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Demand Management of Congested Public Transport Systems: A Conceptual Framework and Application Using Smart Card Data

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Abstract

Transportation Demand Management (TDM), long used to reduce car traffic, is receiving attention among public transport operators as a means to reduce congestion in crowded public transportation systems. Though far less studied, a more structured approach to Public Transport Demand Management (PTDM) can help agencies make informed decisions on the combination of PTDM and infrastructure investments that best manage crowding. Automated fare collection (AFC) data, readily available in many public transport agencies, provide a unique platform to advance systematic approaches for the design and evaluation of PTDM strategies. The paper discusses the main steps for developing PTDM programs: a) problem identification and formulation of program goals; b) program design; c) evaluation; and d) monitoring. The problem identification phase examines bottlenecks in the system based on a spatiotemporal passenger flow analysis. The design phase identifies the main design parameters based on a categorization of potential interventions along spatial, temporal, modal, and targeted user group parameters. Evaluation takes place at the system, group, and individual levels, taking advantage of the detailed information obtained from smart card transaction data. The monitoring phase addresses the long-term sustainability of the intervention and informs potential changes to improve its effectiveness. A case study of a pre-peak fare discount policy in Hong Kong's MTR network is used to illustrate the application of the various steps with focus on evaluation and analysis of the impacts from a behavioral point of view. Smart card data from before and after the implementation of the scheme from a panel of users was used to study policy-induced behavior shifts. A cluster analysis inferred customer groups relevant to the analysis based on their usage patterns. Users who shifted their behavior were identified based on a change point analysis and a logit model was estimated to identify the main factors that contribute to this change: the amount of time a user needed to shift his/her departure time, departure time variability, fare savings, and price sensitivity. User heterogeneity suggests that future incentives may be improved if they target specific groups.

Keywords: Public Transport, Demand Management, Smart Card Data, User Segmentation, Fare Discount

1. INTRODUCTION

Public transport systems are playing an increasingly important role in today's cities. Environmental, technological, and economic trends are leading to a rise in public transport use in mature cities (Hurdle, 2014), while population growth and urban expansion have spurred developing cities to extend their public transport networks. With increases in ridership often come increased levels of crowding and congestion, which can worsen system performance and reduce customer satisfaction (Z. Li & Hensher, 2011). Though an instinctive response to rising public transport demand is to increase capacity, such improvements require long time frames and significant resources. Instead, demand management is another way to better serve customers. Traditionally, travel demand management (TDM) has focused on road congestion; however, with more public transport agencies facing crowding problems, there is an increasing need to develop more structured conceptual and methodological approaches for public transport TDM.

The impacts of TDM on car use are well researched. For example, an examination of three municipality-wide TDM programs - the LA Olympics, an Orange County toll road, and a flexible-hour policy in Honolulu- concluded that programs with meaningful incentives can have large impacts on individuals, but their effects on traffic are generally small (Giuliano, 1992). Ferguson (1990) discusses the roles of different stakeholders and evaluation methods for TDM and finds that programs targeting Transportation Management Agencies (TMAs), Trip Reduction Ordinances (TROs), and negotiated agreements can be successful in shaping travel patterns. Several studies also reported the importance of the identification and measurement of relevant TDM performance metrics with (often) limited, readily available data, and tools (Dale, Frost, Ison, & Warren, 2015; Rose, 2007; Smith & Moniruzzaman, 2014; Taylor, Nozick, & Meyburg, 1997).

Another body of TDM research focuses on the relationship between policy attributes and the behavioral underpinnings of travel decisions. Tommy Gärling et al. (2002) draw on a number of behavior theories to posit a framework in which TDM interventions influence trip chain attributes both, directly and through interactions with users' personal characteristics, goals, and public information. Though they can be generalized, the context and examples are for car traffic. Loukopoulos (2007) presents a TDM structure that relates eight design characteristics of TDM measures to three outcome variables: effectiveness, political feasibility, and public acceptance.

The causes, characteristics, and solutions for road congestion cannot be directly translated to public transport systems. Public transport users tend to have less varied trip purposes than drivers, are constrained by service schedules, and benefit less from avoiding peak use (Maunsell, 2007). Public Transport Demand Management (PTDM) is also more constrained. Public transport agencies generally do not want to lose customers to other modes; they prefer to redistribute demand, either temporally or among different routes (Maunsell, 2007). In addition, public transport is a public service so preventing or discouraging access to it is politically unappealing (Henn, Douglas, & Sloan, 2011). Traditional TDM and PTDM are not necessarily complementary; shifting people from cars to public transport in congested periods may be at odds with PTDM policies that encourage off-peak travel.

Effective and efficient policies for public transportation have not yet been nearly as well studied or widely deployed. Price discrimination is well-established for dealing with peak period congestion (Cervero, 1990; Mark & Phil; Wang, Li, & Chen, 2015; J. Zhang, Yan, An, & Sun, 2017; Z. Zhang, Fujii, & Managi, 2014) and research has shown that people are willing to pay to avoid crowding (Prud'homme, Koning, Lenormand, & Fehr, 2012). A review of crowding valuation research by Z. Li and Hensher (2011) found that while most studies considered only in-vehicle crowding, passengers exhibit willingness to pay for reduced crowding in access-way, entrance, platform/station, and in-vehicle crowding. A number of studies estimate the value of crowding in public transport using smart card or survey data (Batarce, Muñoz, & Ortúzar, 2016; Hörcher, Graham, & Anderson, 2017; Kroes, Kouwenhoven, Debrincat, & Pauget, 2014; Tirachini, Hurtubia, Dekker, & Daziano, 2017; Yap, Cats, & van Arem, 2018). For example, Hörcher et al. (2017) conclude that the disutility caused by one additional passenger per square meter onboard a train, on average, is equivalent to 11.92% of their travel time. This is consistent with the disutility reported in Kroes et al. (2014) based on a survey of transit users in Paris.

Public transport specific TDM strategies include free pre-peak fare programs in Singapore and Melbourne (Currie, 2009; Pluntke & Prabhakar, 2013), as well as route-based incentives for Hong Kong's MTR system (S.-M. Li & Wong, 1994). Similar discounts or peak surcharges have also been implemented in cities such as Washington, D.C., London, Tokyo, and Sydney. Other PTDM options include working with employers to encourage company-specific programs (LTA, 2014), lottery/rebate rewards schemes (Pluntke & Prabhakar, 2013), or providing public crowding information (BART and JR East). Most recently, BART tested the Perks rewards program that encourages riders to travel outside the morning peak period. BART riders who opt into the program automatically earn 1 point for every mile traveled on BART. They can earn up to six times as many points by starting their trip during the pre-peak and after peak periods (6:30 A.M. to 7:30 A.M., and 8:30 A.M. to 9:30 A.M.). Points can be exchanged for small cash rewards and lottery games (Greene-Roesel, Castiglione, Guiriba, & Bradley, 2018).

Empirical studies on the effectiveness of such PTDM strategies report that 2-5% of the users shift out of peak hours in response to off peak discounts (Currie, 2009; Halvorsen, Koutsopoulos, Lau, Au, & Zhao, 2016). A recent evaluation of the BART PERKS reward experiment shows a 10% shift of travelling from peak hours (Greene-Roesel et al., 2018). Empirical studies also conclude that the behavior of passengers with respect to time-shifting in response to a PTDM strategy (e.g. discount, free trip, etc.) is governed by many factors, including flexibility, displacement time, trip length, fare and discount level, sociodemographic attributes, etc. (Anupriya, Graham, Hörcher, & Anderson, 2018; Halvorsen et al., 2016). Survey studies concluded the passengers' willingness to change their time of travel during the morning peak period in response to fare discounts and/or faster trips (Henn et al., 2011; Kroes et al., 2014; Z. Li & Hensher, 2011; J. Zhang et al., 2017).

The wide availability of automatic data collection systems (ADCS) in public transport, such as smart card data has become the enabler for analyses not possible in the past (Koutsopoulos, Ma, Noursalehi, & Zhu, 2018; Pelletier, Trépanier, & Morency, 2011), including analyses to support the design and evaluation of PTDM. In addition to aggregate trends of when and where users and vehicles travel, this data provides detailed information on the travel patterns of specific groups and even individuals to inform program design. Of particular interest to this research are methods to segment users into more homogeneous groups. By differentiating between types of users and their response to PTDM strategies, policymakers can better understand the factors leading to a policy's success (or failure) and how to target particular customers. Such analyses were far more difficult with only aggregate or limited survey data. ADCS also streamlines the monitoring phase of policy evaluation; since data is collected continuously, behavioral changes can be compared to any prior period and evaluated retroactively.

The paper discusses the main steps for developing PTDM programs, building on a synthesis of previous TDM literature and real-world PTDM experience. Developing detailed protocols/methodologies in each step is out of scope of the paper, as not all of these may be relevant for a particular system and specific concerns would need to be addressed. The main steps are demonstrated in a case study of a discount strategy implemented by MTR in Hong Kong. A new, multi-level, multi-scale approach is proposed to evaluate PTDM effectiveness using AFC data, with special focus on users' behavior, an important but less understood area in PTDM.

The main contributions of the paper are:

- Framing and discussion of the steps required for PTDM development using the information provided by AFC data to drive problem identification, efficient design, and effective evaluation and monitoring.
- Application of the main steps using an off-peak discount strategy implemented in Hong Kong's MTR network with focus on evaluation and behavioral response.
- A novel approach for evaluation of PTDM strategies at three levels of aggregation: system, group, and individual levels, taking advantage of detailed disaggregate AFC data.
- A change point method to identify passengers who changed their behavior in response to the PTDM strategy and a discrete choice model to identify the most important factors that contribute to behavioral change using AFC data.

The remainder of the paper is organized as follows: Section 2 discusses main steps for developing PTDM programs. Section 3 applies the framework to MTR's Early Bird Discount Promotion, introducing the MTR context and design, and evaluating the policy. Section 4 discusses the main findings and suggests three areas of improvement to the PTDM program. Section 5 concludes the paper.

2. PUBLIC TRANSPORT DEMAND MANAGEMENT CONCEPTUAL FRAMEWORK

Development of TDM programs consists of the following main phases (adopted from (Loukopoulos, 2007) to give a stronger sense of process to policy design and public transport centric attributes):

- Problem identification and program goals
- Design
- Evaluation
- Monitoring

A key enabler for the adoption of the framework presented below is automatically collected data. AFC systems are particularly advantageous for demand management applications because they facilitate detailed understanding of the spatiotemporal characteristics of individual travel patterns. More detailed data allow for deeper analyses of existing conditions, models to forecast the impacts of a design and estimate its costs, and evaluations of congestion relief. Furthermore, AFC data can facilitate panel analysis of users to provide insights into their behavior before and after the introduction of a PTDM strategy. However, this anonymized data may not be sufficient for analyzing certain factors, such as demographic characteristics and user perceptions of the policy, so surveys may still be needed to complement such data.

2.1 Problem Identification and Program Goals

Generally, the overarching motivation for a PTDM program is to reduce congestion in the network, but robust policy designs must account for the local context and the particular nature of its demand problems. In order to set specific goals and targets for the program, important considerations are the congestion patterns, the involved stakeholders, and the time horizon.

Congestion Patterns: At its core, congestion is a result of an imbalance between the supply of service and user demand for it both, in space and time. In the context of PTDM, the level of supply is fixed, as are user characteristics like the population's socio-demographic profile and lifestyle preferences. However, other user characteristics may be malleable if targeted by a PTDM policy, which could induce behavior change.

AFC data provide useful information related to the spatiotemporal characteristics of the usage of the system relevant to the PTDM program. The extent of the congestion problem, including its distribution across modes, times, and individual facilities, as well as specific resource constraints that affect the system's ability to meet demand can be derived from AFC data. They are important aspects as they guide the nature and type of PTDM strategies appropriate for the problem. AFC data, especially combined with sociodemographic attributes, provide insight into user's constraints, attitudes, and other factors that may affect their responsiveness to PTDM and hence, the likelihood of its success.

Stakeholders: in addition to public transport agencies, potential stakeholders include current (and potential) riders, planning agencies and other government bodies, employers and businesses, and other local transportation operators. Though public transport agencies may develop PTDM programs on their own, working with other groups can present additional opportunities. An integrated approach, where the government works together with all local public transport agencies and gets input from community groups and businesses will likely have different goals and methods than one led primarily by a single agency with more limited oversight.

Time Horizon: Demand management policies can be developed for the short term to cope with anticipated surges in demand, like Transport for London's Olympics initiatives, or in the medium term to redistribute demand, and use available capacity more effectively, until capacity expansions are possible. In the long term, PTDM may be used in conjunction with additional capacity or to influence demand through broader growth patterns. Factors that can inform the appropriate scale for a given program include forecasts of future demand, capacity, and budget constraints that limit feasible congestion management programs.

The above aspects inform the specific goals of the PTDM program. Though different stakeholders may have different priorities for the program, agency goals will likely include decreased passenger flows at certain times or locations (within a particular budget constraint). Understanding the spatiotemporal characteristics of the congestion problem as well as user attributes, guides policy makers decisions, e.g. shifting users to different times of day, different routes, or different (public transport) modes. Goals may also include more qualitative guidelines, such as policies that are well-received by users or simple to understand. The time horizon may influence the rate at which these goals are to be met, when to place various milestones, and, along with the stakeholders, what designs and outcomes are even feasible.

2.2 Design

Based on the understanding of the problem both, from the demand and supply sides, Figure 1 describes a PTDM design process and key aspects to consider. While the importance of each of these factors will vary depending on the context and goals of the agency, acknowledging each encompasses the full scope of the design being considered and increases the likelihood of positive impacts.

The first step of PTDM design is determining the dimensions of intervention, and then various parameters should be set. If any data is already available, it can be used in forecasting to ensure the effects approach those desired. After checking the design is feasible, a final step is to determine how to promote the program through public information and marketing materials. The design process may be an iterative one, as stakeholders' feedback impacts the final design.

Different approaches have been proposed in the literature to characterize the various interventions. One commonly cited scheme distinguishes between the precursors of travel demand, grouping policies into physical changes, legal policies, economic policies, and education and information campaigns (Steg, 2003). Furthermore, measures may be "hard," changing the attributes of different alternatives (e.g. fares differentials or shaping land use), or "soft," changing users' perceptions of their travel options through, for example, marketing or trip planning tools (Bamberg, Fujii, Friman, & Gärling, 2011). Hard measures are further divided into market-based policies, which influence users through prices, and, though less common in public transport, regulatory policies, which set laws to require or promote certain actions. Depending on their level of coercion, a measure can be classified as "push" or "pull" (Tommy Gärling et al., 2002). Push measures make one option less appealing to force users away from it (e.g. peak surcharge), while pull measures make another more appealing to attract users (e.g. off-peak discount). Typically, push measures are more effective (Eriksson, Nordlund, & Garvill, 2010), though less acceptable to users (Steg & Vlek, 1997). T Gärling and Fujii (2006) argue that combining measures helps activate more of the psychological variables (cognitive skills, moral obligation, etc.) associated with behavior change.

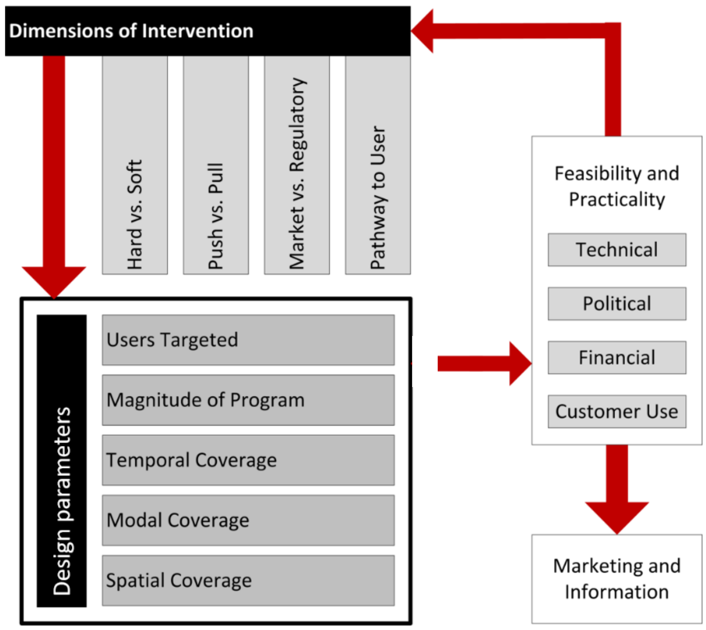


Fig 1. PTDM design considerations

In addition, agencies can manage user demand through several pathways:

Customers: Measures that directly influence the customer can apply to any user of the system, only users who meet certain criteria, or only those who choose to register in the program. They might fall under pricing mechanisms (peak/off-peak differentials, route-based fares), other benefits (lotteries, coupons), or information provision (journey planners, crowding data).

Employers: Because employers and other large institutions fix the timing of many users' travel activities, agencies can help them implement internal PTDM programs such as flexible-hour policies. For major employers, tailored demand-management incentives may yield system-wide benefits.

Broader Channels: Some policies, like those to shape land-use patterns or directly regulate use of the transportation network, may affect regional travel patterns more broadly rather than directly on public transport use. These measures typically involve additional stakeholders and take more time to have evident impacts.

The design parameters define how the policy will be implemented. One crucial parameter is the targeted user population: PTDM interventions that target specific users can be more effective or efficient than generic strategies (Bamford, Carrick, Hay, & MacDonald, 1987), especially if they are in the form of incentives. Theoretically, each user has his/ her own threshold for a behavior change: a "willingness to shift." Identifying this characteristic and giving someone only the minimum necessary incentive allows the agency to either increase its efficiency (by spending less money for the same results) or effectiveness (by having higher response rates with the same resources), such a scheme may be practically infeasible and politically difficult. Instead, the problem can be approached through the use of more homogeneous groups. Policies can be designed to induce a behavior change by recognizing the needs of a specific group, or by relying on self-selection, requiring users who are likely to respond to opt into getting an incentive. There are a number of ways to classify users, e.g. based on socio-economic characteristics, system usage by route or time, etc. Identifying appropriate classification factors is an important element of the design process.

The magnitude of the program (e.g. the level of fare differentiation or number of participants) is a critical parameter, particularly for hard policies (Eriksson et al., 2010). The congestion and crowding analysis carried out in the problem identification stage can be used to establish a policy's temporal, modal, and spatial coverage, ensuring that the most overcrowded periods and parts of the system are covered. Another temporal aspect is the program duration.

While the optimal design of car traffic TDM strategies, dealing with the optimization of toll locations and pricing levels, has received some attention in the literature (Ekström, Sumalee, & Lo, 2012; Hamdouch, Florian, Hearn, & Lawphongpanich, 2007; Kachroo, Gupta, Agarwal, & Ozbay, 2017; Wie, 2007; Wie & Tobin, 1998), PTDM strategies are often developed on a trial-and-error basis. Recently, Ma and Koutsopoulos (2018) proposed a methodology for the 'optimal' design of promotion based PTDM strategies, systematically evaluating the effectiveness of various promotion design structures, and demonstrating its applicability using empirical data. Yang and Tang (2018) describe a fare-reward scheme (FRS), assuming a simple network, that rewards a commuter with one free trip during shoulder periods after a certain number of paid trips during the peak hours.

The practicality and feasibility of the design, in terms of appropriate technological enablers and implementation costs, is an important consideration. The emergence of mobile sensors and the widespread use of smart cards in recent years have increased the technological options to support innovative strategies. Implementing such options, however, can incur costs including lost fare revenue, increased staff hours, technology procurement, and marketing. However, some policies may also increase revenue by attracting new customers or reduce cost by allowing the agency to purchase new infrastructure (Currie, 2009).

The policy should have the necessary support of the public and decision makers. Acceptance levels are shaped by a number of factors, including problem awareness, perceptions of effectiveness and fairness, perceived responsibility for the problem, and social norms and values (Schade & Schlag, 2003; Schlag & Teubel, 1997). Political acceptance often depends on public opinions (Tommy Gärling & Schuitema, 2007), though Schlag and Teubel (1997) point out that politicians may not always perceive public views accurately.

The design must also acknowledge how people will use the system with the policy in place: will users be able to take advantage of loopholes? How will the policy function under service disruptions? Is it so complicated that its effectiveness may be degraded? Maruyama and Sumalee (2007) argue that a complex design may be theoretically optimal, but a more understandable design is likely to have higher participation and approval. Once the design is finalized, a plan for marketing and publicizing the campaign may be instrumental in encouraging fast adoption and wide participation among users.

2.3 Evaluation

Evaluation of a PTDM program includes a number of dimensions as summarized in Figure 2.

- Effectiveness of the program in achieving its desired impact
- Efficiency in achieving benefits that outweigh costs either from the agency's perspective or from

a broader societal view

- Acceptability by the public and local decision-makers

While each is important in its own right, these factors are also interrelated. For example, users who see that a program is effective may be more accepting of it and, with the same resources, a more effective program will also be more efficient. System impacts relate most directly to effectiveness but can be combined with agency impacts and/or societal impacts to study efficiency. Customer impacts can also be used to study effectiveness, as well as allow the agency to understand people's perceptions of the program.

A number of metrics can be used to measure each of these. The metrics are organized into system impacts, directly related to congestion reduction goals; customer impacts reflecting other changes users might see in service as a result of system impacts and how they perceive these effects; agency impacts, reflecting resource usage; and social impacts that capture broader effects. Depending on the objectives of the TDM program, different measurements, supported by AFC data, could be developed and prioritized. For example, for congestion reduction objectives, useful metrics include:

- System impact: Passenger accumulation in system (total number of passengers in the system – stations and trains – at any given point in time; calculated from AFC data as the cumulative entries into the system minus the cumulative exits), key station entry/exit flow, link flows or average vehicle loads by time, direction.

- Customer impact: Number of passengers/standees per area, denied boarding/waiting on platform (Ma, Koutsopoulos, Chen, & Wilson, 2019; Zhu, Koutsopoulos, & Wilson, 2017a, 2017b), journey time reliability (Koutsopoulos et al., 2018; Ma, Ferreira, & Mesbah, 2014)

- Agency impact: Program cost, changes in patronage/revenue and resource allocation

- Societal impact: Distribution of effects (equality and fairness) on different types of riders

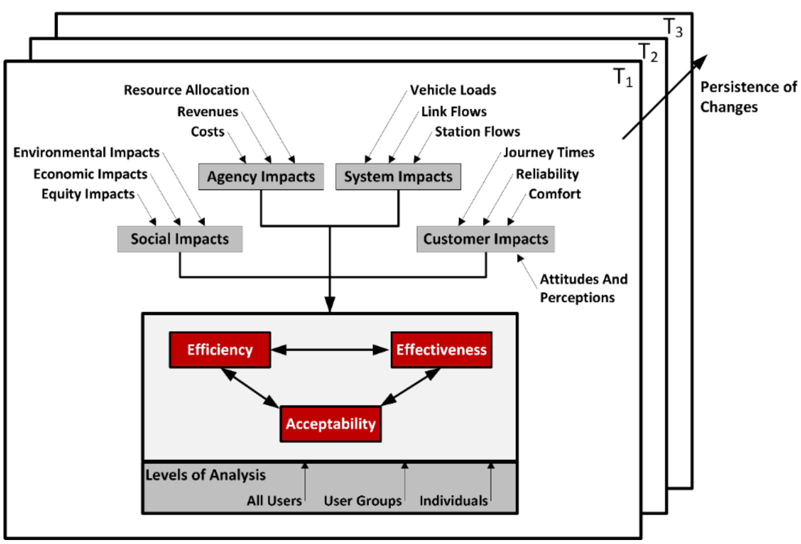


Fig 2. PTDM evaluation

The availability of AFC data facilitates novel evaluation approaches at three levels of aggregation:

- **System wide** (all passengers): Fully aggregated passenger data at the system level, i.e. link or station flows, is useful from an operational perspective. It gives a basic understanding of how aggregate demand has changed, potentially reflecting service quality and the typical user experience. For agencies with less detailed passenger data, this might also be the only type of analysis that is possible.

- **User Groups:** Detailed analysis of user behavior can provide insight into a policy's particular impacts. Monitoring the behavior of specific user groups can help understand which characteristics made people more likely to respond to the intervention and how strategies can be adapted to account for differing behaviors. The effectiveness of a group-based analysis depends on the identification of appropriate groups. Using AFC data over a period of time, clustering methods based on a feature vector relevant to the design of the PTDM intervention can be used to identify groups of interest.
- **Individual Passengers:** Panels of individual users, observed anonymously over time using AFC data, provide a unique tool to monitor passenger behavior before and after the implementation of a PTDM strategy. It is a powerful means to understand how travel patterns of individuals change in the face of new policies, gain useful insights, and inform the development of improved designs that better account for user heterogeneity and the degree to which individual behavior changes sustain themselves over time. Change point analysis methods can be used to identify systematically users who change their behavior in response to the PTDM strategy. Based on the inference of users who changed their behavior, discrete choice models are used to identify the main factors that contribute to passengers' decision to change behavior and hence, inform more efficient future designs.

2.4 Monitoring

The effectiveness of PTDM programs may change over time. Monitoring of how impacts change should continue beyond the initial evaluation to capture the medium and long-term changes that the strategy induces (Currie, 2011; Maunsell, 2007). There may be seasonal changes to its impacts, depending on events like holidays and weather. More importantly, long-term user acceptance may change as a result of the "hedonic treadmill", which argues that an intervention alters people's satisfaction with their travel, but over time they adjust and return to their previous satisfaction levels (Brickman & Campbell, 1971). Monitoring targeted users in that regard is particularly insightful. Similarly, public or political acceptance may evolve such that the behavioral levers of PTDM policies become weakened over time.

3. APPLICATION

To demonstrate the proposed framework, Hong Kong's MTR system is used as a case study. Although operational improvements have been made when possible and network expansions are planned, MTR has also experimented and introduced PTDM strategies to deal with increased demand. The most recent example is a 25% discount to users who travel during the morning pre-peak period introduced on September 1, 2014. This strategy is the subject of the analysis.

Anonymized smartcard records were the primary data source for the analyses described in this section. MTR is a closed system, requiring users to tap their cards on entry and exit, so complete trip records were available. The anonymized data includes entry and exit station, entry and exit time, and fare type. Data from July-October 2013 and July-October 2014 were used for the analysis. The methods described in this section are also applicable to open systems. For such systems, OD matrix estimation methods have been developed that infer individual passenger's destination (e.g. Gordon, Koutsopoulos, Wilson, and Attanucci (2013))

3.1 Problem Identification

This phase identifies the spatiotemporal characteristics of the system congestion and provides a better understanding of usage patterns. The demand patterns at stations and on links that prompted interest in demand management are illustrated in Figure 3. In the AM peak period, system-wide entrances peak at

8:15, exits at 8:45, and train loads at 8:30 though there is some variation among stations and links. In particular, Figure 3a shows that there is a major split in peak exits: a sizable group of stations peak at 7:45, while most peak at 8:45 (possibly these two groups of stations serve activities that follow different schedules).

These patterns suggest that PTDM attempting to incentivize passengers to change their exit times would be a strong candidate for reducing congestion particularly in the 8:15-9:15 period. The spatio-temporal concentration of the entries and exits also suggests that, if station crowding is the motivation for PTDM, exit-based PTDM strategies could be more effective in the morning.

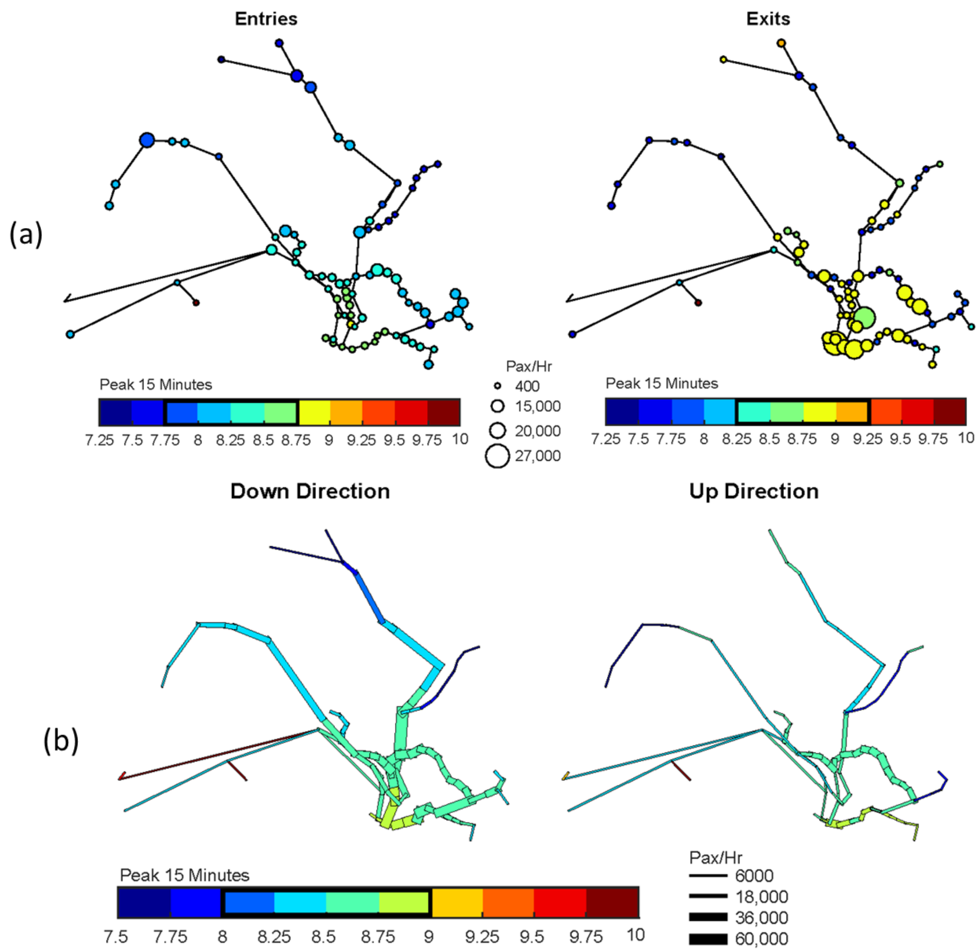


Fig 3. Demand patters: a) at each station; and b) on each link. (The size of circle and width of link represent the demand and flow, respectively. The color indicates the peak 15-minute period)

3.2 Design

The details of the PTDM strategy implemented are outlined in Table 1, organized in a way consistent with the design framework proposed in the previous section.

Table 1: Dimensions of Early Bird promotion design

Type of Intervention	Fare Differential: Pre-Peak Discount, Hard, Economic, Pull, Directly for Customers. It reduces the price of traveling before the peak, making it a pull measure to attract people to travel earlier. It is customer-based since it does not directly involve employers and is not dependent on broader government policies.
Users Targeted	Only adult card users are eligible (users with other concessions are not). No other groups were specifically targeted.
Magnitude	25% fare discount (HK$1-12, or US$0.13-1.5, depending on trip distance).
Temporal Coverage	Trips that exit between 7:15 and 8:15 in the morning. As discussed in Section 3.1 train loads peak in the morning around 8:00 to 9:00, with the peak of the peak from about 8:30-8:45. The discount period 7:15-8:15, was chosen so that the peak itself did not just shift earlier (but not too early that no peak hour travelers were willing to shift their departure time). Though Section 3.1 shows that different links and stations reach their peaks at different times, the same discount period was used for all stations. This highlights the trade-off between simplicity and effectiveness. Setting different time periods for different stations might better manage demand in different parts of the network, but if it is confusing for the passengers, it may not achieve its potential effectiveness. Implementing a discount after the peak was not considered due to the fact that flexible work hours are not practiced in Hong Kong and, therefore, there may not be enough flexibility for commuters to switch to a later time period.
Spatial Coverage	Trips that end at 29 heavy rail stations in Hong Kong's urban core (of 87 total stations, Figure 4). The analysis found that 80% of trips exiting these 29 stations travel through a congested link. While other strategies may have been more effective, for simplicity, the discount was based on passengers exiting certain stations. OD level discounts for example, may lead to more efficient designs as they target passengers more effectively, but were not considered for practical considerations. Having one contiguous zone recognizes the need for simplicity; selecting all stations within a boundary is easier for users to understand.
Modal Coverage	Heavy rail only. Other modes operated by MTR (e.g. light rail, Airport Express) were not targeted. Although, there is anecdotal evidence of overcrowding on the light rail system, it lacks the same AFC technology as heavy rail, and hence the feasibility of a unified strategy was not as easy from an implementation point of view. Future incentive designs may also consider the interplay between these systems and how additional incentives on one mode could enhance the impacts on others.
Implementation	Policy could be easily implemented by changes through the AFC system. Buffer time was added on either side of the pre-peak hour to account for minor delays and user/system clock discrepancies. Cost of implementation was manageable.
Marketing	Publicity campaign included press releases, notices on MTR website, in-station advertisement, and social media outreach.

In summary, the program targeted the AM peak because of the higher strain on capacity, sharper rise in demand, and the possibility to influence later trips without having to actively incentivize them. The discount level was chosen based on experiences in other cities, and the temporal and spatial coverage of congestion. The pre-peak hour aligns with the hour prior to peak loads at critical links in the system, while the 29 stations were selected such that 80% of travelers who use at least one critical link (operating at or close to capacity) in the AM peak hour exit a station with a discount. The stations are contiguous, hence simplifying the design and facilitating user understanding and acceptance (see Figure 4).

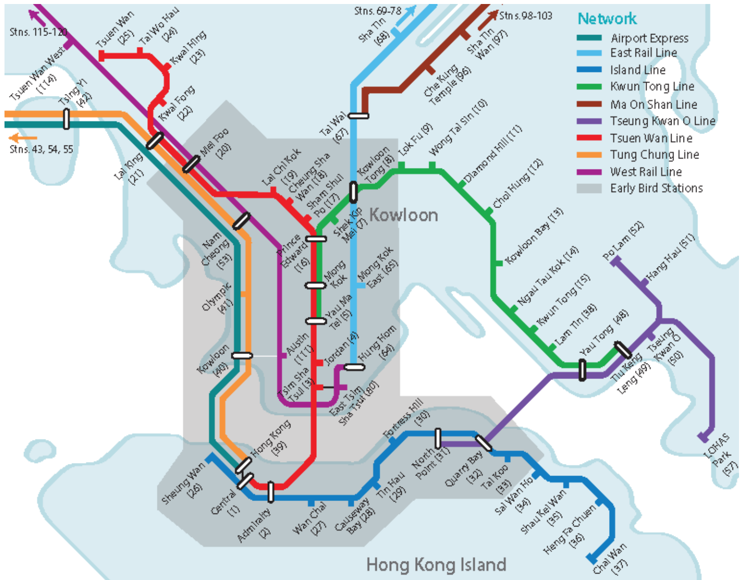


Fig 4. Stations eligible for the fare discount (network has been expanded since the study)

Ma and Koutsopoulos (2019) recently proposed a systematic approach to optimally design the operational characteristics of promotion based PTDM. The approach aims at helping decision makers make informed decisions about the spatio-temporal, and discount characteristics of the PTDM design (station vs. OD based, participating stations or ODs, station specific discount time period, etc.) given network, demand, budget, and implementation feasibility constraints.

3.3 Evaluation

Of the three evaluation dimensions, the paper focuses on program effectiveness using detailed AFC transaction data to infer aggregate and individual user behavior before and after the promotion. AFC data, as is demonstrated through this application, can provide critical insight into user behavior over time in response to the implemented strategy. Such insight is valuable for guiding future policy formulation.

System-wide Impacts

The exit time distribution of eligible trips (adult trips to one of the 29 stations) showed that September 2014 had distinct patterns compared to months before the promotion. The most obvious changes were small peaks at either end of the pre-peak hour because of users waiting to exit until the promotion began or shifting only to the minutes just before it ended. Of all trips between 7:00 and 9:30am, about 2.5% shifted out of the peak. With the additional early morning trips that shifted to the pre-peak period, about 3% of all trips between 7:00 and 9:30am moved into the pre-peak hour. This represents a 10% increase in pre-peak trips. Corresponding changes were not observed among trips made by non-eligible users or to non-eligible stations. Figure 5 shows the change in link loads, with changes particularly evident around areas covered by the promotion. More detailed results can be found in Halvorsen et al. (2016).

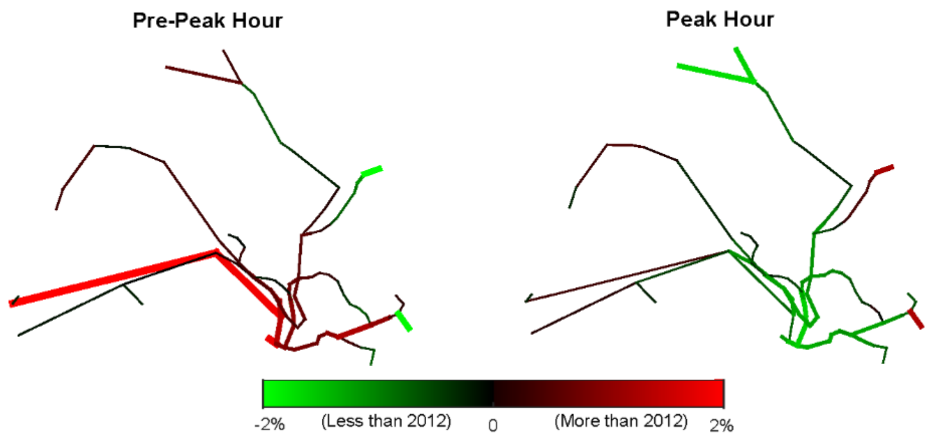


Fig 5. Change to passenger flows from Sept. 2012 to 2014, down direction (Halvorsen et. al., 2016)

User Groups

An aggregate analysis is useful to determine the effects of a promotion, but it does not provide insight into why or how these impacts came about. Understanding how different user groups responded to the promotion and what travel behaviors are more responsive to peak-spreading strategies can help an agency to refine and focus its future strategies. In particular, the ability to segment users has implications for increasing the efficiency of the program. While over 27% of adults traveling in the 7:00–9:30 AM period to eligible stations receive a discount by virtue of exiting in the pre-peak hour, the analysis above found that only about 2.5% of AM trips actually shifted from the peak. Most users who receive the discount did not make changes to their behavior. Market segmentation has the potential to identify user groups that are more responsive to the promotion and hence inform a more targeted design, either in terms of time or locations, increasing program efficiency. For example, segmentation may identify a smaller group with a high response to be as valuable as a larger group but indifferent to the promotion.

In order to understand the general behavior patterns exhibited by passengers, a clustering analysis was performed using AFC data. This allowed for the measurement of the impact each group has on network traffic, as well as further analysis of how different groups responded to the demand management strategy. Because the goal of this analysis was system-wide usage, AFC transactions were sufficient, particularly given the high quality of the data. The variables used for clustering were selected for their potential to identify broad usage patterns system-wide, especially with respect to PTDM response.

Three two-month samples of AFC transactions were used in this study. Approximately 400,000 users were selected from each September-October 2013, July-August 2014, and September-October 2014 period (about 4% of all IDs in any period), representing 11 million trips per period. The variables used to cluster users are listed below, grouped under primary characteristics of how often someone travels, when their trips take place, and where in the network they visit. These variables were chosen to capture the spatiotemporal characteristic of the trips: how frequently and regularly someone uses the system, how widely they travel over the network, whether they use stations of particular interest, and when they typically travel (peak or off-peak).

1. Frequency Characteristics

- Range of Travel (number of days between first and last trip; variable index = 1)
- Number of Weekdays/Weekends Traveled (6, 10)
- Number of Weekday/Weekend Trips (7, 11)
- Number of Gaps in Travel (number of times a users goes at least one day without traveling on

MTR; 15)

- Average/Minimum/Maximum Gap Length (16, 17, 18)

2. Temporal Characteristics

- Median Start Time for First Trip of Day, Weekday/Weekend (8, 12)
- Median Start Time for Last Trip of Day, Weekday/Weekend (9, 13)
- Number of Days Started within 30 min of Median Start Time (14)

3. Spatial Characteristics

- Number of Distinct First and Last Origin Stations (2, 3)
- Number of Distinct ODs Traveled (4)
- Number of Days with First Trip at Border Crossing with Mainland China (19)

Principal component analysis (PCA) was used to reduce the dataset's dimensionality (Jolliffe, 2011). PCA provides a set of uncorrelated vectors for the clustering analysis, preventing variables whose values stem from similar underlying behavior from dominating the results, and allowing a smaller number of inputs that still capture most of the variation in the data. PCA serves as a useful tool to reduce the dimensionality of the feature space for cluster analysis, and has been applied for transit passenger flow analysis in different contexts, (Goulet-Langlois, Koutsopoulos, & Zhao, 2016; Luo, Cats, & Lint, 2017).

In this application, the first six principal components were used for clustering. They explain about 85% of the data's variability (Figure 6a). The inclusion of additional components had little impact on the results. Figure 6b illustrates how the principal components are correlated with the original data (with the indices listed above). The first principal component is mostly correlated with the "amount" someone travels (number of trips, days, distinct ODs, etc.), the second with gap length, the next three with time, and the sixth with trips into China. The principal components beyond the sixth are less correlated with any particular characteristic.

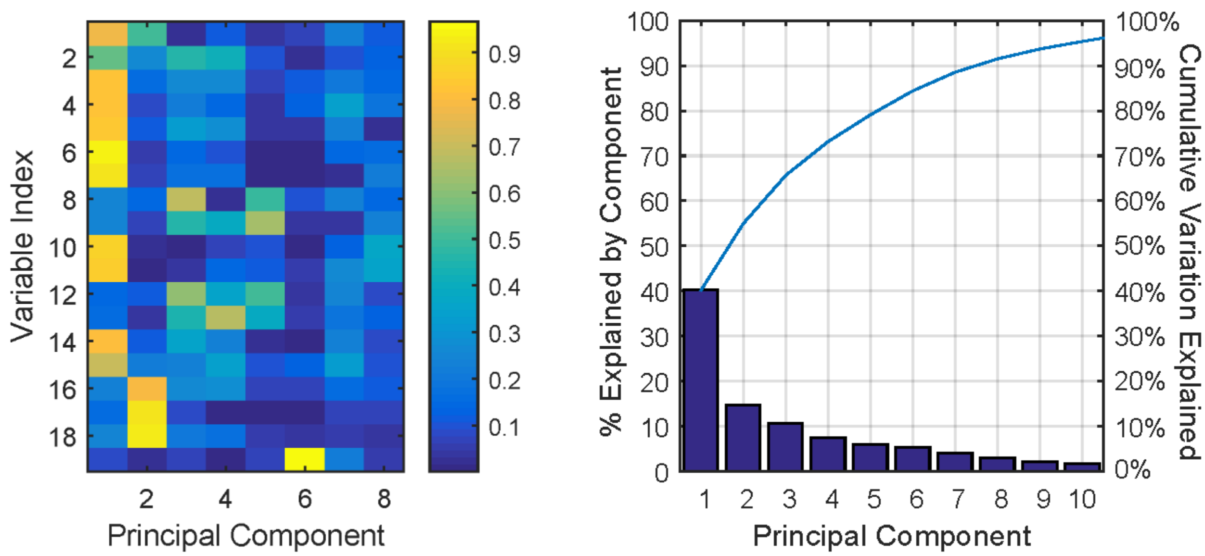


Fig 6. Principle component analysis. (a) Variation explained; (b) PC correlation with original data

Groups were identified using k-means++ clustering (Arthur & Vassilvitskii, 2007). For this analysis, the Euclidean distance was found to work best as a distance measure. Analysis based on the silhouette criterion (Rousseeuw, 1987; Tibshirani, Walther, & Hastie, 2001) suggested six clusters. Groupings in each of the three periods showed similar attributes, so clustering was consistent over time.

The characteristics of the groups and their relevance to the PTDM strategy are summarized below.

1. **Hong Kong Commuters**: With an average range of almost the whole period and the most frequent travel, these are the heaviest users of the MTR system. They also take most of their trips in the AM and PM peaks, so this group can be assumed to include those commuting within Hong Kong.
2. **Casual Hong Kong Users**: These users have a long range but less frequent travel than Group 1, particularly in the AM peak. They may use MTR in conjunction with other modes or only for non-commute trips, e.g. going out after work.
3. **Intermittent Hong Kong Users**: This group has a moderate range and travel on MTR about twice per week, using stations throughout the system. They could be Hong Kong users who primarily rely on other modes, but also users that switch between several smart cards.
4. **Short Term Users**: Largely characterized by a short range, these users tend to travel from the late morning into the night and to areas with more commercial activities. This group most likely includes tourists who are in Hong Kong for only a short time on vacation; however, it could also include Hong Kong residents who use their Octopus for only a few days of MTR trips.
5. **Occasional Cross-Border Travelers**: Somewhat similar to Group 3, these users have a moderate range, but relatively infrequent use. Their proportion of days beginning at a border crossing station is notably higher. They typically travel to stations near touristic or shopping centers and start their trips later in the day. This group could include visitors who come to Hong Kong once or twice a month.
6. **Cross-Border Commuters**: This group has a long range and relatively high number of days traveled. Their first trip is typically early in the morning and last trip in the late afternoon, like a commuter, but they start most of their days at a border crossing station. This group could include the "parallel traders" who travel regularly between Hong Kong and China to buy and sell goods.

Actual spatial-temporal travel patterns are shown in Figure 7, which illustrates the relative number of trips started by each group at each station in each hour of the day (i.e. the percent of trips started by that group at a station in a hour). Yellow corresponds to more common entry points. Stations are in order of their numerical code; the 29 stations eligible for the Early Bird Discount are indicated with gray boxes or black lines.

Groups 4 and 5 traveled more in the middle of the day, and their trips were fairly concentrated in tourist or shopping destinations. The more common morning entries at border crossing stations for Group 5 suggests they were more likely to come from the mainland while the single visit users are of more variable backgrounds. Group 6, the most frequent cross-border users, indeed traveled almost exclusively from the border in the morning. Their PM entry stations show that they typically confined themselves to the end of the East Rail Line and took only a small number of trips elsewhere in the system. In fact, in the morning, only about 25% of their trips were to stations eligible for the promotion, compared to 40-50% for all other groups. These three groups represent only about 3% of AM trips to eligible stations. For Groups 4 and 5, this is likely due the fact that few members traveled at all at these times. For Group 6, it is because of the small size of the group, as well as its members' tendency to travel on the north end of the East Rail Line, away from the central areas of Kowloon and Hong Kong Island.

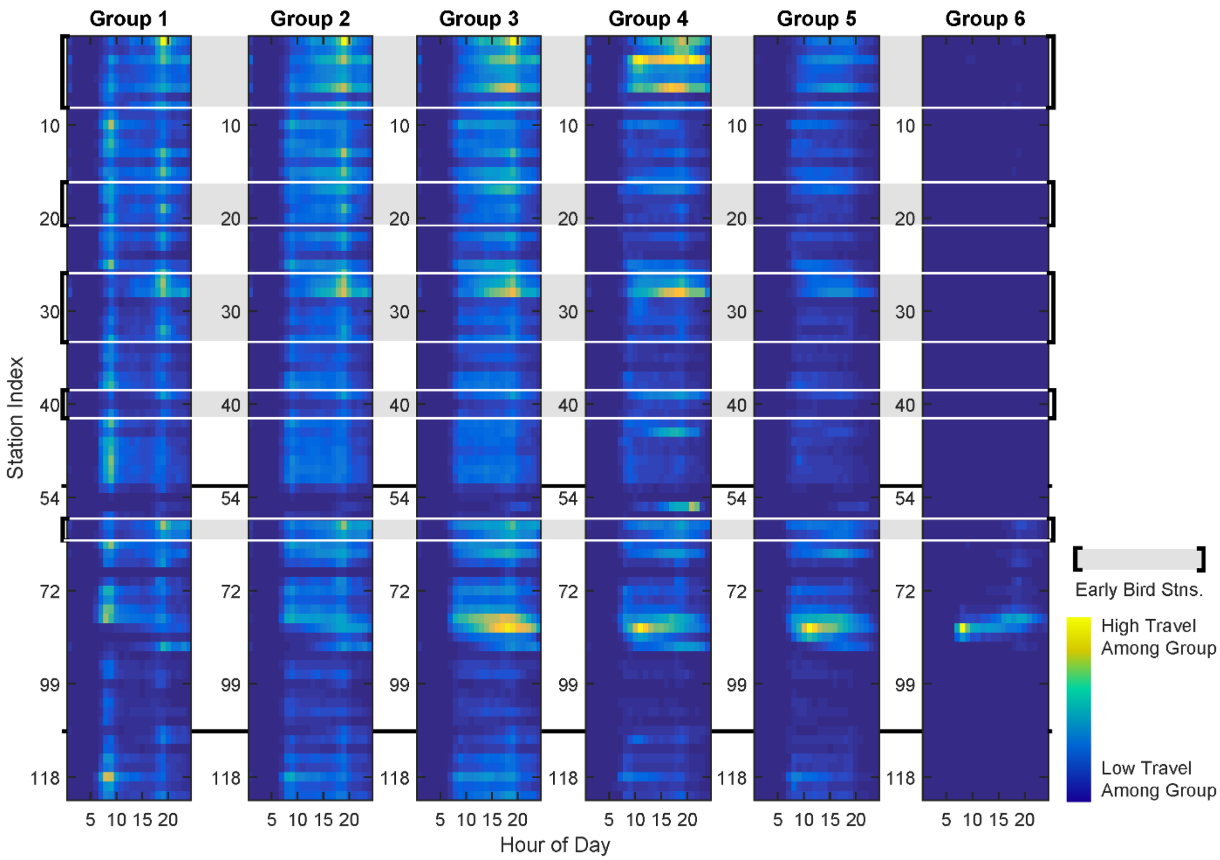


Fig 7. Relative number of entries at each station in each hour of the day by group

Group 1 exhibited peaking patterns similar to those that characterize system usage as a whole: many entries between 8:00–9:00 or 18:00–19:00 and fewer trips in the middle of the day, when people are presumably at work or school. They also have fewer dominant stations; this group's travel was more dispersed across the system. It took the majority (80%) of the trips to stations eligible for the discount. Group 3, the intermittent Hong Kong users, had a peak only in the evening and, while its travel was more spread out in the network than groups 4–6, it was still mostly from commercial centers and border crossing stations in the evening (i.e. day visits to the city of Shenzhen, China). Group 2 falls between 1 and 3. Travel from commercial centers was common in the evening, but they had less cross-border travel and a higher proportion of trips in the morning peak. These groups (2 and 3) took a non-negligible 18% of AM trips to early bird stations.

These patterns also provide additional insight to the aggregate congestion patterns. The sharper morning peak is largely due to commuters, while the more gradual evening peak is a result of all groups traveling. While PTDM policies may be useful in the AM and PM peaks, these different types of travelers, along with the longer duration of high demand in the afternoon, means that different policies may be needed in each period. In deciding whether to take advantage of promotions, users face a trade-off between flexibility and incentives. As frequent travelers, the total discount commuters receive will be large, but the greater time constraints on commute trips make earlier travel more burdensome, especially since flexible start hours are not common. Other groups, like the intermittent and casual users, may have fewer constraints on their travel times, but if they do not often use MTR in the morning, a 25% discount may not be enough to entice them to travel even earlier. Tourist groups are not negligible, especially in the PM peak, but effective marketing campaigns and information will be important to ensure they are aware of these discounts.

Table 3 summarizes the change in peak and pre-peak hour travel for each group, comparing September 2014 to August 2014 and September 2013, using the ratio:

$$r = \frac{\%Trips_{Sep14,i}}{\%Trips_{m,i}} \tag{1}$$

where %Trips is the percentage of all trips between 7:00 and 9:30am that took place in hour i, either pre-peak (7:15-8:15) or peak (8:15-9:15) in September 2014 or base month m.

Table 3: Ratio of September 2014 travel to prior months, for pre-peak and peak hours

	Pre-Peak (7:15-8:15am)		Peak (8:15-9:15am)	
	Sept14/Sept13	Sept14/Aug14	Sept14/Sep13	Sept14/Aug14
Group 1	1.11	1.13	0.96	0.96
Group 2	0.99	1.01	1.00	1.00
Group 3	1.07	1.11	0.96	0.94
Group 4	1.07	1.10	0.98	1.00
Group 5	1.18	1.02	0.90	0.92
Group 6	0.94	1.04	1.05	1.05

The total percentage of AM trips taking place in these two hours (7:15-9:15am) versus the remaining shoulder periods (7:00-7:15am, 9:15-9:30am) was relatively consistent from month to month. However, commuter groups 1 and 6 did have users shifting from the early morning to the pre-peak hour and Groups 3 and 5 had increased post-peak travel, likely due to summer coming to an end, not because of the promotion. The groups with the largest decreases in peak hour travel compared to the previous September were Groups 1 and 3, which had larger increases in pre-peak travel as well. While Group 5 appears to have a large response, the group took very few trips in these periods, making its values less reliable. Group 6 did exhibit changes, but not in the expected direction; peak travel increased and pre-peak travel decreased from the previous September. These changes are likely due to unrelated changes to cross-border travel patterns. Group 2 showed no change in September but did reduce its peak travel in October. This suggests another characteristic of this group: they may be dependent on both bus and rail. When its members could no longer take the bus during a period in September, (when demonstrations in Hong Kong disrupted bus services, they switched to rail. Whether because of their typical bus schedules or peak crowding, they were more likely to travel in the pre-peak hour.

The group based analysis of the impact of the Early Bird promotion strategy, provides useful insight into potential improvements targeting specific groups. Commuters are obviously an important target for demand management: they take a large number of trips and seem to have responded to the promotion. Programs that work with major employers could be considered in the future (similar to the Travel Smart program in Singapore). However, Group 3 could also be prioritized since it exhibited relatively large changes and may have more flexibility than the commuters. Emphasizing the reduced crowding and lower likelihood of denied boarding in the pre-peak may be more effective for these users. Though there does seem to be some evidence of Group 5 changing behavior, it may not be worthwhile to target these users. They, as well as Group 4, made few trips and are less likely to live in Hong Kong, making them harder to reach. Considering the casual users of Group 2, a series of inter-modal incentives may be more effective. Finally, Group 6 travelers might be best targeted through promotions specific to the East Rail Line, which serves Shenzhen-bound commuters.

Individual Analysis

The individual analysis uses a panel of passengers who travel through the system before and after the promotion in the periods of interest. It identifies passengers who shift the exit time from the target stations in response to the promotion, and uses them to provide an understanding of the factors that influence their behavior.

A. Customer Panel

By tracking the same individuals before and after the start of the promotion, it is possible to study how the changes seen at the aggregate and group levels relate to the behavior of each customer. Assuming a customer uses the same smart card, his or her system usage can easily be observed over time. This allows the persistence of travel behavior change to be studied over extended periods of time. Furthermore, it also helps control for changes in ridership due to seasonality and exogenous changes in the Hong Kong population.

An initial sample of 20,000 frequent peak hour users was selected from August 2014. These are users who traveled at least 15 times in the peak hour (8:15-9:15) to one of the 29 eligible stations. After excluding those who never traveled in the pre-peak hour (7:15-8:15) during September 2014 and those with travel passes (not charged a fare on trips covered by a pass), a total of 4,591 panel members remained. Hence, the panel focused on frequent, peak hour users who traveled to stations eligible for the discount, ensuring that panel members took enough trips to provide context to trends in their usage. Since the user group analysis showed frequent users to be so dominant and the peak-hour users are the ones targeted by the promotion, better understanding of the factors that influence their response to the promotion can provide useful insight for updating the promotion design. Users who shifted from the early morning to the pre-peak hour or did not previously use MTR were outside the scope of the analysis.

B. Identifying Shifters

To understand the extent of behavior change and the particular factors associated with responding to the promotion, breakpoint detection analysis was used to identify "shifters": users who exhibited a behavior change that could be linked to the promotion (Bai, 1994). Breakpoint detection is a special case of change point analysis, which is used to identify changes in time series. In this case, the focus was changes in mean exit time - did someone's typical exit time change in a way that could be associated with the promotion?

This shifter identification analysis has two parts: individual breakpoint analysis to determine a set of change points for each user; and inference of behavior shift to identify those whose changes corresponded to the promotion.

A time-series dataset was generated for the 4,591 panel members, where each day in the period of analysis was associated with an AM exit time. The setup is as follows:

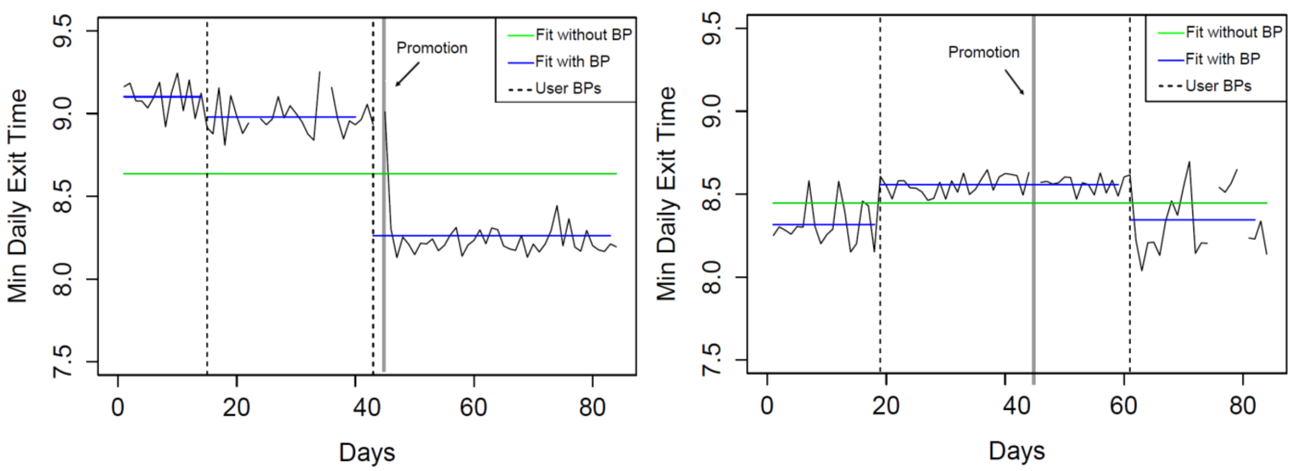
- **Dates:** Weekday data for four months (July-October 2014) were used. Weekends and other unusual days (holidays or days with extreme weather) were excluded.
- **Independent Variable:** Of all the panel member's trips, the ones that could reasonably be shifted to the pre-peak hour were of most interest. "AM Trips" were defined as those that finished before 10:30am (the number of exits was small and relatively constant after 10:30 and shifting departure time by more than two hours for a 25% discount would be unlikely). To deal with users who traveled multiple times each morning, a user's first exit after 7:15 to an eligible station was selected as the data point for each day.

The individual breakpoint analysis was carried out using the breakpoints function in R's strucchange package (Zeileis, Kleiber, Krämer, & Hornik, 2003). The breakpoint analysis segments the time series and fits each segment using ordinary least square regression. Given parameters for minimum segment size (h) and maximum number of breakpoints (m), the method identifies breakpoints in a set of linear regressions. For the change of exit time considered here, a one-dimensional model was used to find the best intercept, or mean of each segment (constant exit time across a series of days):

$$y_{in} = \beta_{0,n}^{j} + \varepsilon_{in} \;\; \left(i = i_{j-1} + 1, \dots, i_j, j = 1,2, \dots, m + 1\right) \tag{2}$$

where y_{in} is the exit time of user n on day i, $\beta_{0,n}^{j}$ the mean exit time of user n in segment j, and ε_{in} the error term. j denotes the segment index and i_j the breakpoint (date) between segments j and $j + 1$.

After experimentation, the minimum segment length h was set at 10 days and the maximum number of breakpoints m at 2 (3 segments). Figure 8 shows an example of results for two individuals, the first of which has a change that may be associated to the promotion (a significant drop of exit time at around the time the promotion begins) and the second of which does not (a slight change of exit time across segments).



(a) (b)

Fig 8. Breakpoint analysis results for two users: (a) Change likely due to promotion and (b) Change may not be associated with promotion

In order to identify the users who may have a change actually associated with the promotion, their breakpoints were compared with the promotion start date and the results of the regression (the mean exit time in each segment) were compared to each other and to the hour of the promotion. Four criteria were used:

- **Date:** The user had a change point between the end of August and middle of September. This wider range captures users who may have not responded to the promotion right at the beginning and accounts for noise in the data.
- **Direction:** The mean exit time at a breakpoint in the specified date range decreased—the user should begin exiting stations earlier in the morning rather than later.
- **Magnitude:** The mean exit time after a change that meets both of the above criteria was before 8:25 (even users who had a fairly strong response to the promotion would not be expected to travel in the pre-peak hour every day).

- **Number of Trips:** After a breakpoint that met all of the above criteria, the user continued to travel and took at least four trips between the breakpoint and the end of October. This better controls for breakpoints that are more due to frequency changes than exit time changes.

Based on these criteria, 794 of the 20,000 panel members were identified as shifters. This corresponds to 3.94% of the panel, which is in line with the aggregate and commuter group findings. The 794 shifters represent 17.3% of the panel of the 4,591 users who had traveled in the pre-peak. The actual reason behind a user's actions cannot be identified from AFC data alone. Some of these users may have lifestyle changes that influenced their travel patterns. The promotion might have also influenced how much they changed their exit times; perhaps without it, users who shifted from 8:30 to 8:10 would have shifted only to 8:20. On the other hand, regardless of the factors that led to this behavior change, these are the users who benefited from the promotion and contributed to system-wide benefits. Future research might consider a panel analysis in conjunction with a survey to have more certainty in user responses and better understand the impacts of external lifestyle characteristics and socio-demographics.

C. Modeling the Panel's Response

A binary logit model was used to estimate the probability of shifting exit time as a function of various explanatory factors. Its coefficients can be used to quantify the panel's demand elasticity with respect to fare savings as well as other marginal effects. The following model specification best explains the shifting behavior.

$$U_{shift,n} = \beta_0 + \beta_1 \text{SAVE} + \beta_2 \text{DT} + \beta_3 \text{SAVE} * \text{DT}_{\text{High}} + \beta_4 \text{SAVE} * \text{DUR}_{\text{High}} + \beta_5 \text{VAR} + \beta_6 \text{DISC} + \varepsilon_{shift,n} \quad (3)$$

$$U_{nonshift,n} = 0 \quad (4)$$

where β_0 is the alternative specific constant, and $\beta_1, \dots, \beta_6$ is a vector of coefficients of the explanatory variables. ε captures the impact of all unobserved factors that affect the person's choice. The explanatory variables are defined as follows:

- *SAVE*: the fare savings associated with pre-peak travel, given the typical fare in August 2014 (fares are distance-based)
- *DT*: displacement time, the amount of time someone would have to shift their departure time earlier, given their median AM exit time in August (the difference between a user's median exit time in August and 8:15, the end of the pre-peak hour)
- DT_{High}: a dummy variable with value 1 if a user's displacement time is larger than 15 minutes
- DUR_{High}: a dummy variable with value 1 if a user's trip duration is larger than 25 minutes
- VAR: standard deviation of someone's departure times of August AM trips. It is used as a proxy for flexibility in departure time
- *DISC*: number of trips by the passengers that received another MTR discount (qualifying bus-to-rail transfers and tapping one's card at one of the "Fare Saver" terminals located in various shopping centers). This variable serves as a proxy for an individual's price sensitivity.

As only AFC data was available for estimating the variables related to the model, socio-demographic characteristics or employment could not be included, though they are likely salient for the shift decision.

The estimation results are summarized in Table 4. The results make sense from a behavioral point of view. As expected, the increase of fare savings increases the probability of users shifting their departure times to take advantage of the discount. The impact of fare savings is not the same for all users. The magnitude of the savings is less important for users who need to shift by more than 15 minutes to receive a discount.

People are less likely to respond to the promotion as trips get longer. This may be because users making long trips do not want to leave even earlier. Longer trips are also less reliable Wood (2015). Furthermore, the socio-economic and employment characteristics of users who live farther away from the city center (trips ending at discounted stations with duration larger than 25 minutes, typically lower-income with less flexible jobs), may also impact their behavior.

Table 4: Model estimation results

Shift Utility	Estimate	t-stat
Intercept	-2.197	-13.780 ***
SAVE	0.138	1.997 *
DT	-1.865	-9.157 ***
$SAVE*DT_{High}$	-0.058	-1.890 *
$SAVE*DUR_{High}$	-0.076	-2.195 *
DISC	0.034	4.681 ***
VAR	1.366	4.593 ***
Log-Likelihood:	-2990.6	
Adjusted McFadden R^2:	0.123	
Likelihood ratio test:	χ^2 = 686.6 (p <2.22e-16)	
No. of observations:	4591	

*Note: ***: p(t)<0.001; **: p(t)<0.01; *: p(t)<0.05*

The variables have the expected sign, and all are significant at the $\alpha = 0.05$ level. The constant is negative, reflecting a disinclination to change behavior. As expected, displacement time variable is very important and has a negative coefficient. Users who have more variability in their travel times were more likely to shift. This could mean that different incentives are needed to influence users with strict routines, and could also imply the importance of flexible work hours policies to complement such PTDM strategies. Users who target and receive other discounts are also more likely to shift. Most users who received these discounts were using the MTR "Fare Saver" terminals (a HK$2 discount for tapping the card at specified locations throughout the city) rather than a qualifying bus-to-rail transfer, which implies that users who are more price sensitive and discount seeking are more likely to also take advantage of this incentive. The interaction terms indicate that people were much more elastic to fare savings when they traveled close to the end of the eligible period (low displacement time) and with low trip durations. And people tend to be not elastic with respect to fare savings when they have long trips and high displacement times.

3.4 Monitoring

AFC data facilitate the monitoring of a PTDM strategy and the assessment of its effectiveness over time. As mentioned in the introduction, the concern is that the promotion incentivizes passengers only temporarily and after some time they return to their previous behavior. The number of shifters who identified in the previous sections and who continued using the system consistently (regardless of the time period they travel) in the following 24 months were used as the panel for the longitudinal analysis to monitor their behavior over time.

Sustained shifters are those early shifters who maintain their behavioral change and keep traveling in the promotion time period. Figure 9 shows the sustainable shifters as a percentage of the initial shifters who continue to use the system the period October 2014 to October 2016. There is a decreasing trend with about 65% early shifters sustaining their travel behavior after two years. Most early shifters sustain their behavior for the first two months after the promotion (October and November) but there is a sharp decrease at the third month. After that, the decreasing trend becomes more stable. The large drop in July and August in 2015 and 2016 is probably related to the summer vacation period.

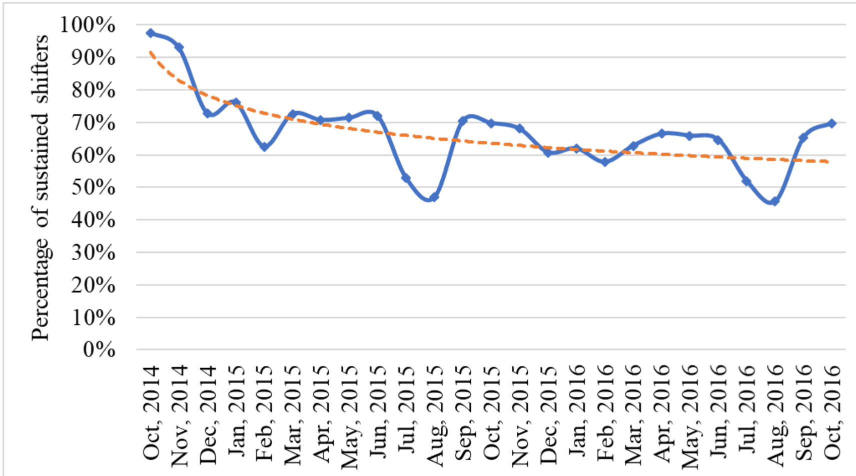


Fig 9. Percentage of sustained shifters by month

The results highlight the need for continues motoring of a strategy and occasional refinements to maintain the public's interest in the program and avoid the "hedonic treadmill" effects (Brickman & Campbell, 1971).

4. DISCUSSION

The results from the case study inform several ways that an agency can improve upon simple fare discount schemes. The suggestions listed below can account for different user characteristics by targeting certain groups or by easing constraints that users may have in time-shifting. An agency may choose to target a group or not, but could also target different groups with different degrees of intervention. The feasibility of these interventions depends on the customers' attitudes towards complexity, partnership opportunities, as well as fiscal implications.

- **Pricing Structure:** The discount could be structured more like a rebate, providing a single, large payout over a period of time (e.g. weekly). This may attract users who overlook small, regular discounts by accentuating aggregate savings. Another option is to introduce a lottery policy instead of a guaranteed pay-out. By making users register to have a chance at winning, only those who are more price-sensitive or interested in participating will enter, meaning fewer people who do not change their behavior are rewarded. Requiring enrollment allows the agency to give users higher rewards or a higher likelihood of winning, particularly if it is willing to pay out the same amount as in a user-wide fare differential scheme.
- **Pricing Basis:** Rather than providing a discount based only on the exit station, a promotion could target OD pairs, particular links, or alternative routes. These options better manage uncertainty with travel time, in-vehicle congestion, or the need to change one's departure time, respectively. Discounting travel on less-crowded routes can balance demand across the network and improve capacity utilization. The integration of smartphone and location services with public transport payment enables the deployment of such route-based strategies.
- **Targeted Customer Information:** Providing more individualized information will help users make better travel decisions, conveying the benefits of off-peak travel that best match their needs.

Possible strategies include station- or user-specific marketing, or enabling online journey planners, to display time-specific fares and crowding data. Users could also be given specific travel tips through a personalized page on the agency's website (possibly using insights from the group the user belongs to or how the user's characteristics relate to the factors analyzed in a panel analysis).

Demand interventions are quicker and more cost efficient than adding capacity with new infrastructure, but in the context of public transport, are often seen as transient solutions to use until those additions are made. However, when service is added, it may be complemented by PTDM policies, giving agencies a larger set of tools to find solutions that best meet their congestion and business needs.

5. CONCLUSION

The paper presents a framework for the design and evaluation of demand management strategies for public transport systems. Recognizing the demand patterns associated with crowding and the context in which policies are implemented can help design more relevant policy interventions, especially when decision-makers link this insight to the various design parameters. Evaluation and monitoring that do not just consider aggregate changes in demand, but also analyze passenger response in more detail, are beneficial and guide future refinements of the program. AFC data is a valuable source for this evaluation. It allows demand patterns to be studied at a much finer level than past data sources. Compared to aggregate data analysis, clustering and panel analyses provide better insight into user responses to a policy, and unlike survey data, they can be performed on a large scale.

The evaluation component was verified in a case study using data from a congested system. The results show that the pricing incentive was effective in shifting users out of the peak period, causing a temporal redistribution of demand. Analyzing the changes in demand patterns over all users showed that the Early Bird Promotion did make a difference, though perhaps not enough to reverse the effects of exogenous ridership growth. More disaggregate analysis suggests that attention should be given to the commuter and intermittent users. These groups take a sizable number of the trips targeted by the promotion and seemed amenable to fare differentials. Other groups take too few trips to be a priority or seem to require other types of incentives to travel outside the peak. The panel analysis further suggests that the design may need adjustments to account for users' strong opposition to changing their departure time. Increasing users' flexibility in when they travel, improving inter-modal transfers, and better targeting users who are price-sensitive are interesting ways to improve effectiveness. In addition, monitoring through the longitudinal analysis can inform the potential for long term interventions.

The shifter identification analysis relies on smart card data to associate the behavior change to the promotion design. Future research considering a panel analysis in conjunction with a survey will have more certainty in user response and better control other factors, such as lifestyle characteristics and socio-demographics. The extend of the change can also be modeled in more detail. A sequential choice model for example, can be used to model at the first level the decision to shift or not and at the second level the % of trips that shifted (Ben-Akiva, Lerman, & Lerman, 1985).

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A Halvorsen: Literature search and review, Experiment design, Analysis, Modeling, Manuscript writing; HN Koutsopoulos: Content planning, Analysis, Modeling, Manuscript writing; Z Ma: Analysis, Modeling, Manuscript writing and editing; J Zhao: Content planning, Analysis, Manuscript writing.

CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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