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Subway Expansion and Traffic Flow: A Spatiotemporal Analysis of Urban Congestion Dynamics

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Abstract: This study investigates the impact of new subway line openings on urban road traffic congestion through a spatiotemporal analysis. Focusing on the southern section of Beijing Subway Line 8, which commenced operation in late 2018, the research employs a difference-in-differences (*DID*) approach to analyze traffic congestion data from 2018 to 2021. The study examines both short- and long-term effects on road congestion in areas surrounding the new subway stations. The findings reveal that the effects of subway expansions on congestion vary by time of day and diminish over time. While the subway extension was intended to alleviate congestion, its impact is limited during morning peak hours but more pronounced during evening peaks. These results highlight the complexity of urban traffic management and underscore the importance of considering the interplay between subway expansions and existing traffic systems to optimize congestion mitigation strategies.

Keywords: spatial autocorrelation; spatial difference-in-differences; subway expansion; traffic congestion; urban mobility

1 INTRODUCTION

Road traffic congestion in contemporary society underscores its complexity and far-reaching multidimensional impacts, adversely affecting individuals' daily lives while posing significant long-term threats to environmental sustainability [1, 2]. The loss of time efficiency caused by traffic jams not only undermines socio-economic vitality but also contributes to excessive carbon emissions and exacerbates local air pollution, thereby increasing the urban environmental burden [3-5]. Moreover, traffic congestion negatively impacts public health by heightening psychological stress and reducing opportunities for physical activity, further diminishing the quality of life for urban residents [6, 7]. Consequently, road traffic congestion is not merely a traffic management issue but a multifaceted challenge that intersects with urban planning, environmental conservation, and social welfare [1, 2].

The introduction of subway systems as a key strategy for improving urban transportation has a direct and significant impact on alleviating road congestion [7-9]. By offering an efficient, high-capacity public transport alternative, subways attract passengers who might otherwise depend on private vehicles, thereby reducing the number of cars on the roads and easing traffic pressure [10, 11]. Additionally, the high speed and reliability of subways enhance the overall efficiency of urban transportation, making them a more convenient and dependable travel option for many commuters [12].

However, the opening of subway lines can also introduce potential side effects, which, in some cases, may exacerbate road congestion. Firstly, the construction of subway networks often requires occupying road space, which can temporarily increase traffic loads on surrounding roads. Secondly, areas around subway stations may experience significant inflows of people and vehicles, especially during peak commuting hours. This concentration near station entrances and connecting transportation points can lead to localized congestion [12, 13]. Additionally, subway openings often stimulate the development of nearby commercial and residential areas, which, over time, may increase traffic demand and place additional pressure on road networks.

While the positive impact of subway openings in alleviating urban road congestion is well-recognized, their potential negative effects and long-term consequences warrant further investigation. Current research primarily focuses on the overall effects of subway openings, with relatively less attention paid to their spatiotemporal dynamics. For instance, the differences in subway impacts over time (short-term vs. long-term), spatial variations (around subway stations vs. citywide effects), and differences across urban contexts remain underexplored.

Studying the spatiotemporal dynamics of subway openings on road congestion can provide a more nuanced understanding of their effects on urban transportation systems. Such insights would enable more accurate assessments of subway impacts, offering a scientific foundation for urban traffic planning and management. This approach not only complements existing research but also informs the optimization of urban transportation development strategies, ensuring a balanced and sustainable approach to addressing urban mobility challenges.

This paper aims to address the following questions: (1) Does the opening of new subway lines impact nearby road congestion? (2) How does the effect of subway openings on road congestion evolve over time? (3) What differences exist in the impacts of various new subway lines on their surrounding road congestion?

To investigate these questions, this study compiled road speed data from Beijing spanning 2018 to 2021 to construct a road congestion index dataset. The southern section of Beijing Subway Line 8, which opened at the end of 2018, was selected as the focal point of the analysis. Using a difference-in-differences (*DID*) model, the study estimates the effects of these new subway lines on nearby road congestion over both short- and long-term periods. The results are analyzed to identify similarities and differences in the impacts of the two subway lines, ultimately drawing general conclusions from the findings.

The innovative aspects of this paper are primarily reflected in three key areas:

(1) Modeling Short- and Long-Term Effects: This study develops a difference-in-differences (*DID*) model to analyze both the short- and long-term impacts of subway openings on nearby road congestion. Unlike previous studies that often focused solely on short-term effects due to data limitations, this research tracks congestion patterns around newly opened subway stations through July 2021, covering a span of over two and a half years. This extended timeline enables a more comprehensive examination of medium- and long-term effects, providing deeper insights into the evolving influence of subway expansions.

(2) Analyzing Different Commuting Periods: The model used in this study differentiates between morning peak, evening peak, and off-peak periods to evaluate the varying impacts of subway openings on road congestion. This targeted approach avoids overgeneralizing results across all time periods and sheds light on how subway expansions influence traffic during specific commuting times. By addressing temporal variations, the study offers nuanced insights into the effectiveness of subway openings in reducing congestion.

(3) Incorporating Spatial Autoregression to Account for Spillover Effects: Traditional *DID* models often overlook spillover effects, where congestion at one station influences nearby stations. To address this limitation, the study integrates a spatial autoregressive component into the *DID* model, allowing it to account for spatial spillovers and produce more accurate estimates. To enhance the robustness of the findings, the paper employs multiple forms of spatial *DID* models, drawing conclusions based on consistent patterns observed across these approaches.

These methodological innovations enable the study to provide a more precise and comprehensive understanding of the impacts of subway openings on urban road congestion.

2 RELATED WORKS

2.1 Factors Influencing Traffic Congestion

The causes of traffic congestion are multifaceted and complex, encompassing factors such as urban scale, economic conditions, socio-economic indicators, public transportation development, and natural environments [14]. Rahman et al. [15], in their research on urban areas in the United States, identified urban scale factors-such as population density and city expansion-as key contributors to traffic congestion. From an economic perspective, Marshall and Dumbaugh [16] highlighted that while congestion is often perceived as a barrier to economic growth, it can also signify the prosperity and vibrancy of regional economic activities.

Using multivariate time series analysis, Dadashova et al. [17] revealed a strong relationship between traffic congestion and urban socio-economic indicators, indicating that factors like economic development levels and employment rates are closely tied to the severity of congestion. Similarly, Abdulrazzaq et al. [18] emphasized the role of optimizing and expanding public transportation systems in alleviating traffic congestion, advocating for reduced reliance on private vehicles and increased adoption of public transit as effective solutions. Additionally, Yao et al. [19] found that natural factors, such as rainfall, have a direct impact on urban traffic congestion, underscoring the importance of considering weather conditions in traffic management and planning.

Collectively, these studies demonstrate that traffic congestion is an intricate phenomenon influenced by a variety of interrelated factors. Addressing it requires a comprehensive, multidisciplinary approach, offering valuable insights for urban planning and traffic management strategies.

2.2 The Impact of Subway Expansion on Traffic Congestion

Research on the impact of subway expansion on traffic congestion has provided valuable evidence and insights. Li et al. [20], in their study on the effects of Beijing's subway expansion on surrounding property values, found that subway network expansion not only increases property values but also enhances the attractiveness of urban areas. This suggests that subways promote the efficient transportation of people and goods, potentially mitigating traffic congestion. Similarly, Gu et al. [21], focusing directly on the relationship between subway expansion and road congestion, concluded that the expansion of subway systems significantly reduces road traffic congestion, highlighting their role in improving urban traffic efficiency.

Cheng et al. [22], while discussing the role of intelligent transportation systems in alleviating traffic congestion, emphasized the potential for enhanced transportation intelligence to ease congestion. Although not directly addressing subway expansion, their findings indirectly support the importance of subways and other public transit systems in urban traffic management. Wang et al. [23], in their analysis of the impact of new subway lines on PM10 concentrations, demonstrated that subway expansion may indirectly alleviate traffic congestion by reducing car usage. Additionally, Gonzalez-Navarro and Turner [24] confirmed a positive correlation between subway expansion and urban growth, indicating that expanding subway networks not only helps to alleviate traffic congestion but also contributes to the overall development of cities.

These studies collectively demonstrate that subway expansion, by providing efficient public transportation options, reduces reliance on private vehicles, alleviates urban road congestion, and enhances the overall efficiency of city transportation systems. However, the magnitude and mechanisms of these impacts require further investigation. Specifically, how to maximize the positive effects of subway expansion and how to effectively integrate subway systems with other urban transportation modes and planning to fundamentally address traffic congestion remain critical areas for future research.

3 METHODS

3.1 Data Description

This study is based on empirical research utilizing traffic congestion data from Beijing's roads, collected from January 1, 2018, to July 31, 2021. In Beijing, new subway stations are typically inaugurated at the end of the year. To comprehensively evaluate both the short-term and long-term impacts of subway openings-and to meet the difference-in-differences (*DID*) method's requirement for pre-opening data, this study focused on two lines that began operations at the end of 2018: the southern section of Beijing Subway Line 8. The timing of these openings provided a unique opportunity to analyze the immediate effects of subway inaugurations and to observe their longer-term impacts on nearby road congestion.

Including subway lines opened at the end of 2019, such as the eastern extension of Subway Line 7, could have allowed for 19 months of post-opening data. However, the COVID-19 pandemic in 2020 led to several atypical periods of reduced congestion due to public health measures, significantly altering traffic patterns. These disruptions severely compromised the effectiveness of the *DID* model, making it challenging to assess the short-term and long-term effects of subway openings accurately. As a result, subway lines inaugurated at the end of 2019 were excluded from this study.

For the application of the *DID* method, the study divided the sample into treatment and control groups. The treatment group consisted of areas surrounding the newly opened subway lines, while the control group included comparable areas unaffected by the subway expansions. This setup allowed the *DID* methodology to isolate the impact of subway openings on the treatment group while ensuring the stability and reliability of the control group, thereby enhancing the accuracy of the findings.

To ensure the validity of the *DID* analysis, it was critical that the treatment and control groups exhibited similar trends before the intervention. Additionally, control variables such as socio-economic conditions and seasonal changes were carefully considered. The control group was matched with the treatment group based on geographical location, economic characteristics, and other relevant factors to ensure accurate measurement of the subway openings' impact. Subsequent analyses focus on the selected segments of Beijing Subway Line 8, which met these criteria. Detailed analyses and results are discussed in the following sections of the paper.

3.2 Experimental and Control Groups

This study examines the impact of new stations along the southern section of Beijing Subway Line 8, which includes twelve stations from Zhushikou to Yinghai that opened on December 30, 2018. These stations are located within and south of the Fourth Ring Road. The areas within the Fourth Ring Road, particularly north of Dahongmen South, are characterized by higher population densities and more commercial activities compared to the lower-density areas beyond the Fourth Ring Road.

To effectively implement the *DID* methodology, seventeen stations from the southern section of Beijing Subway Line 4, which has been operational since late 2010, were selected as the control group. This selection enables precise evaluation of both short-term and long-term effects of the new subway stations on road congestion.

The choice of the southern section of Line 8 as the treatment group and Line 4 as the control group was based on several considerations. Beyond geographical proximity, both lines run in a north-south direction and exhibit similar administrative and economic characteristics. Additionally, the urban development and population density along their routes are comparable, helping control for confounding variables such as climate and demographic structure. Importantly, prior trends in traffic patterns between the two groups were consistent, ensuring the validity of the *DID* methodology.

3.3 Models

This paper uses the Difference-in-Differences (*DID*) model, suitable for evaluating public policies like subway expansion. *DID* allows for isolating the policy's impact by comparing changes in traffic congestion between affected and unaffected areas, while controlling for external factors [25]. The model is ideal because it handles time and spatial trends effectively, ensuring that observed effects are due to the subway expansion itself [26].The classic *DID* model is expressed as:

$$Y_{it} = \mu_i + \theta_t + \alpha DID_{it} + \beta X_{it} + \varepsilon_{it} \tag{1}$$

where, Y_{it} represents the traffic congestion index around subway station i during period t, X_{it} includes control variables for station i at time t, and DID_{it} is the policy dummy variable for subway openings, which is an interaction term ($Treatment_i \times Post_t$). If station i is in the treatment group ($Treatment = 1$) and t is after the policy impact ($Post = 1$), then $DID_{it} = 1$; otherwise, it is 0. μ_i denotes spatial fixed effects, and θ_t time fixed effects. α is the estimated coefficient of the policy effect, assessing the impact of subway openings.

Acknowledging that the opening of nearby subway stations may affect adjacent traffic congestion, the study constructs a spatial difference-in-differences model to control for cross station spatial spillovers:

$$Y = \mu + \theta + \left(\alpha + \gamma W\right) DID + \beta X + \rho WY + \left(I - \lambda W\right)^{-1} \varepsilon \tag{2}$$

where μ stands for spatial fixed effects, θ for time fixed effects, and *DID* for the dummy variable of subway opening policy effects. α indicates the impact of the policy effect, W is the spatial weight matrix representing connections between different subway stations, ρ is the spatial autocorrelation coefficient of the dependent variable, β represents the coefficients of the independent variables, and γ reflects the spatial spillover effects of subway station openings.

The spatial difference-in-differences model takes various forms, depending on the coefficients:

When $\rho = \gamma = 0$, it reduces to a spatial error model (SEM):

$$Y = \mu + \theta + \alpha DID + \beta X + \left(I - \lambda W\right)^{-1} \varepsilon \tag{3}$$

When $\gamma = \lambda = 0$, it represents a spatial lag model (SAR):

$$Y = \mu + \theta + \alpha DID + \rho WY + \beta X + \varepsilon \tag{4}$$

When $\gamma = 0$, it becomes a general spatial model (SAC):

$$Y = \mu + \theta + \alpha DID + \rho WY + \beta X + \left(I - \lambda W\right)^{-1} \varepsilon \quad (5)$$

When $\lambda = 0$, the model is referred to as the spatial Durbin model (SDM):

$$Y = \mu + \theta + \alpha DID + \rho WY + \gamma WDID + \beta X + \varepsilon \quad (6)$$

4 RESULTS

This study uses daily traffic congestion data to assess the impact of the southern section of Beijing Subway Line 8 on nearby road congestion, with stations on Line 4 serving as the control group. A difference-in-differences (*DID*) approach is applied to estimate effects over four time periods one month, six months, one year, and two and a half years post-opening-across various commuting times.

The *DID* method relies on the parallel trends assumption, which states that the treatment and control groups should follow similar trends before the policy change. To verify this, pre-2018 data was used to simulate the policy implementation. By regressing the traffic congestion index against time, treatment interactions, and control variables, the study confirms whether both groups followed parallel trends before the subway line's opening.

Table 1 Experimental parallel trend test results for the southern section of Line 8

Model Selection	Commuting period	Interaction term coefficient	p-value
DID	Morning peak	0.007	0.796
	Off Peak	0.007	0.756
	Evening Peak	0.023	0.353
SAR	Morning peak	–0.002	0.847
	Off Peak	–0.004	0.612
	Evening Peak	0.013	0.13
SDM	Morning peak	–0.033	0.055
	Off Peak	–0.002	0.888
	Evening Peak	0.006	0.689
SAC	Morning peak	–0.018	0.218
	Off Peak	–0.004	0.62
	Evening Peak	0.013	0.087
SEM	Morning peak	–0.018	0.231
	Off Peak	–0.006	0.681
	Evening Peak	0.013	0.388

The results in Tab. 1 show that most models have p-values above 0.2, some reaching 0.8, indicating highly insignificant results. This confirms that the treatment and control groups followed similar trends before the policy implementation, supporting the parallel trends assumption. Therefore, using the southern section of Line 4 as the control group and the southern section of Line 8 as the treatment group is appropriate.

Before conducting the spatial difference-in-differences analysis, spatial autocorrelation of the road congestion indices near subway stations was tested using Moran's I. Global Moran's I indicates overall spatial clustering, while Local Moran's I identifies specific clusters. Values greater than 0 suggest positive spatial correlation, and values less than 0 indicate negative correlation. A Moran's I of 0 means spatial randomness.

Using Stata, the Global Moran's I for road congestion around subway stations was calculated, reflecting spatial correlation and spillover effects. Data from January 2018 to July 2021, covering 36 months, were used to compute the Moran's I for morning peak, off-peak, and evening peak periods (Tab. 2 to Tab. 4).

Table 2 Experimental morning peak Moran index measurement for the southern section of Line 8

Time	Moran's I	p-value	Time	Moran's I	p-value
20181	0.199	0.019	20197	0.223	0.011
20182	0.266	0.004	20198	0.169	0.037
20183	0.224	0.012	20199	0.213	0.015
20184	0.214	0.015	201910	0.221	0.01
20185	0.244	0.007	201911	0.155	0.048
20186	0.252	0.006	201912	0.128	0.072
20187	0.271	0.004	20204	0.154	0.045
20188	0.238	0.009	20205	0.129	0.063
20189	0.153	0.051	20209	0.113	0.088
201810	0.151	0.051	202010	0.069	0.178
201811	0.086	0.14	202011	0.135	0.065
201812	0.134	0.059	202012	0.098	0.113
20191	0.155	0.036	20211	0.081	0.14
20192	0.164	0.039	20212	0.128	0.073
20193	0.157	0.039	20213	0.079	0.154
20194	0.214	0.011	20214	0.148	0.053
20195	0.133	0.068	20216	0.149	0.053
20196	0.133	0.068	20217	0.18	0.029

Table 3 Experimental off-peak time Moran index measurement for the southern section of Line 8

Time	Moran's I	p-value	Time	Moran's I	p-value
20181	0.368	0	20197	0.329	0.001
20182	0.308	0.001	20198	0.296	0.002
20183	0.227	0.011	20199	0.249	0.006
20184	0.264	0.004	201910	0.392	0
20185	0.273	0.004	201911	0.339	0.001
20186	0.263	0.005	201912	0.25	0.007
20187	0.206	0.016	20204	0.247	0.007
20188	0.287	0.002	20205	0.132	0.072
20189	0.068	0.179	20209	0.166	0.039
201810	0.091	0.122	202010	0.215	0.014
201811	0.092	0.118	202011	0.247	0.007
201812	0.209	0.017	202012	0.179	0.032
20191	0.395	0	20211	0.157	0.048
20192	0.208	0.017	20212	0.228	0.011
20193	0.242	0.008	20213	0.277	0.003
20194	0.259	0.004	20214	0.319	0.001
20195	0.163	0.036	20216	0.336	0.001
20196	0.143	0.046	20217	0.258	0.002

Table 4 Experimental evening peak Moran index measurement for the southern section of Line 8

Time	Moran's I	p-value	Time	Moran's I	p-value
20181	0.142	0.062	20197	0.227	0.011
20182	0.171	0.036	20198	0.236	0.009
20183	0.132	0.072	20199	0.197	0.022
20184	0.125	0.081	201910	0.236	0.01
20185	0.151	0.052	201911	0.166	0.04
20186	0.159	0.046	201912	0.164	0.042
20187	0.111	0.101	20204	0.027	0.291
20188	0.194	0.023	20205	0.056	0.211
20189	0.089	0.139	20209	0.136	0.068
201810	0.09	0.133	202010	0.103	0.115
201811	0.08	0.155	202011	0.114	0.098
201812	0.126	0.082	202012	0.074	0.172
20191	0.21	0.017	20211	0.033	0.275
20192	0.179	0.031	20212	0.11	0.102
20193	0.193	0.024	20213	0.111	0.103
20194	0.21	0.016	20214	0.162	0.044
20195	0.17	0.037	20216	0.193	0.024
20196	0.162	0.042	20217	0.216	0.015

To examine the short-term and long-term impacts of the newly opened stations on the southern section of Beijing Subway Line 8 on nearby road congestion, this chapter divides the sample data into four time periods:

one month, six months, one year, and over two years. Daily data from these time periods are used to analyze the effects of the subway openings on local road congestion.

Tab. 5 to Tab. 7 summarize the regression results for different commuting times across these time periods, while Tab. 8 specifically presents the coefficients of the core explanatory variable interaction term, α. This section begins with a detailed explanation of the regression results shown in Tab. 5 to Tab. 7, emphasizing spatial spillover effects and the coefficients of the independent variables. It then focuses on the regression results for the interaction term as presented in Tab. 8, offering a more targeted discussion.

Table 5 Morning peak regression results for the southern section of Line 8

SDID	Coefficient term	Morning peak			
		One month	Six months	One year	Two and a half years
SAR	α	–0.0203**	–0.00652*	–0.0147***	–0.000545
	β_1	–0.0226	–0.0252	–0.0299	–0.0315
	β_2	0.0728	0.0509	0.0453	0.0333
	β_3	–0.0812***	–0.0793***	–0.0772***	–0.0433***
	ρ	0.631***	0.645***	0.642***	0.721***
SDM	α	0.000456	0.0116	–0.00571	0.00348
	β_1	–0.0221	–0.0247	–0.0296	–0.0313
	β_2	0.0774	0.0545	0.0471	0.0344
	β_3	–0.0821***	–0.0794***	–0.0774***	–0.0433***
	ρ	0.625***	0.644***	0.640***	0.721***
	γ	–0.0302	–0.0261***	–0.0129*	–0.00579
SAC	α	–0.0233*	–0.00351	–0.0186***	0.00156
	β_1	0	0	0	0
	β_2	0	0	0	0
	β_3	–0.130***	–0.186***	–0.175***	–0.175***
	ρ	0.406***	0.163*	0.182**	–0.128***
	$\lambda(\varepsilon)$	0.345***	0.549***	0.532***	0.768***
SEM	α	–0.0213	–0.00194	–0.0178***	0.00122
	β_1	–0.04	–0.043	–0.051	–0.0513
	β_2	0.0966	0.0726	0.067	0.0574
	β_3	–0.221***	–0.224***	–0.215***	–0.155***
	$\lambda(\varepsilon)$	0.637***	0.646***	0.643***	0.721***

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

In the spatial difference-in-differences models, ρ represents the spatial spillover effect of the dependent variable, the traffic congestion index, while λ indicates the spatial correlation among the error terms. As shown in Tab. 5 to Tab. 7, significant ρ values were observed across all commuting times in all four spatial difference-in-differences models. Additionally, the SAC and SEM models, which account for spatial correlations in the error terms, also reported significant λ values.

Within the SDM (Spatial Durbin Model), γ represents the spatial correlation between interaction terms of different samples. Significant results for γ were found in all experiments except for the morning peak experiments conducted for one month and over two and a half years, as well as the off-peak morning peak experiments.

Table 6 Evening peak regression results for the southern section of Line 8

SDID	Coefficient term	Evening peak			
		One month	Six months	One year	Two and a half years
SAR	α	–0.0215**	–0.0198***	–0.00738***	–0.00167
	β_1	0.0107	–0.0265	0.0154	0.0133
	β_2	0.108	0.0917	0.0934	0.0856
	β_3	–0.0128**	–0.0219***	–0.0202***	–0.0187***
	ρ	0.616***	0.622***	0.623***	0.608***
SDM	α	0.0345**	0.0285***	0.0388***	0.0516***
	β_1	0.0115	–0.0329	0.0165	0.0152
	β_2	0.119*	0.103*	0.103*	0.0996*
	β_3	–0.0125**	–0.0221***	–0.0205***	–0.0188***
	ρ	0.603***	0.614***	0.618***	0.602***
	γ	–0.0817***	–0.0700***	–0.0667***	–0.0768***
SAC	α	–0.0210**	–0.0164***	0.0147***	0.0271***
	β_1	0	0	0	0
	β_2	0	0	0	0
	β_3	–0.0148*	–0.0137***	–0.0646***	–0.0583***
	ρ	0.556***	0.757***	–0.231***	–0.262***
	$\lambda(\varepsilon)$	0.111	–0.308***	0.731***	0.730***
SEM	α	–0.00931	–0.00954	0.00784*	0.0180***
	β_1	–0.0272	–0.035	–0.00829	–0.00234
	β_2	0.099	0.0986*	0.0858	0.0793
	β_3	–0.0344**	–0.0584***	–0.0537***	–0.0477***
	$\lambda(\varepsilon)$	0.628***	0.627***	0.628***	0.613***

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

The widespread significant results for ρ, λ, and γ underscore the pronounced spatial spillover among the samples, confirming the necessity of incorporating spatial regression components into the difference-in-differences model to accurately capture these dynamics.

Although not statistically significant, the trend of coefficient changes aligned with the results of the other three models. The most substantial congestion relief (or least increase) was observed in the one-month and one-year experiments, while the least relief (or greatest increase) occurred at six months and two and a half years.

The control variables from Tab. 5 to Tab. 7 indicate that holidays significantly reduce congestion around subway stations, particularly during the morning peak on non-holiday days, with less pronounced effects during the evening peak. Contrary to previous studies, this analysis found no significant impact of stations outside the Fourth Ring Road on nearby congestion. While the SAR, SDM, and SAC models showed negative coefficients during the morning and off-peak periods and positive coefficients during the evening peak, none were statistically significant.

Tab. 8 summarizes the effects of subway openings on congestion across different periods using spatial *DID* models. During the morning peak, the SAR model demonstrated significant congestion relief, with reductions of 2.03% at one month, 0.65% at six months, and 1.47% at one year. However, by two and a half years, the effect had diminished to -0.0545%, which was not significant. The SAC model showed similar results, with significant reductions of 2.33% at one month and 1.86% at one year. The SEM model followed a comparable trend, with the most relief occurring at one month and one year. Conversely, the SDM model indicated increased congestion across all periods, though these findings were not statistically significant.

Overall, the results suggest that the most notable congestion relief occurred within one month and one year after the subway openings, while the effects weakened or even reversed by six months and two and a half years.

Table 7 Regression results for the southern section of Line 8 at off-peak time

SDID	Coefficient term	Off-peak			
		One month	Six months	One year	Two and a half years
SAR	α	0.00607	–0.00810**	–0.0172***	–0.0185***
	β_1	–0.0406	–0.0178	–0.024	–0.0186
	β_2	0.0213	0.0308	0.0305	0.0288
	β_3	0.0352***	0.0127***	0.0124***	0.00834***
	ρ	0.580***	0.620***	0.652***	0.631***
SDM	α	0.0184	0.000528	0.00385	0.0166***
	β_1	–0.0401	–0.0176	–0.0236	–0.0176
	β_2	0.0239	0.0325	0.0347	0.0383
	β_3	0.0353***	0.0128***	0.0125***	0.00860***
	ρ	0.582***	0.620***	0.648***	0.621***
	γ	–0.0178	–0.0124*	–0.0305***	–0.0512***
SAC	α	0.0109	–0.00816**	–0.0166***	–0.0171***
	β_1	0	0	0	0
	β_2	0	0	0	0
	β_3	0.0568***	0.0136***	0.0117***	0.00731***
	ρ	0.337***	0.593***	0.673***	0.679***
	$\lambda(\varepsilon)$	0.346***	0.0497	–0.0445	–0.105***
SEM	α	0.012	–0.00861*	–0.0160***	–0.0124***
	β_1	–0.0814	–0.0437	–0.0559	–0.0383
	β_2	0.0274	0.0364	0.038	0.0364
	β_3	0.0839***	0.0333***	0.0355***	0.0225***
	$\lambda(\varepsilon)$	0.583***	0.621***	0.656***	0.637***

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

During off-peak periods, the SAR, SAC, and SEM models all produced very consistent significant results. The six-month experiments demonstrated congestion relief effects of over 0.8%, one-year experiments showed significant congestion relief ranging from 1.6% to 1.72%, and the two-and-a-half-year experiments yielded significant congestion relief results between 1.24% and 1.85%. These findings indicate that the opening of new stations on Subway Line 8 has mitigated nearby road congestion in the medium to long term, with congestion relief effects gradually increasing over time.

Table 8 Regression results of experimental interaction term coefficients for the southern section of Line 8

Commuting hours	Model	One month	Six months	One year	Two and a half years
Morning peak	SAR	–0.0203**	–0.00652*	–0.0147***	–0.000545
	SDM	0.000456	0.0116	–0.00571	0.00348
	SAC	–0.0233*	–0.00351	–0.0186***	0.00156
	SEM	–0.0213	–0.00194	–0.0178***	0.00122
Evening Peak	SAR	–0.0215**	–0.0198***	–0.00738***	–0.00167
	SDM	0.0345**	0.0285***	0.0388***	0.0516***
	SAC	–0.0210**	–0.0164***	0.0147***	0.0271***
	SEM	–0.00931	–0.00954	0.00784*	0.0180***
Off peak	SAR	0.00607	–0.00810**	–0.0172***	–0.0185***
	SDM	0.0184	0.000528	0.00385	0.0166***
	SAC	0.0109	–0.00816**	–0.0166***	–0.0171***
	SEM	0.012	–0.00861*	–0.0160***	–0.0124***

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

During the evening peak, spatial difference-in-differences models consistently showed significant results. The SAR model produced significant congestion relief effects of 2.15%, 1.98%, and 0.738% for one month, one year, and two years respectively. The SDM model indicated increased congestion over the periods from one month to two and a half years, with results of 3.45%, 2.85%, 3.88%, and 5.16% respectively. The SAC model showed congestion relief in the first month and six months at 2.1% and 1.98% respectively, but indicated increased congestion after one year and two and a half years, with coefficients of 1.47% and 2.71%. The SEM model also showed increased congestion at one year and two and a half years with results of 0.78% and 1.8%.

These results suggest that while different models produced both positive and negative outcomes across various experimental periods, a consistent trend was observed: the ability of new subway stations to alleviate traffic congestion weakens over time, even potentially leading to an increase in congestion.

Table 9 Estimated evolution of the subway opening effect at morning peak

Direct effects evolution	Morning peak			
	SAR	SDM	SAC	SEM
First month of operation	–0.0193***	–0.0144*	–0.0322**	–0.0326***
2nd month	–0.0557***	–0.0508***	–0.0475***	–0.0529***
3rd month	–0.000255	0.0047	–0.00813	–0.0071
4th month	0.00766	0.0126	0.00395	0.00513
Opened 5th month	0.0215***	0.0264***	0.0312**	0.0317**
6th month	0.0051	0.0101	0.00934	0.00924
Opened 7th month	–0.0215***	–0.0165*	–0.0272**	–0.0280**
Opened 8th month	–0.0363***	–0.0314***	–0.0433***	–0.0451***
Opened 9th month	–0.0283***	–0.0233***	–0.0489***	–0.0485***
Opened 10th month	–0.00479	0.000159	0.011	0.00912
Opened 11th month	–0.0101	–0.00519	–0.00707	–0.00813
Opened 12th month	–0.00772	–0.00277	–0.0121	–0.0122
Opened 16th month	0.0166**	0.0216***	0.0200*	0.0213*
Opened 17th month	0.0433***	0.0483***	0.0470***	0.0501***
Opened 21st month	0.0145*	0.0195**	–0.00962	–0.00545
22nd month	0.00606	0.011	0.0163	0.0154
23rd month	0.0132*	0.0182**	0.0236*	0.0231*
Opened 24th month	0.0191***	0.0241***	0.0201*	0.0209*
25th month	–0.00735	-0.0024	–0.00921	–0.0104
Opened 26th month	–0.0381***	–0.0331***	–0.0188	–0.0245*
Opened 27th month	0.0241***	0.0291***	0.0306**	0.0314**
Opened 28th month	0.0267***	0.0317***	0.0453***	0.0454***
Opened 30th month	0.00721	0.0122	0.0245*	0.0232*
Opened 31st month	0.00424	0.0092	0.0169	0.0155

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

Table 10 Estimated evolution of the subway opening effect at off-peak time

Direct effect by month	Off peak			
	SAR	SDM	SAC	SEM
First month of operation	0.00629	0.0400***	0.00534	0.0104
2nd month	–0.0424***	–0.00994	–0.0395***	–0.0361***
3rd month	–0.00346	0.0299***	–0.00349	0.00433
4th month	–0.00499	0.0285***	–0.00451	–0.00844
Opened 5th month	–0.0100*	0.0232***	–0.00917*	–0.0073
6th month	–0.0285***	0.00458	–0.0257***	–0.0459***
Opened 7th month	–0.0332***	–0.00034	–0.0310***	–0.0344***
Opened 8th month	–0.0378***	–0.00509	–0.0353***	–0.0401***
Opened 9th month	–0.0434***	–0.0106*	–0.0401***	–0.0548***
Opened 10th month	–0.0116*	0.0214***	–0.0111**	0.00346
Opened 11th month	–0.0151***	0.0180***	–0.0141***	–0.0104
Opened 12th month	–0.0145**	0.0187***	–0.0136**	–0.0118
Opened 16th month	–0.0121**	0.0210***	–0.0115**	0.00082
Opened 17th month	–0.0166***	0.0163**	–0.0156***	–0.00316
Opened 21st month	–0.0197***	0.0133*	–0.0184***	–0.0131
22nd month	–0.0246***	0.00807	–0.0231***	–0.0103
23rd month	–0.0197***	0.0133*	–0.0184***	–0.00903
Opened 24th month	–0.0109*	0.0222***	–0.0101*	–0.00286
25th month	–0.0260***	0.00653	–0.0243***	–0.00599
Opened 26th month	–0.0271***	0.00536	–0.0255***	–0.00132
Opened 27th month	–0.0129**	0.0200***	–0.0123**	0.0016
Opened 28th month	–0.0102*	0.0229***	–0.00954*	–0.00121
Opened 30th month	–0.0334***	–0.0008	–0.0309***	–0.0265***
Opened 31st month	–0.0273***	0.00553	–0.0249***	–0.0302***

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

Observing these outcomes, it is clear that the effect of subway openings on nearby traffic congestion is dynamic. To further explore why the α coefficient varies over different periods, considering the potential lag in the impact of subway openings on nearby road congestion, this paper develops a new model:

$$Y = \mu + \vartheta + \sum\left(\alpha DID_i + \gamma WDID_i\right) + \\ + \beta X + \rho WY + \left(I - \lambda W\right)^{-1} \varepsilon \tag{7}$$

where i represents each month within the sample group, and $\alpha_i\alpha_i$ represents the direct effect of subway openings on traffic congestion for each individual month. Tab. 9 to Tab. 11 display the estimated α values for each month, which explain some trends shown in Tab. 8.

Table 11 Estimated evolution of the subway opening effect at evening peak

Direct effect by month	Evening peak			
	SAR	SDM	SAC	SEM
First month of operation	0.000394	0.0527***	–0.000789	0.00502
2nd month	–0.0558***	–0.00443	–0.0475***	–0.0339***
3rd month	–0.0132*	0.0389***	–0.0120*	–0.00919
4th month	–0.00978	0.0423***	–0.00919	0.00029
Opened 5th month	–0.00067	0.0513***	–0.00159	0.0250**
6th month	–0.0139*	0.0380***	–0.0113*	–0.00704
Opened 7th month	–0.0234***	0.0285***	–0.0209***	–0.0104
Opened 8th month	–0.0233***	0.0285***	–0.0210***	–0.00488
Opened 9th month	–0.0297***	0.0221***	–0.0253***	–0.0244**
Opened 10th month	0.0160**	0.0681***	0.0115*	0.0449***
Opened 11th month	0.0223***	0.0747***	0.0178***	0.0365***
Opened 12th month	0.0186**	0.0710***	0.0143**	0.0342***
Opened 16th month	–0.00232	0.0497***	–0.00392	0.0285**
Opened 17th month	0.0194***	0.0716***	0.0138**	0.0540***
Opened 21st month	0.0111	0.0634***	0.00737	0.0356***
22nd month	0.0189**	0.0711***	0.0143**	0.0539***
23rd month	0.0298***	0.0822***	0.0236***	0.0552***
Opened 24th month	0.0205***	0.0730***	0.0172***	0.0271**
25th month	–0.0190**	0.0328***	–0.0154**	0.00256
Opened 26th month	–0.0309***	0.0205**	–0.0262***	0.00312
Opened 27th month	0.00809	0.0602***	0.00572	0.0327***
Opened 28th month	0.00624	0.0583***	0.0039	0.0301**
Opened 30th month	–0.0143*	0.0376***	–0.0127**	0.00347
Opened 31st month	–0.00145	0.0506***	–0.0019	0.0146

Note: *, **, ***, indicate 10%, 5% and 1% significance levels, respectively.

During the morning peak, no significant congestion relief was observed between the second and sixth months, with all models indicating increased congestion in the fifth month, explaining why the six-month results showed weaker effects than those at one month or one year (Tab. 9). In contrast, the evening peak exhibited more significant congestion relief, but with relatively smaller negative values and larger positive values, indicating weaker effects compared to the morning peak (Tab. 11). During off-peak times, the SAR and SAC models consistently showed significant congestion relief, while the SDM model showed mixed results, with only a significant positive value in the first month (Tab. 10).

Based on the analysis above, this paper draws the following preliminary conclusions regarding the impact of the newly opened stations on the southern section of Beijing Subway Line 8 on nearby road congestion:

(1) Morning Peak Periods: Within the first year of operation, the southern section of Beijing Subway Line 8 alleviated nearby road congestion to some extent during morning peak hours. However, the congestion relief effects became less noticeable after the first year.

(2) Evening Peak Periods: During evening peak hours, the initial positive effects of the southern section in reducing road congestion weakened over time, while negative effects, such as increased congestion, became more pronounced.

(3) Off-Peak Periods: The congestion relief effects during off-peak hours were insignificant within the first six months of operation but became more noticeable around one year after the line's opening.

(4) Impact Across Commuting Periods: The most significant impact of the southern section of Beijing Subway Line 8 on traffic congestion was observed during evening peak periods, with smaller effects during off-peak and morning peak periods.

(5) Temporal Shifts in Effectiveness: Across all commuting times morning, evening peak, and off-peak the congestion relief effects experienced a sudden negative shift starting in the tenth month of operation. This included a sharp decline in congestion relief effectiveness and a sudden increase in congestion levels. Similar patterns were observed in the fourth and fifth months following the line's opening.

These findings highlight the varying and evolving effects of the subway line on nearby road congestion, underscoring the importance of ongoing monitoring and adaptive traffic management strategies.

5 DISSCUSSION

Based on the empirical findings, this paper offers several policy recommendations for traffic management authorities and planners of subway expansion projects to maximize the positive impacts on urban economies and quality of life:

Prioritize Evening Peak Congestion in Subway Expansion Plans: If reducing congestion is a primary objective in the short to medium term, this study recommends prioritizing areas with severe evening peak congestion when planning subway expansions. The findings indicate that new subway stations have a more significant impact on evening peak congestion compared to morning peak and off-peak periods. To effectively alleviate congestion through subway expansion, it is critical to analyze traffic patterns, pedestrian flow, and spatial layouts during evening peak hours. Such an approach will provide a more accurate assessment of the potential congestion relief achievable in targeted areas.

Monitor Medium- and Long-Term Effects on Surface Traffic: The impact of new subway stations on road congestion varies across different commuting periods and evolves over time. Some subway lines initially alleviate congestion but lose their effectiveness as time progresses, while others may demonstrate delayed congestion relief [27]. Therefore, it is essential to closely monitor and evaluate the medium- and long-term effects of subway expansions, particularly one to two years after new stations become operational. Continuous evaluation will help planners understand how traffic dynamics evolve and adjust strategies to sustain congestion relief.

Incorporate Broader Benefits Beyond Congestion Relief: The study shows that the effectiveness of new subway lines in reducing road congestion tends to weaken over time, particularly during peak hours. Thus, beyond congestion relief, planners should also consider other long-term benefits of subway expansions. These include enhanced transport accessibility, economic development, job creation, pollution reduction, and improved social equity. A comprehensive evaluation of these broader societal benefits should be integrated into the decision-making process for subway expansion projects. Such a holistic approach ensures that the value of subway investments extends beyond immediate traffic management goals, contributing to sustainable urban growth and improved quality of life.

By adopting these recommendations, policymakers and urban planners can design and implement subway expansion projects that not only address traffic congestion but also deliver lasting economic, social, and environmental benefits.

6 CONCLUSIONS

This study presents three key conclusions:

(1) Indeterminate Impact of New Subway Openings: The effects of new subway lines on nearby road congestion are inconsistent, varying across time and space. This analysis of two subway lines opened in Beijing in late 2018 reveals differing impacts, even within the same line across various periods. Consequently, a definitive conclusion on congestion alleviation cannot be established without specific, tailored analyses for each line, station, and timeframe.

(2) Temporal Variability of Effects: The impact of subway openings on road congestion evolves over time. During evening peak periods, initial congestion relief tends to diminish, and congestion may worsen in the medium to long term. Conversely, during off-peak periods, significant congestion relief is often observed only in the medium to long term, rather than immediately following subway openings.

(3) Variability Across Commuting Times: The effectiveness of new subway openings in reducing congestion is most pronounced during evening peak periods. The results indicate a greater influence on road congestion during this time compared to other periods, with morning peak hours showing limited short-term effects and off-peak periods reflecting impacts mainly over the medium to long term.

However, the findings of this study are subject to several limitations. First, the reliance on available data and the specificity of the case study to Beijing limit the generalizability of the results to other cities or subway systems, where urban planning, public transportation infrastructure, and commuting patterns may differ. Second, the study focuses on short- and medium-term impacts, without an extensive longitudinal analysis to fully capture long-term trends.

Future research should address these limitations by incorporating broader datasets spanning multiple cities and longer timeframes to enhance the generalizability of the findings. Additionally, further studies could explore the interplay between subway systems and other transportation modes, including emerging mobility services, to better understand their collective impact on urban traffic congestion. Investigating the socio-economic benefits of subway expansion, such as improved accessibility, economic development, and environmental sustainability, would provide a more comprehensive view of its impact on urban development.

In summary, this study contributes valuable insights into the complex dynamics of subway expansions and road congestion, offering actionable recommendations for policymakers and urban planners to optimize the design and implementation of public transportation systems.

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