

Reducing Subway Crowding

Analysis of an Off-Peak Discount Experiment in Hong Kong

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Increases in ridership are outpacing capacity expansions in several transit systems. By shifting their focus to demand management, agencies can instead influence how customers use the system and get more out of their present capacity. This paper uses Hong Kong's Mass Transit Railway (MTR) system as a case study to explore the effects of crowding reduction strategies and how to use fare data to support these measures. The MTR system introduced a discount in September 2014 to encourage users to travel before the peak and reduce onboard crowding. To understand the impacts of this intervention, first, existing congestion patterns were reviewed and a clustering analysis was used to reveal typical travel patterns among users. Then, changes to users' departure times were studied at three levels to evaluate the promotion's effects. Patterns of all users were measured across both the whole system and for specific rail segments. The travel patterns of the user groups, who have more homogeneous usage characteristics, were also evaluated and revealed groups who had differing responses to the promotion. The incentive was found to have affected morning travel, particularly at the beginning of the peak hour period and among users with commuter-like behavior. Aggregate and group-specific elasticities were developed to inform future promotions and the results were also used to suggest other potential incentive designs.

With some public transportation systems now facing significant crowding, transit agencies are showing increased interest in the traditionally car-oriented concept of travel demand management (TDM). TDM policies encourage demand to spread more evenly throughout the network or over the day and allow agencies to make better use of their resources and improve their customers' experiences. In many cases, demand management policies are also quicker and less expensive than adding capacity with new vehicles or rail infrastructure (1), though the TDM concept can also be used in conjunction with such additions. In use since the 1970s for controlling automobile traffic (2), TDM's applications to public transportation are still emerging and more research, particularly using real-world applications, can help understand its effects.

As one of the world's most densely populated cities, Hong Kong is one place where transit demand management has begun to be explored

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Transportation Research Record: Journal of the Transportation Research Board, No. 2544, Transportation Research Board, Washington, D.C., 2016, pp. 38–46. DOI: 10.3141/2544-05

in more depth. Its citizens are overwhelmingly dependent on public transportation, with 81% of nonwalk trips on this mode (3). The backbone of the city's transit services is the Mass Transit Railway (MTR) system's urban rail network, which facilitates nearly 1.8 billion trips per year (4). Although MTR is often lauded for its operational performance, concerns about crowding and congestion have been increasing in recent years among the public, the Hong Kong government, and the agency itself. The MTR system is in the midst of building several network expansions and continues to make operational improvements when possible. However, it is also seriously considering policies that aim to shift demand patterns instead.

One of those policies, the Early Bird Discount Promotion, provides a strong case study for demand management in the public transportation context. There are relatively few transit TDM program evaluations in the literature, particularly when compared with road traffic, so a comprehensive analysis of this case can aid the development and evaluation of future programs. In particular, typical interventions in transit, such as fare differentials or mass marketing, can be highly inefficient with respect to the number of people they target versus how many actually respond. Therefore, this research investigated ways to segment users into more homogeneous groups and differentiate between them in policy evaluation and design.

To carry out such goals, new methods for using automatically collected data for demand management were also explored. Automatic fare collection (AFC) systems are particularly promising for demand management purposes. AFC systems not only support the study of aggregate trends of when and where users travel, but also allow long-term travel patterns of specific user groups or even individuals to be monitored. By more accurately characterizing demand conditions, policy makers can design more relevant and effective TDM strategies and perform more comprehensive evaluations.

The primary objectives of this paper are to understand the effects of the MTR promotion and the lessons it might provide for future promotions in Hong Kong or elsewhere. After a review of transit-focused TDM research in the next section, the analysis is in three parts. The second section describes the system's preintervention demand patterns and user characteristics, the third section evaluates the impacts of the intervention, and the fourth section builds off of this evaluation to develop fare elasticities to use for future design. A discussion of results concludes the paper.

LITERATURE REVIEW

The term "travel demand management" is used to describe strategies that increase transportation system efficiency by altering demand patterns, rather than increasing the supply of service (2). For road traffic, measures have often included physical changes such

as improvements to pedestrian and bicycling facilities, legal policies such as parking regulations, economic or pricing policies, and information and marketing campaigns (5). Many of these traditional measures, however, are irrelevant in the context of public transit. The study by Faber Maunsell distinguishes between traffic and transit TDM by noting that mode shift is less desirable for transit than road traffic, trip purposes tend to be less varied on transit, transit users are constrained by service schedules, and transit users often experience only reduced crowding when they travel off-peak, while drivers are more likely to also have lower travel times, fuel costs, and stress levels (6). For a more detailed study of demand management in public transportation, a paper by Halvorsen draws on additional academic literature to develop a framework for the design and evaluation of these programs and furthers the analysis of this MTR case study (7).

The impact of cost on travel behavior is well studied, including its use in TDM and its impact on transit use. Road and parking pricing are regularly cited as TDM measures; higher prices for vehicle use are one of the most effective measures (8). Cervero performed an extensive review of transit pricing literature and found that flat fares penalize off-peak users and off-peak discounts have been successful (9). In recent years, rail and transit agencies have begun to explore TDM for their services, by engaging consultants and researchers to study their options. A survey commissioned by Passenger Focus (a United Kingdom rail passenger watchdog) found that more than 40% of commuter rail riders could arrive outside of the peak, with almost all preferring to arrive earlier (10). Factors found to affect time shifting included work flexibility; trip length, with those traveling farther being less inclined to travel earlier; and the season, with people less willing to travel earlier in darker fall and winter months (6, 10). In the Passenger Focus survey, more than half of the respondents said that reducing fares by 25% to 30% could encourage them to travel earlier. Several researchers have developed models to simulate travel choices with fare differentials (11, 12). For the Sydney, Australia, rail case studied by Douglas et al., the most effective combination was a 30% discount in the peak shoulders and a 30% surcharge in the peak, forecasted to reduce peak loading by 10% (12). However, both Whelan and Johnson (11) and Fearnley (13) note the unpopularity of increasing peak fares and the possibility that increased fares drive people to car travel instead.

Several cities have actually implemented TDM strategies in their transit systems. The Washington, D.C., Metropolitan Area Transit Authority (WMATA) system has always had peak pricing, but added peak-of-the-peak surcharges from 2010 to 2012 (14). Transport for London also uses peak surcharges, but extended its demand management efforts following positive experiences with TDM during the 2012 Olympics (including employer programs and public information campaigns) (15). Several agencies offer crowding information to help users avoid congestion when planning trips, including BART in the San Francisco Bay Area in California (from historical data) and JR East in Tokyo (real time). In an overview of rail demand management policies, Henn et al. concluded that combining different types of measures; targeting measures to particular users groups, locations, and times of day; and integrating policies among transit providers and modes can make programs more effective (16). They found the most effective interventions to include increasing transparency about peak conditions (through more detailed customer information) and reducing shoulder fares.

Programs in Melbourne, Australia; Singapore; and Hong Kong have been given more attention by researchers. Currie provides a case study of Melbourne's Free Before 7 campaign (which made rail trips before 7:00 a.m. free) (17, 18). Through a rider survey, he found that 23% of

travelers before 7:00 a.m. had shifted from the peak, by an average of 42 min, and 10% started using rail because of the discount. Ridership data showed loads increased by 41% in this period. Reasons given for traveling before 7:00 a.m. included saving money (66%), traveling then anyway (33%), and for less crowded trains (13%). Given the increases in early morning trips, Currie found that the program led to enough savings in capital and operating costs to cover its costs (17, 18). The system still showed ridership growth, however, so the policy likely slowed overcrowding rather than actually reducing it.

Singapore's vehicle policies are well studied, but its Land Transport Authority has also implemented policies for transit overcrowding since 1997. The current program includes fare differentials, including free fares before 7:45 a.m. in parts of the network; a rewards program that offers bonus points for travel in the peak shoulders (redeemable for smart card value or lottery entries); and an employer program to support company-specific TDM policies (19). As a result of those schemes, Singapore's MRT urban rail has experienced a 6% to 7% decrease in trips between 8:00 and 9:00 a.m., with the peak to prepeak trip ratio declining from 2.7 to 2.1. The effects were slightly greater among participants of the Travel Smart Rewards program; 7.5% of these users' trips shifted from the peak period to the off-peak period (20). Reward program members who traveled in the peak shoulders even before the discount, who benefited with no behavior change, still made a difference by convincing friends to participate and by driving the competition for points among their social network.

The MTR system itself has used fare differentials in the past. Staggered hours discounts, which began in 1990, used both time period and route choice dimensions:

- A peak surcharge and off-peak discount for trips over the congested central harbor crossing and
- The same discount for peak trips that used the newly built Tseung Kwan O (eastern) crossing instead.

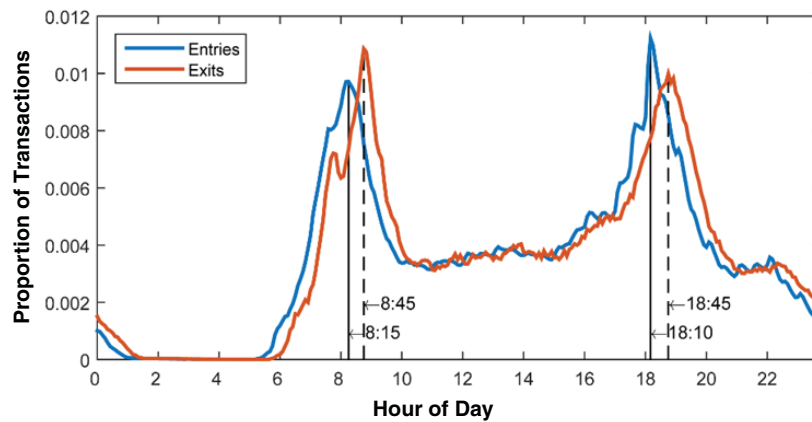
Li and Wong investigated user response to the route choice aspect through user surveys and discrete choice models (21). They found that wealthier users, users with professional jobs, and users who regularly used the surcharged route were less likely to have shifted to the eastern crossing. However, their model's trip length coefficient led them to conclude that the pricing policy was not particularly successful and making the eastern crossing's transfer quicker could be more effective. Ultimately, this program was completely repealed in 1999 with the opening of the Tung Chung harbor crossing (22). The Early Bird Discount Promotion is the latest attempt at a major TDM program.

MTR CASE

With several MTR segments exceeding loading standards in the a.m. peak (23), the agency introduced the Early Bird Discount Promotion. This fare differential strategy offers a 25% discount for trips to 29 heavy rail stations (Figure 1a) that end in the prepeak hour of 7:15 to 8:15 a.m. Given the system's distance-based fares, this discount corresponds to about HK\$1 to \$12 (HK\$1.00 = US\$0.13 in March 2015). Though onboard congestion motivated the promotion, it was more practical to link the discount to particular stations; MTR staff found that 80% of the trips that traveled over a congested link ended at these stations. Only users of adult fare cards, who receive no other concessions, are eligible for the discount. The promotion began on September 1, 2014, and initially ran for a trial period of



(a)



(b)

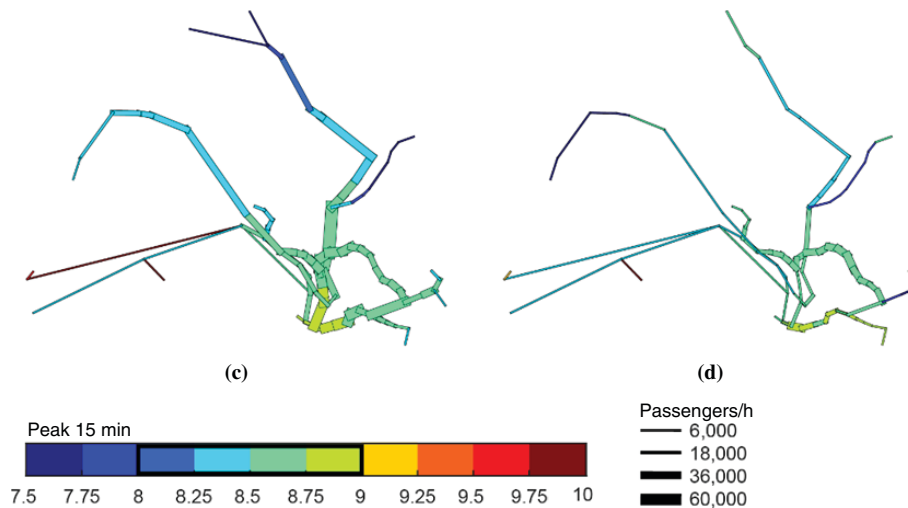


FIGURE 1 Predemand management usage patterns: (a) stations eligible for Early Bird Promotion, (b) systemwide entry and exit transaction distributions, and peak hour demand and peak 15 min of each link for (c) down direction (south or west) and (d) up direction (north or east) (stns. = stations).

9 months. Internal goals were to shift about 3% of peak hour trips to the prepeak hour. Figure 1, *b* and *c*, uses AFC transaction data to illustrate some of the congestion patterns that led to this design. Figure 1*b* shows the proportion of entries and exits that happened in each 5-min interval of an average weekday in September 2013, with the peaks of each marked. Spikes reach similar levels in the morning and evening peaks, though demand grows more slowly and is elevated for a longer time in the afternoon. The peak 5 min of entries is about ½ h before the peak of exits in the morning and evening. The pattern is the same for the peak hour of demand: in the morning it is 7:45 to 8:45 for entries and 8:20 to 9:20 for exits, and in the afternoon, 17:50 to 18:50 for entries and 18:20 to 19:20 for exits. MTR's policy, which runs from 7:15 to 8:15, does then roughly align with the prepeak hour of exits.

Figure 1*c* uses link flow data (generated with AFC records) to show link-specific demand patterns in the a.m. peak period. The width of each link corresponds to the passenger flow in the a.m. hour with the highest flow systemwide (8:00–9:00). The most crowded link, which operates above capacity, is on the East Rail Line from Tai Wai to Kowloon Tong in the “down” (south) direction. There are also high levels of crowding down the Tsuen Wan and Tseung Kwan O Lines into the central business district (i.e., the areas covered by the promotion). The color of each link marks the 15-min period in which it actually has its highest passenger flows. The downward movement of passengers is evident; the peaks near the central district are later than those farther north. The links in Hong Kong's urban core peak 15 to 45 min after the end of the prepeak hour, meaning that users were required to shift their exit times by at least that much to get a discount.

Additional insight about such aggregate demand patterns can be gained by delving deeper into the usage of individual customers. A clustering analysis allowed the patterns to be broken down into the contributions of different user types and was subsequently used for a group-level analysis of the promotion's effects. A sample of about 400,000 user IDs were selected from September and October 2013 for the analysis, or about 4% of all IDs seen during the period. Their trip records were converted into a number of usage characteristics:

1. Frequency characteristics:
 - Range of travel (number of days between first and last trip),
 - Number of weekdays and weekends traveled,
 - Number of weekday and weekend trips,
 - Number of gaps in travel, and
 - Average, minimum, and maximum gap lengths.
2. Temporal characteristics:
 - Median start time for first trip of day, weekday, and weekend;
 - Median start time for last trip of day, weekday, and weekend;
 and
 - Number of days started within 30 min of median start time.
3. Spatial characteristics
 - Number of distinct first and last origin stations,
 - Number of distinct origins–destinations traveled, and
 - Number of days with first trip at Chinese border crossing.

These travel characteristics were used to cluster users by using the *k*-means method. In *k*-means, objects are partitioned into groups so that each object is assigned to the group with the nearest mean, thus minimizing the distance between points and their clusters' center (24). The number of clusters, *k*, must be set by the analyst through the use of various evaluation criteria, as well as any prior knowledge of potential groups and interpretability. Because several of the travel

characteristics above showed correlation, they were first converted to variables better suited to clustering by using principal component analysis (25). The first six components that resulted from this analysis encompassed 85% of the data variability and had meaningful relationships to the original characteristics (1 = amount of travel; 2 = gaps in travel; 3–5 = typical travel time; and 6 = border crossing travel), so they were used as the clustering variables. Several values for *k* were tested, and the value 6 was determined to be the preferred level on the basis of clustering evaluation statistics and interpretability. This methodology is further detailed by Halvorsen (7).

The six general behavior types found among MTR customers are as follows:

1. Hong Kong commuters. With a range of almost the whole period (their travel spanned an average of 59 of the 61 days in the period) and the most frequent travel, these are MTR's heaviest users. They also take most of their trips during the a.m. and p.m. peak periods, 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. They may use MTR in conjunction with other modes or only for noncommute trips.

3. Intermittent Hong Kong users. With a moderate range, these users travel less frequently than the previous two groups and even less in the a.m. peak period. They could be Hong Kong users who primarily rely on other modes, but also users who switch between several smart cards.

4. Short-term users. Largely characterized by a short range, this group most likely includes tourists visiting Hong Kong for a few days. It could also include locals who use cards for only a few days of MTR trips.

5. Occasional cross-border travelers. Though somewhat similar to Group 3, these users travel even less frequently and less widely throughout the network, by starting more days at a border crossing station. This group likely includes the visitors who come to Hong Kong once or twice a month from the mainland.

6. Cross-border commuters. This group shows many of the characteristics associated with commuters, but its members start most of their days at a border-crossing station from mainland China.

The group means for several key characteristics are listed in Table 1, and a figure detailing their temporal patterns is in Figure 2. These contour plots show when each group typically takes their first and last trips of the day. Contours that are bright yellow represent more common combinations among the group's members. Tighter contours imply that most of the groups' members travel around the same time, while larger contours suggest more variability; people who take their first trip at a given time do not also take their last trip at similar times. The commuting patterns of Group 1 are clear; nearly all its members take their first trips of the day between 6:30 and 10:00 (*x*-axis), and their last trips between 16:00 and 21:00 (*y*-axis), with the most common combination being 8:15 and 18:15. There are similar, though less concentrated, commuting patterns in Group 6, which also has some users who travel only in the afternoon (the contour centering around 14:00 and 17:00). Groups 2 and 3 have more members who travel only in the afternoon and evening. There is greater spread among touristic Groups 4 and 5, with Group 4 typically traveling later at night, perhaps because they are more likely to be staying in Hong Kong than returning to the Chinese border.

TABLE 1 Group Means for Selected Characteristics

Characteristic	Means by Group					
	1	2	3	4	5	6
Percentage of users	14.1	17.1	27.3	35.8	5.4	0.4
Percentage of trips	52.8	27.1	12.6	5.5	1.0	1.1
Percentage of a.m. trips	80.0	11.8	5.1	2.0	0.3	0.6
Range (days)	59.47	55.36	40.48	3.09	37.71	57.3
Weekdays traveled	37.65	17.84	5.19	1.43	1.7	30.34
Weekends traveled	10.09	6.53	2.37	0.65	0.98	7.32
Avg. trips or days in range	1.67	0.76	0.3	1.32	0.13	1.39
Weekday median first start	9:12	14:21	13:11	12:48	12:51	10:34
Weekday median last start	17:53	17:36	15:38	16:25	15:38	17:41
Avg. gap (days)	1.56	2.97	8.54	0.69	29.25	2.1
Distinct O-Ds	22.37	20.15	7.28	3.48	3.98	13.51
Percentage of days from China	0.7	2.98	9.81	23.76	21.17	85.85

NOTE: O-D = origin–destination.

EVALUATION

The evaluation focused on how the Early Bird Promotion affected the time when MTR customers chose to travel. The AFC data used for analysis provides detailed records of changes to system use, but the data are not enough for in-depth evaluation of other dimensions, such as cost efficiency or user perceptions of the program.

An aggregate evaluation was performed at systemwide and link levels, and systemwide changes were also studied for the user groups identified in the previous section. Studying users in aggregate, which may be the only option for some agencies, is useful from an operational perspective because it is most directly related to service quality and the typical user experience. On the contrary, disaggregating customers by their usage characteristics can give a sense of which types of users actually responded to the promotion. It can also inform an agency how it might better target its future policies.

Throughout the analysis, it was important to recognize several confounding effects. The first two are common among all before-and-after analyses: seasonality and year-on-year ridership changes. Therefore, to uncover patterns that might be obscured if only absolute numbers of trips were considered, most analysis was done on a relative basis. The a.m. commuting period was defined as 7:00 to 9:30 a.m. to encompass the MTR-defined prepeak hour (7:15–8:15) and peak hour (8:15–9:15), plus 15 min on either side. Comparing the percentage of a.m. trips that took place in subsets of this period revealed whether the promotion spurred any changes in the distribution of exit times. A final factor, unique to this context, was Hong Kong’s Umbrella Movement, which lasted from the end of September 2014 to December 2014. These protests disrupted bus services and caused dramatic ridership increases on the MTR. This increase made longer-term impacts of the Early Bird Promotion challenging to investigate, so the scope of this analysis was largely limited to the first month.

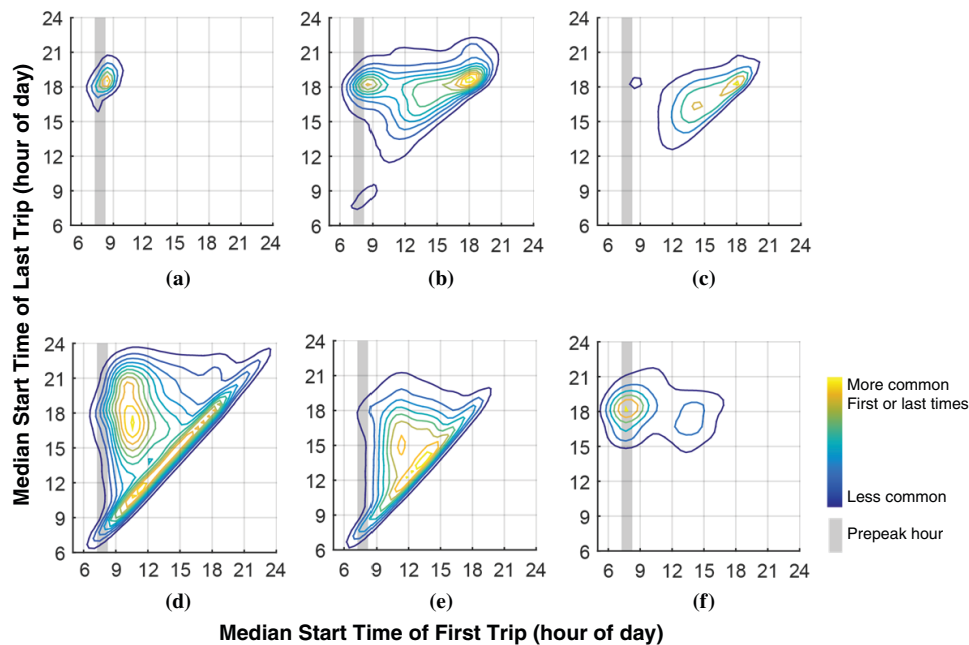


FIGURE 2 Distributions of median start times of first and last weekday trips for (a) Group 1, (b) Group 2, (c) Group 3, (d) Group 4, (e) Group 5, and (f) Group 6.

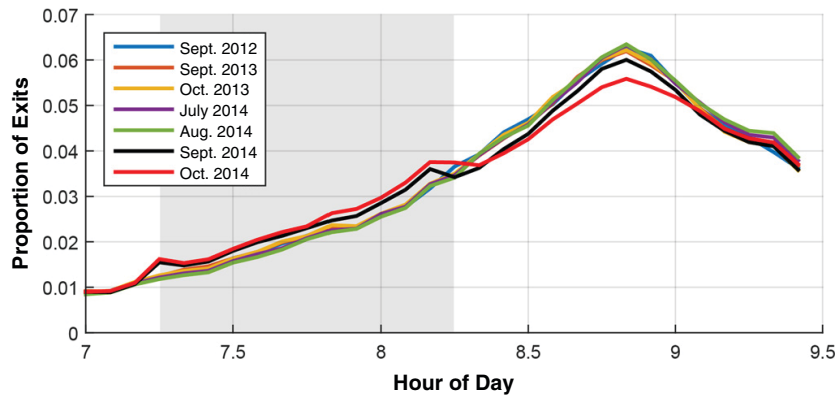


FIGURE 3 Morning exit time distribution for adult cards at early bird-eligible stations (with 5-min intervals).

Systemwide

The exit time distributions of eligible trips (adult cards to one of the 29 covered stations) are shown in Figure 3 for several past months. All the months before the promotion follow a tight band, but this pattern changes in September 2014. The proportion of trips is higher in the prepeak period and lower in the peak period. There are also small spikes at either end of the promotional period: early morning travelers waiting to exit at 7:15 and peak hour users shifting just enough to exit before 8:15. October 2014 is shown to demonstrate the protests’ effects; the shift toward the prepeak period is more extreme, though there were actually about 12% more trips in the peak hour compared with September 2014.

The differences among eligible trips are further quantified at the top of Table 2, which lists how the percentage of trips in the prepeak

hour (7:15–8:15) and peak hour (8:15–9:15) compare over all users. The values are the percentage of a.m. trips that shifted into or out of the particular hour. September 2014 is distinct from prior months, with 2.5% of trips shifting out of the peak (corresponding to a 3% decrease since about 60% of a.m. trips take place in the hour). About 3% of the a.m. trips shifted into the prepeak hour because some users also shifted from the early morning period.

Among trips that would not have been eligible for the discount, either to noneligible stations or by nonadult fare cards, there were negligible changes. Though these trips are not a perfect control group, this finding does help rule out any overall changes in ridership and supports conclusions about the promotion’s effects. The proportion of those trips in the prepeak hour was nearly constant from September 2013 to 2014, increasing only from 41.9% to 42.1%. This finding also means that the promotion’s effects are diluted when all stations

TABLE 2 Percentage of Travel in Prepeak and Peak Hours by Group

Travel Characteristic	Prepeak Hour (7:15–8:15) by Month (%)			Peak Hour (8:15–9:15) by Month (%)		
	Sept. 2014	Sept. 2013	Aug. 2014	Sept. 2014	Sept. 2013	Aug. 2014
All users						
a.m. travel (%)	27.5	24.9	23.9	57.9	60.0	60.6
Sept. 2014 change	na	2.6	3.6	na	-2.2	-2.8
Group 1						
a.m. travel (%)	27.7	25.0	24.5	58.2	60.5	60.9
Sept. 2014 change	na	2.7	3.1	na	-2.4	-2.8
Group 2						
a.m. travel (%)	21.8	22.0	21.5	60.5	60.4	60.4
Sept. 2014 change	na	-0.2	0.4	na	0.1	0.1
Group 3						
a.m. travel (%)	28.2	26.3	25.5	54.0	56.4	57.5
Sept. 2014 change	na	1.9	2.7	na	-2.4	-3.5
Group 4						
a.m. travel (%)	23.9	22.3	21.8	57.0	57.9	56.9
Sept. 2014 change	na	1.6	2.2	na	-0.8	0.1
Group 5						
a.m. travel (%)	23.3	19.7	22.8	54.8	60.9	59.5
Sept. 2014 change	na	3.5	0.5	na	-6.1	-4.7
Group 6						
a.m. travel (%)	35.1	37.3	33.8	54.2	51.6	51.6
Sept. 2014 change	na	-2.2	1.4	na	2.6	2.6

NOTE: na = not applicable.

and fare types are included. There is a prepeak exit increase of only 1.4% and peak trip decrease of 1.3% among all cards to any station in September 2014 compared with September 2013 or September 2012. MTR must recognize this discrepancy as it designs and sets expectations for its TDM measures.

In addition, as shown in the 5-min distributions in Figure 3, the peak-of-the-peak experienced a smaller decrease than did the first 15 min of the peak hour. Although the MTR system is judged on hourly capacity standards, more discrete periods better describe how customers actually experience the system at different times of day. This fact suggests that a different policy design may be necessary to really target peak crowding, since most people do not seem willing to shift more than 30 min for just a 25% discount.

Links

Because overcapacity links were the impetus for this policy, they were chosen for a more spatially detailed analysis. Again relative values were considered, but the absolute number of trips was also used for comparison to loading standards.

Figure 4 shows how the percentage of a.m. loads in each hour changed from September 2012 (detailed 2013 data were not available) to September 2014 on each link in the down direction (i.e., south, or west for the Island Line). The proportions for each hour were calculated against the total number of trips that pass over the link between 7:00 and 9:30 a.m., accounting for users of all fare types. The color indicates both the magnitude and direction of change: redder links saw increases, greener ones saw decreases, and darker ones saw minimal change. The width of each segment also reflects the magnitude, with wider links having larger changes. The figure shows that the promotion had the desired impact, with more flows increasing in the prepeak hour and more flows decreasing in the peak hour. In particular, the areas that were more congested saw relief, such as along the Island Line, Nathan Road Corridor, and harbor crossings. The magnitudes are on the low end of the targeted changes but are in line with the systemwide changes.

The MTR system and the Hong Kong government have monitored passenger flows with the absolute train loads on key links (23, 26). By using the lines' peak hour (8:15–9:15) frequencies

and train capacities based on MTR's loading standards (now four people/m²), they calculate the ratio of load to capacity for the most crowded link of each line.

These ratios ranged from 0.8 (loading = 80% of capacity) to 1.04 on different lines. Though the Tung Chung and Tseung Kwan O Lines showed decreases (from 0.8 to 0.84 and 1.01 to 0.98, respectively), most lines were relatively constant. However, this metric fails to account for MTR's ridership growth (about 4% annually in recent years). By reporting only peak hour flows, no consideration is given to changes in the distribution of loads over the morning (observed in the relative analysis). Since most peak hour ratios were flat, the promotion could have helped avoid further peak congestion by encouraging growth to occur in the prepeak hour. The largest increase was on the West Rail Line (1.00 to 1.04), which was not prioritized by the spatial coverage of the Early Bird Promotion. More detailed study of this line's users and their specific travel patterns (where they travel, trip durations, integration with other modes, etc.) could help develop policies for it.

User Groups

The same clustering methodology from the MTR case section was used for this analysis; however, separate samples were taken from September to October 2013, July to August 2014, and September to October 2014 to ensure that groups with short ranges were represented in all periods. Each set of clusters showed similar characteristics to those described in the MTR case section.

Among trips taken between 7:00 and 9:30 a.m. to eligible stations, the commuter group (Group 1) takes 80% of trips, with the other Hong Kong-based groups taking nonnegligible 12% (Group 2) and 5% (Group 3). Combined, the remaining groups take only 3%, either because they tend not to travel so early (Groups 4 and 5) or do not travel to eligible stations (Group 6). Though there is local concern about tourists causing crowding on MTR (27), in the a.m. peak period it seems that MTR should direct its policies toward locals, and commuters in particular.

The groups also differed in how they responded to the promotion as shown in Table 2. The groups with the largest decreases in peak hour travel compared with the previous September are Groups 1, 3,

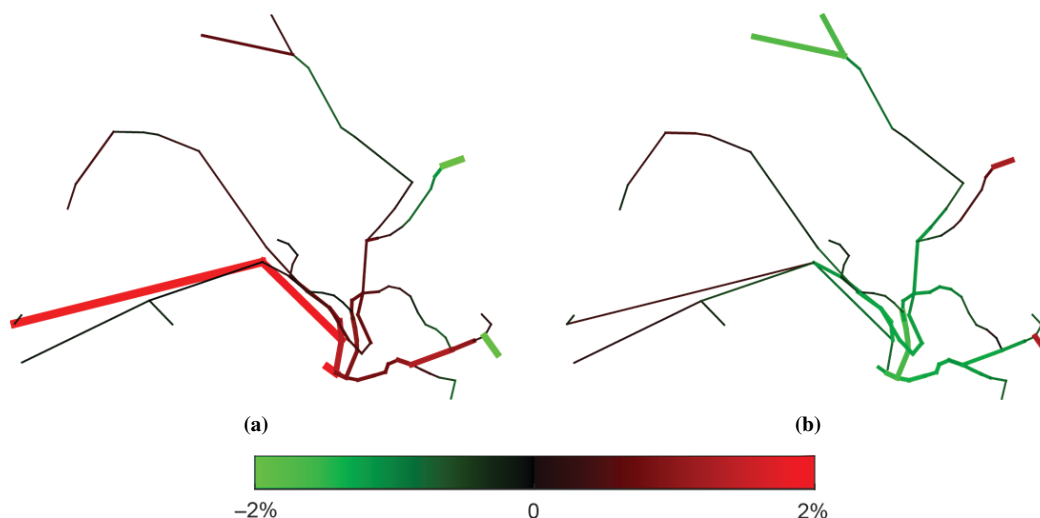


FIGURE 4 Change to passenger flows on each link from September 2012 to September 2014 (downward direction) for (a) prepeak hour and (b) peak hour.

and 5, though the results for Group 5 are based on so few trips that they are not particularly reliable. These groups have larger increases in prepeak travel as well.

If the MTR system continues this type of program, commuters are obviously important; they take many trips and seem to be responding to the fare differential. Perhaps employer programs, such as Singapore's, could raise rates even further. However, Group 3 could also be relevant since it exhibited relatively large changes and may have more flexibility than commuters. Emphasizing reduced crowding and lower denied boarding rates in the prepeak may be effective for these more intermittent users. Conversely, MTR may need other types of incentives to influence the behavior of Group 2. This group did show significant shifts when protests began in October, so it may be dependent on both the MTR and bus. Intermodal or otherwise integrated incentives might be useful to shift their behavior.

FARE ELASTICITY

By furthering the systemwide evaluation, elasticities for user response to the fare differential can be calculated. However, the demand changes from the promotion are not a pure elasticity. For many users, the discount is only available alongside a change in departure time, and there were not enough data to develop a demand model that controls for this availability in this work. Therefore, the elasticities presented here are better represented as elasticities of proportions than of demand. They capture the fact that demand changes could be from existing users shifting between the peak and prepeak hours as well as from new customers in the prepeak hour, without distinguishing between these types of new trips. The elasticities were calculated by using the midpoint formulation:

Midpoint elasticity:

$$E = \frac{(Q - Q_0)(P + P_0)}{(Q - Q_0)(P - P_0)}$$

where P_0 and Q_0 are the fare and demand, respectively, before the fare change, and P and Q are the fare and demand afterward, respectively. Fare was calculated as the average adult fare for a.m. trips to early bird-eligible stations in a particular month (excluding free fare trips and trips that received other discounts). The demand proportions in each period were calculated with the following formula:

$$\% \text{ demand} = \frac{\text{avg. trips}_i^j}{\text{avg. trips}_{7:00}^{9:00}} * 100\%$$

where avg. trips_i^j is the average number of trips per day between i and j for a particular month, with $i = 7:15$ and $j = 8:15$ for the prepeak period and $i = 8:15$ and $j = 9:15$ for the peak period. The base period is kept from 7:00 to 9:30 a.m. Extending this period later introduces more seasonality differences, while very few trips are completed before 7:00.

July 2014 was used as a basis for comparison to avoid the larger seasonal differences that are seen in August and the annual fare increases that occurred in June 2014. For the Early Bird Promotion, both own-price elasticities and cross-elasticities can be calculated. The own-price elasticities measure how fare changes in the prepeak hour affect demand in the prepeak hour, while the cross-elasticities measure how prepeak fare changes affect peak demand.

The elasticities over all users in Table 3 are in line with those found elsewhere: typically -0.1 to -0.2 in the peak hour and -0.3

TABLE 3 Midpoint Elasticities for All Users and Specific User Groups

Characteristic	Prepeak Own-Price Elasticity		Peak Cross-Elasticity	
	July 2014	Sept. 2014	July 2014	Sept. 2014
All users				
a.m. demand (%)	24.2	27.5	60.4	57.8
Avg. prepeak fare ^a	9.60	7.01	9.60	7.01
Elasticity		-0.40		0.14
Group 1				
a.m. demand (%)	24.0	27.1	61.8	59.1
Avg. prepeak fare ^a	9.05	6.73	9.05	6.73
Elasticity		-0.42		0.15
Group 2				
a.m. demand (%)	22.2	21.8	60.2	60.8
Avg. prepeak fare ^a	9.84	7.25	9.84	7.25
Elasticity		0.06		-0.03
Group 3				
a.m. demand (%)	25.5	27.6	57.8	55.1
Avg. prepeak fare ^a	10.17	7.52	10.17	7.52
Elasticity		-0.26		0.16
Group 4				
a.m. demand (%)	21.1	23.3	56.2	57.6
Avg. prepeak fare ^a	11.12	7.10	11.12	7.10
Elasticity		-0.22		-0.05
Group 5				
a.m. demand (%)	17.7	23.3	60.3	55.2
Avg. prepeak fare ^a	10.66	7.06	10.66	7.06
Elasticity		-0.68		0.22
Group 6				
a.m. demand (%)	36.7	36.3	51.6	53.8
Avg. prepeak fare ^a	31.97	24.86	31.97	24.97
Elasticity		0.04		-0.17

^aIn Hong Kong dollars.

to -0.5 in the off-peak period (9). With a cross-elasticity of 0.14 and MTR's desired change in peak hour loads, a 25% discount was appropriate at the aggregate level. However, this calculation considers only eligible trips, which make up just 44% of all a.m. trips. To see a similar decrease throughout the network and among all users, the discount would have to be higher.

The differences between groups in the previous section are reflected in their elasticities. Because Group 1 makes up most morning users, its elasticities are closest to those of the population. Group 3 has similar values, with the difference in prepeak elasticity caused mostly by a lack of users shifting from the early morning. The other groups are quite different. Group 5 again has high values, but from very few trips. Group 4 has negative own-price and cross-elasticities, largely attributable to more significant seasonality from postpeak summer travel. Comparisons to the previous fall (not shown here) do show more intuitive signs. Future analysis of tourist response to TDM measures will need to recognize stronger seasonal differences. Groups 2 and 6 show unexpected signs for both elasticities, but for Group 2, the magnitudes are small enough to conclude again that this group did not respond to the promotion. In the initial group characterization, Group 6 was found to have relatively distinct travel patterns from the other groups, especially spatial patterns, so its elasticities further suggest that its travel patterns are guided by other trends. Changing the discount by a moderate amount will likely not compel members of these two groups to change their behavior, and other types of incentives are needed instead.

DISCUSSION OF RESULTS

Analyzing changes in travel patterns among all MTR users showed the Early Bird Promotion had a small impact on demand patterns. Among eligible trips in MTR's a.m. period (7:00–9:30 a.m.), the proportion of peak hour trips decreased by about 3%. Links with higher levels of crowding, at which the promotion was specifically aimed, saw larger changes. Therefore, even when onboard congestion is the key motivator for demand management, a simpler station-based discount may be sufficient when technology for route- or origin–destination-based incentives is not available. (If feasible, such designs could be explored to better target congestion.) However, these conclusions are based on the distribution of trips across time. Ridership increases mean that the policy may have helped slow peak congestion rather than actually reversing it. The MTR system did find the policy successful enough that it was renewed for an additional year following the initial 9 months.

The impacts were not distributed uniformly among users. Customers with commuter-like characteristics both took a majority of a.m. peak trips and responded to the promotion at higher rates, making them an important target for TDM objectives. Customers with regular but low-frequency use also showed fairly high shifts out of the peak, making them another group for MTR's focus. The particular factors that lead to those groups' different responses should be studied in more detail; linking usage to sociodemographic data (unavailable here) could be particularly useful for understanding price sensitivity or constraint-related characteristics.

Though the analysis methods used here can be generalized to other places, Hong Kong is a uniquely transit-dependent city and particular TDM policies may need to be adjusted for the local context. Nevertheless, these results suggest several improvements for policy design. For example, rather than using a single discount, an agency could taper its fare differential, giving a higher discount farther from the peak period. This action could better discriminate between time- and cost-sensitive users and encourage more shifting from the peak-of-the-peak period. An agency could also provide more personalized information to its users. The MTR case showed that different types of users had different proclivities toward fare differentials. By using station- or user-specific marketing, more detailed journey planners, or direct communication, an agency could better convey specific benefits of off-peak travel, such as price, comfort, and reliability. The feasibility of any of these plans depends on the complexity that customers tolerate and partnership opportunities, plus financial implications.

This research has shown that demand management has promise for transit. AFC data were very effective for a detailed study of demand patterns, particularly for group-level study that controls for heterogeneous system use. However, financial records would allow for a better business case for TDM; the costs and lost revenue of such a program could be a major barrier for agencies on tight budgets. In addition, the long-term benefits of the program must still be investigated because people may have reverted to prior behavior or taken more time to adjust their travel habits. Reevaluating the impacts of this promotion a year or two after its introduction could give a better sense of the long-term effectiveness of fare incentives.

ACKNOWLEDGMENTS

The authors acknowledge the support of MTR, including funding and data for analysis. Discussions with MTR staff about the development and evaluation of this policy also provided valuable insights.

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The Standing Committee on Public Transportation Marketing and Fare Policy peer-reviewed this paper.