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Distributional effects of subway fare surges: Evidence from Beijing

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ABSTRACT

This study estimates the impact of subway fare increases on ridership and explores the distributional effects across demographic groups. We utilize a natural experiment involving a subway fare surge in China's capital, Beijing. We combine daily subway ridership data by subway lines with household travel survey data collected around the time when fares increased. Based on the regression-discontinuity-in-time research design, we find that the subway fare surge led to a 10.4 % reduction in short-run subway ridership, which corresponds to a price elasticity of −0.090. The heterogeneity analysis indicates that households with higher income, greater travel demand during rush hours, and limited access to other transportation modes have relatively lower price elasticity. We further demonstrate that this price reform brought Beijing subway fares closer to their optimal level. These findings highlight the efficient and distributional consequences of public transit price reforms.

1. Introduction

Low-cost public transit is essential for mass commuting in cities, particularly for the residents of developing countries. According to World Metro Figures (UITP, 2021), the world's metros carried approximately 190 million passengers per day in 2019. As an affordable substitute for driving, public transit has attracted enormous public investment (Cervero, 1998). Substituting automobile use and alleviating the external problems caused by private vehicle usage, such as congestion and air pollution, are important rationales for maintaining low transit fares (Parry & Small, 2009). According to Parry and Timilsina (2010), if the substitution between private and public transportation is high, the government should subsidize public transit to reduce private car usage. Conversely, if private and public transportation are poor substitutes, the government should avoid intervening in the pricing of public transportation to minimize distortion.[1] In other words, the price elasticity of subway ridership is important for policy efficiency. Meanwhile, the heterogeneity across demographic groups has significant policy implications for equity considerations. Therefore, the magnitude and heterogeneity of the price elasticity of subway ridership are two crucial parameters in public transit pricing policy evaluation.

Price elasticity remains quantitatively vague in the literature because of a lack of high-frequency data and exogenous price scheme changes in public transit systems. Surprisingly, existing studies provide little evidence on how commuters respond to public transit price changes or how the response varies across demographic groups. Recent literature on public transit focuses on the impact of subway shutdowns (e.g., Anderson (2014)) and openings (e.g., Gu et al. (2023)) while paying relatively little attention to the pricing of existing public transportation.

In this study, we estimated the impact of a subway fare change on ridership by leveraging an exogenous fare structure adjustment in the Beijing subway system. The subway fare reform, implemented on December 28, 2014, shifted Beijing's subway fare from a uniform fare (2 CNY) to a distance-based fare starting at 3 CNY. According to the Beijing Municipal Development and Reform Commission, the average price of a new subway ticket is approximately 4.3 CNY, indicating an average price increase of 115 %.[2]

Based on a regression discontinuity in time (RDiT) research design, we found a significant and enduring reduction in ridership following the implementation of the fare adjustment. In the preferred setting, which models the time trend of ridership as a second-order polynomial and uses a 30-day bandwidth, the increase in subway fare resulted in a decrease of 715,800 daily ridership, accounting for 10.4 % of the total. When combined with the 115 % price increase, this implies an inelastic

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[1] The potential distortions of intervening in public transportation prices are two-fold. First, it could distort the transportation mode choice. Second, the public transportation subsidy is typically funded by government revenue, which could come from distortionary taxation.

[2] Refer to http://politics.people.com.cn/n/2014/1013/c70731-25825159.html.

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price elasticity of −0.090. Based on the extant analytical framework (Parry & Small, 2009; Parry & Timilsina, 2010; Small, 2004; Small et al., 2024), we demonstrate that the price reform enacted in 2014 aligns the Beijing subway ticket fare more closely with its optimal level.

We further investigated the heterogeneous effects based on commuter demographics using subway-line-level ridership data and the 2014 Beijing Household Travel Survey (BHTS). The heterogeneity analysis shows that households with higher incomes, greater travel demand during rush hours, and limited access to alternative transportation modes exhibit relatively lower price elasticity.

Our findings have important implications for public transportation policies. This relatively low price elasticity implies that public transit and private vehicles are not close substitutes in Beijing. Consequently, implementing extensive subsidies for public transportation pricing may not be justified. The findings of the heterogeneity analysis suggest that subway subsidies should be further reduced for higher-income groups, commuters with greater travel demands during rush hours, and commuters in regions with limited alternative transportation options. Subway systems place a significant financial burden on the government, and implementing price discrimination based on income group, time, and location is challenging. Therefore, we conclude that alternative non-distortionary policies, such as lump-sum transfers or travel vouchers, could be more efficient than subsidizing public transportation.

The remainder of this paper is organized as follows. Section 2 provides a literature review on the impact of subway fare increase on ridership as well as the impact of Beijing subway price reform. Section 3 introduces the subway fare reform in Beijing and the two datasets used in this study. Section 4 presents the main empirical findings and a series of robustness checks. Section 5 exploits the heterogeneity by accessibility to alternative transportation modes, travel urgency, income level and more. Section 6 calculates the optimal subway fare, discusses the policy implications, and compares our price elasticities with those in the literature. Section 7 concludes.

2. Literature review

Extant literature has estimated the impact of subway fare increases on ridership. On one hand, our study is similar to that of Davis (2021) because we use similar identification strategies. Davis (2021) investigated fare changes in three Mexican cities to estimate the price elasticity of demand for urban rail transit. In two cities, there was a noteworthy fare increase, whereas in the third city, a 60-day fare holiday led to a 100 % fare decrease. The authors discovered a marked and enduring ridership response opposite to fare changes across all three cities. This implied that price elasticity spanned from −0.23 to −0.32 across different cities. Our study used more granular data and explored the heterogeneity effects across demographic groups.

Furthermore, Gu et al. (2023) estimated the sensitivity of subway rider trip schedules to price schemes using discontinuities in the distance in the new fare structure. They found that subway travel demand was relatively inelastic, trip schedules were inflexible, and regular commuters were more sensitive to price changes. Our study complements this pioneering work by focusing on subway ridership decisions at the extensive margin, whereas it primarily examined trip schedules at the intensive margin.

On the other hand, our study is similar to that of Zhao and Zhang (2019) because both studies examine the distributional effects of subway fare increase. Using retrospective survey data, Zhao and Zhang (2019) evaluated the effects of the Beijing subway fare increase in 2014 on transport equity. They found that the reform significantly increased the cost burden on low-income and young workers. Their study also investigated the interaction effects of residential location and housing tenure and found that suburban residents who have housing tenure experienced a lighter increase in transit burden. Our study differs from theirs in two ways. First, we employed a regression discontinuity in time approach to estimate the impact of fare changes on subway ridership. Second, we further examined the distributional effect induced by differences in rush hour travel demand and access to alternative transportation modes.

Our study relates to three strands of literature. First is the literature that examines the Beijing subway price reform from various perspectives. Wang et al. (2015) evaluated the effect of subway fare changes on ridership and revenue before the actual reform was implemented using a network approach. Using Hierarchical Tree-based Regression (HTBR) models, Zhang et al. (2017) found that the new fare structure lowered riders' degree of satisfaction, did not depress subway demand—ridership decreased sharply in the first month, but gradually returned to the previous level four months later and remained steady afterward. Yang and Tang (2018) found that a fare increase caused a 16.28 % rise in air pollution in the short run but did not affect air quality in the long run. Our findings are similar to those in previous literature in that an increase in subway fares would lead to a decrease in ridership. By estimating the distributional effects of price changes on ridership, our study extends the understanding of this significant price shock in the economics literature.

Second, our study is related to literature that examines the factors that affect subway ridership. Sohn and Shim (2010) found that employment, commercial floor area, office floor area, net population density, number of transfers, number of feeder bus lines, and a dummy variable indicating transfer stations affect station-level subway ridership significantly. Zhao et al. (2013), meanwhile, found that the CBD dummy variable, the number of education buildings, entertainment venues and shop centers, and bicycle P&R spaces affect station-level subway ridership significantly. In another study, An et al. (2019) found that commercial land use, rail transit system factors, bus stops, tourist spots, and healthcare factors have a significant effect on both weekday and weekend subway ridership, while job-related land use only have a significant effect on weekdays. By integrating smart card data with point of interest (POI) data, Chen et al. (2019) found that the surrounding built environment affects station-level subway ridership. In conclusion, extant literature mainly focused on demand-side factors that affect subway ridership, which makes our study a complement to this strand of literature, since we mainly focus on supply-side factors.

The heterogeneous response analysis is commonly used for understanding distributional effects in the environment, economics, urban, real estate, and other social sciences studies (Rode et al., 2021). However, the difficulty of applying it to studying transportation policies is the lack of detailed data with both transportation model choices and individual demographics. The household travel survey data per se might serve as a solution, but it still bears the limitation of sample size and coverage. Thus, our innovation is to combine this "detailed but limited coverage" survey data with "widely covered but anonymized" subway ridership data in a statistical model.

Although the magnitude and the heterogeneity of the price elasticity of subway ridership are two crucial parameters in public transit pricing policy evaluation, they remain quantitatively vague in the literature because of a lack of high-frequency data and exogenous price scheme changes in public transit systems. We estimate the impact of a subway fare change on ridership by leveraging an exogenous fare structure adjustment in the Beijing subway system.

3. Context and data

3.1. Subway fare reform in Beijing

The Beijing subway system is the second longest metro network in the world, immediately after Shanghai (UITP, 2021). According to 2019 data from the UITP, its annual ridership exceeded two billion trips. As a result of government subsidies, the Beijing subway system maintained low fares, with a uniform fare of only 2 CNY (0.3 US Dollars) before the reform, making it one of the cheapest subway systems in the world (Liu et al., 2023). According to the 2014 Beijing Public Transport Price and Cost Supervision Report, the total cost of Beijing Subway in 2013 reached 14.7 billion CNY. Combined with the 1.7 billion annual ridership, the cost recovery level of the fare price is calculated to be 8.56 CNY.[3] It implies that only 25 % of the cost can be recovered by fare, and the operation of the Beijing Subway system relies largely on subsidies. These large-scale subsidies have placed a significant financial burden on the Beijing municipal government. According to China Economic Net, the subsidies to the subway system reached 18 billion CNY in 2013, accounting for 6.3 % of Beijing's annual fiscal expenditure.[4] Given that there are 17 operating lines in 2013, the per-line subsidy exceeds one billion CNY on average.

To alleviate the government's financial burden and address subway congestion, the Beijing Subway initiated a systematic pricing reform to increase subway fares. The new Beijing subway fare scheme was officially implemented on December 28, 2014. It has two prominent features (refer to Fig. 1). First, it transitioned from a uniform fare structure to a distance-based fare structure. Under this structure, the fare was set as follows: 3 CNY for the first 6 km; 4 CNY for distances ranging from 6 km to 12 km (inclusive); 5 CNY for distances between 12 km and 22 km (inclusive); 6 CNY for distances between 22 km and 32 km (inclusive); an additional 1 CNY for every 20 km beyond 32 km, without a maximum fare. The other feature is that the fares were increased across all levels, with even the lowest fare (3 CNY) being higher than the uniform fare prior to the reform.

3.2. Daily subway ridership data

We collected daily subway ridership data from May 27, 2012, to November 19, 2019, by web scraping on social media platforms and the official website of the Beijing Subway Company — a state-owned enterprise responsible for operating most subway lines in Beijing, except Line 4 and Line 14.[5] We focused on this period because it includes the price reform date (December 28, 2014), which allows us to quantify the effect of fare surges on daily ridership using an RDiT research design.

To account for the impacts of festivals and holidays, we manually collected holiday and festival schedules from the National Development and Reform Committee during the sample period. We collected geocoded data from Beijing's subway and bus networks using web mapping services.

Fig. 2 shows the daily ridership around the fare-change day. This indicates a significant decrease immediately after the subway fare surge. In Fig. A1, we have broken down the daily ridership to the line level and presented the ridership around the fare change day. Although the ridership of all the lines decreased after the fare surge, the extent differed. The ridership of suburban lines only experienced a slight decrease (e.g., Line 15, Changping Line, and Yizhuang Line), whereas the ridership of urban lines dropped significantly (e.g., Line 2 and Line 10).

3.3. Subway-line-level household characteristics

Subway ridership and price elasticity are affected by the characteristics of nearby residents (Huang et al., 2018; Zhang et al., 2017). To construct subway-line-level household characteristic variables, we employed the Beijing Household Travel Survey (BHTS), conducted annually by the Beijing Transportation Research Center (BTRC).

We used the 2014 survey because it was conducted three months prior to subway fare changes. It is reasonable that the characteristics of nearby residents remained relatively stable during this short period. The survey covered approximately 40,000 randomly selected households in Beijing and included demographic questions and a travel diary documenting the households' trips on the survey day. The travel diary recorded the origin and destination, travel purpose, departure and arrival times, and all travel modes involved in each trip.

We merged household survey data with subway ridership data to obtain subway line-level household characteristics. We assumed that households are more likely to take a subway line with a station close to their residence. Specifically, we assigned the geographic coordinates of household residential locations as the centroids of the corresponding travel zones (TAZs) and calculated the distance from each household to all subway stations. We matched each household to the nearest station and excluded households for which no subway stations were located within five kilometers of their residential places. This approach enabled the construction of a set of potential riders for each subway line. Subsequently, we obtained subway line-level variables by averaging the household-level characteristics from the set of potential riders.

The variable "$Log\ ridership_t$" refers to the logarithm of subway ridership of line i at day t. "$\%Vehicle\ trip_i$" indicates the proportion of households near a subway line that choose to travel by driving. "$\%Own\ vehicle_i$" represents the proportion of households near a subway line that own a vehicle. In our context, private vehicle usage and ownership were correlated with household income levels. To measure the pure accessibility to private vehicles, we defined the variable "$Vehicle\ usage\ tendency_i$" as follows[6]:

$$Vehicle\ usage\ tendency_i = \frac{\%Vehicle\ trip_i}{\%Own\ vehicle_i} \tag{1}$$

The variable "$Bus\ network\ density_i$" represents the density of bus lines surrounding each subway line, which is used as an indicator of the accessibility to bus networks. The calculation of the bus line density for each subway station followed the methodology outlined by Li et al. (2019) and Liu et al. (2023), and the values were aggregated at the subway line level. Subway line characteristics also affect subway ridership. However, as we have ridership panel data, we can use subway line fixed effects to capture the effects of the subway's time-invariant characteristics.

The variables "$\%Rush\ hour_i$" and "$\%Work\ or\ school_i$" refer to the proportion of households that must travel during rush hour and have full-time workers or students. "$Income_i$" and "$Travel\ distance_i$" represent the average income and travel distance of households residing near a subway line, respectively.

Table 1 presents the summary statistics of all variables used in this study.

4. Empirical analysis

4.1. Regression discontinuity in time

In this study, we employed a regression discontinuity (RD) design to estimate the impact of fare changes on subway ridership.

$$ridership_t = \gamma_0 + \gamma_1 D_t + f(t) + \gamma_2 X_t + u_t \tag{2}$$

where $ridership_t$ is the daily ridership (Ten thousand) on day t. D_t is an indicator variable that equals one for observations at and after the fare change and zero otherwise. γ_1 is the parameter of interest, which measures the fare change effect. $f(t)$ captures all the other variables that affect ridership. It should be a smooth function in time because fare price

[3] Refer to https://www.beijingprice.cn/upload/resources/file/2023/03/15/46166.pdf.

[4] Refer to http://district.ce.cn/newarea/roll/201401/13/t20140113_2106488.shtml.

[5] Lines operated by the company include Lines 1, 2, 5, 6, 7, 8, 9, 10, 13, 15, Batong Line, Fangshan Line, Changping Line, Yizhuang Line, Capital Airport Express, and Line S1.

[6] For example, consider ten households that live near Line 1. Five of them have their own vehicle, and three of these five households choose to travel by car. Subsequently, $\%Own\ vehicle_1$, $\%Vehicle\ trip_1$, and $Vehicle\ usage\ tendency_1$ equal 0.5, 0.3, and 0.6, respectively.

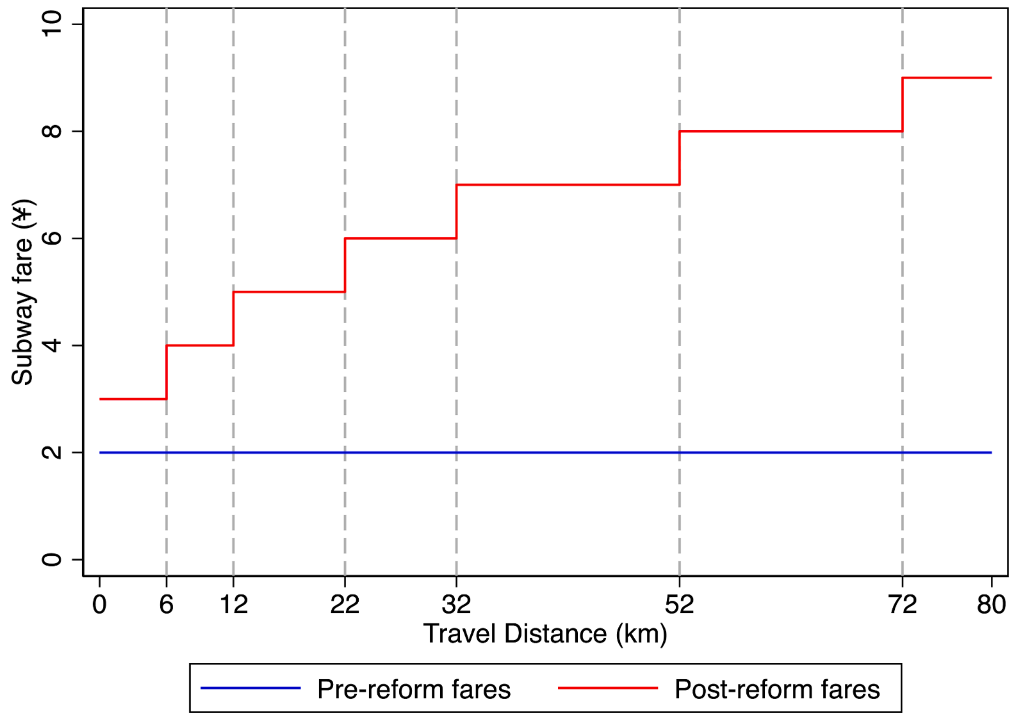

Fig. 1. Price scheme of the Beijing Subway system.
Notes: The new Beijing subway fare scheme, officially implemented on December 28, 2014, is illustrated by the red line, and the previous uniform fare is given in blue. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

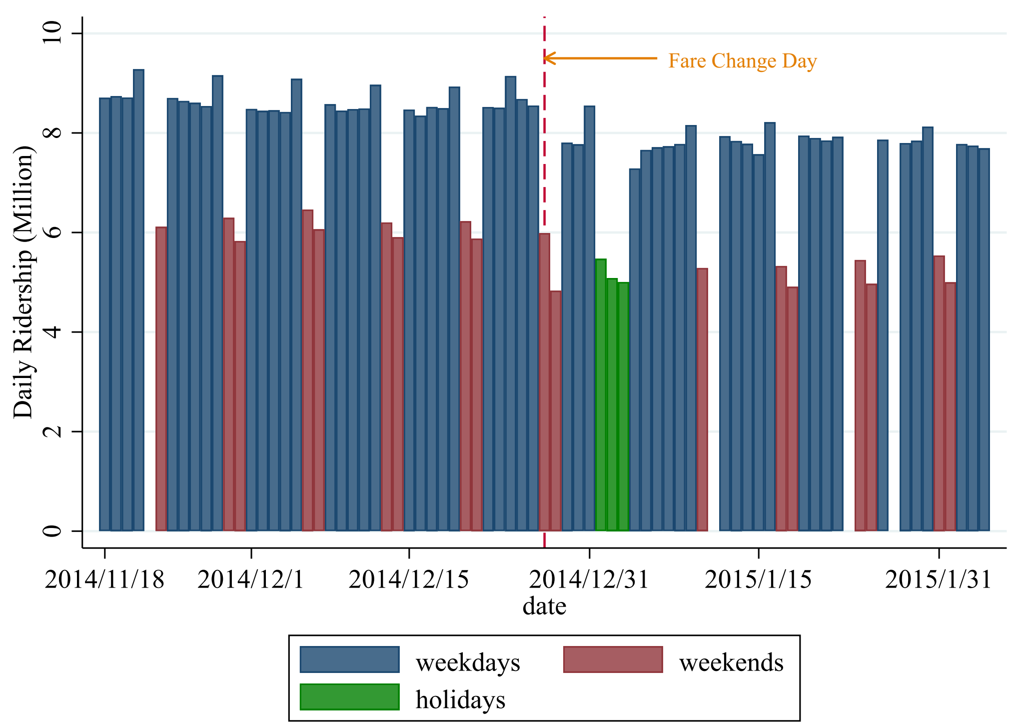

Fig. 2. Daily ridership around the fare-change day.
Notes: Daily ridership within 40 days of the fare change is shown in this figure.

is the only discontinuity variable around the cutoff, and we have included it in our model. In this study, we modeled $f(t)$ as a lower-order polynomial in time. X_t is the vector of control variables, including event year, month, day, day of the week, festival, and holiday dummies.

The validity of using the RD approach is no possibility of the subject manipulating their position at around the cutoff. We justified this in three ways. First, although travelers knew that the fare price would

Table 1
Summary statistics.

Variables	Definition	Mean	SD	Min	Max
$Ridership_t$	Daily ridership (Ten thousand)	55.632	45.256	1.72	207.65
$Log\ ridership_t$	Logarithm of daily ridership	3.607	1.023	0.542	5.336
$Vehicle\ usage\ tendency_i$	$\frac{\%Vehicle\ trip_i}{\%Own\ vehicle_i}$	0.381	0.05	0.317	0.497
$\%Vehicle\ trip_i$	The proportion of households that choose to travel by their own car	0.197	0.036	0.152	0.277
$\%Own\ vehicle_i$	The proportion of households that have their own vehicle	0.513	0.044	0.442	0.61
$Bus\ network\ density_i$	The density of bus lines around a subway line	0.879	0.964	0.105	3.998
$\%Rush\ hour_i$	The proportion of households that need to travel in rush hour	0.634	0.034	0.562	0.695
$\%Work\ or\ school_i$	The proportion of households that have full-time workers or students	0.366	0.058	0.267	0.464
$Income_i$	The average household total income (Ten thousand CNY)	9.545	0.802	7.712	10.814
$Travel\ distance_i$	The average travel distance of households resides near a subway line (km)	5.42	0.979	4.223	8.337

Notes: The number of observations of ridership and log ridership is 23,904 (1653 days times 16 lines with missing data), and that of the subway-line-level household characteristics is 16 (which is the number of lines). According to the seventh National Census, 41.67 % households in China had their own vehicle in 2020, and this ratio is 46.94 % among urban households. In our sample, the average number of $\%Own\ vehicle_i$ is 0.513, which is representative of the urban level.

increase,[7] it is not likely that they were informed about the exact date. Notice that December 28 is not a common policy implementation date in China. Typically, a new policy comes into effect at the beginning of a month or a year (e.g., Jan 1). This fact would have partially alleviated the concern that riders would manipulate their trips as a result of anticipating the reform. Second, about 70 % of travelers in Beijing are commuters,[8] which means that their travel demand is inelastic in time. Therefore, even if travelers knew the exact timing of the price increase, they were unlikely to change their travel behavior accordingly. Finally, to ensure that there was no subject manipulation around the cutoff that led to the sharp decline in ridership after the fare increase, we used a "donut" regression discontinuity design excluding the samples that are ±5 days from the cutoff, and the result remained largely unchanged (see Table A1). The logic of this method is that if the multiplication behavior exists, days closer to the reform cutoff are more likely to be impacted.

In the baseline results, we used the aggregated data for the whole Beijing subway system to estimate the average effect of price reform. For the heterogeneity analysis part, we used subway-line-specific data and included the line-fixed effects in addition to the aforementioned controls. Thus, we could control for the influence of different route types on ridership (as they are absorbed by the fixed effects) and consider the heterogeneous effects by subway lines.

4.2. Main results

Fig. 3 presents a plot of daily ridership, the outcome of interest, against time within a "±30 days" window. Ridership is displayed as gray diamonds, and the fare change date is shown as a vertical line. Further, the continuous line represents the predicted values from our RD model. As Fig. 3 shows, daily ridership experienced a significant drop after the subway fare reform, and ridership changes appeared to persist.

To further analyze the influence of weekdays and holidays, we fitted the RD model separately for weekdays and holiday observations before and after the fare change. As Fig. A2 shows, both weekdays and weekends/holidays ridership experienced a significant drop.

Table 2 summarizes the estimation results for Eq. (2). We used two dependent variables—ridership and the logarithm of ridership—and presented their estimation results in Panels A and B, respectively. In Columns (1)–(4), we modeled $f(t)$ as a first-order polynomial; in Columns (5)–(8), we modeled $f(t)$ as a second-order polynomial. We also reported the RD results for different bandwidths to assess the short-run (one month, bandwidth = 30 days), mid-run (three months, bandwidth = 90 days), and long-run (optimal bandwidth and full sample) effects of price reform. Columns (1) and (5) show the full sample results, Columns (2) and (6) show the optimal bandwidth (250 days) results, Columns (3) and (7) show the 90-days bandwidth results, and Columns (4) and (8) show the 30-days bandwidth results.

Based on Table 2, we can draw three key conclusions. First, all the coefficients were negative and statistically significant at the 5 % significance level. This supports the finding in Fig. 3 that an increase in subway fares resulted in a substantial decline in ridership. Second, the results from the full-sample analysis showed larger effect sizes than those from the restricted sample analysis. As using a distant sample may lead to biased estimates, we adhered to the settings in Column 6 (second-order polynomial, bandwidth of 30 days) for the remainder of our analysis. Third, the preferred setting (Column 6) revealed that an increase in subway fares led to a reduction of 715,800 daily riders, which accounted for 10.4 % of the total ridership. According to the Beijing Municipal Development and Reform Commission, the average new subway fare was approximately 4.3 CNY, indicating an average price increase of 115 %. These findings imply an inelastic price elasticity of −0.090, which is consistent with previous studies (Davis, 2021; Gu et al., 2023), albeit with a smaller effect size.

Moreover, we broke the RD estimation coefficient down to subway line level to further investigate the influence of different route types, and the results are shown in Fig. A3. As the figure shows, the decline in ridership was larger for lines with higher ridership, with the relation largely driven by the downtown lines.

4.3. Robustness checks

We conducted two placebo tests to confirm that the observed discontinuity in ridership is indeed attributable to subway price reform and not merely a result of a ridership pattern specific to December 28th or any other unrelated event around the reform date. We also employed a nonparametric RD analysis to demonstrate that our estimates do not depend on assumptions about the functional form of the relationship or

[7] In our knowledge, the fare changes communicated to the population through various channels, including but not limited to: (1) Official Announcements: The official website of Beijing Subway and its official social media accounts (such as Weibo, WeChat public accounts) posted notices of fare adjustments, which was the most authoritative source of information. (2) Media Coverage: Local news media, television stations, and radio stations reported on the subway fare adjustments to help disseminate the news to a wider audience. (3) In-Station Notifications: Notices were displayed in the subway stations through signs, electronic displays, and announcements to inform passengers about fare adjustments. (4) Subway Staff: Subway station staff verbally informed passengers about the fare adjustments and provided assistance and explanations when necessary. (5) Mobile Applications: The official "Beijing Subway" app updated the fare information and pushed notifications to users. (6) Brochures and Posters: Brochures and posters displaying the new fare information were placed in subway stations and train cars.

[8] Refer to 2014 Beijing Transport Annual Report, https://www.bjtrc.org.cn/List/index/cid/7.html.

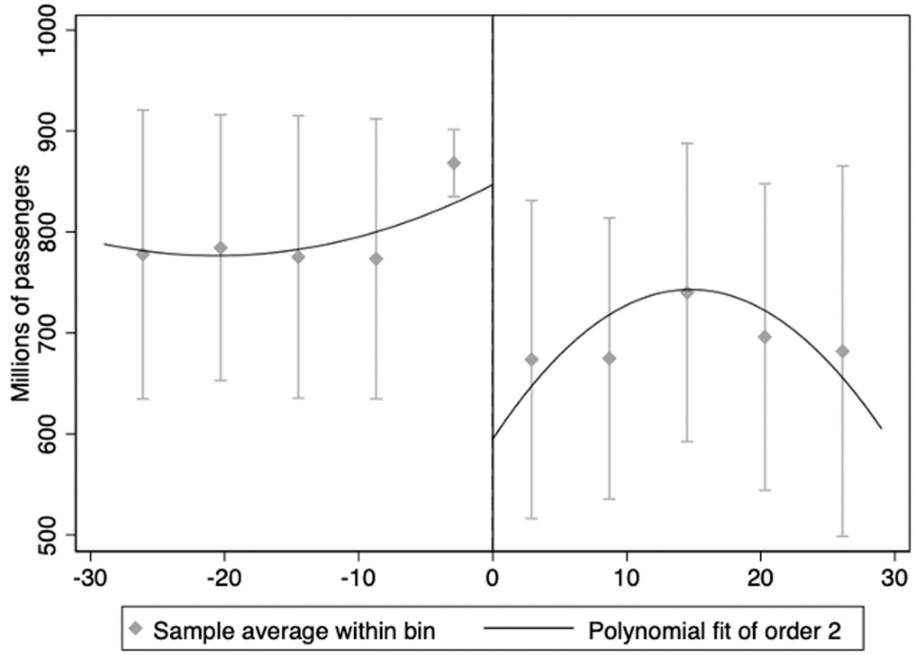

Fig. 3. Impact of subway fare changes on ridership.
Notes: The figure shows a plot of daily ridership, the outcome of interest, against time within a "±30 days" window. The fare-change day is displayed on a vertical line.

Table 2
RD estimation table.

	Order of polynomial = 1				Order of polynomial = 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Optimal (h = 250)	h = 90	h = 30	Full	Optimal (h = 250)	h = 90	h = 30
Panel A: Ridership								
Post	−100.7***	−72.84***	−79.35***	−65.14***	−91.55***	−78.77***	−78.58***	−71.58***
	(21.841)	(24.781)	(24.555)	(19.739)	(22.056)	(25.444)	(30.029)	(21.062)
R^2	0.859	0.902	0.886	0.983	0.86	0.903	0.888	0.984
N	2656	478	172	57	2656	478	172	57
Panel B: Log of ridership								
Post	−0.146***	−0.106**	−0.113**	−0.0944***	−0.135***	−0.110**	−0.114**	−0.104***
	(0.039)	(0.044)	(0.047)	(0.032)	(0.039)	(0.044)	(0.056)	(0.036)
R^2	0.849	0.88	0.864	0.978	0.85	0.881	0.867	0.979
N	2656	478	172	57	2656	478	172	57
Elasticity	−0.127	−0.092	−0.098	−0.082	−0.117	−0.096	−0.099	−0.09

Notes: The table reports the results of our RD design (see Eq. (2)). Bandwidth (h) choose 30,90, optimal, and full to assess the short-run (one month, bandwidth = 30 days), mid-run (three months, bandwidth = 90 days), and long-run (optimal bandwidth and full sample) effects of price reform. The optimal h is determined non-parametrically to minimize the mean squared error (MSE). Event year, month, day, day-of-week, and festival fixed effects are included in the model. Robust standard errors are in parentheses; significance levels are * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

the selection of bandwidth. Furthermore, we conducted a two-step RD in time estimation to avoid disregarding observations that were considerably distant from the event date and to ensure a more comprehensive analysis.

4.3.1. Ridership pattern placebo test

Fig. 4 summarizes the results of the placebo tests using the pseudo-subway price reform date of December 28 (2012, 2013, 2015, and 2016). These dates, occurring in different years but on the same day as the actual price reform (December 28, 2014), serve as intuitive placebo cutoffs. The figures show the daily ridership and predicted values from the baseline regressions against the running variable. The results indicated no significant breaks in the placebo cutoff values.

4.3.2. Pseudo reform date placebo test

To address the concern of spurious regressions, we conducted falsification tests using randomly chosen pseudo-reform dates from the entire sample period (Fauver et al., 2017). Fig. 5 shows that when applying the RD estimation with these pseudo-breakpoints, the distribution of the pseudo-RD estimates closely resembles a normal distribution centered at 0. The *p*-value of our estimates in Table 2 is 5.7 % (or 4.9 %), indicating that factors unrelated to the fare reform dates were not the main cause of the significant drop in daily ridership.

4.3.3. Nonparametric RD estimate

To address the potential sensitivity of the parametric RD estimates to the degree of polynomial fitting, we conducted a nonparametric RD analysis using local first-order polynomials (Gelman & Imbens, 2019). In

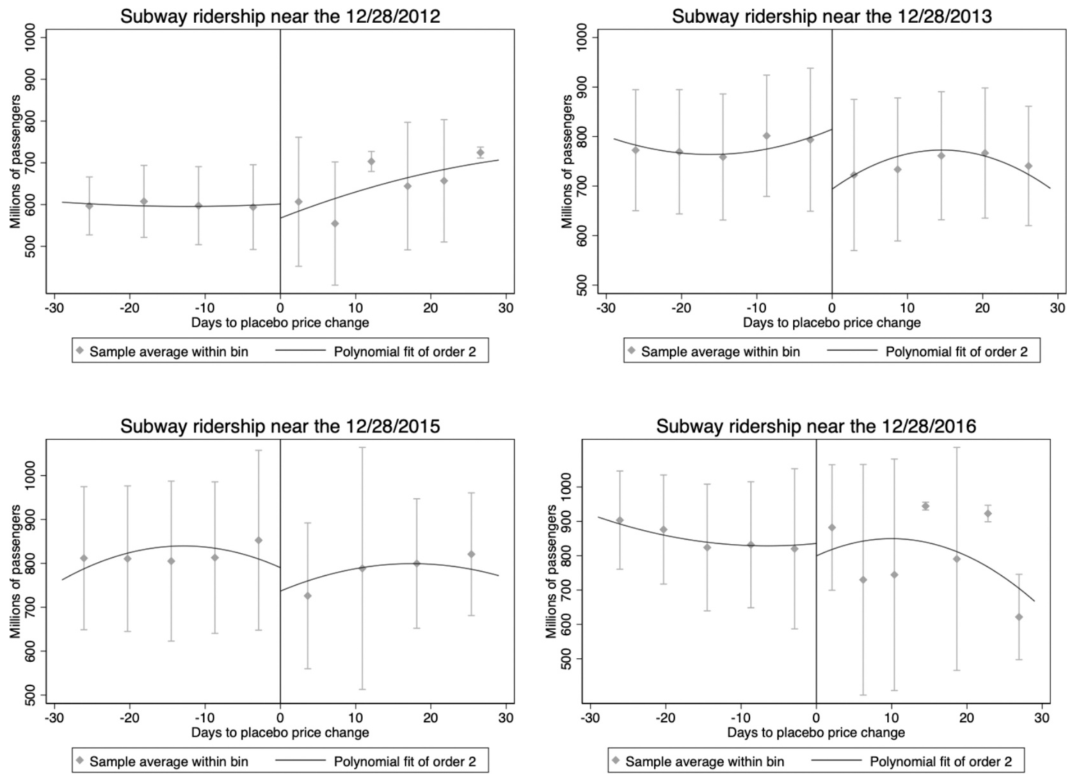

Fig. 4. Ridership pattern placebo test.
Notes: We assume that the subway price reform happened on 12/28/2012, 12/28/2013, 12/28/2015, and 12/28/2016, the same dates as the actual price reform date (12/28/2014) but in different years, to provide an intuitive placebo test.

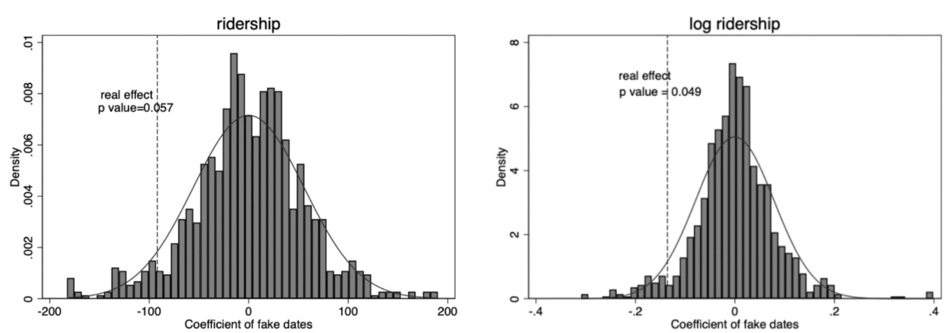

Fig. 5. Empirical distribution based on placebo date.
Notes: The figures show the empirical distribution of the estimated coefficients of the RD estimation by randomly choosing the pseudo-reform date within the entire sample period.

the nonparametric estimation, local linear regression is used to construct the point estimator, local quadratic regression is used to construct the bias correction, and the triangular kernel function is used to construct the local polynomial estimators.[9] Table 3 presents the results. In Columns (2) and (6), the bandwidth is determined nonparametrically to minimize the mean squared error (MSE), resulting in a fully nonparametric model. To ensure comparability with the baseline regression results in Table 2, we reported the results of the local first-order polynomial approach with full bandwidth in Columns (1) and (5), a bandwidth of 90 in Columns (3) and (7), and a bandwidth of 30 in Columns (4) and (8).

The coefficients in Table 3 are more negative than those in Table 2, suggesting that the baseline model does not overstate the effects of the subway fare reform. Note that the results of nonparametric RD at the optimum bandwidth have a magnitude of point estimate about twice the corresponding parametric regression. We agree that a coefficient twice as large represents a significant difference for point estimates. We believe this difference is due to the statistical nature of non-parametric methods, which are relatively more sensitive to the choice of function form. Similar issues and patterns have also been detected in the extant literature on RD (Lee & Lemieux, 2010).

4.3.4. *Two-step RD in time*

In line with Hausman and Rapson (2018), we implemented a two-step RD using the time estimation approach. This approach allowed us to utilize data points that may be relevant, even if they are farther from the actual event date. In the first stage, we elicited year, day-of-the-

[9] We use statistical software Stata 17 package **rdrobust** and **rdbwselect** command for the nonparametric regression and the optimal bandwidth selection.

Table 3
Nonparametric RD estimate.

	Ridership				Log of ridership			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Optimal (h = 250)	h = 90	h = 30	Full	Optimal (h = 250)	h = 90	h = 30
Post	−104.2***	−161.6***	−91.71**	−182.2***	−0.158***	−0.260***	−0.116**	−0.261***
	(9.821)	(22.478)	(37.386)	(60.477)	(0.014)	(0.033)	(0.055)	(0.091)
N	2656	478	172	57	2656	478	172	57

Notes: This table reports the results of the nonparametric RD estimate that uses a local first-order polynomial to estimate $f(t)$. Bandwidth (h) chooses 30,90, optimal, and full to assess the short-run (one month, bandwidth = 30 days), mid-run (three months, bandwidth = 90 days), and long-run (optimal bandwidth and full sample) effects of price reform. In Columns (2) and (6), the bandwidth is set in a nonparametric manner that minimizes the mean squared error (MSE). Robust standard errors are in parentheses; significance levels are * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

week, and festival effects using the full sample by regressing daily ridership on year, day-of-the-week, and festival dummies. In the second stage, we estimated the treatment effect using the elicited data (residuals in the first-stage regression) close to the event date. The results are presented in Table 4 and are consistent with the baseline RD estimates in Table 2.

The discernible difference is that the estimates in Table 4 are slightly less precise when using a bandwidth of 30, as indicated by the larger standard errors resulting from a smaller sample size. Nonetheless, the overall findings remain robust and are consistent with our previous analysis.

5. Heterogeneity

5.1. Regression specification

In this section, we explored the heterogeneous effects of subway fare increases on daily ridership by considering the travel and demographic characteristics of each subway line. We derived these variables by averaging the survey data for households residing near each subway line, as explained in Section 3.

The population model for the heterogeneity analysis is as follows:

$$lnridership_{lt} = \gamma_0 + \gamma_1 D_t + \gamma_2 D_t \times HC_l + f(t) + \eta_l + \gamma_3 X_t + u_{lt} \quad (3)$$

where HC_l is the subway line level variable aggregated from household characteristics, as summarized in Table 1. To simplify the interpretation of the heterogeneity results, each variable was normalized by dividing it by the standard deviation. $D_t \times HC_l$ is the interaction term of the treatment dummy in the time- and line-averaged household characteristics. η_l is the line dummy, with which we need not add HC_l to the regression. The parameter of interest, γ_2, quantified the heterogeneous response of lines with different household characteristics. Standard errors were clustered at the date level. Fig. 6 summarizes the estimation results. As the figure shows, seven of the nine interaction terms in our heterogeneous analysis were significant at the 5 % significance level, which shows that the coefficients were statistically significant. In addition, the coefficient of the interaction term captures the difference in the reduction of ridership after the subway price increase for families whose household characteristics (*HC*) differ by one standard deviation. Therefore, a 0.01 coefficient (roughly the average coefficient estimation in heterogeneous analysis) indicated that two groups of households with the same other characteristics except for a difference of one standard deviation in *HC* would have a 1 % difference in ridership decline after the subway price increase. The daily ridership of the Beijing subway is around 6,880,000, and, in our baseline scenario, the ridership decline is 10.4 %. The coefficients from the heterogeneous analysis account for 68,800 daily riders and are close to 10 % of the baseline regression coefficient, which indicates that the coefficient has strong economic significance.

More specifically, we can take income as an example. Based on the summary statistics displayed in Table 1, one standard deviation difference in income is equivalent to around 8000 CNY. Combined with a 0.111 heterogeneity analysis coefficient, it indicates that two groups of households with the same other characteristics except for a difference of 8000 CNY in annual income would have a 1.11 percentage point difference in ridership decline after the subway price increase.

Therefore, we would prefer to view our finding as "low estimated coefficients but with high economic significance.". A similar pattern is common in environmental, urban, and transportation studies (Parry et al., 2014).

5.2. Results

5.2.1. Heterogeneity by travel distance

With a population of over 20 million, Beijing has a complex urban structure and diverse commuting needs. Theoretically, some long-distance subway lines connect downtown and suburban Beijing and might be greatly influenced by the price reform. This is because the post-reform fare is distance-based, thus, those lines face greater fare increments. However, there are fewer alternative commute options for the riders of those subway lines to substitute as the transportation network is denser and more well-connected when closer to the city center. Hence, heterogeneity is ex-ante ambiguous. We examined this by examining the

Table 4
Two-step RD in time estimates.

	Ridership			Log of ridership		
	(1)	(2)	(3)	(4)	(5)	(6)
	Optimal (h = 250)	h = 150	h = 30	Optimal (h = 250)	h = 150	h = 30
Post	−77.82***	−67.61***	−56.93	−0.129***	−0.0907**	−0.0927*
	(16.361)	(24.177)	(37.359)	(0.026)	(0.038)	(0.053)
N	694	165	57	594	165	57

Notes: This table reports the results of the two-step RD for time estimates. We examine the effects of year, day of week, and festivals in the first stage using a full sample and estimate the treatment effects in the second stage using samples close to the event date. Robust standard errors are in parentheses; significance levels are * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

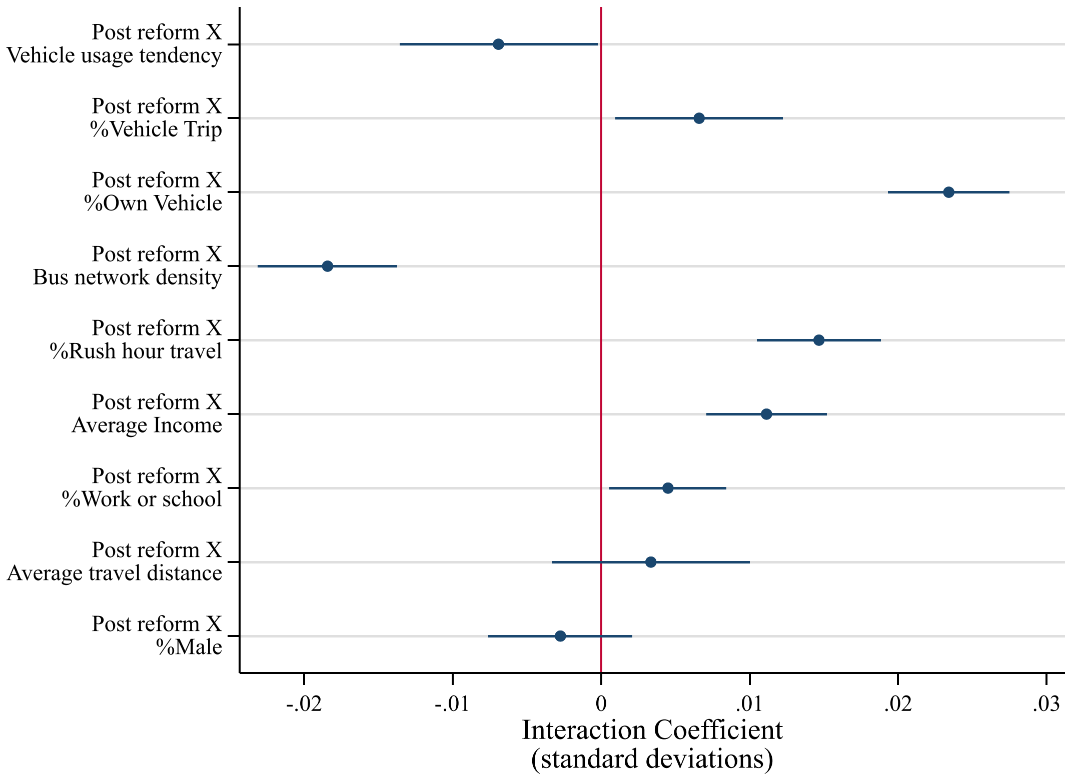

Fig. 6. Household's heterogeneous response toward the fare increase.
Notes: The figure shows the normalized interaction coefficients and the corresponding 95 % confidence intervals of post-reform dummy and line-averaged household characteristics in Eq. (3). The bandwidth is set nonparametrically to minimize the mean squared error (MSE). Year, month, day, day-of-the-week, and festival fixed effects were included. Standard errors are clustered at the date level.

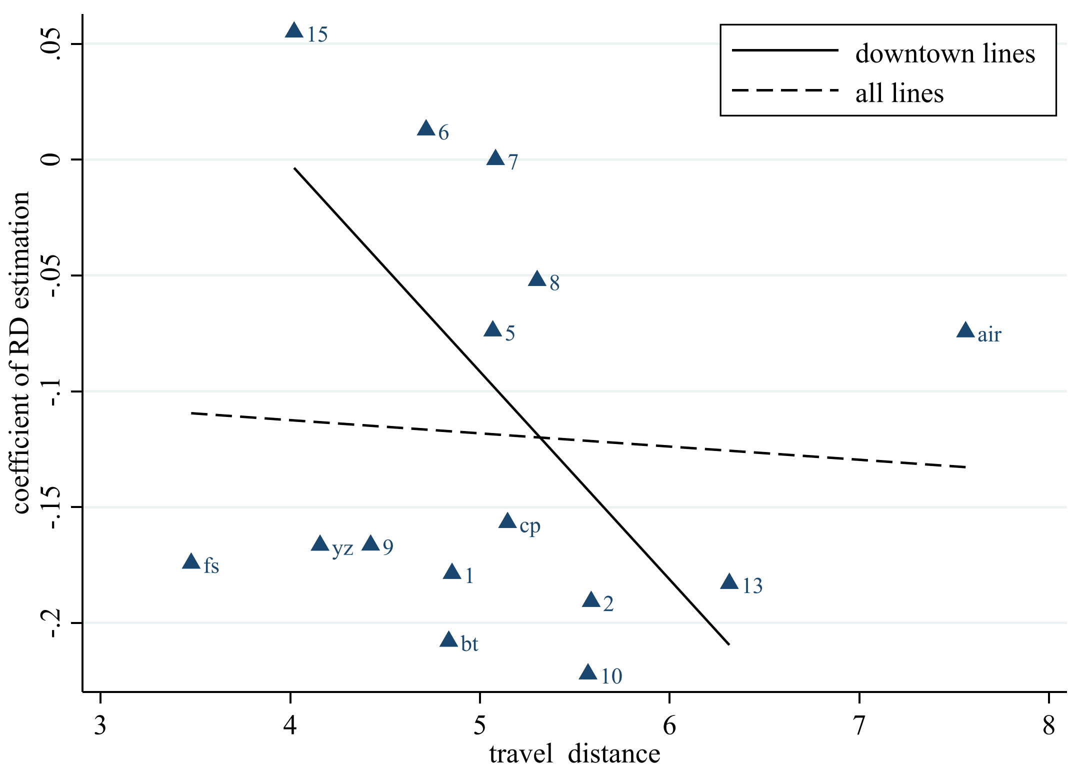

Fig. 7. Heterogeneity by travel distance.
Notes: The figure shows a scatter plot of each subway line's RD estimation coefficient against travel distance. Each subway line is displayed as a triangle dot, with the line name on the right. A dashed (solid) line is used to fit the relationship between the RD estimation coefficient and ridership for all (downtown) lines. Suburban lines are Batong Line, Fangshan Line, Changping Line, Yizhuang Line, Capital Airport Express, and Line S1. The rest are downtown lines.

heterogeneity effects of travel distance. Unfortunately, we did not have individual smart card data to record individual travel distances both before and after the price surge. Instead, we had access to individual subway smart card data from one month in 2018 and can calculate the average travel distance of each subway line as the measurement.

Using this measurement of average travel distance and a separate RD estimation coefficient for each subway line, we can explore the heterogeneity by travel distance. As Fig. 7 shows, the decline in ridership was larger for subway lines with higher ridership, with the relation largely driven by the downtown lines.

5.2.2. Heterogeneity by accessibility to alternative transportation modes

The first three rows of Fig. 6 show the heterogeneous responses of accessibility of private vehicles. The coefficient of $Vehicle\ usage\ tendency_i$ (first row) is negative and significant, indicating the presence of substitution effects. The coefficient of $\%Vehicle\ trip_i$ (second row) is positive and significant, suggesting that the heterogeneity induced by income outweighs the substitution effect, resulting in a positive mixed effect. Finally, the interaction between the post-reform dummy and $\%Own\ vehicle_i$ (third row) shows a positive and significant coefficient, indicating elasticity to price decline with income.

The fourth row of Fig. 6 shows the heterogeneous response by bus network density, which measures the likelihood of substitution from subway to bus travel. Our estimation result for the relationship between bus density and subway ridership was negative and significant, indicating a substitution between bus and subway travel. The magnitude of the normalized estimate suggests that bus subway substitution is more prevalent than private-car subway substitution, as the first row shows. This implies that, as expected, buses are closer substitutes for subways than automobiles.

5.2.3. Heterogeneity by travel urgency

In the fifth row of Fig. 6, we examined the heterogeneity in the urgency of the need to travel during rush hour, measured by the variable $\%Rush\ hour_i$ travel. We hypothesized that higher urgency during rush hour results in less substitution away from the subway, as the subway is more reliable than ground transport when congestion is severe. The positive and statistically significant estimate supported this hypothesis, suggesting that the effect of fare increase on ridership is indeed attenuated during rush hours compared with other times.

5.2.4. Heterogeneity by income level

In the sixth row of Fig. 6, we examined income heterogeneity. The coefficient of the interaction term between the reform dummy and income is positive and statistically significant, indicating that higher income is relatively unresponsive to price changes. Specifically, fare increase has a larger impact on ridership for individuals with lower income, whereas it has a relatively smaller effect on those with higher incomes. This finding highlights the importance of considering income disparities when analyzing the effects of fare changes on ridership. It indicates that a fare increase may disproportionately harm lower-income individuals.

5.2.5. Heterogeneity by other demographics

In the seventh row, we examined the proportion of households with full-time workers or students because these households tend to have relatively constant travel needs, resulting in lower price elasticity. The positive and significant estimates supported this hypothesis. In the eighth row, we analyzed the heterogeneous responses of households based on different travel distances. The insignificant coefficient suggested that a fare increase has a similar effect on households regardless of their travel distance. In the ninth row, we examined the interaction between the post-reform dummy variable and gender. The statistically insignificant coefficient suggested that fare increases affect males and females equally.

6. Optimal Subway fare and discussion

6.1. Optimal subway fare and policy implication

Our findings have important implications for government policies on public transit pricing and subsidies. The estimated price elasticity allowed us to calculate the optimal subway fare, which helps evaluate the welfare effect of the fare change. If the fare change moves the subway price toward (away from) its optimal value, it has a positive (negative) welfare effect.

We applied our estimated price elasticity to the frameworks developed by Parry and Small (2009) and Parry and Timilsina (2010) to calculate the optimal subway fare. Specifically, the optimal fare for public rail (i.e., subway) is given by the following equation.

$$P^{R^*} = \theta^R + E^R + E^A\rho^{AR} + E^B\rho^{BR} \tag{4}$$

The elements of the equation are defined as follows:

- θ^R: Marginal cost of subway per passenger km
- E^R: External cost of subways per passenger km
- E^A: External cost of automobiles per passenger kilometer
- E^B: External cost of buses per passenger kilometer
- $\rho^{jR} = \frac{d\ \ln(M^j)\ /\ d\ P^R}{d\ \ln(M^R)\ /\ d\ P^R}\cdot\frac{M^j}{M^R},\ j = Auto,\ Bus$: The unit change in passenger km on mode i per unit change in price of public rail.
- $M^j,\ j = Auto,\ Bus$: Aggregated passenger traveling share in mode j

The optimal fare of the subway P^{R^*} comprises 1) the social cost of the subway ($\theta^R + E^R$), which is a positive value, and 2) the social benefit of reducing external costs from private automobiles and buses ($E^A\rho^{AR} + E^B\rho^{BR}$), represented as a negative value. The key parameters, ρ^{AR} and ρ^{BR}, known as the "leakage share" in the public finance literature, measure the extent to which changes in subway travel due to fare changes are diverted to other transportation modes. The intuition behind this equation is as follows. If the leakage share is large, the optimal subway fare should be relatively low to avoid the leakage of subway riders to other transportation modes with higher external costs. It is clear that a higher ρ^{AR} value can be driven by either low subway price elasticity or high cross-price elasticity between the subway and other transportation modes.

We first assigned values to the parameters based on the previous literature and estimates in this study. The parameter values are listed in Table A2, along with their respective sources. The external costs associated with private vehicles and buses were based on gasoline and diesel costs per liter from Parry et al. (2014) and are further adjusted considering factors such as fuel economy and carrying capacity. The impact of changes in Beijing subway fares on private vehicle usage was derived from Liu et al. (2023). Based on our baseline estimation of an 11.1 % decline in ridership, ρ^{AR} was calculated to be −0.05. This magnitude was much smaller than that of Mexico City in Parry and Timilsina (2010). The lower likelihood of riders switching to driving can be attributed to driving restrictions and vehicle quota policies in Beijing.

Subsequently, we conducted a back-of-the-envelope calculation for the optimal subway price in Beijing based on the formula and values of the parameters. We found that the optimal subway fare for Beijing ranges from 0.39 to 0.51 CNY per passenger-km or 5.12 to 7.36 CNY as a flat rate. This is lower than the cost recovery level (8.56 CNY) since the social benefit of the subway system is larger than the social cost, but still higher than the new average subway fare (4.3 CNY). Hence, we concluded that the pre-reform subway fare of 2.00 CNY is lower than the optimal fare, and a price increase brought it closer to the optimal value calculated using Parry and Timilsina (2010)'s formula.

To better understand the sensitivity of this calculation to price elasticity, we conducted simulations for counterfactual ridership-change scenarios. In the case of a 1 % ridership decline, the corresponding optimal fare decreased significantly to a range of −2.46 to 2.69 CNY as a flat rate. With a 5 % in ridership, this range expanded to 4.20 to 6.80 CNY. Surprisingly, with a 20 % decline in ridership, the range increased slightly to 5.45 to 7.57 CNY. This is because, as the price elasticity increases, the social benefit derived from subway subsidies approaches zero, and the optimal fare is predominantly determined by engineering and operational costs.

Our findings have important implications for public transportation policies. This relatively low price elasticity implies that public transit and private vehicles are not close substitutes in Beijing. This may be attributed to issues such as congestion in metropolitan areas, driving restrictions (Viard & Fu, 2015), and vehicle quota policies in Beijing (Li, 2018). Consequently, implementing extensive subsidies for public transportation pricing may not be justified. The findings of the heterogeneity analysis suggest that subway subsidies should be further reduced for higher-income groups, commuters with greater travel demands during rush hours, and commuters in regions with limited alternative transportation options. Subway systems place a significant financial burden on the government,[10] and implementing price discrimination based on income group, time, and location is challenging. Therefore, we conclude that alternative non-distortionary policies, such as lump-sum transfers or travel vouchers, could be more efficient than subsidizing public transportation.

6.2. Compare with those of existing studies

Before conclusion, we compare our estimates with those of existing studies to evaluate the price elasticity of subway demand.

As shown in Table 5, the price elasticity of subway demand in this study was relatively small compared with previous studies. Two possible reasons may account for this difference. First, from a methodological perspective, we employed granular daily data, captured higher-frequency variations, and used a regression discontinuity method to estimate the effects of an exogenous price shock. This approach helps alleviate the confounding of omitted variables bias.

Second, our estimation reflects the extensive margin— the choice between taking the subway and using other modes of transportation. This relatively low price elasticity implies that subways and private vehicles tend to be poor substitutes in Beijing.[11] The first potential explanation is that the congestion problem is severe in metropolitan areas such as Beijing, and the estimated value of time (VOT) is high (Akbar et al., 2023; Barwick et al., 2021). Therefore, passengers selected the subway to avoid congestion and save time, not merely for monetary cost savings. The second potential explanation is the presence of driving restrictions (Viard & Fu, 2015) and vehicle quota policies in Beijing (Li, 2018), which make driving an infeasible alternative in some cases.

7. Conclusion

Public transit price changes have efficient and distributional effects. In this study, we utilized Beijing's subway fare reforms to study the impact of subway fare changes on ridership. We explored the heterogeneous effects across demographic groups. Combining daily subway ridership data by subway lines with household travel survey data, we adopted a regression discontinuity in time (RDiT) approach and found that the fare increases lead to a 10.4 % reduction in short-run subway ridership, which corresponds to the price elasticity of −0.090. Using the variation in traveling and demographic characteristics of each subway line, we found that both substitution effects and income levels contribute to the heterogeneous responses toward fare increases. Households with higher incomes, greater travel during rush hour, and limited access to other transportation modes exhibited relatively lower price elasticity.

Our findings have significant implications for public transportation policies. First, given that public transit and private vehicles are not close substitutes in Beijing, extensive subsidies for public transportation pricing may not be justified. Second, subway subsidies should be further reduced for higher-income groups, commuters with greater travel demands during rush hours, and commuters in regions with limited alternative transportation options. However, implementing price discrimination based on income group, time, and location is challenging. Therefore, alternative non-distortionary policies, such as lump-sum transfers or travel vouchers, may be more efficient than direct subsidies for public transportation.

Our study has limitations that could be addressed in future studies. First, even though we are innovative in exploring the distribution effects of Beijing subway fare changes, we combined two different data sources using a statistical model due to the lack of individual subway ridership data. Given the importance of the distribution effects of urban transportation policies, future studies could advance our results using data with linked ridership and household demographic information. Second, our optimal subway fare framework is derived from the established public economics literature, which primarily focuses on addressing the social cost of externalities, such as waiting time and congestion. In the future, researchers can consider the changes in equilibrium speed and congestion as well as the resident local response due to the commuting behavioral changes, as in Barwick et al. (2021).

Table 5
Price elasticity comparison.

	Price elasticity	Sample	Method
This paper		Beijing, China	RD in Time
Average	−0.09		
Private car tendency > mean	−0.105		
%Vehicle trip > mean	−0.091		
%Own vehicle > mean	−0.078		
Bus network density > mean	−0.099		
%Rush hour > mean	−0.088		
Income > mean	−0.092		
%Work or school > mean	−0.094		
Travel distance > mean	−0.095		
Litman (2004)	−0.33 to −0.22	Multiple countries	Based on past empirical researches
Woo et al. (2020)	−0.07	China	Generalized Leontief system
Davis (2021)	−0.32 to −0.23	Mexico	RD in Time
Sianturi et al. (2022)	−0.074	Indonesia	RD
Gu et al. (2023)	−0.33	China	RD in Trip Distance

Notes: The ">mean" price elasticities are calculated based on the following steps. First, we calculate the mean value of household characteristics above their mean. Next, we use this mean value and the estimated coefficients of D_t and $D_t \times HC_l$ to calculate the percentage change in ridership. Finally, we divide the percentage change in ridership by the percentage change in subway fares to obtain the underlying price elasticity.

[10] From 2007 to 2013, the Beijing municipal government provided various types of financial subsidies totaling approximately 22.1 billion yuan CNY for subway operations. Source: http://finance.ce.cn/rolling/201410/27/t20141027_3784048.shtml.

[11] This can be shown using a simple discrete choice model of transportation mode (McFadden, 1974; Train, 2009), where self- and cross-price elasticity are functions of the price parameter.

CRediT authorship contribution statement

Lunyu Xie: Writing – review & editing, Investigation, Conceptualization. **Huning Wan:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Yucheng Wang:** Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Appendix

Table A1
Donut test.

	Ridership				Log of ridership			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full	Optimal (h = 250)	h = 90	h = 30	Full	Optimal (h = 250)	h = 90	h = 30
Post	−103.0***	−161.8***	−62.73	−160.9*	−0.157***	−0.265***	−0.0702	−0.238*
	(9.936)	(23.316)	(41.757)	(91.101)	(0.014)	(0.035)	(0.061)	(0.132)
N	2647	469	163	48	2647	469	163	48

Notes: This table reports the results of the donuts test of the nonparametric RD estimate that excludes the sample that are ±5 days from the cutoff. In Columns (2) and (6), the bandwidth is set in a nonparametric manner that minimizes the mean squared error (MSE). Robust standard errors are in parentheses; significance levels are * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A2
Parameters in calculating optimal subway fare.

Parameters	Interpretation	Range	Source
θ^R	Average operation cost per passenger km (CNY)	0.419–0.559	China Urban Rail Transit Association
E^R	External cost of Subway per passenger km (CNY)	0	Parry and Timilsina (2010)
E^A	External cost of Automobile per passenger km (CNY)	0.17–0.28	Parry et al. (2014); Wang et al. (2008)
E^B	External cost of Bus per passenger km (CNY)	0.05–0.08	Parry et al. (2014); Zhang et al. (2014)
$d\ ln(M^A)$	Change in vehicle usage due to subway fare increase	0.0054	Liu et al. (2023)
$d\ ln(M^B)$	Change in bus ridership due to subway fare increase	0.0185	Back out from Parry and Timilsina (2010)
$d\ ln(M^S)$	Change in subway ridership due to subway fare increase	−0.111	Authors' estimation
M^A	Traveling share of private vehicle	0.163	Authors' calculation
M^B	Traveling share of buses	0.183	Authors' calculation
M^S	Traveling share of subway	0.087	Authors' calculation

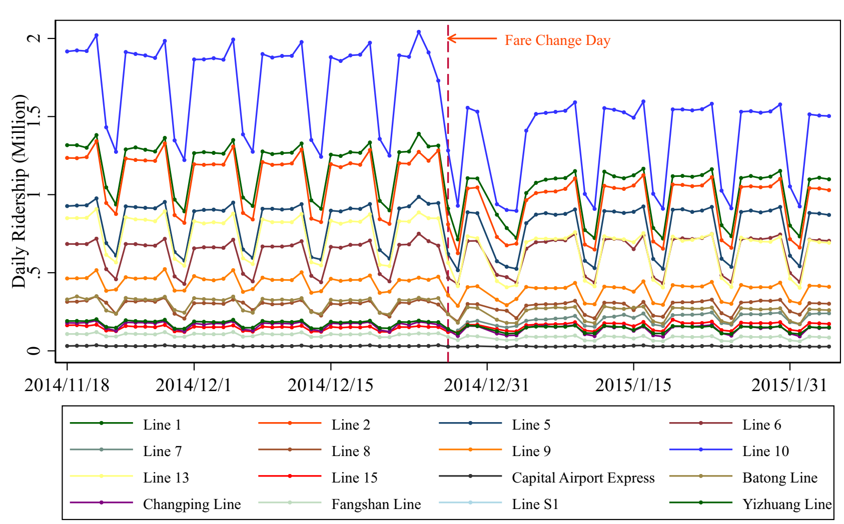

Fig. A1. Daily ridership by line around the fare change day.
Notes: The daily ridership of each subway line within 40 days of fare change is shown in this figure.

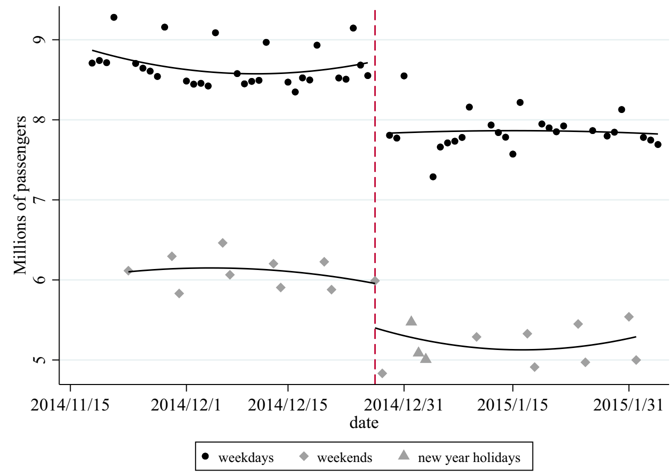

Fig. A2. Impact of subway fare changes on weekdays and weekends.
Notes: The figure shows a plot of daily ridership, the outcome of interest, against time within a "±40days" window. Ridership on weekdays is displayed in black dots, while ridership on weekends and New Year holidays is displayed in gray diamonds and triangles, respectively. The continuous line represents the predicted values from our RD model separately for weekdays and weekends/holidays observations before and after the fare change. The fare change day is displayed in the vertical dash line.

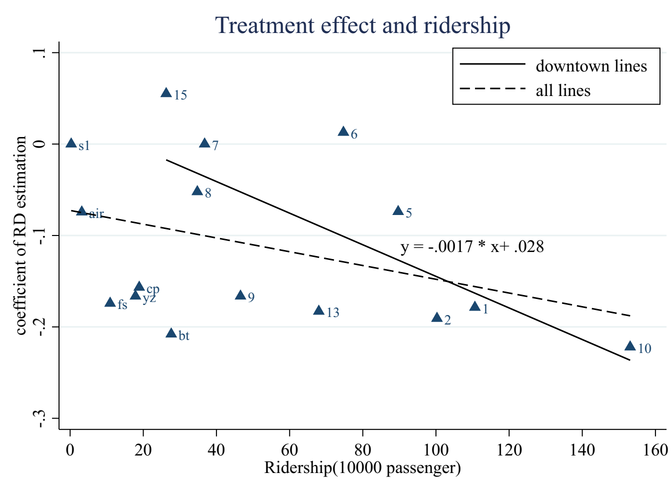

Fig. A3. RD estimation coefficient and ridership by line.
Notes: The figure shows a scatter plot of each line's RD estimation coefficient against ridership. Each line is displayed as a triangle dot, with the line name on the right. A dashed (solid) line is used to fit the relationship between the RD estimation coefficient and ridership for all (downtown) lines.

Data availability

Data will be made available on request.

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