Fare Adjustment's Impacts on Travel Patterns and Farebox Revenue: An Empirical Study Based on Longitudinal Smartcard Data

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ABSTRACT

Fare policy plays an important role in transit operations and management. To better coordinate and achieve the multidimensional goals of a proposed fare adjustment policy (e.g., increasing revenue, managing demand, and improving equity), a fundamental step is to evaluate its travel pattern impacts, which helps us consider the policy in a bigger socioeconomic context. Existing studies rarely investigate the impacts of such a policy on different users' and user groups' travel patterns and transit operators' farebox revenue using longitudinal data from sources such as smartcard data. To fill this gap, we exploit 24 weeks' smartcard data from Wuhan, China, to empirically quantify those impacts. We find that (a) the fare increase had significant but varying impacts on travel patterns across users and user groups; (b) confronting the fare increase, commuter groups identified by the topic model reduced their trip frequency more but later as compared to other groups; (c) low-accessibility, long-distance, and single-destination metro riders were less sensitive to the fare increase; (d) when there was a system-wide fare increase with a distance-based structure, trip purposes and socioeconomic statuses could better predict the impacts on the travel demand and farebox revenue than spatiality. These findings indicate that increasing average fares while offering discounted tickets for frequent and/or captive riders could maintain the existing ridership and farebox revenue and possibly increase additional ridership.

Keywords: Transit Fare, Transport Policy Evaluation, Empirical Data, Rail Transit, Unsupervised Learning, Wuhan

1 INTRODUCTION

Fare policy plays an essential role in transit operations and management. It is a tool to manage both revenue and demand (McCollom & Pratt, 2004). To fight external inflation and to ease corresponding financial burdens, many transit operators regularly review and propose to increase their fares within their respective regulatory regimes. On the one hand, fare increases might boost the farebox revenue, thereby reducing the governments' transit subsidies (Batarce & Galilea, 2018; Wang et al., 2018). On the other hand, like many other goods, fare increases reduce transit demand (Taylor & Fink, 2013). Unmet transit demand could see unintended consequences, e.g., car reliance, road traffic congestion (Litman, 2005), air pollution (Zheng et al., 2019), transportation inequity, and related social exclusion (Wang et al., 2021; Zhou et al., 2019). To mitigate and avoid those consequences, predicting and managing the travel pattern impacts of fare adjustments appropriately across users and user groups is the key.

Normatively speaking, there are four distinct objectives of a fare reform: (a) increasing revenue; (b) maximizing ridership in order to stimulate mobility; (c) triggering a ridership shift in time in order to reduce congestion; (d) improving equity among users (McCollom & Pratt, 2004). Compromises have to be undertaken when achieving those objectives. Wuhan Metro is a case in point. With a rapidly expanding network and a relatively low fare level, it has always been heavily subsidized since its inception (Wuhan Metro, 2019). Compared to other metro systems in mainland China, its fare recovery ratio[i] (0.54 in 2018) was far below the national average (0.78, China Association of Metros, 2018). To change the situation, Wuhan Metro proposed a fare increase in 2018. The local government accepted the proposal and implemented it in 2019. The corresponding governmental document stated that the primary purpose of the increase was to add farebox revenue and to reduce the financial deficit of Wuhan Metro (Wuhan Development and Reform Commission, 2019). Against the aforementioned backdrop, Wuhan Metro can serve as an empirical case for us to investigate whether and to what degree a fare increase can achieve the aforementioned objectives that people have prescribed for fare reforms, especially whether and how the increase affected different users and user groups' travel patterns and the local farebox revenue.

In this paper, we investigate two research questions concerning the fare increase policy: (a) whether and how did it influence travel patterns of different users and user groups? (b) how did it influence the farebox revenue and bring unintended consequences? To answer the question (a), we explored the multidimensional changes of individual travel pattern, namely, frequency of metro usage, average distance of metro trips, and choice of destinations before and after the fare increase. In addition, the changes were also explored at the user group level in three dimensions: whether different groups' travel patterns changed? If so, how soon the change happened after the policy was introduced and how significant was the change? And at the individual level in two dimensions: the intensity and speed of response. To answer the question (b), we investigated the revenue impacts across users, user groups, and locales by calculating farebox revenue per capita/station/trip and/or demand elasticities.

We hypothesize that those users highly reliant on the metro system, i.e., captive riders like commuters, were more likely to response to fare increases, e.g., they reduced their metro trip frequency by minimizing non-essential trips and went to fewer destinations; also, they changed more quickly and to a more considerable extent as compared to other users. We used two-years' smartcard data of Wuhan Metro to conduct the individual- and group-level analyses. This enables us to exclude the effects of compounding factors and include more details about the changes from a disaggregated perspective.

In the remainder of the article, Section 2 reviews the existing literature. Section 3 describes the empirical case of Wuhan, China. Section 4 introduces the methodologies adopted. Section 5 presents the results. Section 6 concludes.

2 LITERATURE REVIEW

Fare scheme is an important policy instrument in the transit sector. Under most circumstances, transit is regarded as quasi-public goods, and fare adjustments would lead to changes in its demand (Dai et al., 2021; Wang et al., 2015). This makes it an important tool in travel demand management. For example, Hong Kong, China, has proposed an off-peak discount in congested areas during peak hours to reduce the local metro crowdedness (Halvorsen et al., 2016).

Increasing fare sometimes helps increase farebox revenue. As the price elasticity of transit travel demand is often between -1 and 0, increasing fare level could add to the overall farebox revenue (Cervero, 1990; Litman, 2004; Stuntz, 2018). A study in Beijing suggests that the weekly revenue increased 82.64% after a fare increase in 2014 even though the ridership declined after the increase (Wang et al., 2018). The annual report of Wuhan Metro shows that the increase in fare level boosted its annual revenue by nearly 60% in 2019 (Wuhan Metro, 2019).

Farebox revenue has become more important to metro companies in China. On the one hand, these companies have less and less developable land allocated by the government to make profits to supplement net farebox income; on the other hand, they still must carry more passengers on relatively low fare levels initially approved by the government (MTR, 2018; Wuhan Metro, 2019). Given these, increasing fares tends to be pursuable for both the metro companies and local governments.

Apart from those demand and/or revenue impacts, fares can have transportation equity implications. Empirical studies suggest that equity is an unintended but important consequence of most fare (adjustment) policies (Farber et al., 2014; Verbich & El-Geneidy, 2017; Wang et al., 2021; Zhao &

Zhang, 2019; Zhou et al., 2019). In summary, the existing studies have shown the importance of simultaneously analyzing the demand, financial, and equity implications of (new) fare policies.

The demand and travel behavior impacts of transit fare adjustment have been studied extensively. Price elasticity, defined as the change in demand relative to the change in price, is the most common measurement. Price elasticity can be calculated by the line, mid-point, or arc methods depending on the premise of its form (Cervero, 1982). To measure the elasticity, traditional datasets like stated preference surveys concerning a given fare increase (Cervero, 1982; Wang et al., 2015) and travel surveys recording before-and-after behavior (Cats et al., 2017; Sharaby & Shiftan, 2012; Shin, 2021) are often exploited. These datasets facilitate before-and-after comparisons, and the differences identified through corresponding comparisons can be regarded to be caused by policy interventions (i.e., fare adjustments). Also, the sociodemographic information provided in surveys often enables fruitful analyses. However, surveys are usually expensive, complicated, and sometimes impractical. To solve this problem, longitudinal ridership data and regression models are widely used to estimate fare elasticities (Davis, 2021; Guzman et al., 2020). However, studies in this vein could hardly generate insights into the social, temporal, or spatial dimensions of a policy.

The advent of massive and passive transportation datasets (e.g., smartcard data) has propelled the study of travel demand and patterns into a new stage (Pelletier et al., 2011). De Grange et al. (2013) adopted the aggregated smartcard data in Transantiago and calculated the demand-fare elasticity with different regression models. With two one-week smartcard datasets before and after a fare adjustment, respectively, Wang et al. (2018) estimated the demand-fare elasticity of metro riders in Beijing, China, at different spatial and temporal intervals. Combined with socioeconomic data, Kholodov et al. (2021) extended the previous work by deriving specific fare elasticities of different user groups and public transportation modes (metro, trains, and buses). Guzman et al. (2021) found that the BRT fares in Bogotá had different effects concerning the socio-economic characteristics of its users and the time of the day. Smartcard data contain trip records for almost all individual transit users. In the above-mentioned studies, however, authors often aggregated such records using some pre-defined criteria (e.g., card types) and calculated elasticities subsequently. This could have oversimplified the complex reality and overlooked changes at the individual level.

Compared to those aggregated analyses, disaggregated analyses at the individual or user group levels can better understand the policy's heterogeneous impacts. However, analyzing disaggregated data generated by smartcards requires suitable data augmentation methods because that kind of data itself is big but sparse and short of sufficient information such as socioeconomics of users (Anda et al., 2017). To tackle this, data fusion and clustering methods are commonly used. The former tries to add surveyed features to those anonymous smartcard data based on locations (Kusakabe & Asakura, 2014). The latter clusters the latent groups of smartcard holders by their respective travel behaviors (Kieu et al., 2015). Multiple methods have been used to identify user groups. Traditional clustering approaches (e.g., K-means, K-means++, and DBSCAN) have been widely used and proved to be effective (e.g., Ma et al., 2013, 2020). However, those methods require a priori structure of low-dimensional features, which might not be transferable and comparable across contexts. Advanced clustering methods which possess a probabilistic feature could deal with high-dimensional features (e.g., Gaussian mixture models and topic models). They have been increasingly used to analyze mobility typologies (Hasan & Ukkusuri, 2014), pattern evolution (Briand et al., 2017), and trip purposes (Zhao et al., 2020). Such methods can avoid inappropriate aggregation of fine-scale mobility datasets (e.g., smartcard data). They have also provided a more transferable framework.

According to our knowledge, however, few existing studies have used them to investigate the impacts of a transportation policy (e.g., the fare adjustment). One reason could lie in the complexity of individual travel patterns. It is easy to reveal the aggregated trend of ridership using smartcard data. But in reality, individual riders' travel pattern can be complex. It is also hard for people to interpret. Advanced methods like change detection in signal processing or activity imputation by machine learning can extract the useful information from the sparse smartcard-swiping records (Han & Sohn, 2016; Ma et al., 2020; Zhao et al., 2018).

Adopting the abovementioned methods, scholars have explored and validated the fare adjustment impacts at the user group and individual user levels. Authors studied the demand response under an off-peak discount policy in Hong Kong, China. They explored the divergent impacts across user groups and generated policy implications from a new perspective (Halvorsen et al., 2016; Ma et al., 2020). Even though the group-level descriptive analysis could generate rich insights into market segmentation and management it produced little knowledge on mechanisms governing group-level behaviors. Regression models could validate the impacts and their influencing factors more rigorously (see a summary in Appendix A). In those analyses, we can find that most used ridership (e.g., Liu et al., 2019) as the dependent variable, only several looked at how mode choice/shift or travel distance were affected by fare adjustments (e.g., Farber et al., 2014; Halvorsen et al., 2020). Most of the research has explored the direction and size of impacts. However, none has considered the temporal dimension, especially the timing of changes. In the existing studies, a linear relationship between two sets of variables is usually pre-assumed. Nobody has considered and visualized the potential non-linear relationship. Nevertheless, there are still consensus reached: low-income, peak-hour, and long-distance users are often more sensitive.

Heterogeneity in travel patterns across users and user groups have important policy implications. In most cities, there are multiple types of transit fares, such as one-way tickets, monthly/seasonal passes, and discounted/free tickets for special groups (e.g., the elderly, disabled, or students) (Cervero, 1990). However, it is hard and inappropriate to devise special tickets for a group of people with specific socioeconomic features. Given these facts, those studies uncovering varying demand and travel pattern responses of different sociodemographic groups could have more theoretical rather than practical contributions (Kholodov et al., 2021; Miller & Savage, 2017). Specifically, exploring the heterogeneity in travel patterns (e.g., commuter or non-commuter) can assist with the optimization of fare policy (e.g., setting benchmark of discounted tickets for frequent riders).

For a system-wide fare adjustment policy (e.g., the fare increase studied in this paper), disaggregated (i.e., individual or group level) and/or longitudinal (i.e., more than a before-and-after one) analyses considering multiple aspects of response have not been identified in the existing literature that we collected and reviewed in Google Scholar. Also, transferability concerning methods, conclusions, and policy implications are rarely explored in the existing studies. But it is important for any other city which is ready to or has already implement(ed) a fare adjustment and/or requires an evaluation.

To fill the aforementioned gaps, we (a) extracted the two-year individual-level detailed travel records from a massive metro smartcard dataset in Wuhan, China; (b) identified latent user groups and categorized corresponding travel patterns before and after the implementation of a fare increase in the city; (c) analyzed the impacts of the fare increase at both the group and individual levels from multiple perspectives; (d) compared the original policy objectives with the actual outcomes concerning the fare increase and explored corresponding policy implications, some of which we believe to be transferable.

Our study could complement the existing studies in three dimensions. Firstly, our context is the impacts of a fare increase on an expanding metro network in a transit-dominant city, which is commonly seen in developing countries but has not been extensively studied in the existing literature. Secondly, we adopt novel machine-learning methods (e.g., two-dimensional spatiotemporal topic model) to enrich the sparse but big smartcard data without excessively aggregating it, which is proved to be effective in this case and more transferable across contexts than existing methods such as K-means++ (Ma et al., 2020). Thirdly, we measure different aspects of the impacts, e.g., intensity/timing and trip frequency/trip distance/destination stickiness, which can complement the existing findings and generate new insights.

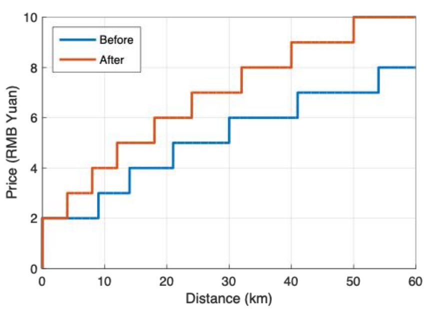
3 THE CASE

3.1 Metro Fare Adjustment Policy in Wuhan

Wuhan has the 7th largest metro system in mainland China in terms of the total network length. Its metro system boasts 189 stations and 318+ kilometers of track length (China Association of Metros, 2018). In 2019, the system carried about 3.5 million passengers per day. With a relatively low fare level, Wuhan Metro cannot break even financially. In 2018, the operational cost of Wuhan Metro was about CNY 30.08 billion. However, the gross profit from transit fares was only CNY 16.20 billion, covering only 53.85% of the operational cost (Wuhan Metro, 2019). Such divergence in gross profit and operation cost led to a heavy burden for the local government. In 2018, Wuhan Metro proposed a fare increase.

Following the decision-making process of major public affairs in China, Wuhan Metro proposed two different new fare structures in 2018 and held public hearings. After that, the Wuhan government (2019) approved the second fare structure proposal. Implemented on 1 February 2019, metro fares at different distance intervals rose by from CNY 1 to 3 (Figure 1 (a)). After this, Wuhan Metro's farebox revenue (CNY 16.20 billion in 2018) increased by nearly 60%, reaching CNY 25.72 billion in 2019. The revenue covered 64.82% of the operational cost in 2019 (CNY 39.70 billion) and reduced the company's and the local government's financial pressure (Wuhan Metro, 2019).

(a)



(b)

Card Type	Discount	Count	Proportion
Wuhan Tong	10% off	31702	80.0%
Elderly Card	730 free rides/year	5436	13.7%
Disabled Card	Free	1868	4.7%
Student Card	30% off	617	1.6%
Sum	/	39623	100%

(c)

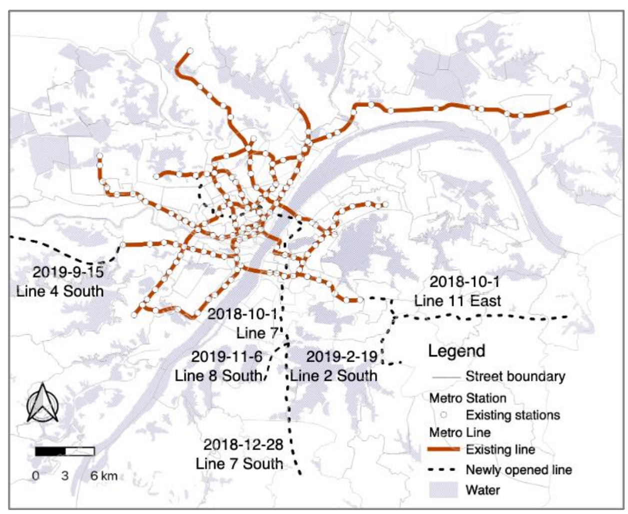


Figure 1 Case description: (a) Fare level before and after the fare adjustment; (b) Profile of different cardholders; (c) Metro system expansion from Jan 2018 to Dec 2019

3.2 Smartcard Data

By collaborating with the Wuhan Transportation Development Strategy Institute, we collected the January 2018 to December 2019 smartcard data of Wuhan Metro to undertake our empirical study. The data consists of one-week smartcard data each month. Both the weeks in February 2018 and 2019 exclude the Chinese New Year holidays when the travel patterns are distinct as many migrants left the city for their respective hometowns. The data contains the transaction records of all the cardholders in the given periods, in which the unique card numbers are considered identical users. We filtered the riders who had at least one transaction record every week as frequent riders, namely the object of this study. We then extracted the travel sequences of all the frequent riders. The exact period and quantity of the data used in this study can be seen in Appendix B. As shown in Figure 1 (b), the number of frequent riders is 39,623, which is quite a large sample size for the two-year data. The smartcard data used in this study covers thirteen and eleven months before and after the fare adjustment, respectively; thus, they can provide rich information on the fare increase's impacts in the temporal dimension as well. To get rid of the new lines' confounding effects (see Figure 1 (c)), we adopted the method in Wang et al. (2018) and removed the trips to and from those lines.

3.3 Basic Travel Pattern Changes

We provide a system-wide analysis of the travel pattern changes before and after the fare adjustment, which can also help the readers understand the dataset. In Figure 2 (a), we can find a declining pattern of ridership from the core (i.e., stations inside the inner ring road) to the periphery (i.e., stations outside the outer ring road). Further, when we visualize the changes in station-level ridership after the fare increase by color, we can find the peripheral stations suffered a smaller decrease than those core stations. The results of travel distance distribution in Figure 2 (b) indicate that there is no clear pattern of distance changes at the system level. The distribution of departure time in Figure 2 (c) indicates that the ridership after the fare increase had fallen in most time intervals, though the basic pattern of metro usage did not change significantly. We will further explore the changes and their rationale in the ensuing section.

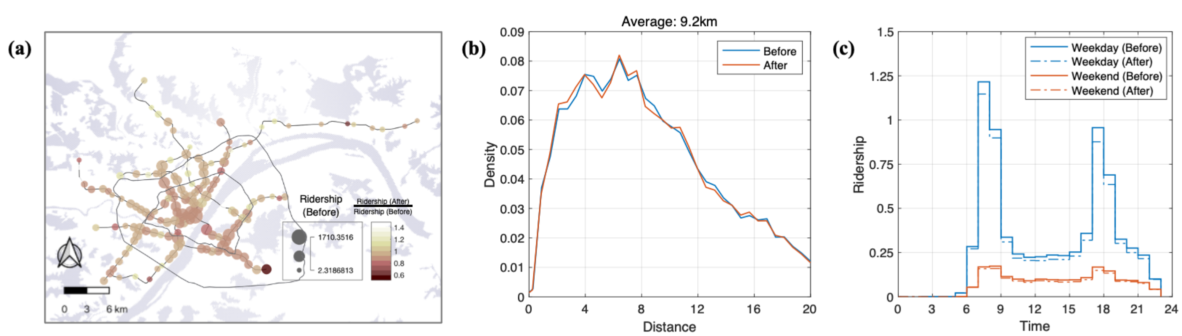


Figure 2 Metro riders' basic travel pattern changes before and after the fare adjustment: (a) Spatial distribution of origins; (b) Travel distance distribution; (c) Trip departure time distribution

4 METHODOLOGY

Figure 3 describes the research framework. We consider three steps in a transportation policy evaluation: characterization, evaluation, and recommendation. Step 1: Characterization. In the case of

Wuhan, the policy documents are collected and interpreted to qualitatively characterize the main objective of the fare reform. Also, necessary empirical data (e.g., smartcard and metro network data) is obtained for quantitative analysis. Details have been given in the former section. Step 2: Evaluation. Due to the sparse nature of smartcard data, necessary user profile mining is a prerequisite: we identify the latent user groups based on their spatiotemporal travel patterns using topic models and extract the travel pattern changes amid the fare increase policy using the break point detection method. We then visualize the travel pattern changes of the latent user groups and interpret their respective travel pattern changes with regression models. Lastly, we evaluate the revenue impacts and some other unintended consequences of the fare increase. The exact evaluation methodologies adopted are described below. Step 3: Recommendation. Based on the findings of Steps 1 and 2, recommendations are made and presented in the conclusion section of this article.

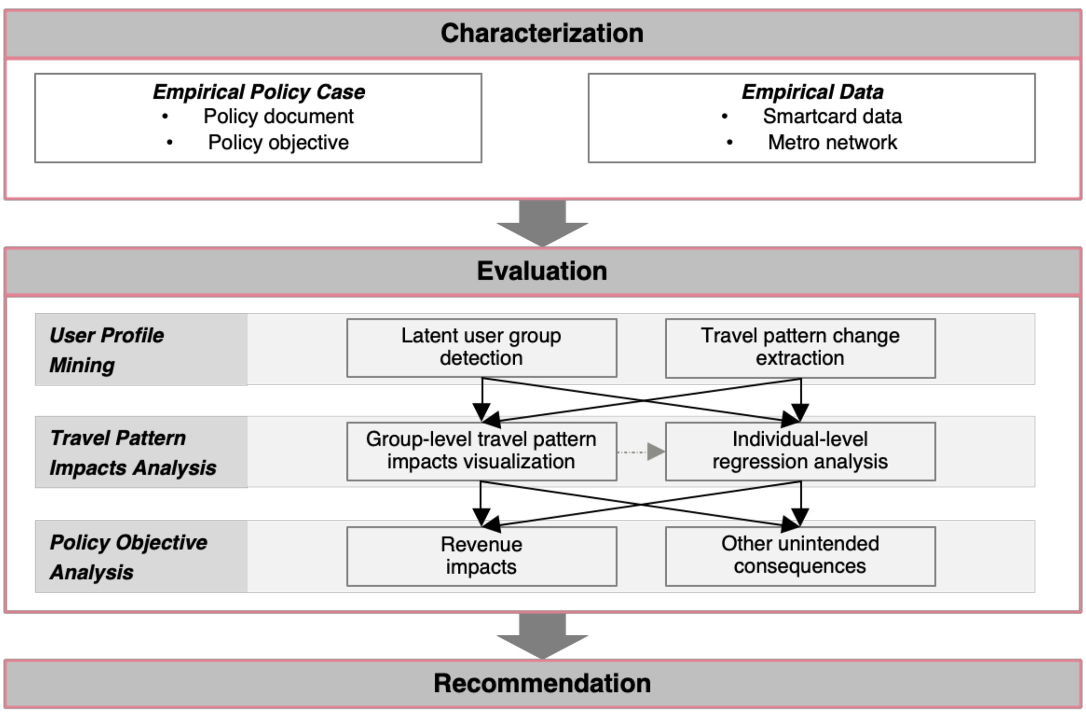


Figure 3 Research framework

4.1 User Profile Mining

4.1.1 Latent User Group Detection

Categorizing users into groups according to their travel patterns and/or socioeconomic statuses is a widely used to analyze anonymous mobility datasets (Briand et al., 2017; Mahrsi et al., 2017; Jiang et al., 2012). To explore transit fare policy impacts, scholars have classified user groups with a priori structures using traditional clustering methods like K-means++ (Halvorsen et al., 2020; Ma et al., 2020). Although these methods are effective in a given context, they significantly reduce the smartcard data into a series of indicators and lack transferability. We develop a novel two-dimensional spatiotemporal topic model which can directly learn the high-dimensional travel patterns before and after the fare increase and identify latent user groups without a priori structure. Details of the model are as follows.

Step 1: Building the spatial and temporal profiles of each user. The spatial profile considers the origin and destination of each trip, where the stations are categorized into 63 "streets" (Jie Dao)—Jie Dao is the smallest administrative unit in China (see Figure 1). The temporal profile considers the boarding time, weekday or weekend, and time intervals from the last trip (durations longer than 24 hours are rounded down), where the time is recorded by the hour. The selection, procession, and simplification of variables follow the mainstream method in existing literature (Cheng et al., 2021; Mahrsi et al., 2017; Hasan et al., 2013; Zhao et al., 2020). To properly reflect the impacts of the fare increase, we differentiate the trips before and after the policy intervention; thus, the dimensions of spatial and temporal profiles double. Overall, the spatial and temporal profiles consist of 7,938 (=63*63*2) and 2,304 (=24*2*24*2) dimensions, respectively. This allows us to well capture many aspects of the travel patterns.

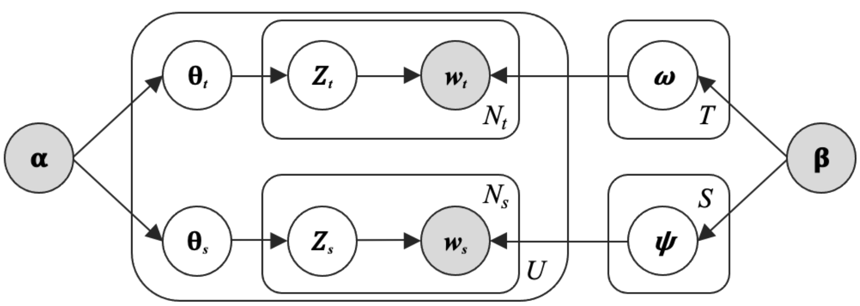


Figure 4 Plate notation of the two-dimensional spatiotemporal topic model (Note: shaded nodes are observed variables or model parameters, unshaded nodes are latent variables.)

Step 2: Identifying the spatial and temporal user groups, respectively, with the two Latent Dirichlet Allocation (LDA) models. The LDA is a widely used machine learning approach in the field of natural language processing (NLP), where high-dimensional text datasets commonly exist (Blei et al., 2003). Different from traditional clustering methods (e.g., K-means, K-means++, and DBSCAN), LDA is based on a generative process and can deal with thousands of dimensions. Inspired by the work of Hasan & Ukkusuri (2014), we developed our topic model by regarding individuals as documents and spatial and temporal travel features as words to uncover divergent spatial and temporal groups (i.e., topics) among users. Specifically, the LDA's input is documents with corresponding word distributions. Our goal in implementing LDA is segmenting documents into specific topics. In our case, the goal is to detect latent group membership of the users with different spatial and temporal profiles. As shown in Figure 4, a collection of U users with temporal and spatial profiles are imported, the prior concentration parameters α and β are defined, and the numbers of topics S and T are determined. LDA generates documents (users) and words (dimensions) in the following process:

- Sample a topic (group) mixture θ~Dirichlet(α). The random variable θ is a probability vector of length S or T, where S and T are the numbers of spatial and temporal topics (groups), respectively;
- For each word (dimension) of a given document (user):
    - Sample a topic (group) Z~Categorical(θ). The random variable Z is an integer from 1 through S or T;
    - Sample a word (dimension of profiles) w_t~Categorical(ω) or w_s~Categorical(ψ). The random variable w is an integer from 1 through V, where V is the total words (dimension of profiles);
- After formulating the aforementioned model, we solved it using Gibbs sampling method (Griffiths & Steyvers, 2004) and generated the user-topic probabilities, which reflect the probabilities of observing each topic in each user used to fit the LDA model. To find the most probable structure, we assigned the spatial (S) and temporal (T) topics (i.e., groups) to each user using the highest probability assignment method. The group membership can reflect the spatial and temporal characteristics of each user. The algorithm was implemented in MATLAB 2021a.

Step 3: Visualizing and interpreting the spatiotemporal profiles of each topic. We visualize and interpret the results. Also, we do a robustness check by changing the number of topics in the models and comparing the differences between corresponding results.

4.1.2 Travel Pattern Change Extraction

Besides automatically identifying user groups using the LDA model, another important goal of this research is to define the changes in individuals' travel patterns after the fare increase. To achieve this goal, we developed a set of methods that can: (a) measure individuals' travel behaviors using indicators such as trip frequency, trip distance, and destination stickiness index; (b) identify the disruption points in difference sequences of those indicators at the individual user level; (c) classify individuals' states of changes. Figure 5 is the diagrammatic representation of the method execution steps. Mode details are as follows.

Firstly, we used three indicators to measure the state of an individual's travel pattern by month. The first indicator is the trip frequency (F) of an individual, which stands for the weekly metro usage . Although widely used to measure the demand impacts of a transportation policy, F is still too coarse to provide a clear picture of travel pattern changes. We thus adopted two extra indicators to measure the structural changes of travel characteristics, namely trip distance (D) and destination stickiness index (S).

D measures the average distance of metro rides in a given period, and the *D* changes can tell whether the long-distance or short-distance trips are more probable to be forgone after the fare increase. *S* measures to what degree a rider's trip destination choice is diverse (or unitary), which is inspired by Simpson (1949) and Kim et al. (2017). It has been adapted in Zhou et al. (2021) to examine metro travel patterns changed in Hong Kong after COVID-19. The increase in *S* reveals that riders went to fewer and more unitary destinations after the fare adjustment. The calculation of *F*, *D*, and *S* uses the following equations:

$$F_{i,m,y} = count(t_{i,m,y}) \tag{1}$$

$$D_{i,m,y} = \frac{\sum_{j=1}^{n} d_{i,l,m,y}}{F_i} \tag{2}$$

$$S_{i,m,y} = \sum_{q=1}^{n} \left(\frac{count(t_{i,q,m,y})}{F_i}\right)^2 \tag{3}$$

where, $F_{i,m,y}$, $D_{i,m,y}$, and $S_{i,m,y}$ are the trip frequency, trip distance, and destination stickiness index for individual *i* in month *m* of year *y,* respectively. $t_{i,m,y}$ stands for all the metro rides of individual *i* in month *m* of year *y*, $t_{i,q,m,y}$ stands for the metro rides with the q^{th} types of distinct origin and destination for individual *i* in month *m* of year *y*. $d_{i,l,m,y}$ is the distance of trip *l* of individual *i* in month *m* of year *y*.

Secondly, we detected disruption points in the individual sequence of *F*, *D*, and *S*. The year-to-year differences in *F*, *D*, and *S* serve as the key measurement of travel pattern changes in the analysis, which is defined as the difference between individual's monthly *F*, *D*, and *S* in month *m* of the year 2019 and 2018. If the *F*, *D*, or *S's* difference of a metro rider is negative in a given time, it suggests that he or she reduces his or her trip frequency, trip distance, or destination stickiness compared to 2018, or vice versa. This measurement considers the travel patterns in 2018 as control groups, which can minimize the impacts of confounding or hidden factors (e.g., seasonal effects mentioned in Järv et al., 2014). The detail is as follows.

- The individual sequences of differences in *F*, *D*, and *S* (from January to December) were input. Adopting the function *findchagepts* in MATLAB 2021a, we detected the abruption points of the input sequences based on a classic signal processing method (Lavielle, 2005). Particularly, a changepoint is a time at which the mean of a signal (namely the year-to-year difference sequence in this paper) changes abruptly. Given the parameter τ of the maximum number of points, we can alter the sensitivity of the function. The detected points will break the sequence into different segments (e.g., the sequence in Figure 5 has been broken by points between Feb and Mar, May and June).

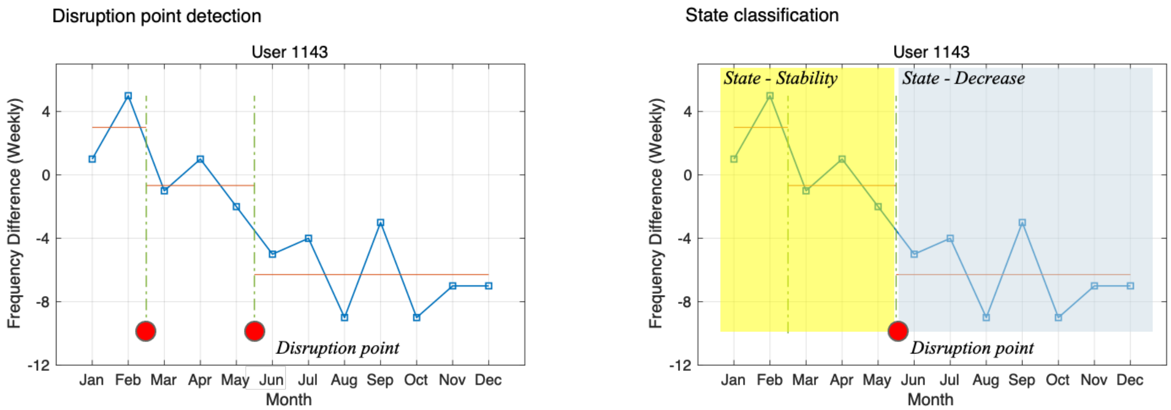


Figure 5 Schematic diagram of the travel pattern change extraction method

Thirdly, we simplified the continuous sequences of differences in *F*, *D*, and *S* to discrete sequences of users' states (namely increase, stability, and decrease) based on their mean values. As segments holding a mean value close to zero indicate a very small change which might be a fluctuation, we defined a benchmark parameter σ to overcome this problem. Considering the $mean_{seg}$ of each segment and the $mean_{total}$ of the sequence, the states are defined:

- if $mean_{seg} > \sigma * mean_{total}$, the segment is classified as increase;
- if $mean_{seg} < -\sigma * mean_{total}$, the segment is classified as decrease;
- if $mean_{seg} \in [-\sigma * mean_{total}, \sigma * mean_{total}]$, the segment is classified as stability.

For any consecutive segments holding the same state, we merged them and calculated the mean value of the merged segments; the disruption point between them was deleted (e.g., the disruption point between Feb and Mar in Figure 5 had been deleted, and the sequence had been classified into two segments).

Finally, the disruption points, classified states, and the mean value of states would be extracted and output for further analysis.

4.2 Travel Pattern Impacts Analysis

4.2.1 Group-level Travel Pattern Impacts Visualization

The individual state sequences and their mean value are interpreted at the group level for the comparison purpose. Theoretically, without policy interventions, the number of increase and decrease states for *F*, *D*, and *S* of a specific user group should be roughly identical, i.e., the number of users who chose to decrease and increase their trip frequency, trip distance, and/or destination stickiness should resemble. However, if there are policy interventions, there should be disruptions. Then there would be differences between the number of users who increase and decrease their *F, D,* and *S*, then the differences can reflect the policy impacts. To uncover such the disruptions, we designed an indicator called *Total Change Ratio* (*TCR,* see Equation 4 and 5), which measure the relative tendency of changes in *F*, *D*, and *S* for a specific user group:

$$TCR_j = \frac{count(S_{j,increase}) - count(S_{j,decrease})}{count(S_j)} \tag{4}$$

$$TCR_{j,m} = \frac{count(S_{j,m,increase}) - count(S_{j,m,decrease})}{count(S_{j,m})} \tag{5}$$

where, TCR_j and $TCR_{j,m}$ are *Total Change Ratio* of segment *j* in total and in month *m*. $S_{j,increase/decrease}$ and $S_{j,m,increase/decrease}$ stand for the number of increase/decrease states of users in segment *j* in all the eleven months and in month *m*. S_j and $S_{j,m}$ are the number of total distinct states of users in segment *j* in total and in month *m*.

The value of *TCR* can represent the proportion of users who choose to respond to the fare increase overall or in each month, which can uncover whether or when the users change their travel patterns. In our case, the overall *TCR* was visualized using bar plot, and the monthly *TCR* was visualized using line chart. The *TCR* of all users was calculated and visualized as a benchmark for comparison. *TCR* tells the status of travel pattern changes. However,, it cannot show the intensity of changes once a decision is made. Given this, we developed two more metrics characterizing the relative and absolute magnitudes of changes for *F*, *D*, and *S*, namely *Change Value* (*CV*) and *Change Percentage* (*CP*). We visualized the results of *CV* and *CP* with boxplots categorized by groups for a clearer comparison. We further used Kolmogorov-Smirnov (KS) test to estimate the statistical difference of *CV* and *CP* across groups to provide more evidence. KS is a widely used method to test the differences between two groups of data (Lilliefors, 1967). We calculated the metrics with the following equations:

$$CV_{i,j,m} = mean_{i,j,m,s} \tag{6}$$

$$CP_{i,j,m} = \frac{CV_{i,j,m}}{mean_{total,i,j}} \tag{7}$$

where, $CV_{i,j,m}$and $CP_{i,j,m}$ denote the month *m*'s *Change Value* and *Change Percentage* of individual *i* in segment *j* respectively. $mean_{i,j,m,s}$ is the state *s*'s mean value in the state sequence of individual *i* in segment j in month m, the state s is chosen according to the tendency of changes revealed by *TCR*. $mean_{total,i,j}$ denotes the mean value of the given parameter in 2018.

4.2.2 Individual-level Regression Analysis

To predict and interpret fare impacts on travel patterns, we used regression models. The results of regression models helped us validate the findings in group-level descriptive analysis and existing literature. Also, we tried to complement the existing knowledge by presenting evidence in temporal dimensions.

Table 1 presents the description of the dependent variables and corresponding descriptive statistics. D_FREQ measures the changes in trip generation, which is in line with many existing studies (e.g., Cats et al., 2014; Farber et al., 2014; Guzman et al., 2020; Liu et al., 2019; Miller & Savage, 2017; Shin, 2021). D_DIST and D_STIC measure the trip distribution changes from the perspective of distance traveled and destination choice, which were not often mentioned in the existing studies. Further, we used T_FREQ, T_DIST, and T_STIC to add a temporal dimension of travel pattern response analyses, which had been seldomly seen in the existing studies.

Table 1 Description of dependent variables and descriptive statistics

Variable	Description	N	Mean	SD	Min	Max	Implication
D_FREQ	Individual's change in the weekly average number of trips (D_FREQ), trip distance (D_DIST), or destination stickiness (D_STIC) after the fare increase.	39623	-1.308	6.658	-40	38	The intensity of changes in trip generation.
D_DIST		39623	-0.037	6.789	-44.868	37.163	The intensity of changes in trip distribution.
D_STIC		39623	0.07	0.395	-0.955	0.953	
T_FREQ	The number of months after the fare increase when an individual is detected a state of change in trip frequency (T_FREQ), trip distance (T_DIST), or destination stickiness (T_STIC) for the first time.	28849	3.160	3.460	0	10	The response speed of changes in trip generation.
T_DIST		21164	3.840	3.437	0	10	The response speed of changes in trip distribution.
T_STIC		30113	3.680	3.527	0	10	

Table 2 shows the independent variables. We used COST to measure the monetary impacts of the fare increase policy, which is identical to existing studies (Guzman et al., 2020; Halvorsen et al., 2020; Liu et al., 2019; Sharaby & Shiftan, 2012) and serves as the most important independent variable in the analysis. We designed the other control variables in each category mentioned in Table A.1 (i.e., current travel behavior, spatial features, and socioeconomic statuses) afforded by the smartcard data we used. Also, group membership identified from the topic model is included as well.

The regression models consider non-linear and interactive effects by adding quadratic and interactive terms. There are four models for each dependent variable:

- Model 1 test the linear relationship between COST and travel pattern changes;
- Model 2 test the non-linear relationship between COST and travel pattern changes using quadratic terms. If the COST and COST^2 are not significant in Model 2, there is no confident non-linear relationship, and thus the linear assumption would be accepted in Models 3 and 4.
- Model 3 adds the control variables and check the robustness of the relationships;
- Model 4 adds the interactive terms to check interactive effects.

Table 2 Description of independent variables and summary statistics

Variable	Description	Mean	SD	Min	Max
Fare adjustment impacts					
COST	Individual's average weekly increase in fare expenditure if he or she does not change his or her travel pattern after the fare increase.	6.867	5.354	0.000	37.523
Current travel behavior					
FREQ	Individual's average weekly trip frequency before the fare adjustment.	8.969	3.290	1.077	60.154
DIST	Individual's average weekly trip distance before the fare adjustment.	9.302	4.594	0.000	56.692
STIC	Individual's average weekly destination stickiness before the fare adjustment.	0.370	0.131	0.044	1.000
PEAK	The proportion of individual's trips in peak hours (7:00~9:00, 17:00~19:00 on weekdays)	0.357	0.233	0.000	1.000
Spatial features					
YEAR	The weighted average initial years of operation of all boarding and alighting stations used by an individual before the fare adjustment.	2012.416	2.335	2004.000	2017.000
ACCE	The weighted average numbers of accessed stations within 30 mins for all boarding and alighting stations used by an individual before the fare adjustment	39.303	8.631	7.761	64.321
BUS	The weighted average numbers of bus lines in all boarding and alighting stations' 800-meter buffer zones used by an individual before the fare adjustment.	51.330	15.154	2.350	112.658
Socioeconomic statuses					
CARD	The card type of an individual (dummy variables for elderly, disabled, and student card users, respectively).				
Group membership					
SPAT	The spatial topic membership of an individual (dummy variables for each spatial topic, respectively).				
TEMP	The temporal topic membership of an individual (dummy variables for each spatial topic, respectively).				
N = 39623					

4.3 Policy Objective Analysis

4.3.1 Revenue Impacts

Given that the original purpose of the fare increase policy in our case is to boost the farebox revenue and release the financial burdens, we first examine the policy's revenue impacts. Specifically, we measure the revenue changes per user across the smartcard user population and quantify the weekly revenue per user. Then corresponding results were also visualized and aggregated by the latent user group and metro station.

We calculated the demand-fare elasticity (E) of distinct user groups for different periods using the mid-point method in Equation (8):

$$E = \frac{(Ridership_2 - Ridership_1)/(Ridership_2 + Ridership_1)}{(Fare_2 - Fare_1)/(Fare_2 + Fare_1)} \tag{8}$$

where $Ridership_1$ and $Ridership_2$ are the total ridership before and after the fare increase in a given period (e.g., peak hours), $Fare_1$ and $Fare_2$ are the average ticket price per ride before and after the fare increase.

4.3.2 Other Unintended Consequences

Besides the farebox revenue, the fare increase policy can bring about other secondary unintended consequences. Without continuous and near-population-size big data such as smartcard data, few fare policy assessments could well consider individual- or group-specific effects of a policy proposal. In existing studies, scholars have examined the transit fare equity impacts from the spatial (Wang et al., 2021; Zhou et al., 2019) and social group (Farber et al., 2014; Zhao & Zhang, 2019) perspectives. Inspired by these existing frameworks, we have analyzed the heterogeneous impacts among different user groups, socioeconomic statuses, and spatial locations. Results were presented as follows.

5 RESULTS

5.1 User Profile Mining

5.1.1 Latent User Group Detection

Following the above-mentioned framework, we performed the two-dimensional spatiotemporal topic model with the profiles of 39,623 users. The number of topics is a variable parameter in the model. A larger number of topics could better split the users but could lose much interpretability, a smaller number of topics might not be able to detect distinct enough patterns across users. As most of the related literature clustered users into 4 to 20 groups (Mahrsi et al., 2017; Halvorsen et al., 2016; Kieu et al., 2015; Ma et al., 2013; Ma et al., 2020), we started by setting the number of spatial and temporal topics both at 4, indicating a total number of 16 (=4*4) groups. Meanwhile, we selected $\alpha = 50/T$ or $50/S$ and $\beta = 0.1$, which is the widely accepted choice in existing studies such as Bao et al. (2017), Hasan & Ukkusuri (2014) and Zhao et al., (2020).

The above handlings generated the baseline results (see Figure A.1). The internal correlation indices among the spatial and temporal topics were smaller than 0.3 in panel (a), indicating significant independence among topics. Figure A.1 (b) shows the relationships between the latent user groups and card types. The temporal model clearly distinguished the distinct card type users: the elderly and disabled card users were mainly classified into Group 2, while the student card users were mainly classified into Group 1. This suggests that the user group detection analysis is generally in line with the reality. We name the groups with initials (i.e., S1…S4, T1...T4). Combining spatial and temporal topic memberships, we had 16 distinct user groups. We named them S1T1, S1T2,… S4T4.

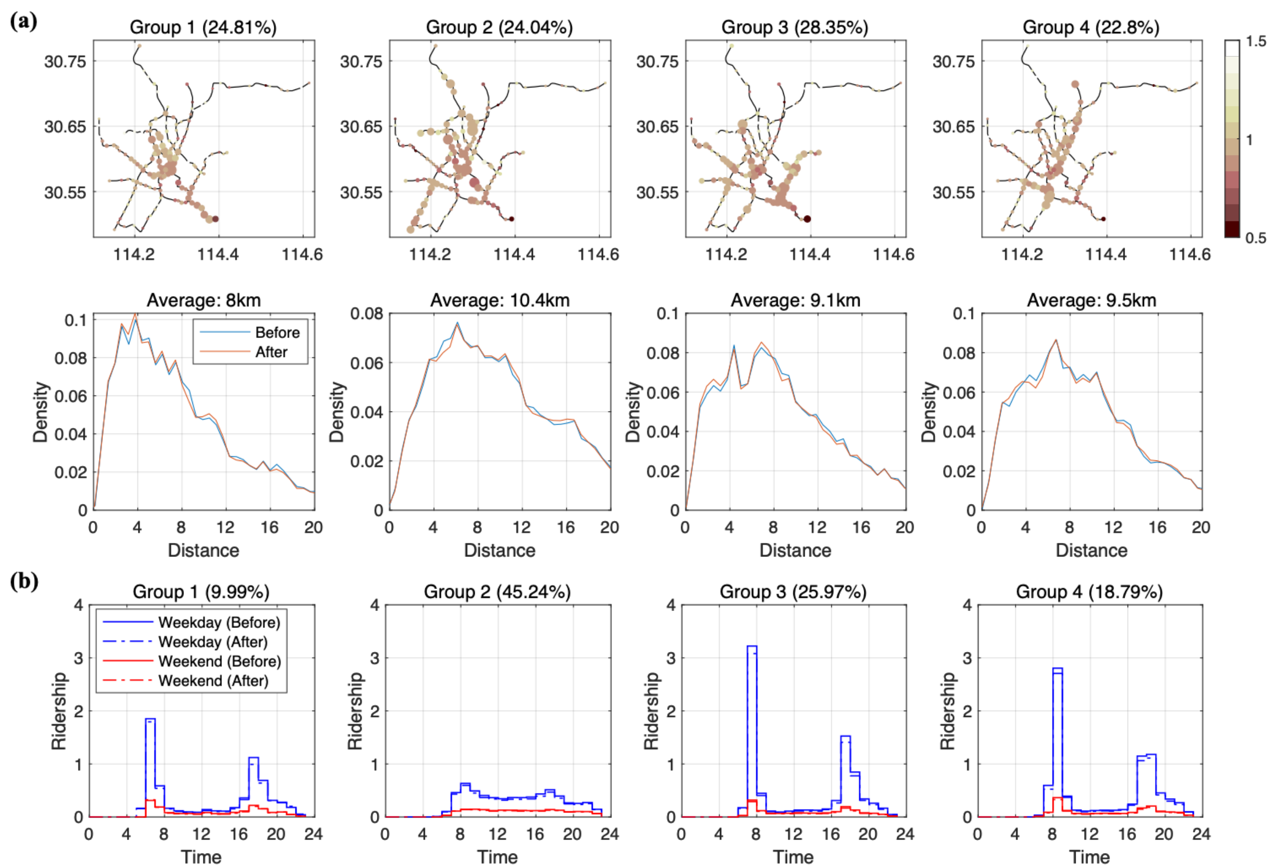


Figure 6 Features of the spatial and temporal user groups: (a) Spatial model results - spatial distribution of origins (the size and color indicate the ridership intensity and ridership change ratio, respectively) and travel distance distribution; (b) Temporal model results - trip start time distribution

We plotted the features of the spatial and temporal user groups in Figure 6. The spatial and temporal groups displayed distinct patterns in spatial distribution, trip distance, and travel time. This indicates the topic model has well categorized the users. Interpretations of each category are as follows.

S1 users mainly traveled along Line 2 between Hankou and Wuchang; S2 users traveled between Hanyang and Hankou, which are separated by the Yangtze River, leading to the longest average travel distance; S3 users are similar to S1 but traveled more frequently in Wuchang; S4 users mainly traveled inside Hankou. The temporal model categorized the users more significantly. T1, T3, and T4 users were more likely to be commuting riders, while T2 users were more likely to be non-commuting riders. By combining the results from the spatial and temporal categorization, each user has two group features, for example, S1T1 users (1) were commuters, and (2) mainly travel along Line 2 between Hankou and Wuchang.

To check the robustness of the categorization, we changed the topical number from 3 to 5 and visualized the spatiotemporal patterns (see Figure A.2). We got robust results and captured similar group categorization in those attempts. For instance, there always existed commuter and non-commuter groups in the temporal model (i.e., Group 2 when the number of topics = 3, 4, and Group 4 and 5 when the number of topics = 5), meanwhile the non-commuter group(s) accounted for a relatively stable share of users (i.e., 49.01%, 45.24%, and 49.67% when the number of topics = 3, 4, and 5, respectively).

5.1.2 Travel Pattern Change Extraction

Following the above-mentioned methods, we also extracted the travel pattern changes of 39,623 smartcard users. There were two non-fixed parameters in this process, i.e., the maximum number τ and a benchmark parameter σ. We started with $\tau = 2$ and $\sigma = 0.5$, the former is identical to the choice of Halvorsen et al. (2020). A robustness check was also carried out. The baseline disruption point characteristics are shown in Figure A.3. There existed the most individuals who have zero disruption point detected in the trip distance sequence, while the individuals' number of disruption points shared similar patterns in trip frequency and destination stickiness sequences (i.e., decreasing numbers of users with 2, 1, 0 disruption points), indicating heterogeneous disruption points across the smartcard users. However, the outcomes of these three sequences shared similar temporal patterns in Figure A.3 (b), indicating the temporal dimension of response has a different rationale and is worth more attention. Further, the individuals' states of change were extracted and were visualized and interpreted in the ensuing text.

We checked the robustness of the non-fixed parameters by changing their values as well (see Figure A.4). By setting $\tau = 2, 3$ and $\sigma = 0.45, 0.5, 0.55$, we visualized the disruption point characteristics of six different scenarios in the same way as Figure A.3. The individuals' number of disruption points in different scenarios held different absolute quantities but shared consistent relative relationships, i.e., individuals with 2, 1, or 2 disruption points were always the majority in trip frequency, trip distance, or destination stickiness sequences. Also, the temporal distributions were almost identical. Those results validate the robustness of the method and suggest the different parameter choices do not significantly change the results.

5.2 Travel Pattern Impacts Analysis

5.2.1 Group-level Travel Pattern Impacts Visualization

Following the above-mentioned framework, we measured the changes in individual-level travel patterns and visualized them at the group level in Figure 7. Lage groups accounting for more than 5% of the total 39,263 users were included (see Figure A.1 (c)), finally, 9 groups combined are 75% of the total. We drew the monthly *TCR, i.e.,* total change ratio we calculated using Equations 4 and 5, for different spatial (line color) and temporal (line type) groups. Major results are summarized as follows.

Let us start with the trip frequency, which is widely examined in the existing studies on travel pattern change. As shown in Figure 7 (a), all user groups' *TCRs* were negative, indicating the fare increase had resulted in less metro usage at the system level. However, different user groups' fare elasticity varied. Commuters (Group 2, 4, 6, 7, and 9) reduced their riding frequency more than non-commuters (Group 1, 3, 5, and 8). Figure 7 (b) reveals the temporal characteristics of the frequency impacts across the groups. We can find that most user groups responded and reduced their frequency immediately in the first month after the fare increase (i.e., February). However, the level of response in that month was the largest only for non-commuters, the commuters' response reached the peak in March. Surprisingly, we witnessed a reversion pattern herein, i.e., the monthly *TCR* became positive later in April to June, indicating some users' metro usage fluctuated. Such results had been rarely reported in existing studies, suggesting that both short-term and long-term demand impacts should be considered when designing and executing a fare adjustment policy. The boxplots of travel frequency's *CV* and *CP* were presented in Figure 7 (c) to explore the intensity of frequency impacts. From the perspective of absolute changes, there were visible differences across the groups. For example, the commuters experienced a larger median *CV* than non-commuters. However, the *CPs* showed reverse patterns, the *CPs* of commuter groups were smaller. The KS test of trip frequency's *CP* and *CV* were conducted to examine the inter-group difference more rigorously (see Figure A.5). At the significance level of 0.1, 0.05, or 0.01, there existed more insignificant KS test results of *CP* than those of *CV*, indicating a larger statistical difference among groups' *CV.* Compared to the divergence among temporal groups, the spatial groups have not showed solid and significant divergence, indicating the temporal characteristics play a larger role in individuals' response in trip frequency to the fare increase than spatial characteristics.

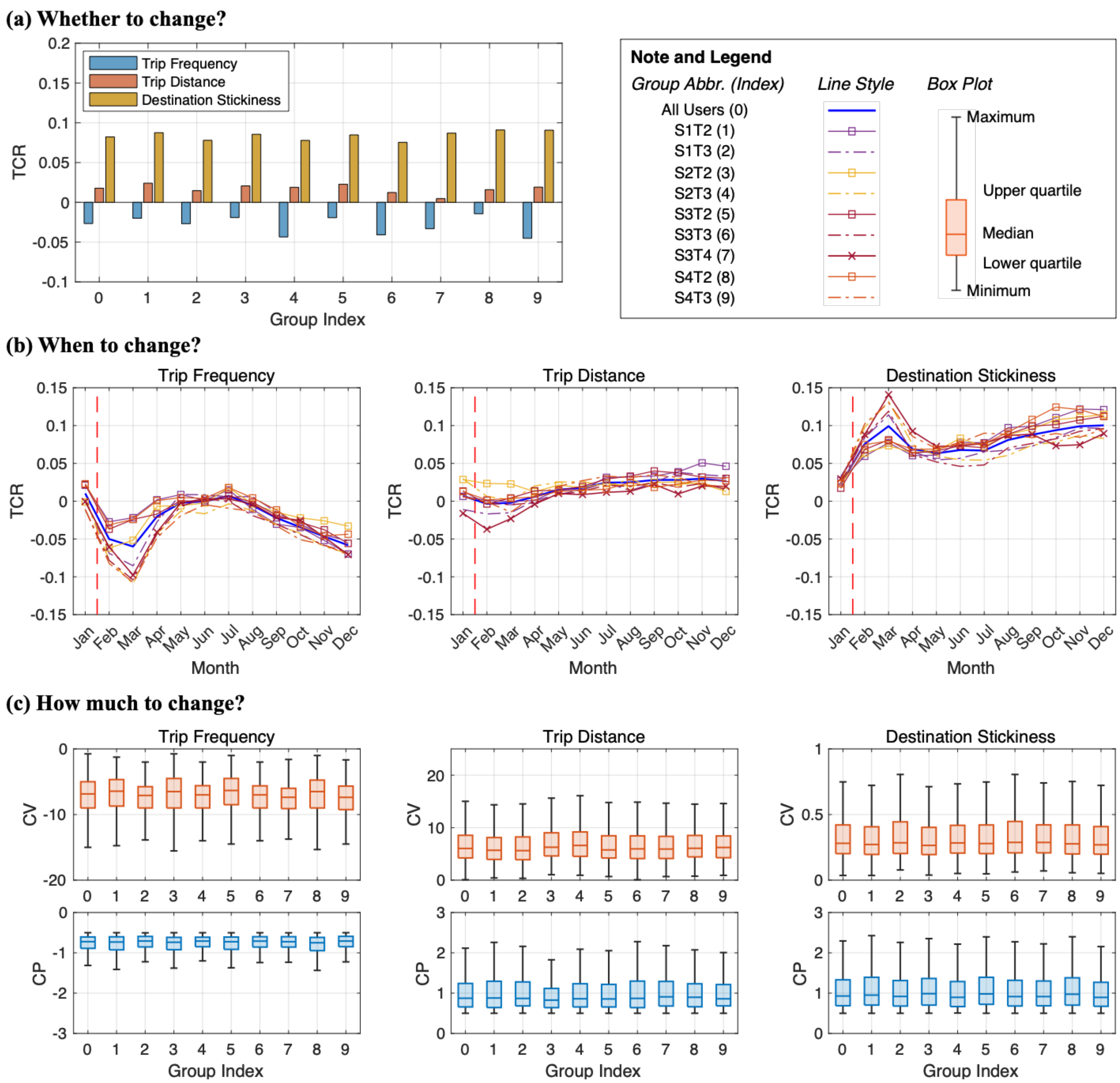


Figure 7 Major user groups' states of travel patterns: (a) Bar plots of TCR; (b) Line plots of monthly TCR; (c) Box plots of CV and CP

Further, we explored the group-level trip distance and destination stickiness changes after the fare increase. As Figure 7 (a) shows, the *TCR* of trip distance and destination stickiness were overall positive, indicating the fare increase might have resulted in increased travel distance and stickiness. The non-commuters had a larger *TCR* value. The temporal patterns of trip distance and stickiness' *TCR* were similar to that of the trip frequency (see Figure 7 (b)), the reversion patterns were witnessed as well.

Corresponding to the monthly *TCR*, the crests and troughs of the trip frequency and destination stickiness synced oppositely, indicating the decrease in the frequency was accompanied by the increase in the stickiness. The box plots in Figure 7 (c) reveal the degree of changes. Similarly, the changes in value (*CV*) differed while the change in percentage (*CP*) were similar, indicating the divergence in changes are mainly contributed by the different baseline value. These results were validated by the statistical test (see Figure A.5). Compared to the response of trip frequency and stickiness, the significance of distance's changes was smaller and fuzzier, which suggests that the impacts of the fare increase on trip distance require deeper analysis at the individual level. We therefore used regression analysis to complement the descriptive analysis.

5.2.2 Individual-level Regression Analysis

With the variables and models described above, we fitted the regression models in the R language. To save the space, we provided the detailed regression results in Appendix C and plotted the notable relationships in Figure 8. The results in Table A.3 focus on the intensity of impacts, and the results in Table A.4 focus on the speed and timing of the response. Coefficients and the significance based on *T-stat* were estimated.

As shown in Table A.3, there existed significant relationships between COST and the dependent variables in Model 1. The values of the coefficients indicate that a larger increase in fare cost would significantly lead to a larger decrease in trip frequency, trip distance, and a larger increase in the destination stickiness. The impacts of the fare increase on the trip frequency and destination stickiness are consistent with the findings in the group-level analysis, however, the negative impact on trip distance is contradictory. Further, we checked the non-linear relationships. The results in Model 2 show that the impacts of COST on the trip frequency and destination stickiness changes had a robust non-linear relationship. By adding control variables, more insights were generated. Users with longer trip distance and larger destination stickiness were less probable to respond in trip frequency. Peak-hour and elderly users were more sensitive to the fare cost increase, which is consistent with the existing research findings (Farber et al., 2014; Guzman et al., 2020). Also, users to and from more centrally located stations were less sensitive to the fare cost increase, which has been found in developed countries as well (Farber et al., 2014; Kholodov et al., 2021). Model 4 presents the results of interactive terms. Only the interactive terms of COST*PEAK and COST*ACCE were significant predictors. However, we used the mean value of COST, PEAK, and ACCE in Table 2 to further estimate the total effects, the results were consistent with those of Model 3 in general.

As shown in Table A.4, the coefficients of COST in Model 1 for all the dependent variables were negative and significant. The results suggest that a larger increase in fare cost is significantly correlated to a more instant response to changes. This complements the existing findings from a temporal perspective. The models also show that users with a larger destination stickiness (i.e., they went to fewer destinations) and users who travel less in peak hours (i.e., more probable to be a non-commuter) would respond to the fare increase more quickly. Those findings are consistent to those at the group level. Overall, comparing different types of independent variables, original travel behavior and socioeconomic statuses can better predict the impacts on the travel patterns than spatiality.

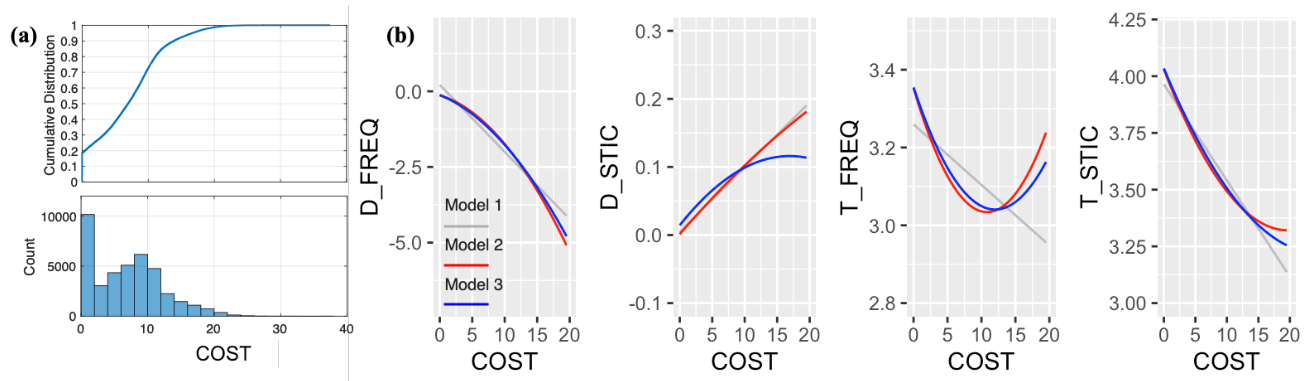


Figure 8 (a) Distribution of COST; (b) Total effects of COST on dependent variables (other variables are set at their mean levels)

To provide a clearer illustration of the non-linear relationships, we plotted the impacts of COST on dependent variables where a robust non-linear relationship was found after controlling the other variables at their mean levels in Figure 8. The distribution of COST in Figure 8 (a) shows that over 95% of the COST value exists between 0 and 20, thus the non-linear relationships should be plotted and interpreted only in that interval. The non-linear relationships between COST and D_FREQ, D_STIC, and T_STIC had no threshold effects, and the trendlines of the three models were nearly identical between 0 and 20, indicating the linear form in existing literature could be an effective proxy for such relationships. However, the impacts of COST on T_FREQ were non-linear, a higher COST indicates an earlier response in the interval between 0 and 11, while the relationship would reverse when COST is larger than 11. The negative relationship is consistent with the response in destination choice (i.e., T_STIC), which is not surprising: a larger increase in COST would stimulate the metro rider to adapt their travel behavior earlier. The surprising reverse and positive relationship for larger COST can be explained as the response of another group. Specifically, the metro riders with a COST larger than 11 faced the top 20% fare increase among the user population and probably spent relatively higher weekly fares. They were likely to be the frequent captive riders (e.g., the commuter groups). They relied more on the metro system and responded later to the fare increase. This can also be observed in Figure 7 (b): the peak month of response in trip frequency for the commuter groups was generally later than the non-commuter groups. This kind of non-linear and inverted relationship can also be found elsewhere, e.g., the income (Ding et al., 2019), housing price (Gan et al., 2020), and distance (Liu et al., 2021) were found to have opposite impacts on travel behavior in different intervals. As a result, the non-linear relationships imply that the linear assumption might be misleading when analyzing temporal impacts for users in the context of fare increase.

5.3 Policy Objective Analysis

5.3.1 Revenue Impacts

We calculated indicators such as weekly revenue per capita to evaluate the revenue impacts of the fare increase and plotted them at the user group, individual, and metro station levels in Figure 9. The interpretations of the results are as follows.

Figure 9 (a) shows that all the user groups' weekly revenue per capita increased after the fare hike and the changes across the groups were similar (about 25%). This can be explained and validated by the similar fare-travel elasticity across the user groups: -0.20 ~ -0.23. However, for the absolute revenue increase, the commuter groups saw larger growth than the non-commuter groups, a plausible explanation is that they had a larger baseline value. Overall, the absolute value of elasticities in this case is much smaller compared to those in car-dominant developed countries (e.g., Litman, 2004). Besides the differences between the groups, the temporal divergence of elasticities is also worth attention. Generally, the absolute value of elasticity in peak hours was larger than that in off-peak hours, which is identical to the previous findings in Guzman et al. (2020).

The relationships between the baseline weekly revenue per capita and its growth and ratio in Figure 9 (b) can provide more insights. We found that a larger baseline weekly revenue per capita would lead to a larger increase in absolute value but a smaller increase in relative ratio. These findings strengthen the aforementioned results, i.e., frequent users (e.g., commuters) would contribute more to the farebox revenue after the fare increase but be affected more as well, i.e., they responded and changed their original travel patterns more significantly than the others.

The analysis of the impact heterogeneity across metro stations is shown in Figure 9 (c). It shows that the peripheral stations (i.e., stations outside the outer ring road) saw larger growth in farebox revenue per trip, whereas the original revenue per trip was larger as well. However, considering the ridership variation across the stations, the overall revenue contribution increases in most peripheral or core stations (i.e., stations inside the inner ring road) were relatively smaller than those in suburbs (i.e., stations between the ring roads).

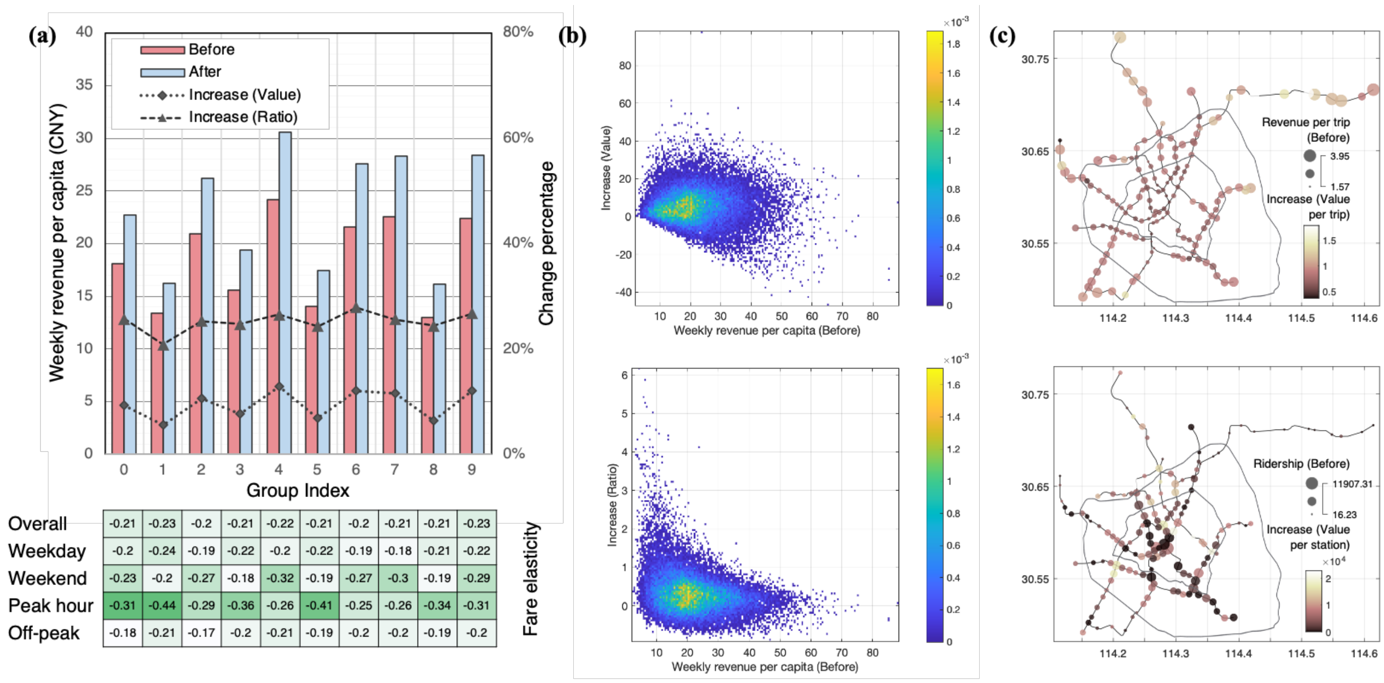


Figure 9 Revenue impacts and fare elasticities: (a) Divergence among user groups (indices are identical to Figure 7); (b) Divergence among individual paid users; (c) Divergence among stations

5.3.2 Other Unintended Consequences

Combining the results and findings in the data analysis, we further looked into the heterogeneous impacts and equity consequences in light of user groups, users' socioeconomic statuses, and spatial locations. This helps us relate the fare increase policy to horizontal equity across user groups. Commuter groups were found to be affected to a larger extent than non-commuter groups. Nevertheless, they still contributed more to the farebox revenue. Surprisingly, elderly users who enjoyed free rides were affected more than other user groups, despite that they might rely more heavily on the metro system than other riders (Wong et al., 2018). Such abnormality might be a representation of stricter checks on elderly card abuse, i.e., young people used metro with elderly cards for fare evasion purposes. The users who used stations with lower metro accessibility (i.e., peripheral stations) were less affected and contributed more to the farebox revenue after the fare increase. Similarly, the long-distance riders who contributed more to the farebox revenue were found to be less affected than the short-distance riders as well. Generally speaking, a system-wide fare increase policy with a distance-based fare structure would generate a larger disparity between travel demand changes and farebox revenue contribution across user groups (e.g., commuters vs. non-commuters). This was consistent with the existing findings in Beijing, China (Zhao & Zhang, 2019). Also, such a policy would have heterogenous impacts on riders from different stations (e.g., core vs. peripheral). In the future, a mixed policy combining distance-based fare structure and discounted tickets for frequent riders (e.g., commuters) might help mitigate possible equity impacts of the fare increase. Such a policy could promote the transit usage of those frequent riders without adding too much operational costs (mostly fixed cost), which might help ease the ground traffic congestion in peak hours.

6 CONCLUSIONS AND DISCUSSION

In different cities, transit fare policy varies in many aspects, and may aim at different public policy goals such as increasing revenue, managing demand, or promoting social equity. However, to understand any given fare policy, the policy's travel demand impacts is essential. Using smartcard data and a set of analytical technics, we propose and implement individual- and group-level analyses to explore the impacts of the fare increase policy using empirical data from Wuhan, China.

Our empirical work generates at least the following findings, some of which can be transferable to other contexts: (a) the fare increase had significant but varying impacts on travel demand across users and user groups; (b) confronting the fare increase, commuter groups identified by the topic model tended to reduce their trip frequency more; (c) users from the peripheral, traveling longer distance and going to fewer destinations than others are less sensitive to the fare increase—it is likely that they have no viable alternatives of travel mode other than metro; (d) when there is a system-wide fare increase with a distance-based structure, travel purposes and socioeconomic statuses can better predict the impacts on the travel demand and farebox revenue than spatiality. Moreover, we illustrate a transferable methodological framework that could be used to analyze similar transportation policies in another context. The framework adopts an unsupervised learning-based method that does not require a priori structure given in advance. Also, it can provide insights at both the group and individual levels. This can facilitate tailor-made decision-making concerning different user groups and individual users.

These findings help advance existing knowledge related to fare reform and its multiple implications. Besides the impacts of decreasing trip frequency revealed in the existing scholarship (Kholodov et al., 2021; Miller & Savage, 2017; Wang et al., 2018), we validate and uncover the divergence among users and user groups to change their trip frequency. Specifically, we validate the finding that commuters possessed larger absolute elasticities and are more sensitive to fare change in Bogotá (Guzman et al., 2020) and Stockholm (Kholodov et al., 2021) still held in Wuhan. Meanwhile, we uncover that users going to fewer destinations were less responsive to frequency reduction in the case, which has not been justified by existing studies yet. Further, we figure out what kind of trips are more likely to be abandoned by measuring the changes in trip distance and destination stickiness. We fitted regression models, which complemented the existing literature revealing the heterogeneity in fare responses and/or elasticities (Wang et al., 2018; Liu et al., 2019; Guzman et al., 2021; Kholodov et al., 2021). Findings are that the short-distance trips and trips in the urban core were the first to be reduced. The former was opposite to that in Stockholm (Kholodov et al., 2021) but consistent with that in Beijing (Wang et al., 2018), which might be due to the divergence in fare level and availability and quality of alternative mode choice, i.e., the transit in Wuhan and Beijing was a competitive transportation mode for long-distance users with good affordability but only a feasible but expensive choice for long-distance users in Stockholm. The latter one is identical to the findings by Liu et al. (2019) and Guzman et al. (2021). Also, our research deepens the existing understanding of fare policy's financial and equity implications by analyzing the demand, financial, and equity impacts together. Considering the mismatch between farebox revenue contribution and demand response, users with different socioeconomic statuses suffer a larger mismatch than those at different locales. These insights are helpful to better understand the heterogenous effects of fare reform on different groups and locales and improve policy design.

In light of all the above, we recommend that metro companies should set special discounted tickets for frequent metro riders and captive user groups (e.g., low-income and/or metro-reliant riders), the results in the group-level and/or individual-level analyses could be the reference for policy design. In particular, discounted tickets could be given to those commuter groups detected by the topic models in 5.1.1, such a group-specific policy design has also been carefully examined in the existing scholarship (c.f., Ma et al., 2020) and proved to be effective. Also, there could be a discounted ticket for metro riders whose patronage is the more than some threshold (in Wuhan's context, for instance, fifty times per month). More generally, identifying those riders whose patronage is an SD larger than the average of all the riders would often allow us to capture the top 5 percent of frequent riders. Because most of the cost of operating a metro system can be regarded as fixed costs, giving discounted tickets to those frequent riders and captive groups could promote the transit usage without losing (much) farebox revenue and adding extra expenses, which might help ease the ground traffic congestion, if any meanwhile.

Despite the above progresses made, this study does face several limitations. Firstly, the reason for the heterogeneity in travel pattern impacts is only explored based on passive smartcard data, while proactively conducted surveys and interviews could provide more insights. Secondly, this paper does not provide an accurate and precise policy recommendations that could be implemented directly by the local metro company. Often, this requires relatively complex optimization methods and/or econometric models (e.g., Ma et al., 2020). In the future, we wish to provide more practical and accurate policy recommendations quantitatively based on more advanced optimization methods and/or econometric models.

APPENDIX A. SUMMARY OF LITERATURE

Table A.1 Summary of the mechanism analysis in fare-related policy literature

Source	Context	Travel Pattern	Factors	Main Data	Method	Relationship Validated
Brown et al. (2003)	Fare-free transit in UCLA (U.S.)	Transit mode share, bus ridership (individual level)	Socioeconomic statuses, current travel behavior	RP survey	Descriptive statistics	Bus ridership for commuting to campus increased by 56 percent during the fare-free transit program's first year, and solo driving fell by 20 percent.
Sharaby & Shiftan (2012)	Fare zone integration in Haifa (Israel)	Travel model choice (individual level)	Fare expenditure saves, socioeconomic statuses, current travel behavior	SP survey	Logistic regressions	Fare reduction was a significant factor in attracting transit users, and the public transportation reform had three important contributions.
Farber et al. (2014)	Potential fare structure switch in Wasatch Front (U.S.)	Transit trip number, distance traveled (individual level)	Socioeconomic status, spatial features	RP survey	Ordinal logistic and OLS regressions	Overall distance-based fares benefit low-income, elderly, and non-white populations. The effect is geographically uneven and maybe negative for members of these groups living on the urban fringe.
Cats et al. (2014)	The fare-free scheme in Tallinn (Estonia)	Change in transit ridership (station level)	Socioeconomic statuses, spatial features, current travel behavior	Ridership report	OLS regressions	The fare-free measure accounts for an increase of 1.2% in passenger demand, with the remaining increase attributed to other factors.
Miller & Savage (2017)	Transit fare increases in Chicago (U.S.)	Change in transit ridership (station level)	Socioeconomic statuses, spatial features	Ridership report	OLS regressions	For one of the four fare changes, the decline in ridership is greater in lower-income neighborhoods than it is in higher-income neighborhoods. However, the reverse is found for another fare increase.
Liu et al. (2019)	Fare zone reform in SEQ (Australia)	Change in transit ridership (individual and SA2 level)	Fare expenditure changes, socioeconomic statuses, spatial features	Smartcard data	Correlation analysis and spatial regressions	Public transit ridership can be boosted by reducing the fare cost per journey, which can then result in overall revenue gain. Such attraction varies substantially by user groups
Halvorsen et al.(2020)	Pre-peak fare discount policy in Hong Kong (China)	Shift in travel time (individual level)	Fare expenditure changes, current travel behavior	Smartcard data	Logistic regressions	The main factors that contribute to travel changes are the amount of time a user needed to shift his/her departure time, departure time variability, fare savings, and price sensitivity
Guzman et al. (2020)	BRT's fare increases in Bogotá (Colombia)	Ridership (station level)	Fare expenditure changes, socioeconomic statuses, spatial features	Ridership report	Panel regressions with fixed effects	The elasticity's absolute value decreases from -0.565 (1 week) to -0.408 after a month. In addition, low-income and peak-hour users are more sensitive to these changes.
Shin (2021)	Transit fare exemptions for older adults in Seoul (Korea)	Ridership, vehicle ownership, trip purpose, time of the day (individual level)	Socioeconomic statuses, spatial features	RP survey	Regression-discontinuity method	Fare-free subway policy for older adults increases the number of subway trips, which partly replaces trips by other transportation modes, but it has no statistically significant effects on outcomes related to social/leisure trips.
Shen et al. (2021)	An incentive program for carpooling in Seattle (U.S.)	Shift in carpooling behavior (individual level)	Monetary incentive, socioeconomic statuses	RP survey	Logistic regressions	The incentive program facilitates the growth of carpooling by making carpooling a competitive commuting option for long-distance commuters, it also contributes to a reduction of regional VMT.

APPENDIX B. DATA INFORMATION

Table A.2 The period and quantity of the smartcard data

Before the Fare Increase		After the Fare Increase	
Period	Number of Frequent Riders' Trips	Period	Number of Frequent Riders' Trips
Jan 15~21, 2018	344804	Feb 18~24, 2019	311994
Feb 5~11, 2018	357420	Mar 11~17, 2019	310490
Mar 12~18, 2018	358345	Apr 15~21, 2019	337471
Apr 16~22, 2018	358841	May 13~19, 2019	345187
May 14~20, 2018	357269	Jun 17~23, 2019	338497
Jun 4~10, 2018	360383	Jul 15~21, 2019	338438
Jul 16~22, 2018	346795	Aug 12~18, 2019	319469
Aug 13~19, 2018	340621	Sep 16~22, 2019	335171
Sep 10~16, 2018	362264	Oct 14~20, 2019	329185
Oct 15~21, 2018	360049	Nov 11~17, 2019	323727
Nov 12~18, 2018	358958	Dec 9~15, 2019	323739
Dec 17~23, 2018	362076		
Jan 14~20, 2019	352295		

APPENDIX C. REGRESSION RESULTS

Table A.3 Regression results of D_FREQ, D_DIST, and D_STIC

	D_FREQ				D_DIST				D_STIC			
	1	2	3	4	1	2	3	4	1	2	3	4
COST	-0.222**	-0.063**	-0.086**	7.567	-0.025**	-0.000	-0.075**	4.331	0.010**	0.011**	0.012**	-0.423
$COST^2$		-0.010**	-0.008**	-0.008**		-0.002				-0.000+	-0.000**	0.000**
FREQ							0.082**	0.080**			0.012**	0.013**
DIST			0.070**	0.068**							0.000	0.000
STIC			7.031**	7.009**			-0.100	-0.108				
PEAK			-1.998**	-2.411**			0.443*	0.621*			0.029*	-0.035*
COST* PEAK				0.061*				-0.025				0.009**
YEAR			0.016	0.039			-0.020	-0.006			-0.000	-0.001
COST*YEAR				-0.004				-0.002				0.000
ACCE			0.012*	0.024**			0.021**	0.013*			-0.000	0.000
COST*ACCE				-0.002*				0.001				0.000
BUS			-0.006+	-0.008+			0.002	0.006			0.000**	0.001**
COST*BUS				0.000				-0.001				0.000
Disabled			-0.107	-0.155			-0.309	-0.295			-0.015	-0.025*
Elderly			-0.634**	-0.732**			-0.662**	-0.629**			0.027**	0.016+
Student			0.436	-0.115			-1.291**	-1.864**			0.005	0.030
COST*Student				0.114				0.124				-0.006
S1			0.244	0.246*			-0.478**	-0.473**			-0.003	-0.004
S2			0.062	0.075			-0.088	-0.089			-0.008	-0.008
S3			0.147	0.147			-0.232*	-0.234*			0.002	0.002
T1			-0.654**	-0.649**			0.194	0.179			0.021*	0.024**
T2			-0.459**	-0.467**			0.255*	0.257*			0.019**	0.019**
T3			0.056	0.036			0.044	0.052			0.015*	0.012+
Constant	0.215**	-0.133*	-33.832	-81.360	0.135*	0.081	38.805	10.307	0.005	0.001	0.207	2.845
N	39623	39623	39623	39623	39623	39623	39623	39623	39623	39623	39623	39623
Multiple R^2	0.032	0.035	0.055	0.055	0.000	0.000	0.004	0.004	0.017	0.017	0.025	0.026
F	1302**	708.5**	136.5**	106.1**	15.48**	8.992**	9.496**	7.519**	670.1**	336.4**	58.93**	47.39**

Note: (1) Significance codes: <0.01 '**', <0.05 '*', <0.1 '+'; (2) Model 1 and 2 test the linear and non-linear relationship between cost and travel pattern changes, model 3 adds the control variables to check the robustness, model 4 adds the interactive terms to check interactive effects.

Table A.4 Regression results of T_FREQ, T_DIST, and T_STIC

	T_FREQ				T_DIST				T_STIC			
	1	2	3	4	1	2	3	4	1	2	3	4
COST	-0.016**	-0.059**	-0.052**	-6.154	-0.025**	-0.032*	-0.014*	7.074	-0.042**	-0.072**	-0.066**	-5.660
COST^2		0.003**	0.002**	0.002**		0.000				0.002**	0.001+	0.002*
FREQ							-0.014	-0.018+			0.012	0.009
DIST			-0.003	-0.002							-0.004	-0.004
STIC			-0.805**	-0.797**			-0.627**	-0.605*				
PEAK			0.351**	0.666**			0.393*	0.637**			-0.133	0.096
COST* PEAK				-0.046*				-0.044+				-0.033+
YEAR			-0.026*	-0.043**			-0.018	-0.002			-0.026*	-0.042**
COST*YEAR				0.003				-0.004				0.003
ACCE			0.001	0.001			0.011**	0.006			0.002	0.007
COST*ACCE				0.000				0.001				-0.001
BUS			-0.002	-0.004			-0.003	-0.006*			-0.002	-0.007*
COST*BUS				0.000				0.001				0.001*
Disabled			0.133	0.151			0.073	0.121			-0.034	-0.020
Elderly			0.144	0.176+			0.043	0.103			0.141	0.150
Student			0.182	-0.279			0.602**	0.354			0.620**	-0.046
COST*Student				0.109*				0.069				0.149**
S1			-0.055	-0.059			-0.177*	-0.159+			0.027	0.025
S2			-0.026	-0.035			-0.094	-0.088			0.042	0.037
S3			-0.016	-0.019			-0.015	-0.019			-0.011	-0.017
T1			0.375**	0.354**			0.469**	0.444*			0.089	0.064
T2			0.056	0.063			0.513**	0.504*			-0.148**	-0.147*
T3			0.131*	0.145*			0.292**	0.308*			0.098	0.107
Constant	3.259**	3.352**	56.705**	90.890**	3.983**	3.996**	40.767	7.979	3.964**	4.030**	57.186**	89.239**
N	28849	28849	28849	28849	21164	21164	21164	21164	30113	30113	30113	30113
Multiple R^2	0.001	0.001	0.003	0.004	0.001	0.001	0.006	0.007	0.004	0.004	0.006	0.007
F	15.92**	18.55**	5.692**	5.005**	26.48**	13.43**	7.317**	6.592**	122.8**	66.54**	11.02**	9.345**

Note: (1) Significance codes: <0.01 '**', <0.05 '*', <0.1 '+'; (2) Model 1 and 2 test the linear and non-linear relationship between cost and travel pattern changes, model 3 adds the control variables to check the robustness, model 4 adds the interactive terms to check interactive effects.

APPENDIX D. MODEL CHECK

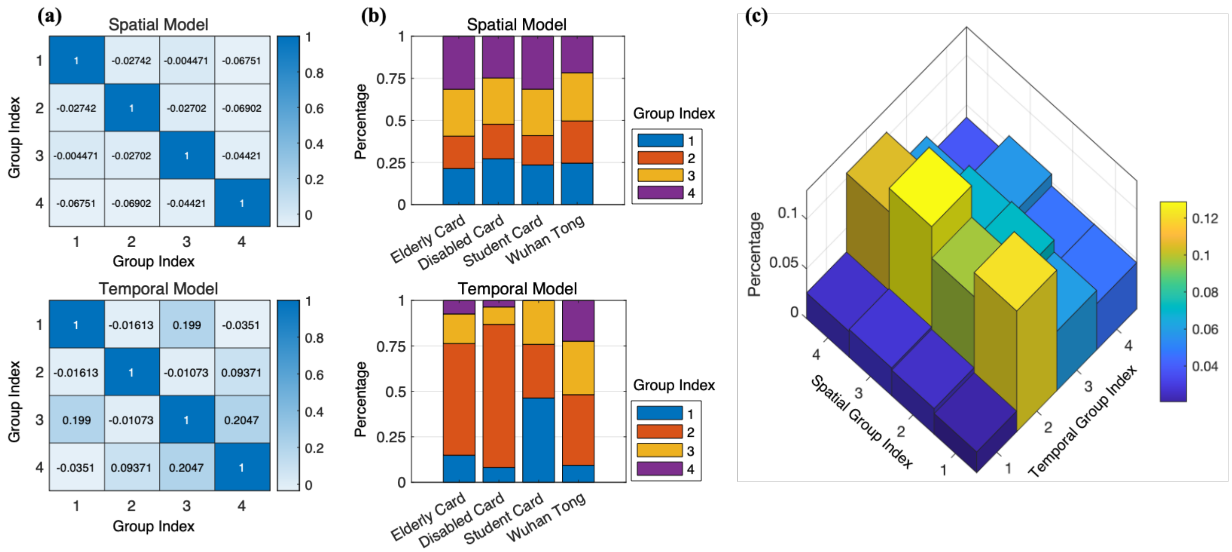


Figure A.1 Basic results of the two-dimensional spatiotemporal topic model: (a) Correlation among latent user groups; (b) Relationships between latent user groups and card types; (c) Percentage of different spatial and temporal groups

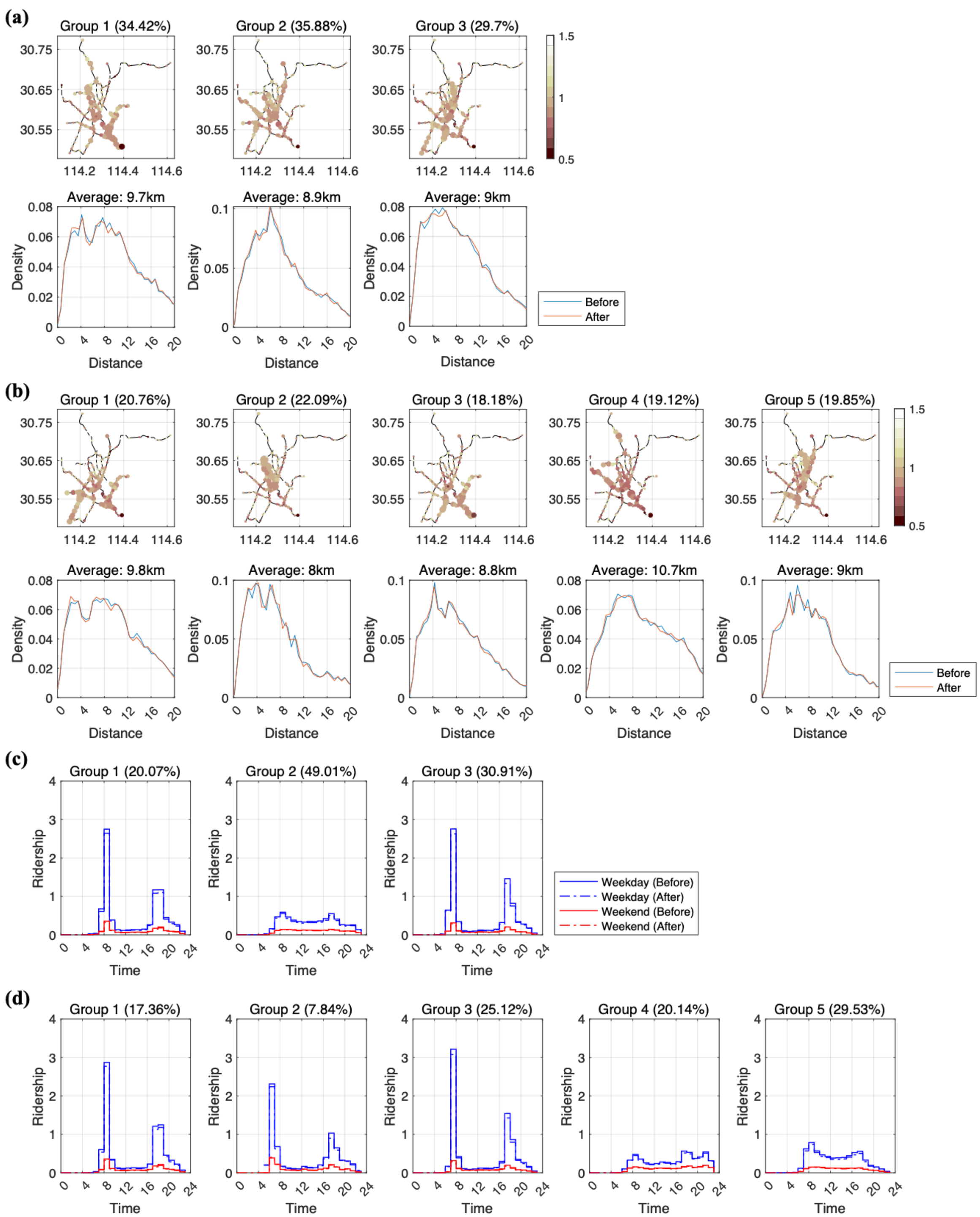


Figure A.2 Features of the spatial and temporal user groups with different topic numbers: (a) Spatial model (topic number = 3); (b) Spatial model (topic number = 5); (c) Temporal model (topic number = 3); (d) Temporal model (topic number = 5)

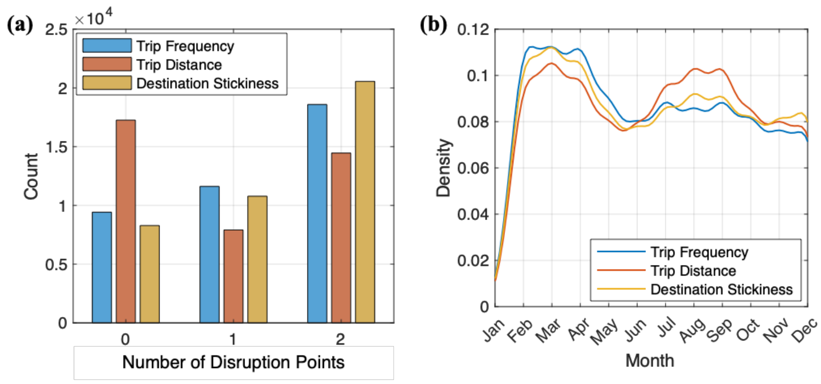


Figure A.3 Disruption points of travel patterns: (a) Individuals' number of disruption points; (b) Temporal distribution of disruption points

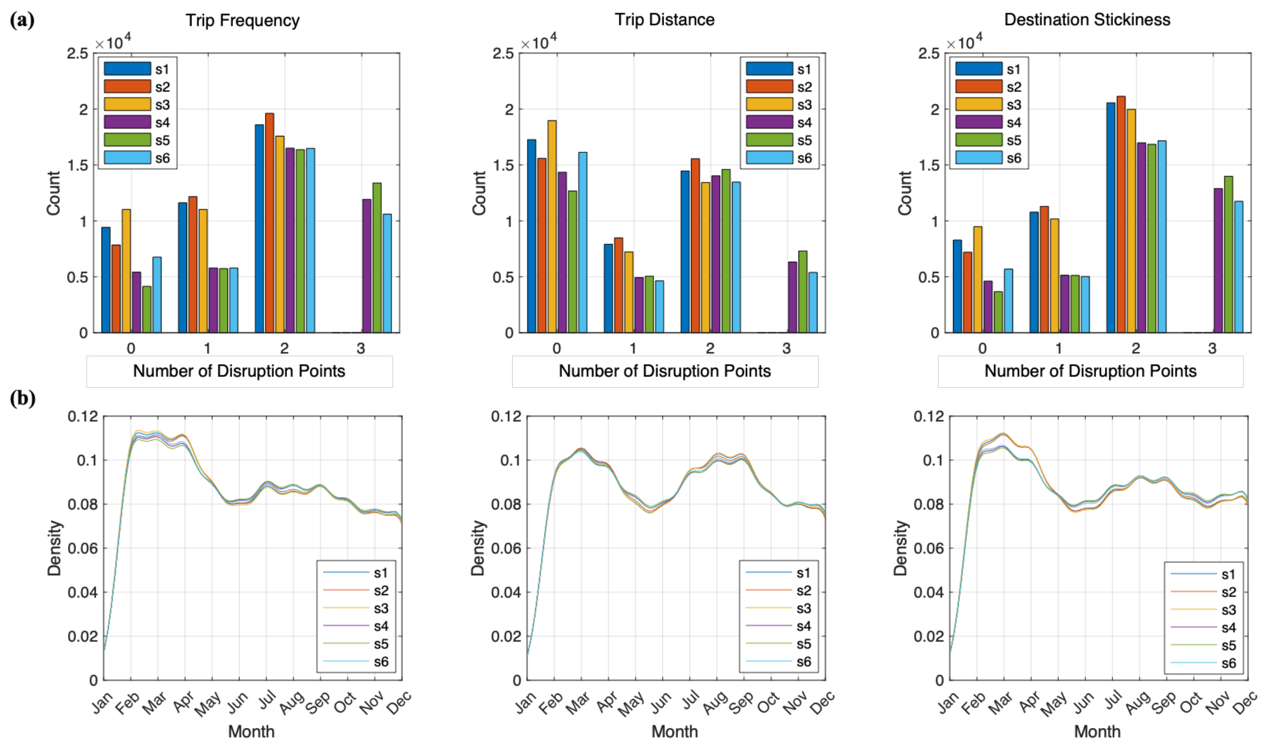


Figure A.4 Robustness check of the travel pattern disruption point extraction methods: (a) Individuals' number of disruption points; (b) Temporal distribution of disruption points (s1, s2, s3, s4, s5, s6 indicate σ= 0.5, 0.45, 0.55, 0.5, 0.45, 0.55 and τ = 2, 2, 2, 3, 3, 3)

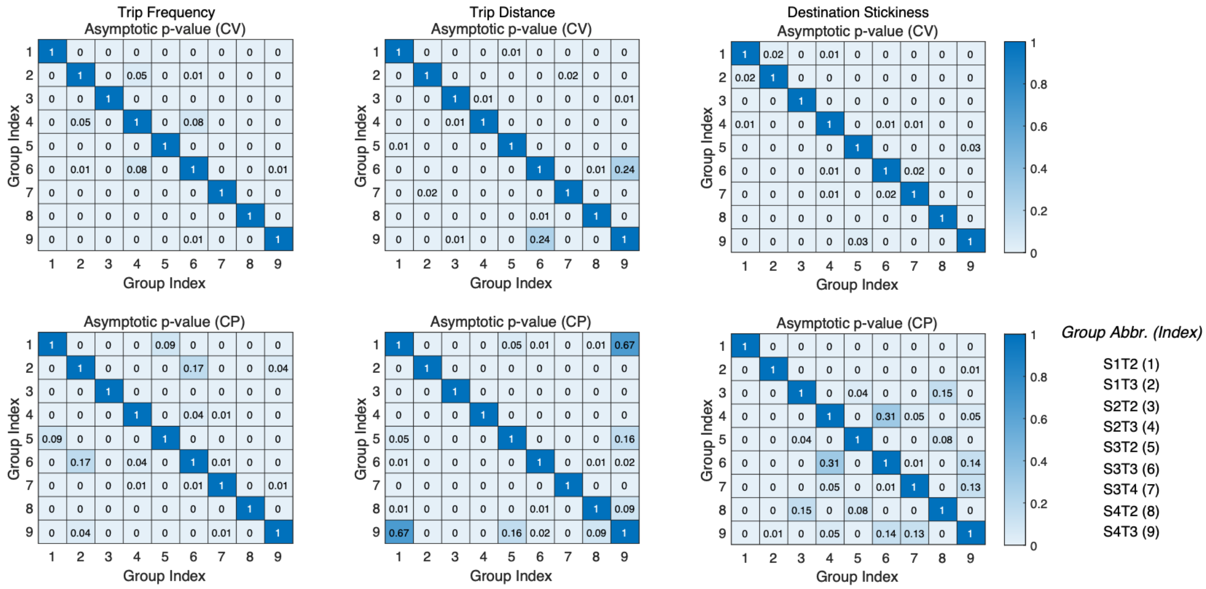


Figure A.5 KS test results of the group-level CP and CV values

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[i] Except for very rare cases like MTR (http://www.mtr.com.hk/ch/corporate/investor/2018frpt.html, accessed on Dec 23, 2021) in Hong Kong, China, or Tokyo Metro (https://www.tokyometro.jp/corporate/profile/pdf/corporateprofile.pdf, accessed on Dec 23, 2021) in Japan which possess a fare recovery ratio over 1 (1.72 & 1.19 respectively), most of the transit systems in the world cannot break even themselves, a typical range of this number is between 0.1 and 0.8 around the world (Chang & Phang, 2017; Parry & Small, 2009; Salon & Shewmake, 2012; Wachs, 1979).