN	Urban population density (person/km^2)	90	8.05	2.58
POP	Urban population (thousand persons)	90	2.36×10^2	3.63×10^2

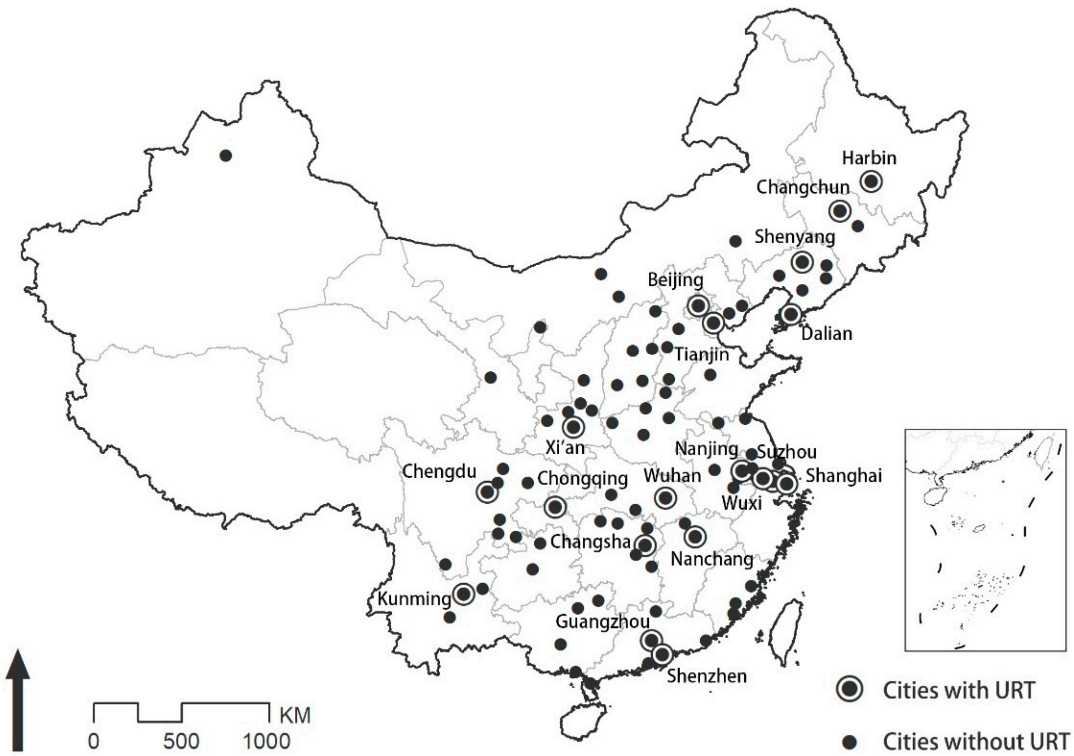

Figure 3. Spatial distribution of 90 sample prefecture-level cities in 2015. Source: Created by the authors from the China Association of Metros [38].

The following three mediating variables (VKT_PV, POLYCENT, and MPK_SHR) are worth mentioning in further detail. First, VKT_PV is estimated using available data, since China does not report official vehicle kilometers traveled (VKT) statistics. For the estimation of VKT, most existing studies directly use incomplete surveyed data [39], but we take a different approach, with reference to Chen and Klaiber [40]. As given in Equation (1), we estimate VKT for Chinese cities (VKT_i) using traffic volume and road lengths for monitored road segments—which offer more accurate and comprehensive sample data—and applying the sample-population ratio.

$$\mathrm{VKT}_i = \frac{w_i}{w_{im}} \cdot \mathrm{ATV}_{im} \cdot \mathrm{RL}_i \tag{1}$$

Here, w_i and RL_i are mean road width and total road length in city i, respectively, and w_{im} and ATV_{im} are mean road width and mean traffic volume per kilometer for monitored district m within city i, respectively. In particular, ATV_{im} is equivalent to VKT computed for a unit kilometer road section in monitored district m. If district m in city i includes total N number of road sections, and C refers to the number of cars traveled along road section k, ATV_{im} is drawn from Equation (2).

$$\mathrm{ATV}_{im} = \frac{\sum_{k\in m}^{N} \mathrm{RL}_{imk}\mathrm{C}_{imk}}{\sum_{k\in m}^{N} \mathrm{RL}_{imk}} \tag{2}$$

Once VKT_i is estimated, VKT_PV can be acquired by dividing it by VO.

Second, POLYCENT is measured in terms of the number of urban centers, as widely practiced within the urban studies field [19,41]. The identification of urban centers is based on the method developed by Liu and Wang [42]. We first set a 95-percentile population density threshold for each city (90-percentile for Beijing, Shanghai, Guangzhou, Shenzhen, and Tianjin) and keep only the population grid above the threshold. Then, we aggregate neighboring population grids under the Rook contiguity criterion and define urban clusters.

These clusters are treated as urban if they consist of $\geq$3 grids with a cluster-level population of >100,000.

Finally, MPK_SHR is used as a proxy of travel-mode choice, given the limited availability of reliable alternative mode-choice measurements. In particular, MPK_SHR is defined as the ratio of urban-rail passenger-kilometers (MPK) to the sum of MPK and VKT as shown in Equation (3).

$$\mathrm{MPK\_SHR} = \frac{\mathrm{MPK}}{\mathrm{MPK} + \mathrm{VKT}} \tag{3}$$

4. Results

The effects of each variable on R_CO2 and the model fit are summarized in Table 3. Overall, our model satisfies all goodness-of-fit criteria recommended in the literature [43,44], including a *p*-value with a threshold of >0.05, a comparative fit index (CFI) with a threshold of >0.90, a normed fit index (NFI) with a threshold of >0.95, a Tucker-Lewis Index (TLI) with a threshold of >0.90, and a root mean square error of approximation (RMSEA) with a reference value of ~0.05.

Table 3. Direct, indirect, and total effects on road traffic carbon emissions, measured in elasticity.

Independent Variable	Total Effects	
	Direct	Indirect
VKT_PV	0.1502	
VO	0.6764	
GDP_PC		0.2257
MTR_DEN		−0.0175
MPK_SHR		−0.0644
POLYCENT		0.0820
POP_DEN		−0.1814
POP		0.6415
Summary statistics		
N	90	
Chi-square	12.993	
Degrees of freedom	10	
p-value (>0.05) *	0.224	
Comparative fit index (>0.900)	0.995	
Normed fit index (>0.950)	0.980	
Tucker-Lewis Index (>0.900)	0.982	
RMSEA ($\approx$0.05)	0.058	

Note: * *p*-value of >0.05 means that the null hypothesis of a perfect fit cannot be rejected.

Both VKT_PV and VO, which directly affect on-road carbon emissions, show positive effects on R_CO2, with elasticities of 0.150 and 0.676, respectively (Table 4). These positive coefficients significant at the 5% level suggest that both travel behavior and vehicle stock are key "direct" contributors to on-road carbon emissions. The other six explanatory variables indirectly affect on-road carbon emissions. Among them, GDP_PC, POLYCENT, and POP beget positive total effects, implying that increased productivity, polycentric urban form, and city size are significant "indirect" emission intensifiers. On the other hand, MTR_DEN, MPK_SHR, and POP_DEN led to negative total effects (net emission abatement). This suggests that urban rail developments, increased share of urban rail ridership, and compact urban form indirectly contribute to abating on-road carbon emissions.

Table 4. Detailed path-specific elasticity estimates.

To		From	Coefficient	SE.
R_CO2	<	VKT_PV	0.1502 *	0.0598
R_CO2	<	VO	0.6764 **	0.0691
VKT_PV	<	MPK_SHR	−0.4289 *	0.2043
VKT_PV	<	POLYCENT	−0.3531 *	0.1572
VKT_PV	<	POP_DEN	−1.2083 **	0.3204
VKT_PV	<	POP	1.1706 **	0.3048
VO	<	POP	0.6885 **	0.0698
VO	<	POLYCENT	0.1997 *	0.0987
MPK_SHR	<	MTR_DEN	0.7237 **	0.0238
POLYCENT	<	MTR_DEN	0.1595 **	0.0292
POP_DEN	<	MTR_DEN	0.0329 *	0.0131
GDP_PC	<	MTR_DEN	0.0975 **	0.0192
POP	<	GDP_PC	0.3518 *	0.1536

Note: * $p < 0.05$; ** $p < 0.01$.

4.1. Emission-Abatement Effects

The emission-abatement effects of MTR_DEN on R_CO2 are closely associated with a substitutive relationship between road and rail (Figure 4). In particular, rail-induced carbon abatement takes three main channels. First, higher MTR_DEN drives up MPK_SHR, and increased MPK_SHR leads to lower R_CO2 through its positive association with VKT_PV with an elasticity of -0.0466 ($0.7237 \times -0.4289 \times 0.1502 = -0.0466$) (Figure 4A). This finding supports a key hypothesis underlying the traffic-diversion effect, where improved urban rail services in terms of accessibility and costs encourage a road-to-rail mode shift [9].

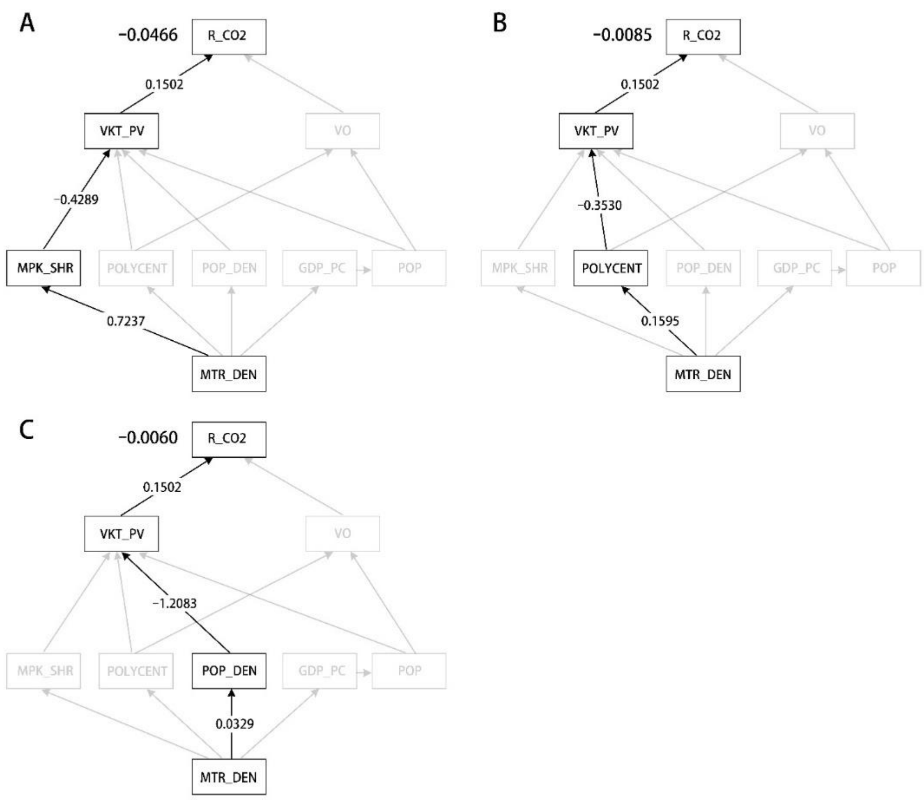

Figure 4. Negative Effects of Metro Density on Traffic-related Carbon Emissions: Mediators of (**A**) MPK_SHR; (**B**) POP_DEN; (**C**) POLYCENT. Source: Created by the authors from Table 4.

Second, higher MTR_DEN promotes POLYCENT and reduces VKT_PV and R_CO2, with a cumulative effect of −0.0085 (0.1595 × −0.3531 × 0.1502 = −0.0085) (Figure 4B). This finding coincides with the negative effects of polycentric urban forms on vehicle use and carbon emissions reported in many Chinese studies [21,45,46]. Polycentric urban form reduces commuting distance by decentralizing employment opportunities and improving the job-housing balance [41] and eventually leads to less use of vehicles and on-road emissions reduction.

Third, increased urban rail density reduces VKT_PV and R_CO2 through its upward pressure on POP_DEN, presenting a cumulative effect of −0.0060 (0.0329 × −1.2083 × 0.1502 = −0.0060) (Figure 4C). The coefficient of 0.0329 means that a unit percentage increase in urban rail density tends to increase population density by 0.03% as an outcome of rail-induced development. The coefficient of −1.2083 means that a unit percentage increase in population density leads to a 1.2% decline in VKT_PV, suggesting a large carbon-abatement potential of high-density urban development. This result is consistent with the findings of previous studies, where shorter travel distance and mixed land use promoted under a compact-city development strategy tend to foster non-motorized travel modes [18,47].

4.2. Emission-Intensification Effects

The climate-mitigation potential of MTR_DEN is partly offset through two emission-intensification channels, representing the traffic-creation effects of urban rail (Figure 5). One channel is that higher MTR_DEN indirectly pushes VO and R_CO2 upward by directly affecting POLYCENT (Figure 5A). This path, including urban form as a mediator, presents an elasticity of 0.0216 (0.1595 × 0.1997 × 0.6764 = 0.0216), where a unit percentage increase in urban rail density leads to a 0.02% increase in on-road emissions. A positive association between POLYCENT and VO can be partly explained by a potential trade-off between polycentricity and transit accessibility. In a polycentric city, decentralized urban functions may increase travel demand or distance while weakening transit accessibility, and incentivize private-vehicle ownership [19].

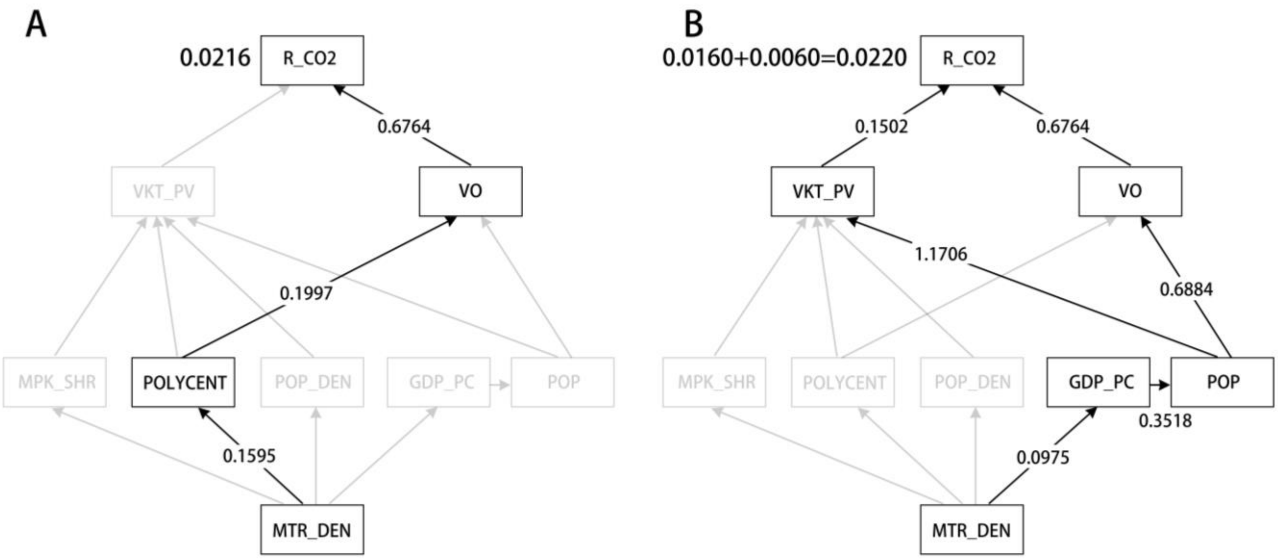

Figure 5. Positive Effects of Metro Density on Traffic-related Carbon Emissions: Mediators of (**A**) POLYCENT; (**B**) GDP_PC and POP. Source: Created by the authors from Table 4.

The other channel is that increased MTR_DEN leads to growth in GDP_PC and POP, and the latter result in higher VKT_PV and VO and thus higher R_CO2 (Figure 5B). The composite elasticity along this channel is 0.0220 (0.0975 × 0.3518 × 1.1706 × 0.1502 + 0.0975 × 0.3518 × 0.6885 × 0.6764 = 0.0220), suggesting that a unit percentage increase in urban rail density increases vehicle emissions by 0.02%. The indirect paths connecting

MTR_DEN to GDP_PC (0.0975) and POP (0.3518) imply that urban rail developments support economic growth and economic growth attracts population to the city. Then, increased city size eventually elevates demand for on-road trips (1.1706) and overall vehicle stock in operation (0.6884).

4.3. Varied Emission Effects by Mediator

The total effect of MTR_DEN on R_CO2 is −0.0175 in net terms, meaning that R_CO2 drops by 1.75% when MTR_DEN is doubled. This net mitigation potential suggests that, in China's context, the rail-induced traffic-diversion effects dominate the traffic-creation effects. However, this estimate is substantially smaller than existing estimates—e.g., an elasticity of −0.055 in automobile fuel consumption estimated by Lin and Du [7]—although a parallel comparison is hard due to dissimilar measurements. This is partly due to our consideration of offsetting effects (i.e., traffic-creation effects) associated with urban form and socio-demographic factors, which are often neglected in other studies. In fact, we find that three abatement paths involving MPK_SHR, POLYCENT, and POP_DEN as mediators jointly lead to a 6.1% decline in R_CO2 for a 100% increase in MTR_DEN if other offsetting channels are ignored (Table 5). This result is very close to existing estimates, such as the 5.5% decrease in vehicle energy consumption mentioned above [7].

Table 5. Emission effects of urban rail transit through different intermediate factors.

Mediator	Mechanism	Emission Abatement	Emission Intensification	Net Emission Effects
MPK_SHR	Substitution	**−0.0466**		−0.0466
POP_DEN	Urban form	**−0.0060**		−0.0060
POLYCENT	Urban form	−0.0085	**0.0216**	0.0131
GDP_PC & POP	Socio-demographics		**0.0220**	0.0220
Total		−0.0611	0.0436	−0.0175

Note: Dominant effects are highlighted in bold.

Along multiple paths, POP_DEN functions as an indirect emission abator by shortening mean travel distance and promoting nonmotorized trips [17]. In contrast, POLYCENT has mixed effects on R_CO2, as hinted at in previous studies—polycentric urban form can reduce driving distance by enhancing the job-housing balance and at the same time encourage vehicle use by reducing transit accessibility [19,45,46]. Of the two opposing effects, the emission-intensification effects (0.0216) dominate the emission-abatement effects (−0.0085) in China's context, leading to a net effect of 0.0131. Finally, POP and GDP_PC are found to be net emission intensifiers with an elasticity of 0.0220, partly offsetting the emission-abatement effects.

5. Conclusions

In this study, we examine the urban-rail impacts on vehicle emissions, using a cross-sectional dataset of 90 Chinese cities. Our results demonstrate that urban rail transit in China's context functions as a net climate mitigator by indirectly contributing to reduced on-road carbon emissions. Overall, a 100% increase in urban rail density is estimated to cause a 1.75% decline in on-road carbon emissions.

Although urban rail transit in China's context is a net abator, it interacts with on-road emissions along both emission-abating and intensifying paths. On the one hand, increased urban rail density indirectly reduces on-road carbon emissions by promoting road-to-rail mode shift (−0.0466), population density (−0.0060), and polycentricity (−0.0085). These three abatement channels altogether beget urban rail's gross mitigation potential of −0.0611 measured in elasticity. On the other hand, these abated emissions tend to be largely offset by the emission-intensification effects involving increased polycentricity (0.0216) and population (0.0220). Neglecting this induced demand can lead to substantial overestimation of the transit-associated abatement effects.

The main contribution of this study is twofold. One is to enrich the empirical literature on the climate-mitigation potential of urban rail transit, which is sparse, particularly in China's context. The other is an SEM-based path analysis presenting advanced methodological features for robust estimation results. Our model clearly describes each causal path and offers ability to decompose total effects by link. This enhances our understanding of the transit-emission nexus, where two opposite effects interact along multiple causal paths. Our approach is potentially applicable to other impact studies subject to similar problems. See Supplementary Materials.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos13111783/s1, Table S1: List of Abbreviations.

Author Contributions: Conceptualization, Y.O., J.Z. and K.-M.N.; methodology, Y.O. and K.-M.N.; software, Y.O.; formal analysis, Y.O. and K.-M.N.; investigation, Y.O., J.Z. and K.-M.N.; writing—original draft preparation, Y.O. and J.Z.; writing—review and editing, K.-M.N.; visualization, Y.O. and J.Z.; supervision, K.-M.N.; project administration, K.-M.N.; funding acquisition, K.-M.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Hong Kong Research Grant Council, grant number 17205021.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This research was supported by the Hong Kong Research Grant Council, grant number 17205021. We also acknowledge the financial support from the University of Hong Kong Research Committee and Faculty of Architecture for Ji Zheng's postdoctoral research.

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

References

1. IEA. Data and Statistics. Available online: https://www.iea.org/data-and-statistics/data-browser/?country=CHINAREG&fuel=CO2%20emissions&indicator=CO2BySource (accessed on 1 June 2022).
2. Ministry of Transport of People's Republic of China. Management Solutions for the Construction of National Public Transit Metropolis Demonstration Projects. 2022. Available online: http://www.gov.cn/zhengce/zhengceku/2022-04/11/content_5684470.htm (accessed on 1 June 2022).
3. National Development and Reform Commission of People's Republic of China. Action Plan for the "14th Five-Year Plan" New Urbanization. 2022. Available online: http://www.gov.cn/zhengce/zhengceku/2022-07/12/content_5700632.htm (accessed on 1 June 2022).
4. China Association of Metros. 2021 Urban Rail Transit Annual Report. 2022. Available online: https://www.camet.org.cn/tjxx/9944 (accessed on 1 June 2022).
5. Anderson, M.L. Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. *Am. Econ. Rev.* **2014**, *104*, 2763–2796. [CrossRef]
6. Bauernschuster, S.; Hener, T.; Rainer, H. When Labor Disputes Bring Cities to a Standstill: The Impact of Public Transit Strikes on Traffic, Accidents, Air Pollution, and Health. *Am. Econ. J. Econ. Policy* **2017**, *9*, 1–37. [CrossRef]
7. Lin, B.; Du, Z. Can urban rail transit curb automobile energy consumption? *Energy Policy* **2017**, *105*, 120–127. [CrossRef]
8. Zheng, S.; Zhang, X.; Sun, W.; Wang, J. The Effect of a New Subway Line on Local Air Quality: A Case Study in Changsha. *Transp. Res. Part D Transp. Environ.* **2019**, *68*, 26–38. [CrossRef]
9. Mohring, H. Optimization and Scale Economies in Urban Bus Transportation. *Am. Econ. Rev.* **1972**, *62*, 591–604.
10. Vickrey, W.S. Congestion Theory and Transport Investment. *Am. Econ. Rev.* **1969**, *59*, 251–260.
11. Yang, J.; Chen, J.; Le, X.; Zhang, Q. Density-oriented versus Development-oriented Transit Investment: Decoding Metro Station Location Selection in Shenzhen. *Transp. Policy* **2016**, *51*, 93–102. [CrossRef]
12. Yang, J.; Quan, J.; Yan, B.; He, C. Urban Rail Investment and Transit-oriented Development in Beijing: Can It Reach a Higher Potential? *Transp. Res. Part A Policy Pract.* **2016**, *89*, 140–150. [CrossRef]
13. Cervero, R.; Landis, J. Twenty Years of the Bay Area Rapid Transit System: Land Use and Development Impacts. *Transp. Res. Part A Policy Pract.* **1997**, *31*, 309–333. [CrossRef]
14. AlQuhtani, S.; Anjomani, A. Do Rail Transit Stations Affect the Population Density Changes Around Them? *Sustainability* **2021**, *13*, 3355. [CrossRef]

15. Zhang, C.; Xia, H.; Song, Y. Rail Transportation Lead Urban Form Change: A Case Study of Beijing. *Urban Rail Transit* **2017**, *3*, 15–22. [CrossRef]
16. Wang, X.; Tong, D.; Gao, J.; Chen, Y. The Reshaping of Land Development Density through Rail Transit: The Stories of Central Areas vs. Suburbs in Shenzhen, China. *Cities* **2019**, *89*, 35–45. [CrossRef]
17. Cervero, R.; Kockelman, K. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [CrossRef]
18. Cervero, R.; Murakami, J. Effects of Built Environments on Vehicle Miles Traveled: Evidence from 370 US Urbanized Areas. *Environ. Plan. A* **2010**, *42*, 400–418. [CrossRef]
19. Lee, S.; Lee, B. The Influence of Urban Form on GHG Emissions in the US Household Sector. *Energy Policy* **2014**, *68*, 534–549. [CrossRef]
20. Zhang, Y.; Wu, W.; Li, Y.; Liu, Q.; Li, C. Does the Built Environment Make a Difference? An Investigation of Household Vehicle Use in Zhongshan Metropolitan Area, China. *Sustainability* **2014**, *6*, 4910–4930. [CrossRef]
21. Liu, X.; Wang, M.; Qiang, W.; Wu, K.; Wang, X. Urban Form, Shrinking Cities, and Residential Carbon Emissions: Evidence from Chinese City-regions. *Appl. Energy* **2020**, *261*, 114409. [CrossRef]
22. Calvo, F.; Oña, J.d.; Arán, F. Impact of the Madrid Subway on Population Settlement and Land Use. *Land Use Policy* **2013**, *31*, 627–639. [CrossRef]
23. Mayer, T.; Trevien, C. The Impact of Urban Public Transportation Evidence from the Paris Region. *J. Urban Econ.* **2017**, *102*, 1–21. [CrossRef]
24. Bothe, K.; Hansen, H.K.; Winther, L. Spatial Restructuring and Uneven Intra-urban Employment Growth in Metro-and Non-metro-served Areas in Copenhagen. *J. Transp. Geogr.* **2018**, *70*, 21–30. [CrossRef]
25. Tao, Z.; Feng, X.; Li, K.; Shi, R. Impacts of Urban Rail Transit on City Growth: Evidence from China. *Urban Rail Transit* **2022**, *8*, 121–133. [CrossRef]
26. Mazzarino, M. The Economics of the Greenhouse Effect: Evaluating the Climate Change Impact Due to the Transport Sector in Italy. *Energy Policy* **2000**, *28*, 957–966. [CrossRef]
27. Ewing, R.; Hamidi, S.; Gallivan, F.; Nelson, A.C.; Grace, J.B. Structural Equation Models of VMT Growth in US Urbanised Areas. *Urban Stud.* **2014**, *51*, 3079–3096. [CrossRef]
28. Fan, F.; Lei, Y. Decomposition Analysis of Energy-related Carbon Emissions from the Transportation Sector in Beijing. *Transp. Res. Part D Transp. Environ.* **2016**, *42*, 135–145. [CrossRef] [PubMed]
29. Li, F.; Cai, B.; Ye, Z.; Wang, Z.; Zhang, W.; Zhou, P.; Chen, J. Changing Patterns and Determinants of Transportation Carbon Emissions in Chinese Cities. *Energy* **2019**, *174*, 562–575. [CrossRef]
30. Bond, T.C.; Streets, D.G.; Yarber, K.F.; Nelson, S.M.; Woo, J.-H.; Klimont, Z. A Technology-based Global Inventory of Black and Organic Carbon Emissions from Combustion. *J. Geophys. Res. Atmos.* **2004**, *109*, D14. [CrossRef]
31. Bond, T.C.; Doherty, S.J.; Fahey, D.W.; Forster, P.M.; Berntsen, T.; DeAngelo, B.J.; Flanner, M.G.; Ghan, S.; Kärcher, B.; Koch, D.; et al. Bounding the Role of Black Carbon in the Climate System: A Scientific Assessment. *J. Geophys. Res. Atmos.* **2013**, *118*, 5380–5552. [CrossRef]
32. CEIC Data. CEIC Premium Database for China. 2021. Available online: https://info.ceicdata.com/en-products-china-premium-database (accessed on 1 June 2022).
33. Baumgartner, H.; Homburg, C. Applications of structural equation modeling in marketing and consumer research: A review. *Int. J. Res. Mark.* **1996**, *13*, 139–161. [CrossRef]
34. China City Greenhouse Gas Working Group (CCG). *China City Greenhouse Gases Emissions Dataset (2015)*; China City Greenhouse Gas Working Group (CCG): Beijing, China, 2019.
35. National Bureau of Statistics of People's Republic of China. *China Statistical Yearbook on Environment*; National Bureau of Statistics of People's Republic of China: Beijing, China, 2016.
36. Ministry of Housing and Urban-Rural Development of People's Republic of China. *China Urban Construction Statistical Yearbook*; China Statistics Press: Beijing, China, 2016.
37. Oak Ridge National Laboratory. LandScan Population Grids. 2022. Available online: https://landscan.ornl.gov/ (accessed on 1 June 2022).
38. China Association of Metros. 2015 Urban Rail Transit Annual Report. 2016. Available online: https://www.camet.org.cn/tjxx/3103 (accessed on 1 June 2022).
39. Huo, H.; Zhang, Q.; He, K.; Yao, Z.; Wang, M. Vehicle-use Intensity in China: Current Status and Future Trend. *Energy Policy* **2012**, *43*, 6–16. [CrossRef]
40. Chen, W.; Klaiber, H.A. Does Road Expansion Induce Traffic? An Evaluation of Vehicle-Kilometers Traveled in China. *J. Environ. Econ. Manag.* **2020**, *104*, 102387. [CrossRef]
41. Veneri, P. Urban Polycentricity and the Costs of Commuting: Evidence from Italian Metropolitan Areas. *Growth Change* **2010**, *41*, 403–429. [CrossRef]
42. Liu, X.; Wang, M. How Polycentric is Urban China and Why? A Case Study of 318 Cities. *Landsc. Urban Plan.* **2016**, *151*, 10–20. [CrossRef]
43. Kline, R.B. Software Review: Software Programs for Structural Equation Modeling: Amos, EQS, and LISREL. *J. Psychoeduc. Assess.* **1998**, *16*, 343–364. [CrossRef]

44. Fan, X.; Thompson, B.; Wang, L. Effects of Sample Size, Estimation Methods, and Model Specification on Structural Equation Modeling Fit Indexes. *Struct. Equ. Model. A Multidiscip. J.* **1999**, *6*, 56–83. [CrossRef]
45. Li, Y.; Xiong, W.; Wang, X. Does Polycentric and Compact Development Alleviate Urban Traffic Congestion? A Case Study of 98 Chinese Cities. *Cities* **2019**, *88*, 100–111. [CrossRef]
46. Zhang, W.; Lu, D.; Zhao, Y.; Luo, X.; Yin, J. Incorporating Polycentric Development and Neighborhood Life-circle Planning for Reducing Driving in Beijing: Nonlinear and Threshold Analysis. *Cities* **2022**, *121*, 103488. [CrossRef]
47. Ewing, R.; Cervero, R. Travel and the Built Environment: A Meta-analysis. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]