Improving Transit Demand Management with Smart Card Data: General Framework and Applications

by

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Abstract

Increases in ridership are outpacing capacity expansions in a number of transit systems. By shifting their focus to demand management, agencies can instead influence how customers use the system, getting more out of the capacity they already have. However, while demand management is well researched for personal vehicle use, its applications for public transportation are still emerging. This thesis explores the strategies transit agencies can use to reduce overcrowding, with a particular focus of how automatically collected fare data can support the design and evaluation of these measures.

A framework for developing demand management policies is introduced to help guide agencies through this process. It includes establishing motivations for the program, aspects to consider in its design, as well as dimensions and metrics to evaluate its impacts. Additional considerations for updating a policy are also discussed, as are the possible data sources and methods for supporting analysis.

This framework was applied to a fare incentive strategy implemented at Hong Kong’s MTR system. In addition to establishing existing congestion patterns, a customer classification analysis was performed to understand the typical travel patterns among MTR users. These results were used to evaluate the promotion at three levels of customer aggregation: all users, user groups, and a panel of high frequency travelers. The incentive was found to have small but non-negligible impacts on morning travel, particularly at the beginning of the peak hour and among users with commuter-like behavior. Through a change point analysis, it was possible to identify the panel members that responded to the promotion and quantify factors that influenced their decision using a discrete choice model. The findings of these analyses are used to recommend potential improvements to MTR’s current scheme.

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Public transportation systems are playing an increasingly important role in today’s cities. Environmental, technological, and economic trends are leading to a rise in transit use in more mature cities, while population and spatial growth have spurred developing cities to extend their transit networks. However, these higher levels of demand cannot always be handled by capacity increases alone; signaling systems may prohibit higher frequencies and geography can limit the addition of lines or routes. Shifting focus to demand management may be one way to better serve customers without the high capital costs or long time frame needed to actually increase capacity.

The concept of Travel Demand Management, or TDM, was first introduced in the 1970’s for controlling automobile traffic. Since then, a number of TDM programs have been successful at reducing congestion and car dependence. With the peak-period congestion problems now being faced by some transit agencies, there is increased interest in using similar strategies in the context of public transportation. By developing policies that can spread demand more evenly throughout the network or over the day, agencies can make better use of their resources and improve their customers’ experiences.

In order for these programs to be effective, however, policies must be designed for an agency’s particular context and problems. This research has developed a framework that can be used to guide the design of TDM programs as well as the evaluation of any impacts. The framework and methods developed in this research are to be broadly applicable any transit agency and the various types of programs that could fit their needs.

The framework has been used in the context of Hong Kong’s MTR system. MTR’s railways serve as the backbone to Hong Kong’s extensive public transportation services but regularly face overcrowding. Though network expansions are planned, MTR has introduced several TDM strategies to deal with this problem in the present. Their Early Bird Discount Promotion serves as the specific application. This scheme aims to shift users out of the AM peak by offering a fare discount for exiting before the peak hour at certain stations.
1.1 Motivation

The primary motivation for this work was to better understand how demand management can be used to control congestion in public transportation networks. To date, most TDM research has focused on road traffic, trying to design better policies for reducing car use, either overall or specifically in peak periods. However, there remains a gap in translating these findings to the transit context and identifying what unique opportunities exist there. Though some agencies have developed demand management strategies, there is still room to more fully understand what impact they have on system conditions and how to make them more effective and efficient. Important considerations include the factors that influence users’ responses to these policies as well as the factors that actually lead to user behavior change.

The ability to implement effective demand management measures has several implications for transit agencies. In most cases, demand management policies will be quicker and less expensive than adding capacity to the network via new vehicles or rail infrastructure. If users can be convinced to shift their behavior, demand can be spread more evenly and underutilized capacity taken advantage of, allowing for more efficient use of resources. Reductions in crowding and potential increases in reliability can improve the customer experience. Finally, the knowledge gained through better understanding congestion patterns and how to incentivize user behavior change can be used for more general agency tasks, including service planning and providing more useful information to customers.

One issue with many of the techniques that are commonly applied to transit systems (like peak/off-peak fare differentials or mass marketing) is that they are highly inefficient in terms of the resources they require versus the users whose behavior they influence. It is often easy for people to ignore the agency’s message or enjoy a benefit without actually changing behavior. Better targeting users can help agencies increase their efficiency by differentiating between people with certain characteristics. Agencies should instead strive to design policies that appeal more to certain groups, either marketing directly to them or relying on self-selection to participate. This thesis also explores methods to segment users into more homogeneous groups and policy designs that do differentiate between users.

A related motivation was thus to improve the way transit agencies use the wealth of data that is becoming available to them. As automatic data collection systems (ADCS) are integrated into operations, agencies have an increasingly detailed view of how their system operates. In addition to aggregate trends of when and where users travel, this information allows for the travel patterns of specific user groups or even individuals to inform program design. It also supports longitudinal analyses to monitor how a policy’s effects change over time. By more accurately characterizing demand conditions, policymakers will have better tools to support the principles underlying TDM. More relevant and effective TDM strategies can be designed and measures more comprehensively evaluated.
For the specific case of MTR, this research was motivated by the agency’s recent attempts to implement TDM policies. The MTR system operates near capacity, and exceeds capacity during peak hours in some parts of the network. Developing a more comprehensive methodology for the evaluation of TDM programs will help the agency better understand the effects of its current measures and those of future schemes. In addition, the knowledge gained through this evaluation and more general analysis of system conditions can inform adjustments to the current policies as well as the design of any further measures.

1.2 Research Objectives

In light of these motivating factors, the overarching objective of this research was to develop a framework for the design and evaluation of demand management programs. This framework was developed through a synthesis of previous travel demand management literature and more general behavior change research, as well as past experiences with transit TDM. The goal of this framework is to guide transit agencies through the process of designing, implementing, evaluating, and revising a TDM program for its own specific needs, including:

- Framing the particular problems faced by the system
- Establishing meaningful goals that target these specific needs
- Relating these goals to particular measures and design parameters
- Determining metrics for evaluating the program’s impact
- Collecting the necessary data to support these metrics
- Developing methods to translate data and metrics into an overall understanding of the program’s impacts
- Utilizing the results of the evaluation to make improvements to the program

This framework is demonstrated using MTR as an example. The analysis has two primary components: quantifying the system’s existing conditions and gaining a more thorough understanding of its customers’ behavior, then evaluating demand management strategies to determine if there were any measurable impacts on congestion in the system. Specific objectives of this analysis include:

1. Existing Conditions
   
   (a) Develop a comprehensive understanding of the spatial and temporal congestion patterns faced by MTR using automatically collected data.
   
   (b) Establish customer groups based on long-term travel behavior as revealed by fare card data. The travel patterns of these groups are also related to MTR’s peak periods, key stations, and critical links to understand their contributions to congestion.

2. Evaluation of Demand Management Strategies
(a) Evaluate the effectiveness of peak-spreading promotions in the MTR network in terms of changes to users’ travel patterns and reductions in peak loading. 
(b) Establish fare elasticities for this context, both overall and for different user groups. 
(c) Develop further demand management strategies, including levels of fare differentiation or other incentives, time periods, necessary technologies for implementation.

1.3 Background of the MTR System

The case study used for this research is Hong Kong’s urban rail system, Mass Transit Railway, commonly referred to as MTR. With a population of 7.2 million, Hong Kong is one of the world’s densest cities and its citizens are overwhelmingly dependent on public transportation to get around. The car ownership rate is just 61 passenger cars per 1000 people (The World Bank, 2014), well below that of most industrialized cities, and 82% of non-walk trips are taken on transit (ARUP, 2014). The city has extensive heavy rail and bus systems, as well as a light rail system and a number of ferry services. Unlike in some cities, however, there are a number of different operators running these services; one agency does not oversee all the transportation needs of the city. And since these operators are largely privately owned, they are in competition for mode share as to increase their profits. Currently, the plurality of transit trips, 47% (Mass Transit Railway, 2014) are taken on MTR services. This can be seen in Table 1.1, which lists major transit services in Hong Kong and the number of trips taken on them in 2013. In the global context, MTR is the ninth busiest metro system in the world by ridership with nearly 1.8 billion trips taken in 2013 (Mass Transit Railway, 2014).

MTR is a relatively new company, established in 1975 to address road traffic problems that began to arise in the 1960’s. The initial system included the Central, Admiralty, Tsim Sha Tsui, and Jordan stations on what is now the Tsuen Wan Line, and the stations between Yau Ma Tei and Kwun Tong on what is now the Kwun Tong Line (see Figure 1-1 on page 16). After beginning service in 1979, a number of extensions have expanded service on Hong Kong Island, in Kowloon, and on Lantau Island. Though the system was initially publicly owned, it was privatized in 2000 (though the government remains the primary shareholder) and began to expand its property development activities around stations, building malls and housing. In 2007, it began operating the services of the Kowloon-Canton Railway Corporation network, adding the East Rail, West Rail, and Ma On Shan Lines in the New Territories to its network.

1.3.1 Current Service and Future Expansions

The current rail network is shown in Figure 1-1 on page 16. Over the nine rail lines plus the Airport Express line, there are now 87 stations¹. However, three of these stations (Sai

¹Appendix A shows the standard system map, along with station codes and line abbreviations
Table 1.1: Trips taken on Hong Kong public transportation operators in 2013 (via Hong Kong Transport Department, 2014)

<table>
<thead>
<tr>
<th>Operator</th>
<th>Trips (1000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Franchised Buses</strong></td>
<td></td>
</tr>
<tr>
<td>KMB</td>
<td>952,813</td>
</tr>
<tr>
<td>CityBus</td>
<td>234,790</td>
</tr>
<tr>
<td>WFB</td>
<td>182,045</td>
</tr>
<tr>
<td>LWB</td>
<td>33,178</td>
</tr>
<tr>
<td>NLB</td>
<td>23,600</td>
</tr>
<tr>
<td><strong>Subtotal</strong></td>
<td>1,426,426</td>
</tr>
<tr>
<td><strong>Railways</strong></td>
<td></td>
</tr>
<tr>
<td>MTR Heavy Rail</td>
<td>1,590,332</td>
</tr>
<tr>
<td>Airport Express</td>
<td>13,665</td>
</tr>
<tr>
<td>Light Rail</td>
<td>171,652</td>
</tr>
<tr>
<td>HK Tramways</td>
<td>72,282</td>
</tr>
<tr>
<td><strong>Subtotal</strong></td>
<td>1,847,931</td>
</tr>
<tr>
<td>MTR Buses</td>
<td>47,738</td>
</tr>
<tr>
<td>Public Light Buses</td>
<td>680,404</td>
</tr>
<tr>
<td>Ferries</td>
<td>49,508</td>
</tr>
<tr>
<td>Taxis</td>
<td>368,832</td>
</tr>
<tr>
<td>Resident Services</td>
<td>86,999</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>4,507,838</td>
</tr>
<tr>
<td><strong>Daily Average</strong></td>
<td>12,350</td>
</tr>
</tbody>
</table>

Ying Pin, HKU, and Kennedy Town on the Island Line) did not open until Winter 2014/15 and have not been included in analysis. In addition to these heavy rail lines, MTR also operates a light rail system with 12 lines and 68 stations in the Northwest New Territories (shown in gold in Figure 1-1), as well as 17 bus lines, four of which serve as feeder buses for the East Rail line, and 13 of which serve the Northwest New Territories more generally. Currently, there are approximately 4.7 million trips per day on the rail lines, 45,000 on the Airport Express Line, and 630,000 on the light rail and buses (Mass Transit Railway, 2015). Demand has been growing in recent years due to increases in population, employment, and tourism (Lee, 2014). Adjustments are regularly made to current service levels to try to handle these high demand levels and several expansions are under construction or being planned.

As can be seen in Figure 1-1, the MTR network is densest in Kowloon and on Hong Kong Island, then fans out to serve populated corridors in the New Territories and on Lantau Island. The city’s central business district is located roughly between the Central and Causeway Bay stations, thus a significant number of morning trips are toward this area. There are also a number of shopping and restaurant destinations in this area that attract
trips in the evenings and on weekends. Similarly, the area between Tsim Sha Tsui and Prince Edward (the Nathan Road Corridor), attracts many shoppers and tourists to its malls and markets. Two other stations of note are Lo Wu and Lok Ma Chau at the northern end of the East Rail Line. These stations serve as border crossings into Mainland China, and connect directly to the Shenzhen Metro. Visitors to these stations must have appropriate documents to enter China or Hong Kong.

Headways on the rail lines range from less than two minutes in peak periods on urban lines to over 10 minutes in off-peak hours on lines that run into the New Territories. For the Kwun Tong, Island, and Tsuen Wan Lines, these headways are as low as they can be given the current signaling system. The Tung Chung Line’s headways are also limited by the sections where it shares track with the Airport Express Line. MTR currently sets
Thus a typical MTR urban rail train with eight cars can hold 1,780 passengers, 340 sitting and 1,440 standing (Subcommittee on Matters Relating to Railways, 2014). East Rail Line trains have 12 cars so they hold more passengers, while trains on the Ma On Shan and Disneyland Resort Lines trains are shorter and the Airport Express Line trains have more seating, so they hold fewer.

Given the constraints of the signaling system and the current rolling stock, MTR is also planning a number of expansions over the next 15 years to meet its growing demand. Figure 1-2 shows the network with all the additions planned through 2031. These are also summarized in Table 1.2 on the next page. In addition, a high speed rail link connecting
<table>
<thead>
<tr>
<th>Expansion</th>
<th>Line Color</th>
<th>New Stations</th>
<th>Estimated Completion</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwun Tong Line Extension</td>
<td>Green</td>
<td>2</td>
<td>2015</td>
<td>Two stations added to west side of KTL</td>
</tr>
<tr>
<td>South Island Line (East)</td>
<td>Light Green</td>
<td>4</td>
<td>2016</td>
<td>Connection between CBD and Southern Hong Kong Island through the center of the island</td>
</tr>
<tr>
<td>East-West Link</td>
<td>Brown</td>
<td>5</td>
<td>2018</td>
<td>Linking MSL and WRL with the addition of 5 stations through Central Kowloon</td>
</tr>
<tr>
<td>Shatin-Central Link</td>
<td>Light Blue</td>
<td>1</td>
<td>2020</td>
<td>New harbor crossing connecting ERL to Admiralty</td>
</tr>
<tr>
<td>Hung Shui Kui Station</td>
<td>N/A</td>
<td>1</td>
<td>2031</td>
<td>Infill station on WRL</td>
</tr>
<tr>
<td>Tuen Mun Extension</td>
<td>Brown</td>
<td>1</td>
<td>2031</td>
<td>Station added to end of WRL</td>
</tr>
<tr>
<td>Tung Chung Extension</td>
<td>Orange</td>
<td>1</td>
<td>2031</td>
<td>Station added to end of TCL</td>
</tr>
<tr>
<td>South Island Line (West)</td>
<td>Dark Red</td>
<td>5</td>
<td>2031</td>
<td>Connection between CBD and Southern HK Island via Island’s West Coast</td>
</tr>
<tr>
<td>North Island Line</td>
<td>Orange/Purple</td>
<td>3</td>
<td>2031</td>
<td>Extensions of TCL and TKL to parallel current Island Line</td>
</tr>
<tr>
<td>East Kowloon Line</td>
<td>Pink</td>
<td>4</td>
<td>2031</td>
<td>Provide service in Eastern Kowloon by connecting Diamond Hill and Po Lam stations</td>
</tr>
<tr>
<td>Northern Link</td>
<td>Dark Green</td>
<td>1</td>
<td>2031</td>
<td>Connect NW New Territories to end of ERL</td>
</tr>
</tbody>
</table>
Hong Kong’s West Kowloon Station to Shenzhen and Guangzhou is under construction. Those listed with completion dates before 2020 are currently under construction. The others are still in the planning stage, but were included in a 2031 network laid out in the government’s 2014 Railway Development Plan. Though these new lines will help control congestion, especially along the Island Line and through the Nathan Road Corridor to Hong Kong Island, their planned completions dates are too far into the future to not consider any shorter term measures to deal with crowding. In addition, several extensions, like the South Island Lines and Kwun Tong Line expansion, will expand the service’s catchment area, potentially increasing trips on the system before the segments that will provide congestion relief are opened.

1.3.2 Fare System

Nearly all MTR transactions are paid for via Hong Kong’s Octopus Card. Introduced in 1997, these stored value cards are accepted by all major transit services in the city, as well as at some shops and restaurants. Passengers can obtain an Octopus card at any station (as well as at other locations in the city) for HK$150\(^2\): a HK$50 deposit and an initial value of HK$100. The cards can be returned to get any remaining value back. A minority of fares are paid via other methods:

**Single Journey Tickets:** Now single use, no-deposit smart cards, this payment method allows users to pay for one trip at a time, though typically at a fare that is somewhat higher than the corresponding Octopus Card fare.

**Monthly Passes:** Five types of "Monthly Pass Extra" can be added to an Octopus card\(^3\). These allow unlimited travel between a particular set of stations, plus a 25% discount between one eligible station and one non-eligible station. (Octopus-level fares are charged for trips that are completely outside the covered stations.) The cards cover portions of the Tung Chung, West Rail, and East Rail lines and are mainly meant for users who travel from the New Territories to the urban core, long trips whose high fares would add up quickly. They cost HK$370-580 and are valid for one calendar month. The CitySaver Card, introduced in June 2014, allows a user to take 40 journeys over 30 days (not necessarily corresponding to a single month) for an upfront cost of HK$400, though trips that use stations on Lantau Island and in the New Territories are not eligible.

**Tourist Passes:** Tourist day passes allow unlimited travel in the heavy or light rail systems (excluding border crossing stations) within 24 hours. Tourist cross-boundary passes allow for two trips involving border crossings and otherwise unlimited use over one or two days.

**Airport Express Tickets:** Several tickets and passes specifically for the Airport Express Line are available for travel to and from the airport.

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\(^2\) US$19.35 at HK$7.75 to US$1.

Fares are based on distance with higher costs to travel further. As of June 2014, adult Octopus fares range from HK$3.5 to HK$27.6 for most OD pairs. However, travel to or from one of the border crossing stations is almost always higher, with a fares ranging from HK$22.4 (to travel just one station into Hong Kong) to HK$51.7. The average fare paid is around HK$7.9, about US$1.

Excluding staff cards that provide free travel, four types of fare concessions are available to Octopus Card users. Those over 65 can use Senior Octopus Cards, entitling them to HK$2 fares on most OD pairs, and those under 12 can use Child Octopus Cards for discounted fares. In addition, disabled users can apply for a personalized card that grants them the same HK$2 fares as seniors. Similarly, students can apply for a card with "student status" to continue getting the child discounts. In contrast, the East Rail Line offers first class cars and users who choose this option must pay a surcharge.

The current Octopus cards and single journey tickets work using RFID technology (radio frequency identification); heavy rail users tap the card at a gate when they enter and when they exit so the appropriate fare can be deducted from the card’s stored value. Looking into the future, the Octopus Corporation is beginning to experiment with NFC (near field communication) technology that would allow users to pay fares by tapping their smartphones at a gate instead of a card. Currently, users can download the Octopus mobile application to an NFC enabled phone or obtain a mobile phone SIM card with Octopus functionality to pay this way.

1.4 Thesis Organization

A discussion of past demand management research is presented in Chapter 2. General theories about behavior change are followed by work that applies these to a successful TDM program design. Research and case studies specific to rail TDM are also covered, as are past uses of automatically collected data. Chapter 3 builds on this literature and presents a framework for developing TDM programs for transit services. Methodologies for goal-setting, designing measures, and evaluating programs are included.

The MTR case is introduced in Chapter 4 with a discussion of pre-demand management spatial and temporal congestion patterns. In addition, the results of customer classification analysis are presented to characterize user behavior in the system. Chapter 5 focuses on the evaluation of the Early Bird Program, from a fully aggregated system-wide level to a panel analysis of individual passengers. These results are used in Chapter 6 to develop elasticities for response to the Early Bird discount. Potential improvements to the current program are explored, as are other TDM strategies. The thesis concludes in Chapter 7 with a summary of key results and recommendations, as well as potential directions for future research.
Travel demand management for personal vehicle use is a well researched area, but applications to public transportation congestion are still emerging. After a brief background of this concept, the broader factors that drive people’s travel choices are introduced in Section 2.2. Findings that apply these concepts to understanding what makes TDM strategies effective and acceptable are covered in Section 2.3. Section 2.4 discusses some of the empirical results from previous transit TDM efforts, including surveys and models for proposed measures as well as post-hoc analysis of actual policies. These bodies of literature are particularly useful to inform policy design, covered in Chapter 6. The last section of this chapter focuses on how automatically collected data sources, which will be used for the analyses in this thesis, can be utilized to measure people’s travel behavior, and their transit use in particular.

2.1 Background and Context

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. The concept emerged in the 1970’s alongside the energy crisis and concerns about auto traffic; policy makers wanted "to save energy, improve air quality, and reduce peak period congestion" (FHWA, 2014). Today, TDM has broader applications, including to other modes, and its goals have expanded to include improving accessibility, predictability, customer information, travel choices, and system performance. TDM solutions are often among the most cost effective, with benefits including congestion reduction, infrastructure savings, increased safety, reduced pollution, and better land use (VTPI, 2014). Many TDM policies also provide direct incentives to customers, such as more flexible work schedules, transit oriented development, or financial incentives (VTPI, 2014).

In many cities, TDM gains traction when other alternatives are not feasible. There may be no space to add road or rail infrastructure, especially in the short term, and further improvements to transport supply, like increased transit frequency or road signal coordination, may not be possible. TDM policies can often be implemented in shorter time frames than infrastructure projects. In addition, a number of different stakeholders can be
involved in the development of TDM, from various government planning agencies and transit agencies to non-profit groups and employers, allowing for a variety of problem-solving methods.

The list below (adopted from Gärling and Schuitema, 2007) gives an introduction to the types of policies TDM has traditionally included:

- **Physical Change Measures**
  - Park and ride schemes
  - Land use planning
  - Walking/cycling improvements

- **Legal Policies**
  - Prohibiting traffic in some areas
  - Parking controls
  - Reducing speed limits

- **Economic Policies**
  - Taxing vehicles or fuel
  - Congestion pricing
  - Lowering transit costs

- **Information and Education Measures**
  - Individual marketing
  - Public information campaigns
  - Social modeling

Many of these, of course, are not applicable in the context of transit. Indeed, relatively little TDM research has focused on reducing congestion in transit systems compared to road traffic. With increased urbanization and transit ridership in many parts of the world, however, it likely will become a priority in many places. Faber Maunsell (2007) 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 have lower travel times, fuel costs, and stress levels. For transit, demand management is more a question of optimization—how to best redistribute users in the network—than in road traffic where less constrained modes (walking, biking, carpooling) are often viable alternatives. Though many previous findings focus on road traffic, the following sections will highlight results that are also applicable to transit use when possible.

2.2 Behavioral Drivers and Behavior Change

A TDM strategy is only successful if it can actually change users’ travel behavior, and there is a large body of literature that aims to understand how users make decisions about their travel. In the short term, these decisions can include route, mode, and departure time choices, while longer term decisions include whether to get a driver’s license, buy a car, and where to live.

Most demand, especially during peak periods, is derived demand: people are taking trips not for the sake of the trip itself, but because they need to get to work, school, or another time sensitive activity. Activity-based travel behavior frameworks (Kitamura, 1988; Axhausen and Gärling, 1992) try to account for this by recognizing the constraints that influence trip-making. Factors like gender (or household roles), employment, age, household structure, and time and cost constraints have all been found to play a role in how
people structure their trips, though when these factors change, travel may not shift in the expected way. According to Kitamura (1988), "travel behavior depends upon the history of contributing factors and perhaps on the past trajectory of behavior itself;" a new TDM policy must contend with factors as they are in the present as well as other ingrained habits in order to find success.

Gärling et al. (2002) draw on a number of behavior theories to develop a framework for the impacts of TDM (Figure 2-1). Following the activity-based model, users choose among trip chains (rather than trips) based on the attributes of those trips (e.g. purpose, time, cost, comfort, etc.), their individual characteristics (household structure, employment, income), and situational factors (weather, time of day, time pressure). TDM measures both directly and indirectly influence trip chain attributes, and also affect users’ goals and intentions through public information.

![Conceptual framework for TDM impacts](adapted from Gärling et al., 2002)

In order to lead to a long-term behavior change, the TDM policy must lead to a shift in beliefs, attitudes, and values (Gärling and Schuitema, 2007). Here, attitudes refer to "psychological tendency that is expressed by evaluating a particular entity [...], with some degree of favor or disfavor" while beliefs "reflect the subjective probability that an object has a certain outcome" (Schuitema et al., 2010). While incentives and disincentives may impact travel choice while they are in place, unless they also influence changes in these internal factors, travelers will likely revert to their initial travel patterns once they are removed. According to Gärling et al. (2002) and Gärling and Fujii (2009) internal changes can be understood with regard to the following theories of behavior:

**Goal-Setting Theory.** Setting goals helps people focus on relevant activities and mobilize energy to work toward their achievement. Goals can be defined according to their content (difficulty, specificity, complexity or number of outcome dimensions,
and conflict with other goals) and intensity (level of commitment, perception of importance, and processes engaged). People typically find goals that are more difficult (but not too difficult) and specific easier to reach. In the context of TDM, people set goals based on their personal characteristics, trip characteristics, and external influences. Altering the attributes of a trip or reshaping how information about that trip is perceived can lead to people setting new goals for their travel.

**Control Theory.** Gaining feedback by comparing the present situation a point of reference can play an important role in supporting goals. Reference values are organized in a hierarchy from the system level (an ideal image of oneself), to the principle level (rules of how to act), program level (making a plan to follow those rules), and perceptual-motor levels (actually carrying out the plan). Different TDM policies can target these different levels, like education and information for the principle level or creating travel plans for the program level.

TDM policies can also create disturbances that affect people’s reference points or values. Control theory also dictates how people change their travel as a result: they will try to minimize the costs. This means there is a bias toward maintaining the status quo, but people will choose the lowest cost alternative if that is not possible.

**Choice Theory.** When deciding how to travel, users select among a set of choices based on the attributes of each and their own characteristics. One model for making choices is the utility maximization framework; people will choose the option with the lowest generalized cost. A trip includes a number of choices both discrete (e.g. mode) and continuous (e.g. departure time), and a choice in one dimension typically influences the choice for others. If the TDM measure changes either the attributes or how people weigh them, it can lead to different choices.

**Attitude Theory.** Often compared to discrete choice theory, Ajzen’s Theory of Planned Behavior (TPB) differs in recognizing that intentions are determined by more than just utilities, including attitudes, social norms, and situational constraints. Under this theory, choices are made by weighing these three factors and selecting the option with the highest value. Though recognized as one way to understand how people implement goals, Gärling and Fujii (2009) finds that attitude theory fails when moral motives drive behavior, does not explain discrepancies between attitudes and behavior, and does not model the process of behavior change. Therefore, it may not be sufficient for studying TDM impacts. Bamberg et al. (2011) does incorporates personal norms from Norm-Activation Theory for a joint theory that captures the moral correctness of an action (e.g. in the context of TDM, personally contributing to congestion relief).

**Habit Theory.** Habits, or repeated choices, reduce information processing through memorized scripts or choice rules that limit the need for additional information. The strength of habits can be influenced by feedback and thus can be adapted to achieve goals. TDM policies need to create salient, beneficial changes to travel options to impact habits.

Several of these theories have been applied by Transport for London in their framing of demand management problems. In particular, they have conceptualized how different types of users will be more or less susceptible to their TDM policies (for London, 2013).
They define three groups: activity-led users who are motivated by the time they need to be somewhere, benefit-led users who desire comfortable journeys, and habit-led users who have developed a travel routine and need some disruption to change their patterns. As they develop policies, staff can use the most relevant theories above to better target users who fall into a particular group.

Underlying many of these theories are assumptions that humans act rationally and are fully informed about their choices. Unfortunately, as the behavioral economics field has found, this is often not true (Kahneman, 2003, among others). As was discussed in habit theory, people use heuristics to simplify decision-making, which biases their decisions. People are also less likely to truly maximize their utility because of the associated risks. According to prospect theory people’s attitude toward risk varies with whether they are dealing with gains and losses and whether the outcome has a high or low probability. Finally, the way a choice is framed can have a large impact on someone’s decision by changing how salient different attributes are to the decision-maker. Social aspects have also found to be influential; people often turn to the decisions of their peers to guide their own travel decisions (from owning a car to how to treat pedestrians while driving, (Gaker et al., 2010 and Avineri, 2012). One caveat in these findings is that they tend to be based on experiments done in Western cultures and may not be applicable in other places (Dolan et al., 2012).

Behavioral economics has been applied to the transportation context in the past both for improving models and designing strategies for behavior change. Avineri (2012) considers influencing travel behavior to reduce the environmental impacts of driving while Dolan et al. (2012) performs a more general study of how behavioral economics can be used in policy design to influence travel behavior. Ben-Elia et al. (2008) performed an experiment to understand how people make route choices based on travel time averages and variability—users overweight the possibility that their trip will be shorter than average. Encouraging more active travel for environmental and health reasons is considered by Zhao and Baird (2014), who used mobile apps to "nudge" users into active travel modes by giving feedback on their travel patterns.

These findings can be utilized when designing demand management programs. Framing the policy by calling on social norms and simplifying the path toward behavior changes, so people do not just fall back on typical heuristics, can help encourage more people to participate (Zhao and Baird, 2014). Dolan et al. (2012) enumerates the impacts that incentives can have on behavior, including that people really dislike losses, overweight small chances (making lotteries more attractive), and highly value the present so may not think about long-term benefits. They also find that incentives can become the only thing motivating a behavior. As a result, people revert their behavior as soon as the incentive ends. Dolan’s MINDSPACE framework gives more detail on the dimensions to consider for a successful behavior change program. Avineri (2012) discusses how information can be better framed in the context of journey planners and travel plans, the possibility of setting "smarter" default choices, and making feedback on behavior more salient.
2.3 Basis for Impactful TDM Programs

According to Loukopoulos (2007), a policy’s outcomes can be measured by its effectiveness, public attitudes toward it, and its political feasibility. These three dimensions are influenced directly by the policies’ design and the factors discussed in the previous section, but are also interrelated. The two sections below discuss findings related to what makes a policy effective and acceptable to the public and by politicians.

2.3.1 Effectiveness

Drawing directly from a TDM behavior framework, Gärling and Schuitema (2007) develop three elements of an effective TDM framework:

1. **Reduce Attractiveness**: measures should trigger goal-setting by carefully considering the design of the measures. Non-coercive measures that just allow people to make better decisions on their own, like travel plans and information, may not be enough to reduce the attractiveness of a behavior on their own.

2. **Activate Goals**: reducing attractiveness is one factor that activates goals, but user characteristics, like household structure and income, must also be considered. Coercive measures, like pricing and regulations, can force goals more strongly, assuming appropriate alternatives are available.

3. **Reduce Costs and Uncertainty**: encouraging travel planning can reduce the uncertainty involved in adopting a new habit, and temporary changes that force people to break their old habits can quicken the adoption of new ones. Simplifying the decisions and steps users must go through to change their behavior can help reduce their associated mental costs.

These factors are fairly general for a reason: several researchers (Meyer, 1999; Gärling and Fujii, 2009; Henn et al., 2011) note that TDM policies must be specific for their context, including matching incentives to travelers in a particular region and to the spatial scale on which the program is implemented (e.g. city vs. region-wide). Meyer (1999) reviews a number of previous studies for car reduction TDM and concludes that some type of incentive or disincentive is needed for a program to be successful. Often these (dis)incentives involve pricing. Steg (2003) suggests that three dimensions are needed for effective pricing strategies: the instruments have immediate consequences, the pricing level is correct, and prices are relevant to the targeted travel behavior (e.g. peak congestion vs. environmental impacts). In terms of pricing levels, she notes that when prices are too low, people essentially disregard them, while if they are too high, people focus only on costs. They never internalize the behavior change and there are no long term effects. Maruyama and Sumalee (2007) also highlight the trade-off between effectiveness and simplicity; a complex design may be (theoretically) optimal when considering effectiveness, but a more understandable design is likely to have higher approval and among the public and government.

Market segmentation can be used to develop groups of users with more homogeneous characteristics. As these groups will likely have more similar responses to a particular
policy, TDM measures that target or market and promote specific user groups can be more effective (Bamford et al., 1987). Such groups can also allow for more detailed evaluation of a program to understand how sensitive different types of users actually were to the policies.

There are a number of different types of strategies that can be used in a TDM program, and important characteristics include how coercive they are (with coercive measures often being called "push" measures and non-coercive ones "pull") and whether they change users opportunities through, for example, pricing or work flexibility ("hard" measures), or if they aim to change users attitudes, beliefs, and values through information and education ("soft" measures). Researchers overwhelmingly report that combinations of these measures are more effective than using just one, with Gärling and Fujii (2009) explaining that combing measures helps to active more of the psychological variables (cognitive skills, moral obligation, etc.) associated with behavior change. Eriksson et al. (2010) focus on how combinations of push and pull measures can improve effectiveness, Richter et al. (2011) on hard and soft measures, and Gärling and Fujii (2009) on both dimensions.

In the case of soft measures, most research into effectiveness has focused on travel feedback programs (TFP), "personalized communication to reduce car travel" (Fujii and Taniguchi, 2006). Gärling and Fujii (2009) also consider mass communication programs, but conclude that it is too difficult to isolate particular effects when evaluating these programs. Travel feedback programs were found to be more effective when they ask participants to set particular goals (Gärling and Fujii, 2009; Fujii and Taniguchi, 2006), and there has been some evidence that TFPs focused on residential locations are more effective than those through a workplace (Gärling and Fujii, 2009), though other results are less conclusive (Fujii and Taniguchi, 2006). Providing high-quality, detailed, and individual information and ensuring there are high quality alternatives to driving have also been found to be important (Fujii and Taniguchi, 2006; Richter et al., 2011). Fujii and Taniguchi (2006) and Richter et al. (2011) also both find that targeting the right users is important; people who have recently moved or experienced some life change are more likely to be responsive to behavior change programs because they haven’t yet developed strong habits. Long-term impacts have been mixed, with some evidence given in Fujii and Taniguchi (2006). However, Richter et al. (2011) note that the results of unsuccessful programs are less likely to be published and even when there was evidence of long term changes, the factors leading to it are uncertain.

Eriksson et al. (2010) studied hard measures (transit improvement and a higher gas tax) through a two-step survey. They found that push measures were more effective than pull ones, though a combination was most effective. Internal factors like social norms and intentions, plus perceived impacts were activated to influence car use reduction. Ben-Elia and Ettema (2011) report on the results of a 13 week field experiment in the Netherlands to understand how rewards could be used to shift drivers out of the peak. Rewards, both money and credit toward a smartphone, were effective at reducing peak hour driving, at least in the period of study. Factors like information, schedules, and habits were more important in explaining exactly how users shifted. Employer cooperation also had a large
effect, particularly among users who shifted to the post-peak period. In addition, providing users with access to travel information (via the smartphone) was also found to encourage behavior change.

While all of the above examples focused on driving reduction, Henn et al. (2011) explore the effectiveness of peak congestion rail TDM programs. Again, combining different types of measures was found to be important, as was targeting measures to particular users groups, locations, and times of day. With so many stakeholders involved in transit, the need to integrate policies among all transit providers and modes was also highlighted. They outline a number of peak demand instruments in terms of their effectiveness, cost, and desirability, and find the most effective to include increasing transparency about peak fares and crowding (though more detailed customer information) and reducing shoulder fares.

Many transit TDM measures are based in economic principles, employing higher or lower costs to encourage people to travel outside of the peak ("fare differentiation" rather than "flat" fares). In particular, agencies turn to peak/off-peak fare differentiation to deal with differences in demand levels across the day. Both Cervero (1990) and Streeting and Charles (2006) state that pricing is one of the most effective ways of dealing with peak period congestion, helping both to capture the higher costs associated with providing peak service and helping to control peak hour demand. Fare differentials are relatively easy to implement (Liu and Charles, 2013), particularly in systems that use smart cards (Streeting and Charles, 2006). About 40% of urban rail networks worldwide have peak surcharges or off-peak discounts (Liu and Charles, 2013).

2.3.2 Acceptability

Closely related to the effectiveness of TDM policies is their acceptance by the public. Some policies, particularly coercive ones, are unpopular with the public and taking steps to understand why people dislike them and make them more acceptable can be worthwhile. If users are more accepting of a policy, they may be more likely to change their behavior. Several researchers have taken up the question of TDM acceptability in their work, trying to understand what factors influence acceptance and develop more overarching frameworks for it. Again, this work is largely focused on personal vehicle travel, but many of the relationships are still applicable to the transit case.

People’s acceptance judgments are indicated by their attitudes and beliefs. Of course, beliefs can change over time, and thus attitudes and acceptance levels can as well. To this point, some work (Schade and Schlag, 2003,Schuitema et al., 2010) makes the distinction between "acceptability," related to people’s attitudes before a measure is implemented, and "acceptance," their evaluation once it begins and its actual impacts are evident.

These attitudes and beliefs are shaped by a number of different factors. At one level, the different types of policies discussed in the previous section tend to have different levels of acceptability associated with them. More coercive push measures are typically less
accepted than pull measures (Eriksson et al., 2006), to the degree that they are often perceived as less effective, even though studies often find them to have a greater impact. In particular, Eriksson et al. (2008) finds people viewed pull measures as "effective, fair, and acceptable" while push measures were seen as the opposite. Schlag and Teubel (1997) and Schade and Schlag (2003) identify the following factors that influence public acceptance of TDM policies:

**Information and Awareness.** Building an awareness of the problem and the proposed solution by explaining its background, objectives, and method of implementation, can increase acceptance. Policymakers should provide "precise and convincing arguments in favor" of the measures. Steg (2003) adds that providing scenarios to describe the benefits of the policy, as well as what will happen if it is not implemented can be helpful.

**Perceived Effectiveness.** Though acceptance can improve effectiveness, effectiveness can also raise acceptance levels. If people believe that the measure is making a difference they tend to have a higher opinion of it. Indeed, Bartley (1995) finds a relationship between higher acceptability, effectiveness, and awareness when comparing opinions about different TDM measures.

**Attribution of Responsibility.** If people perceive their own actions, rather than external factors, to play a role in congestion problems, they may also feel a stronger responsibility to be a part of the solution. In addition, people should feel that their actions will make a difference in solving the problem, particularly since they might not trust others to cooperate also (Steg, 2003).

**Social Norms and Values.** Because people tend to seek the approval of others, they often hold opinions based on how they perceive others to feel. If social norms are more in favor of a policy, individuals tend to be more accepting of it. Policies should also be in line with more general cultural values, like freedom, equity, and fairness in Western cultures (though these may differ in other parts of the world).

**Individual Claims.** Intrusions on perceived freedom, like privacy concerns or limiting someone’s ability to travel as they prefer, reduce acceptability. In particular, care must be taken with personal information when designing policies.

**Revenue Allocation.** If the measure involves surcharges on particular travel patterns, users tend to have higher acceptance levels when they know how the extra revenue will be used, especially if it goes back into the transport sector. Steg (2003) also connects this concept to consistency between different policies; new TDM measures should prioritize similar behaviors as existing policies in terms of how money is being used and what behaviors are targeted.

**Equity.** Users prefer measures that are equitable between individuals and regions. A policy is perceived as more fair when people of different incomes, job type, etc. are affected similarly (relatively or absolutely, depending on the policy dimension). Different parts of the region should experience similar costs and benefits, which can be addressed through coordination among cities.

**Socio-Economic Impacts.** Though not particularly significant, income and other socio-economic variables may play a role in how people rate acceptance. For example, wealthier people with higher values of time may see pricing surcharges as less bur-
densome and experience higher benefits. However, some research has found that income plays no role in acceptance, and low-income groups believe pricing to be most effective compared to other groups.

Schade and Schlag (2003) found that social norms were the most important factor in explaining acceptance. Their explanation for this was that if people lack experience with a policy, they turn to perceived social valuations. This implies that if social norms can be influenced positively, a policy may have higher chances of being acceptable (and thus effective). Also, in addition to the above factors, Steg (2003) adds an additional point about the importance of having alternatives available and well-known. If users are being penalized for certain behavior and see no recourse, particularly high quality options, they will oppose policies.

In two experiments, researchers studied what factors were strongest in determining the acceptability of different TDM policies (Eriksson et al., 2006, 2008). They used surveys to ask respondents about three different TDM measures, two of them the same between experiments, and found that while some factors were important to acceptability in general, others were only important for certain types of measures. The 2006 paper reports that, in general, problem awareness and personal norms were important, but fairness was key for push measure acceptability, while pull measures were more closely related to personal freedom. The 2008 paper focused on the two general factors, finding push measures were associated with personal norms and pull measures with problem awareness. Combinations of push and pull measures were also considered, and their acceptability seemed to be driven more by personal norms, suggesting that when policy measures are combined, similar tactics can be used to enhance opinions about them.

The acceptability of TDM measures has also been studied for several real world road pricing schemes. Toll rings in several cities in Norway became more highly accepted after implementation (Schuitema et al., 2010) because users found them to be effective at controlling traffic. In contrast, support for cordon pricing in Stuttgart declined over time because of people’s low opinions of the effects (Steg and Vlek, 1997). These examples also highlight the importance of longitudinal evaluations. Schade and Schlag (2000) have suggested that acceptance levels rise over time when people see positive impacts (though empirical studies have been limited). Steg (2003) suggests three reasons for this: people have more thoroughly considered the policy, they become more convinced of its advantages, and they have overcome an initial reluctance to change. More specifically, Schuitema et al. (2010) add that people may reconsider how important various consequences are to them, for example, costs really not being as problematic as believed. Schuitema et al. (2010) studied the level of acceptance for the Stockholm congestion charge that began in 2007. They found that acceptance levels were higher afterward, largely due to the realized positive consequences (less congestion and pollution, fewer parking problems) outweighing the foreseen negative consequences (higher costs). They also found higher acceptability and acceptance among people who thought they would or did drive less. This is likely because this group had viable alternatives to driving, further underlining the importance of alternatives (such as improving transit service as was done here). These differences stress
the importance of context and how particular policy designs impact acceptance levels.

The other side of acceptability that is important to consider is political acceptance, which can be key for acquiring the necessary funding and support for implementing TDM programs. Gärling and Schuitema (2007) report that political acceptance is often dependent on public opinions, so the factors listed earlier in this section are again relevant. However, political factors can interfere with public acceptance. Political party stances may prevent decision-makers from approving TDM programs, with some groups preferring less government involvement in these areas. The competing priorities of different levels of government can also play a role. Local governments are often held more accountable to citizen’s day-to-day experiences while federal governments can take a wider and more long-term view of what policies will benefit its transportation systems. Schlag and Teubel (1997) also point out that politicians may not always perceive public views accurately, for example, believing them more pro-car than they really are.

High levels of acceptance are possible through careful policy design, but the importance of effective communication is also called out. Schlag and Teubel (1997) list several components of “intelligent marketing” including creating awareness, communicating the program’s positive impacts for individuals as well as its more broad effects on society, and stressing that mobility will not be constrained and people still have choice. In the Stockholm case, Schuitema et al. (2010) discuss the value of positive publicity by mass media and the city’s official website in increasing acceptance levels over initial acceptability estimates.

2.4 Transit Demand Management

This section reviews some of the findings for public transportation-specific TDM programs. The first section discusses relatively general results from based on surveys in several cities while the second lists several types of transit TDM strategies that have actually been implemented and further details experiences in Melbourne, Singapore, and Hong Kong.

2.4.1 Surveys, Stated Preferences, and Models

In recent years, rail and transit agencies have begun to explore TDM for their services, engaging consultants and researchers to study their options. This work has mainly focused on the factors that affect time-shifting, and the fare differentials that would be most effective.

In London, Consolidated (2006) surveyed commuter rail riders and found that over 40% of respondents said that they could arrive outside of the peak, though almost all said they would prefer to arrive earlier. Preferences for traveling earlier were also found by Faber Maunsell (2007) and Douglas et al. (2011), for London again and Sydney, Australia, respectively. Faber Maunsell (2007) further quantified this preference, finding most users
could be flexible by about 30 minutes and that users’ value of being late was £0.13 to £0.20/min compared to £-0.60 to 0.40/min for being early. Given that there is flexibility, it is just limited in magnitude, in the context of fare surcharges a shorter period that covers only the peak-of-the-peak may be more effective at peak smoothing (Henn et al., 2010).

Both Faber Maunsell (2007) and Consolidated (2006) also found that the primary constraint preventing time shifting was work flexibility. Respondents suggested working with employers to make flexible hours more acceptable (though one third of respondents in a survey conducted by Passenger Focus stated that they just did not want to travel before the peak). This connection to working hours also suggests shifts from the morning peak could benefit the afternoon peak (Henn et al., 2010). Other factors that were found to affect time shifting included trip length, with those traveling farther less inclined to travel earlier. Seasons are also important, as people said they would not want to travel earlier in darker fall and winter months (Consolidated, 2006). This second point suggests a TDM program could have longer-lasting results if it begins in spring or summer, giving people more time to adjust their habits. Ensuring that non-peak travel is more comfortable was important for 14% of Passenger Focus respondents. Making the ticketing policy for these special fares convenient was also a priority.

In the Passenger Focus survey, over half of the respondents said that reducing fares could encourage them to travel earlier, with discounts of 25-30% seen as reasonable. Discounts were preferred to surcharges in both that study and by the study Faber Maunsell (2007). Douglas et al. (2011) developed a model to simulate passenger assignment on one Sydney rail line under different fare differentials. A combination of a 30% discount in the peak shoulders and a 30% surcharge in the peak was found to be most effective at reducing peak loads (-10%). Just offering a 30% discount for peak shoulder trains, more similar to the actual policy, was found to reduce peak loads by 3.1%. Whelan and Johnson (2004) also found that just a surcharge or discount would have limited effects, and a combined strategy could have larger impacts. However, both Whelan and Johnson (2004) and Fearnley (2003) note that increasing peak fares is unpopular and could even push people to travel by car instead.

### 2.4.2 Real-World Program Evaluation

A number of transit systems around the world use TDM policies to control peak hour ridership. Fare differentiation is relatively common, though cities have varied histories in its application and pricing structures. Other cities have also experimented with engaging employers and providing more detailed crowding information to users. After a brief overview of some of the policies being used (summarized in Table 2.1), the cases of Melbourne, Singapore, and Hong Kong whose policies have been evaluated by researchers will be discussed in more detail.

In the U.S., Washington, D.C.’s WMATA has had both AM and PM peak pricing on its MetroRail system since the system opened in 1976. Users who travel before 9:30am or between 3:00 and 7:00pm pay an additional $0.40 to $2.30 over the usual (distance-based)
Table 2.1: Examples of transit TDM policies

<table>
<thead>
<tr>
<th>Type of Program</th>
<th>Sample Cities</th>
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<tbody>
<tr>
<td>Fare Differentiation</td>
<td>Washington, DC, LA, Seattle, Minneapolis/St. Paul</td>
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<td>London</td>
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<td>Hong Kong, Singapore, Tokyo</td>
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<td></td>
<td>Melbourne, Sydney, Brisbane, Adelaide</td>
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<td>Crowding Information</td>
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<td>Tokyo</td>
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<td>Employer Programs</td>
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<td>London</td>
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<tr>
<td>Lotteries/Games</td>
<td>Singapore</td>
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</tbody>
</table>

fare. Hale and Charles (2010) note that this structure does not encourage any travel before the AM peak-of-the-peak; to a cost-sensitive user there is no difference between 7:00am and 8:30am. MetroRail did have peak-of-peak surcharges from 2010 to 2012 (for 1.5 hours in morning and afternoon), creating a tiered pricing structure (WMATA, 2010). The program ended with a system-wide fare increase, perhaps due to the passengers’ relatively low fare elasticity hindering its effectiveness and concerns about public perception and complexity. Some of the other cities that employ fare differentiation include London; Seattle, Los Angeles, and Minneapolis/St. Paul in the US; and Sydney, Brisbane, and Adelaide in Australia. For users whose Underground origin and destination are both outside Zone One, London also offers a discount to users who take a route that bypasses the more crowded Zone One if they also had the option to go through it.

Transport for London (TfL) experimented with more varied policies for short term demand management surrounding the 2012 Olympics. The four primary policies were to encourage reductions in trip-making, re-timing trips, mode shifts to walking and biking, and shifts to less popular routes (Hanely, 2012). Information was provided to the public, but TfL also worked with key employers via a Travel Advice for Businesses (TAB) program. TAB advisers helped carry out employee travel surveys and provided action plans for how employers could support TfL’s policies. These strategies were found to meet their objectives and perhaps have longer term impacts. TfL has since maintained an interest in TDM, with possible projects including providing real-time crowding data and improving coordination during scheduled disruptions. Several agencies already offer crowding information, including BART in the San Francisco Bay Area (from historical data) and JR East in Tokyo (real-time).

Several cities have more extensive demand management programs that have been evaluated both internally and by academic researchers. Experiences in Melbourne, Singapore and Hong Kong are discussed in the remainder of this section.
Melbourne

After large increases in rail travel in the mid 2000’s, Melbourne’s transit services began to experience high crowding levels in the AM peak. An early bird ticket program was introduced in 2007 to reduce loads by offering free travel before 7:00am. Currie et al. (2009) analyzed both survey and ridership data from users traveling before 7:00am to understand the program’s effects. Of those surveyed, 23% said they had shifted from the peak, by an average of 42 minutes. In contrast to the survey results discussed above, long distance passengers were more likely to have shifted. In addition, 10% of these travelers had started using rail because of the discount (though overall system growth was 11.8% in the past year). Most people who used the early bird tickets were regular commuters. Reasons for using the tickets included saving money (66%), traveling at that time anyway (33%), and to enjoy less crowded trains (13%). Among users who did not use the tickets, 23% had passes, 20% did not know about the program, 36% did not want to travel early, and 20% had difficulty accessing the tickets.

Ridership data was not in complete agreement with these survey results. Indeed ridership between 6:00 and 7:00 increased by 41% compared to before the program began. However, loads between 7:00 and 8:00am increased even more—56%. Loads also decreased by 14% between 8:30 and 9:30am, unexpected given the higher displacement times (i.e. required time shift) associated with this later hour. Currie et al. infer that wider changes in travel patterns were occurring with users tending to shift to earlier times anyway. They hypothesize that there may have been “cascading” shifts as some people took advantage of the discount and other traveled only a little earlier on the now less crowded trains. Longitudinal trends showed a slight increase in ticket use over the first few months (“medium term growth”) as well as weak seasonality impacts (Currie, 2011).

Given the increases in early morning trips, Currie et al. found that the program shifted enough people to save 2.5-5 train trips each day, equivalent to about AU$87-174 million in capital and operating cost savings. Given these savings along with the lost revenue, the program at worst is covering its costs and at best is bringing in twice its costs. In addition, though the system still saw growth in the peak, the early bird tickets may have helped slow growth in the peak. As a result, it may have helped reduce overcrowding from ridership growth if not actually reducing crowing.

Singapore

Singapore’s Land Transport Authority (LTA) travel demand management program currently goes by the name Travel Smart. As a densely populated, space-constrained city, as well as a country with a strong central government, Singapore has both strong motivations and abilities to utilize demand management measures. Its vehicle policies, including vehicle licensing and electronic road pricing schemes, are well studied, but the LTA has also implemented transit policies since 1997 to manage overcrowding. The current fare differential policy, which began in 2013, makes trips from outside the city center to 16
central rail (MRT) stations that end before 7:45am free, and gives a SG$0.50\textsuperscript{1} discount on trips to these stations that end between 7:45 and 8:00am. Previously, a SG$0.50 discount was given to trips that ended before 7:45, but stronger measures were deemed necessary. To support these discounts, additional service was added to pre-peak periods and several other TDM strategies were implemented.

One supplemental policy is the Travel Smart Rewards program (previously INSINC). Developed with researchers at Stanford University, it allows users to register to receive "points" when they travel on the MRT. Users get more points for traveling in the peak shoulders and when they convince friends to sign up. These points can be converted to value on one’s smart card, or be used in lotteries for higher value rewards. This program utilizes concepts from behavior economics (like prospect theory): people may respond more to higher payout raffles than lower, guaranteed payouts, plus social motivation and status provide additional incentives (Pluntke and Prabhakar, 2013).

Finally, the LTA’s employer program involves three initiatives. It offers (a) increased points for the Travel Smart Rewards Program, (b) vouchers to companies for studying employer travel patterns and develop TDM policies that fit their needs, and (c) grants to support more flexible work patterns (Singapore LTA, 2014). Because work constraints are a major hurdle to get people out of the peak period, developing a broader employer program could have large impacts on changing people’s habits even if the costs are unsustainable in the long term.

As a result of these schemes, the MRT has experienced a 6-7% decrease in trips between 8:00 and 9:00, with the peak to pre-peak trip ratio declining from 2.7 to 2.1. Few people were found to be shifting transit mode (e.g. from bus) to get this discount, but some people did begin to make less direct rail journeys to get the discount. For example, some users started exiting at the first eligible station they reached before 7:45, then continuing to their actual destination and exiting later. Officials deemed this level of decline acceptable to deal with crowding in the short term while planned network expansions are being completed.

The Travel Smart Rewards/INSINC program was also evaluated on its own. In their analysis of its first six months, Pluntke and Prabhakar (2013) found that over 20,000 users had joined the program at a cost of SG$1.5 per person. They found that 7.5% of these users’ trips had shifted from the peak to the off-peak period, though largely to the period just before shoulder ended at 8:00am. Changes were larger for users who had had been commuting regularly in the peak previously, with users with 10 or more peak trips prior to joining INSINC having over 10% of trips shifted out of the peak. These effects are larger than what was observed in the system as a whole, showing that this program enhanced the fare differentiation. Though it does allow users who already traveled in the peak shoulders to get the same rewards as people who actually shifted out of the peak, Pluntke and Prabhakar (2013) found that these users still made a difference via the social network

\textsuperscript{1}US$0.66 at SG$1 to US$0.75
aspect; they had more friends sign up and their friends tended to shift more to keep up with the "competition."

**Hong Kong’s MTR**

MTR has utilized fare differentials in the past, using both time period and route-choice dimensions. MTR began to experience overcrowding due to large increases in ridership in the late 1980’s: between 1980 and 1991, the percent of transit trips on MTR grew from 7.6% to 22.6% and its share of cross-harbor transit trips grew from 18.2% to 56.7% (Li and Wong, 1994). Because many people lived in Kowloon and traveled to Hong Kong Island for work, the Nathan Road corridor (between Tsim Sha Tsui and Prince Edward stations) and Tsuen Wan Line harbor crossing (the only crossing until 1989) were particularly affected. Thus, a series of TDM policies were introduced to control congestion.

In 1988, an "Early Bird" pass was introduced (LegCo, 1999), allowing users who traveled on particular routes before the peak to use their pass rather than paying full fare. However, the passes were quite restrictive and few people purchased them (Lok-Sang, 2014). They were phased out by 1990.

The next program was more far reaching. "Staggered Hours Discounts," which began in 1990, were meant to not only encourage off-peak travel via a peak surcharge and off-peak discount in certain zones of the system, but also encourage users to shift from the Nathan Road Corridor/Tsuen Wan harbor crossing to the newly built Tseung Kwan O (eastern) crossing (Li and Wong, 1994). The spatial zones of this strategy are shown in Figure 2-2: users who entered a station in Zone A between 8:00 and 9:00 and exited in Zone B had to pay the surcharge (HK$0.80) unless they also swiped their ticket at a station along the eastern harbor crossing, in which case they would receive a discount of HK$0.80. Users who traveled from Zone A to B along the Nathan Road corridor before 8:00 or between 9:00 and 9:30 got the same discount. Because users faced either a discount or surcharge depending on their choice, this policy was touted as "revenue neutral."

Li and Wong (1994) investigated user response by surveying users at key stations and developing three discrete choice models, one based on all respondents and two that divide peak and off-peak travelers. User characteristics found to be important were:

- **Income and Job Type:** Wealthier users and those with professional jobs were less likely to change their route.
- **Habit:** Users who admitted to regularly use the Nathan Road Corridor were less likely to shift their behavior than those who used it less often.

Another important characteristic was the difference in trip length among the two routes. Li found that for every one minute in time savings from taking the eastern crossing, an additional 7% of users would choose that route instead. The model’s fare coefficient implied that the differential had increased the number of users choosing the Eastern crossing by 13%, but the coefficient was not very significant. Thus they concluded that the pricing policy was not particularly successful, and trying to make the eastern crossing transfer
quicker and easier could be more effective.

Ultimately, the staggered hours discounts were not publicly or politically popular, and were completely repealed in 1999 with the opening of the Tung Chung harbor crossing (LEGCO, 1999). More recently, a number of smaller scale efforts have been made. A pass that effectively reduces Airport Express Line fares in peak hours was introduced to shift people from the overlapping Tung Chung Line. In addition, MTR has tried to engage its "MTR Club" members (a program users can enroll in to get information and promotions from the company), by setting up lotteries for off-peak travel offering free rides or theme park tickets. However, relatively few members have participated so these have not been particularly successful. The Early Bird Discount Promotion is the latest attempt at a more major TDM program, and will be the focus of subsequent chapters.
2.5 Travel Behavior Analysis with Automatic Data

Transit networks are increasingly installing automatic data collection systems to improve operations control, fare collection, and service monitoring. These systems can also be used to understand user travel patterns for higher-level service and network planning. In particular, AFC (automatic fare collection) data gives agency staff and researchers the ability to understand travel patterns from the system-wide level to the individual level.

AFC systems using smart cards were initially introduced in the 1990’s in cities like Hong Kong and Seoul, before spreading to Europe and the US (Blythe, 2004). Rather than paying for each trip separately, customers can add value to the card online or at particular locations. At fare validators, users tap the card to subtract the appropriate fare. Smart cards provide several advantages to transit service providers (via Pelletier et al., 2011):

- Improved payment mechanism and information flow
- Flexible and creative fare policies become possible
- Faster boarding and alighting processes
- Reduced driver workload
- Integrated payment for multiple transportation systems (transit, road use, parking, etc.)
- Data collection is faster and easier than through surveys
- If registered, trip data can be associated with socio-economic information.

This data elicits security and privacy concerns among some users (e.g. potential access to payment information and tracking the user’s movements), so it is typically anonymized. There are also some drawbacks in using this data for analysis. In open systems, where a user only taps the card at one end of a trip (as opposed to closed systems, like MTR, where users tap at their origin and destination) reconstructing trip records can be difficult. If smart cards do not have enough market penetration, travel analysis of smart card records may not reflect users as a whole.

Pelletier et al. (2011) organize the use of smart card data into three levels of study: strategic, tactical, and operational. Strategic studies (including market segmentation, temporal and spatial use patterns, and card turnover rates) aid long-term planning. Tactical studies can be used for service adjustments and schedule improvements. Operational studies have focused on developing service performance indicators and monitoring the performance of the AFC systems themselves. In this research, the use of smart card data will be both strategic, focused on developing different customer types, and tactical, looking at the impacts of a specific fare structure on travel patterns.

Smart card data can facilitate the analysis of a number of different dimensions of a user’s travel history. These include frequency of travel, typical departure time, trip duration and distance, origin and destination frequency, and transit mode choice. Some researchers have also combined smart card use with land use data to infer activities (Chakirov and Erath, 2011; Devillaine et al., 2012). Liu et al. (2009) looked at system-wide patterns and found strong regularity in temporal and spatial mobility, with demand patterns repeat-
ing regularly over time and trips concentrating in the city center in peak hours. Patterns have also been found at an individual level, with Ortega-Tong (2013) summarizing several different measures used to capture individual travel variability. These measures have been employed to find different levels of regularity among users, and have also found that trip-based measurements tend to show more variability than time-based measurements. Goulet-Langlois (2015) developed a measure of travel regularity that employs the information theory concept of entropy. It allows regularity to be measured at a user-specific level, rather than just comparing users’ behavior to typical conceptions of regularity. Lathia and Capra (2011) used smart card records to understand whether users are responding to agency incentives. An analysis of peak hour surcharges suggested that they did not decrease congestion but instead drove a shift to travel passes, which are unaffected by the surcharges, over pay-per-trip cards.

User classification is another area for which smart card data has been used. This market segmentation can be used for more effective information and marketing, a better understanding of user response to service or fare changes, and can inform other long term planning initiatives. Most customer classification efforts that use smart cards have used a combination of temporal and/or spatial characteristics. Agard et al. (2006) and Lathia et al. (2010) use only temporal data to group users with similar start times. Agard et al. (2006) use the k-means algorithm with data from Gatineau, Quebec to find four groups: one traveling regularly in the AM and PM peaks, one traveling regularly in the morning, and two with more irregular patterns. Lathia et al. (2010) use hierarchical clustering to find six groups in London: morning only, midday only, evening only, irregular travel, early morning commuters, and peak hour commuters. They then used these groups to develop personal travel time estimates and to predict station visit frequency.

Kieu et al. (2014) used the DBSCAN algorithm to classify users based on both spatial and temporal regularity. Their intended application was improving communication between agency and users. They found four groups (regular in both temporal and spatial patterns, only spatial patterns, only temporal patterns, or neither) and provided different suggestions for reaching each one. Ortega-Tong (2013) performed customer classification for London transit users using the k-medoids algorithm. Using 20 variables related to temporal variability, spatial variability, activity patterns, socio-demographic characteristics, and mode choice, she found eight groups that vary largely on which modes they used (rail, bus, or both), what days they traveled (all days, weekdays only, weekends only), and their frequency of use. Different groups also had distinct spatial distributions among stations. Goulet-Langlois (2015) furthered her work in London, developing user groups based on how users divide their time between different locations. He then found correlations between certain travel patterns and socio-demographic characteristics.

The detailed data provided by ADCS, and AFC data in particular, offer strong support for TDM analysis. For one, they allow for better measurements of effectiveness through the more complete records of system conditions and passenger flows. This thesis will also explore how customer classification can help agency staff understand what impacts their policies have had among different users and how to better target customers.
This chapter introduces a framework for design and evaluation of transit-focused demand management programs. It proposes methods to help decision-makers frame the problems faced by their system and link a design to their particular goals. Since there are myriad ways strategies can be implemented, the aspects that can be considered in design are enumerated, as are considerations for thoroughly and consistently evaluating any impacts. This framework is to be broadly applicable to any transit system, whether it is beginning a demand management program or trying to evaluate one already in place. In subsequent chapters the framework will be applied to the MTR network, with particular attention given to their Early Bird Discount Promotion as a case study.

The framework consists of four parts. In Section 3.1, the possible stakeholders in a demand management program are considered and a methodology for establishing the program’s goals is described. These motivations feed into both the design and the particular evaluation metrics of the program. Section 3.2 details a number of different dimensions to consider when designing policies. Section 3.3 organizes and reviews the areas to include in an evaluation. For many agencies, developing an appropriate set of policies will be an iterative process; Section 3.4 provides one way to link the evaluation of an initial program to the design of a better one. Finally, each of these processes can be improved with data and quantitative analysis, described in Section 3.5. These methods provide the initial information guiding the design process, allow the program’s impacts to be quantified once it is implemented, and inform improvements to future iterations. The methodology is illustrated in Figure 3-1.

### 3.1 Motivations for Transit TDM

Generally, the primary motivating factor for a transit TDM program is to reduce congestion in the network. However, given the local context for the program and the nature of demand problems being faced, the particular driving factors can be quite different. This section will discuss how to set specific goals and targets for the program by identifying the demand issues in the system, recognizing how the involvement of various stakeholders can shift the program’s focus, and determining the appropriate time horizon.
3.1.1 Characterizing System Congestion

While an agency considering TDM is almost certainly experiencing crowding and congestion in its system, there are a number of forms that these problems can take. Different demand patterns will require different solutions, so the congestion in the system should be well understood before setting specific goals for it. Congestion is impacted by both service and user characteristics, and can be understood on both spatial and temporal scales, as shown in Figure 3-2.

At its core, congestion is a result of an imbalance of the supply of service and demand by users. Though network expansions, different vehicles, more frequent service, etc. could help alleviate congestion, in the context of TDM these service characteristics are assumed fixed, constrained by either cost or time. Therefore, while the impacts these factors have on congestion must be recognized, the effects of different user characteristics are even more important. Depending on when and where users are traveling under fixed service levels, various spatial and temporal congestion patterns will be observed. However, underlying these aggregate behaviors are individuals’ particular travel patterns, which themselves are influenced by attitudes, constraints, and socio-demographic characteristics. Though a number of these factors, like the population’s socio-demographic characteristics and certain lifestyle preferences, may be largely outside the agency’s control, others maybe malleable enough for a TDM policy to target and cause behavior change.

Some guiding questions for identifying the importance of each aspect shown in Figure 3-2 on the facing page and quantifying it may be:

**Understanding Agency Services:** Do particular modes or types of rolling stock experience higher congestion levels? How do the current network structure and frequency levels influence demand patterns and problems? What other resource-related constraints may be affecting how well the agency’s service can meet demand?
Figure 3-2: Areas to consider when characterizing congestion

**Spatial Congestion Characteristics:** Is congestion confined to vehicles, or is station or platform crowding a more major concern? Are only certain links and stations bottlenecks to the system or is the problem more widespread? What is the direction of link flows or station movements during congested periods? Is the whole vehicle congested, or only specific cars or areas? Likewise, is station congestion seen on platforms, at gates, or elsewhere?

**Temporal Congestion Characteristics:** When do high demand periods begin and how long do they last? Does peak demand occur at different times in different parts of the network? Does major congestion occur only during short peak periods or does it build and dissipate more gradually?

**Understanding Users:** Where and when are users traveling in the network? Are users that display certain travel behaviors contributing more to congestion? What attitudes and constraints may be influencing these behaviors? How do socio-demographic characteristics inform users’ travel patterns? How do these different attributes affect a user’s ability and willingness to change their behavior?
In addition to aiding the goal-setting process, having a complete characterization of the demand problems can also inform the evaluation stage. If the agency does not know how the system was functioning before the program begins, it will be difficult to understand the effects it is having: what parts of it are working and which need to be adjusted. Therefore, this analysis can also provide baseline figures to use for comparison when later monitoring performance.

3.1.2 Stakeholders

Though the main focus of this research is how transit agencies can use travel demand management in their system, they are by no means the only groups who may be interested in reducing network congestion and improving a system’s efficiency. Other potential stakeholders for transit TDM strategies include current (and potential) riders, planning agencies and other government bodies, employers and businesses, and other local transportation operators.

Depending on the involvement of these different parties, different TDM strategies will be feasible. An integrated approach, where the government works together with all local transit agencies and gets input from community groups and businesses will likely have different goals and consider different methods than one led primarily by a single agency with more limited oversight. For example, if the program is being led by a planning agency who can bring these multiple stakeholders together, broader strategies, like guiding land development patterns or improving infrastructure for non-motorized travel, may be possible. However, if a single agency is spearheading the program, fewer types of programs may be feasible, and particularly if it is semi- or fully private, cost will be a higher priority. Such an operator may be more interested in encouraging passengers to shift their departure time or route, rather than potentially losing them to other modes. Though several of the more sweeping strategies will be discussed, the remainder of this framework will focus on measures that an agency can implement without strong involvement from or dependence on other groups.

3.1.3 Time Horizon for TDM Program

Demand management can happen on multiple time scales. At one end of the spectrum, TDM policies can be developed for short term, major events. If a city expects an influx of passengers all traveling at similar times to a specific set of destinations, incentives can be developed to shift those who do have more flexibility. For example, TDM was used heavily in London for the 2012 Olympics. On the other hand, if major network expansions are planned, TDM can be used as a quicker, relatively inexpensive fix to help tide a system over until they are completed. In some cases, even a long term basis could be considered to avoid the need for new infrastructure. Factors that can inform the appropriate scale for a given program include how demand may change in the future (using population and employment forecasts), as well as what kinds of expansions the agency’s budget and current network allow for.
3.1.4 Setting Goals and Targets

Once an agency has a good understanding of its congestion patterns, who will be involved in the program’s creation, and roughly how long the program will be in effect, it can set more specific goals for its TDM program. The chosen time horizon may influence what designs and impacts are feasible (as will the stakeholders involved in development), the rate at which these goals are to be met, when (or if) to place various milestones. Those developing the program should decide what changes in demand will best solve their particular congestion patterns: shifting users to different times of day, different routes, different modes? This framing of the problem can have strong implications for the types of strategies chosen, as some designs may be more effective at shifting people away from the peak, but at the expense losing customers. Others may be more effective at shifting people to different routes, but more complicated to implement.

Different parties may also have different priorities for the program, which could lead to different targets for different groups. For the agency, these targets could include quantified decreases to passenger flows for certain times or locations (e.g. reduce the flow on Link A by X%, or have fewer than Y passengers/15 minutes exiting Station B), and almost certainly within a particular budget. They could also include more qualitative guidelines, like trying to develop a set of policies that are well-received among users or simple to understand, which can help improve its effectiveness.

3.2 Design of TDM Strategies

The sections below describe a number of design aspects to consider and how they can be incorporated into a policy. While the importance of each of these factors will vary depending on the context and goals of the agency, acknowledging each can broaden the designs being considered and increase the likelihood of positive impacts.

Figure 3-3 describes how to carry out the design process. After choosing a type of program, 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.

3.2.1 Type of Measure

A number of different approaches to demand management have been used in the past and new, innovative strategies are always emerging. Understanding the various dimensions that comprise these strategies can guide the selection of an established strategies or inspiration of a new one. Depending on the goals of the program, the agency’s constraints, and the local context, these different dimensions (shown in Figure 3-4) can be assembled to find a reasonable set of policies.
Hard vs. Soft Measures

As introduced in Chapter 2, hard (or structural) measures are those that aim to change the opportunities of users, while soft measures target beliefs, attitudes, or perceptions about current opportunities. In the case of transit, hard measures could include creating fare differentials between crowded and non-crowded services or using land development to influence demand patterns. A number of attitudinal, norms, and behavioral factors influence the effectiveness of hard policies, and selecting an appropriate "magnitude" for the program (e.g. level of fare differential) is a critical next step (Eriksson et al., 2010). These policies can take longer and be more costly to implement than soft measures. General types of soft measures include support for motivating changes in travel, facilitating the development of travel plans, and providing customized information (Richter et al., 2011). The benefits of using both soft and hard measures were cited in Chapter 2; using both in combination can increase both their acceptability and effectiveness.

Market-Based vs. Regulatory

Hard measures can bring about their changes either through economic, or market-based, concepts, or by setting laws or regulations that influence travel. For transit, particularly with the agency perspective taken here, regulatory policies will be much less common.
Figure 3-4: Several dimensions for categorizing program types

than they are for personal vehicle TDM (where they could include parking regulations or road closures), though these are discussed briefly as "Regionally-Oriented Policies" in the next section. Market-based programs, which are founded on classical economic principles, are far more common. Given the principles that govern supply and demand, these policies aim to adjust prices to get people to travel in certain ways; raising specific prices should drive some users to other less crowded times, modes, or routes, while lowering them could attract users from more congested services. However, the assumptions of rational behavior and complete information that underlie this category of measures do not always hold. Furthermore, fare elasticities for peak travel can be quite low, which may limit the effectiveness of pricing strategies.

Push vs. Pull

When trying to shift users’ travel patterns, policymakers can choose whether to make one choice less attractive or another one more. As introduced in Chapter 2, these relate to coerciveness and are typically referred to as push and pull strategies, respectively. The more coercive pull measures typically limit users’ freedom and force them to behave in a certain way. Pull measures aim to change users’ attitudes so they can decide themselves whether to take advantage of the different option. Generally, pull measures are more attractive to users (Steg and Vlek, 1997), though push strategies have been found to have a larger influence on users, at least in the context of car use (Eriksson et al., 2010). However, some argue hard measure effectiveness can be limited if users find their freedoms threatened and develop negative attitudes, and that their effect on long term changes may be limited because people’s underlying attitudes are unaffected (Geller, 2002).

Measures can fall along a range, with some strongly “pulling” or “pushing” users, and others in between. Some measures on the “push” side could include peak hour fare surcharges, which may force users who cannot or do not want to pay into off-peak hours. Regulations that restrict certain activities would also be push measures. Off-peak discounts would be pull strategies, as would be providing coupons (e.g. free breakfast after pre-peak travel), marketing to promote certain behaviors over others, or providing infor-
mation that empowers users to make better choices.

**Targeted Stakeholders**

Policies can also vary in terms of how they involve different stakeholders. While some directly target the user to shift behavior, others target employers to encourage changes or reduce constraints on travel (e.g. increasing schedule flexibility). Broader, longer term strategies that may require more government involvement, like altering land development patterns, could also be considered.

**Customer Oriented Measures** Measures that directly influence the customer can either apply to any user of the system, only users who meet certain criteria, or be restricted to those who choose to register in the program. These strategies can have a wide reach, since potentially anyone can enjoy the benefits, but setting effective parameters (as discussed in the rest of Section 3.2) is important to make sure the right users are aware of the program and that it covers appropriate times and locations. Examples of such measures include:

- **Pricing Mechanisms**
  Perhaps the most common type of strategy is altering fares in different periods of the day: adding a surcharge to peak fares, a discount to off-peak fares, or even both. Such price differentials can encourage customers to travel outside the peak period, limiting congestion and using capacity more efficiently over the day. For some agencies, deciding on the direction of the differential depends on which is more likely to shift demand rather than gain or lose customers. Depending on the magnitude (Section 3.2.3) of the differential with respect to the fare elasticity, some surcharges could cause customers to simply stop using the service while a discount could induce demand. In addition, though the various ways of creating this differential are all essentially doing the same thing—making the peak more expensive than the off-peak—the way each is framed can bring up issues of equity and customer acceptability. Adding a surcharge to travel in peak periods tends to be seen as less acceptable by users (Consolidated, 2006), particularly as those who work lower paying jobs tend to have even less flexibility to change their departure time (Faber Maunsell, 2007). Off-peak (including pre-peak) discounts are less likely to face these socio-economic criticisms but may be seen as providing unfair benefits to people that already travel in these hours and do not have to change their behavior to take advantage of the discount.

  In addition to solely time-differentiated fares, if multiple routes exist between major OD pairs, surcharges on a congested route or discounts on a less crowded one could be considered. This mechanism begins to address equity issues because departure time flexibility is less of an issue; routes that would be good candidates for such a system are not too dissimilar in duration so a lesser time shift is necessary. If the incentivized route is much less traveled, the fairness considerations are also addressed since most who use it will actually be
changing their behavior. However, this measure does require less ubiquitous technology that can monitor route choice. Customers will have to balance the benefit they receive from taking the incentivized route with a potentially longer travel time, more transfers, or an extra trip validation to prove their route.

If an agency oversees multiple modes (e.g. rail and buses), and one faces more extreme crowding, pricing could be a way to shift users from one mode to another. If the agency only controls part of the region’s transit network, it could consider partnering with others who offer service between similar origins and destinations. Offering cross-operator incentives requires high levels of cooperation and integration of payment systems or other compensation mechanisms.

**Other Customer Benefits**

Rather than simply charging someone more or less to use the system, customers can be offered other types of incentives to encourage behavior change. One type of incentive that has been used in the past is to give coupons to users who travel outside the peak period; for example, offering free breakfast in Shenzhen (Zhang et al., 2014) and Singapore (Singapore LTA, 2014). Other potential benefits could include free wireless internet access (suggested by Zhang et al., 2014), discounts at in-station stores, or a subsidy for a gym or other activity membership to use before or after work or school. Such benefits are typically used in conjunction with pricing to make the departure time change more palatable; users have something to do to occupy the extra time that results from their earlier arrival. However, these systems may be more complicated (e.g. distribution and partnerships) or costly to implement, particularly if the measure is to continue long term and not just be used as a short-term promotional strategy.

Another option is to hold lotteries that give higher rewards to fewer people. People who travel out of peak hours can be entered into a lottery for reaching some level of off-peak travel, and win monetary or other prizes. This "game" aspect of the strategy can help engage users, drawing on their desire to compete with friends and thrill of luck, and encourage them to travel off-peak more often to earn more points and rewards. Such a strategy takes advantage of people’s tendency to overvalue low probability events (Kahneman, 2003). However, it adds an extra barrier to participation, as people will likely have to opt in and their travel monitored more closely.

**Information Provision**

When users have a stronger degree of problem awareness, they can be more inclined to shift their behavior (Eriksson et al., 2006). Improving the information provided to customers can encourage better decisions. In addition to providing more qualitative information via marketing and education, more quantitative information about system conditions can also be used. Real-time vehicle location data, though typically not intended for TDM applications, is becoming increasingly common and could be useful in this context to make less frequent, off-peak service seem like a more dependable alternative (users can know when a vehicle is arriving and plan around long headways).
In the context of system congestion and crowding, however, the emergence of crowding information may be more valuable. Some agencies have begun to experiment with providing historical or real time crowding levels to customers. The San Francisco Bay Area’s BART system uses historical trends to give a crowding estimate for each leg of a trip planned with their website’s journey planner (Figure 3-5a). This allows users to know what to expect and to adjust their departure time if they do have the flexibility and desire to avoid more crowded trains. East Japan Railway provides real time information to customers about the crowding level and temperature on each car (Figure 3-5b). This finer level of detail also allows customers to better allocate themselves along the vehicle so that one car is not overcrowded while others are relatively empty.

In addition to aggregate vehicle conditions, personalized information could also be provided to customers. With fare transaction data (for agencies that encourages users to register smart cards with contact information) information about where and when users typically travel is available. Targeted suggestions related to potential behavior shifts and the benefits the user will expect to see from them could increase the effectiveness of these messages. Computing and data needs would be relatively high, especially in a large system, and security of the user’s transactions and identifying information would have to be ensured.

**Employer Oriented Programs** Rather than designing a policy that impacts users directly, an agency can instead work with the employers (or schools, etc.) that are responsible
for constraints on transit use. In particular, an important variable for a strategy’s effectiveness is the flexibility commuters have in changing their departure time or coming into work at all (further discussed in Section 3.2.2). Agencies can try to work with employers, perhaps with government involvement as well, to encourage flexible hours or telecommuting.

For example, as part of their “Travel Smart” Program, the Land Transport Authority of Singapore offers grants to organizations to develop demand management incentives (Singapore LTA, 2014). Other potential programs could include offering employer-specific transit passes that are specifically for use for certain routes, modes, or hours; offering information sessions for employers to explain the needs to alternative travel behaviors; or even directly providing personal information to companies.

Regionally-Oriented Policies This set of policies takes a broader perspective on what can influence demand. Referring to them as “regional” is meant to underscore their potential for wide-ranging impacts on the community and the need to involve more stakeholders besides the transit agency itself, namely other government bodies. They also may take a longer term view of the problems, such that their effects are not realized for several years.

One option is to work with planning bodies to shape regional land use patterns. Particularly if the agency is more involved in real estate already (like MTR), it could be involved in deciding where to place new developments for managing regional travel patterns. Creating a less monocentric city, where not all workers are traveling to the same location or must use motorized modes, could help reduce future congestion problems, though more polycentric travel brings its own complexities to demand patterns (and thus the service required). These hard measures can either be push or pull, depending on the details of the design.

Though more common for traffic management, working with government bodies to pass laws affecting use of public transportation could also be considered. Some potential examples are stricter rules regarding flexible working time or commuting (like requiring employees to have flexible hours or the ability to telecommute once per week) or even extreme policies like legally restricting how often people can travel in the peak hour (though the effects to the full transport network and the equity impacts of such a law would almost certainly be insurmountable). In the context of transit and this framework’s focus on agency-level changes, such measures have limited applications.

Given all these possibilities, the program’s goals should be kept in the forefront of decision-making. In particular, the stakeholders are important, as are the resources available to the agency. Research has found that a combination of different policy instruments can often be more effective than using just one (Eriksson et al., 2010). In particular, a mix of soft and hard, or push and pull measures can be used, with soft measures supporting hard ones or using pull measures to increase the acceptability of push measures.
3.2.2 Users Targeted

Ultimately, for a demand program to be successful, it needs to actually encourage users to change their travel patterns. However, the users of a transit system are heterogeneous; they will not respond to TDM measures in the same way. To be more effective, policies can be developed to influence only specific users, either through targeted marketing of a general policy or designing policies that are meant for certain groups of users (though this could be politically difficult). User groups can be inferred prior to developing the design (through surveys, fare types, data analysis of travel behavior, etc.) or only once the program and data becomes available. Some relevant features for segmenting users’ responses to a TDM policy include:

- **Travel Patterns:** How do passengers use the system:
  - Which modes do they use?
  - How frequently do they travel?
  - What days and times do they typically make trips?
  - How do they transfer between routes and modes or chain trips together around several activities?
  - What stations do they typically travel between? Are these in congested parts of the network or not?
  - Are there any particular patterns within their spatial and temporal use of the system?

- **Activity Constraints:** Do transit users have the ability to change their travel behavior? How flexible are their work, school, or family schedules?

- **Attitudes:** What degree of problem awareness do users have and what level of responsibility do they attribute to themselves? Are there any other attitudes (e.g. toward the environment or personal safety) that could be targeted?

- **Socio-Economic Characteristics:** How do factors like age, family structure, or income impact users’ ability or likelihood of shifting their behavior?

Examples of program designs that target certain users include tourist or senior passes that are only eligible for off-peak periods, or trying to influence commuter behavior by providing customized information about a program to employers.

3.2.3 Magnitude of Program

The level or degree to which a particular TDM strategy is implemented has strong impact on the extent to which people participate. For various types of measures, this could include the level of the fare differential or other rewards, the number of people or businesses that are part of a program, or the frequency with which a reward is given out. Estimated effectiveness and agency budget will be two driving factors for the magnitude chosen.
The magnitude could also be considered in light of the particular users being targeted. If the program is to be broadly influential to any user, it may only require a small percentage of customers to change their behavior. If specific, smaller groups are targeted, higher response rates may be necessary. Similarly, the necessary magnitude may differ if users who frequently travel at peak times are the focus versus if occasional users are.

Specifically for fare differentials, various levels of differentiation have been used in the past, ranging from free travel in certain off-peak periods, as in Singapore and Melbourne, to a surcharge of several dollars extra in the peak, as on the London Underground. Because transit demand is typically quite inelastic, especially in peak periods, surcharges or discounts must be priced appropriately in order to see any meaningful change in demand. The correct magnitude of the fare differential depends on both the desired change in demand and a fare elasticity, relative to the local context, mode, and time of day targeted if possible. Of course agency financial impacts should also be considered (see Section 3.3.3), as fare changes can affect not just revenues directly, but could also cause customers to start or stop using the system.

As another example, benefits to employers can also be implemented on different scales: the exact program the agency hopes to use, how many employers and employees are to be involved, and what these services are estimated to cost. These types of policies may be better to begin as smaller-scale pilot projects where the agency works with just a few employers to start, and when they are able to understand the costs and impacts, they can adjust as necessary and bring in other employers.

### 3.2.4 Temporal Coverage

There are two temporal components to consider when designing a TDM program: how long the program will run for and what periods of the day it will cover.

**Program Duration**

As was mentioned in Section 3.1.3, programs can have different temporal scopes. In addition to thinking about types of programs that work broadly in the long or short term, the actual duration of the program needs to be decided.

- Is it be just a pilot program for a test of concept or will it immediately be widely implemented? One possible first step could be to introduce a strategy (or several) on a smaller scale, then adjust it for application on a larger and longer term scale.

- How long will the program last for? If it is not to continue indefinitely, the agency needs to consider how behavior may revert once it ends. Without (dis)incentives for users, any improvements that existed during the program may be lost. Otherwise, the end of the program could be set to correspond with other milestones, like the opening of a new rail line or a restructuring of the bus network.
**Time of Day**

Another temporal consideration is the times of day the policies cover. This is particularly important for pricing mechanisms that aim to shift people out of the peak. A peak discount or surcharge should cover a period such that some users will change their behavior, but not so many that the peak itself shifts. These decisions can be made using the preliminary evaluation of system congestion (Section 3.1.1): when does the peak begin and end, and when is it at its worst? Peak periods can vary over space (the downtown peak may be at a different time than the peak in residential areas) as well as the unit of measurement (station entries, station exits, or train loads). The method to determine the peak should be recognized when setting a period—if a discount is given on exit in the CBD, its time period should align with peak exits in the CBD. Combining fare elasticities with users’ value of displacement time in a demand model can help understand how much people are willing to shift their travel times if a peak-spreading strategy is desired.

Several different structures of time periods can be considered for the TDM design. First, the agency should decide if it wants to target the AM peak, PM peak, or both, since the types of trips that happen in these periods will impact which strategies will be effective. It could apply to the entire off-peak period, the peak shoulders (e.g. a one hour before or after the peak), or only the period before or only after the peak. In addition, tapered designs have been proposed (Lok-Sang, 2014) or implemented (Singapore and Washington, D.C.), where fare differentials change in several steps as one travels closer to the peak.

### 3.2.5 Modal Coverage

If an agency controls multiple modes (heavy urban rail, light rail, bus, ferry, commuter rail, etc.), it can decide whether the same strategy should be applied to all modes, adjustments should be made for each mode, or if only some modes should be included in the program. This can be decided using both first order crowding considerations (e.g. the subway is crowded so its fare will get a surcharge), but full network use and the ways people transfer within the system should also be considered. For example, if someone connects to a service that is infrequent during the off-peak period, they may be less likely to shift out of the peak because their full journey becomes even more inconvenient.

### 3.2.6 Spatial Coverage

Since network structure and OD flow patterns are one of the primary reasons congestion arises, they must also be considered carefully when trying to reduce crowding. If congestion is limited to certain parts of the network, perhaps only these sections should be included under the policy. If congestion is more widespread or hard to isolate, the full system could be involved. A common example would be if there is a single, dominant employment center; the routes that flow into this area and the stations in it are likely particularly crowded in the peak.
Some previous policies are zone-based (e.g. London and Singapore), while others are relative to stations. MTR’s Early Bird Promotion, for example, grants a discount to anyone who exits a designated station, no matter where they started. One potential concern with an exit-based design, however, is what happens if the train is delayed by no fault of the passenger. Entry-station based systems could also be considered, and one of their advantages is that passengers’ benefits would not be affected by delays. More complex strategies involving actual bottleneck links could also be used if the technology of the system is capable. Knowing typical travel times for OD pairs could allow for a system where each OD pair has incentives at the specific times that correspond to peak congestion on the links it spans.

3.2.7 Practicalities of Implementation

When a design is being developed, outlining its theoretical impacts is not sufficient; there must also be feasible methods to implement the proposed measures. Beyond requiring reasonable costs, the design should be robust in the face of service disruptions (e.g. should a user who experiences a delay that prevents them from getting a pre-peak discount still be compensated?), and mechanisms should be in place to cope with customers who try to take advantage of it. This can be dealt with using strategies like adding a buffer time to period boundaries and setting clear guidelines about if and how the program will function in minor or major disruptions. In addition, the agency’s technical infrastructure should be able to support the design. The ticketing systems must be able to handle the added complexity related to fare changes, and any new web or mobile interface should be robust enough for customers to use them reliably. More innovative strategies may involve the development (or at least application) of new technologies.

3.2.8 Marketing and Information

Once the design is complete, a plan for spreading information about the new measures needs to be developed. This will build awareness and get users to participate at an early stage. Getting the word out on the agency’s website, travel planner, or mobile app, through traditional media and advertising, or via social media can help the program have a stronger impact than if it is launched more quietly. More targeted marketing information can also be used if the agency has the data to back it up, similar to the possibilities of targeted recommendations or system condition information. The considerations listed in Section 3.2.2 can also be used for this purpose as can the groups of users identified when setting goals for the program.

3.3 Evaluation of TDM Strategies

Though the proposed policies should be evaluated before implementation to estimate their effects and ensure feasibility, strategies aiming to influence human behavior will likely not match their expected results. Thus, evaluating the actual effects post-implemen-
Evaluation will help the agency understand how well it is achieving its goals and how to adjust policies currently in place. Evaluation metrics should be strongly tied to the agency’s goals, as discussed in Section 3.1, and should acknowledge each of the aspects that contribute to its design. Ideally, the relevant dimensions should be decided in advance to allow for appropriate data collection procedures and monitoring to be arranged.

Possible dimensions for evaluation are shown in Figure 3-6, and are detailed in the sections that follow. Following the discussion in Chapter 2, a program can be broadly evaluated in terms of its efficiency, effectiveness, and acceptability. These dimensions can be considered independently, but also in how each affects the others. In order to actually quantify these dimensions, a number of more measurable impacts can be monitored. They are here organized into four main categories: system, agency, customer, and social. In addition, the program should be monitored to measure how sustainable its impacts are as the program matures.

![Figure 3-6: Components of TDM evaluation](image)

### 3.3.1 Dimensions of Evaluation

Three primary dimensions for evaluation are efficiency, effectiveness, and acceptability. Each of these three is influenced by the design of the program and the specific impacts that will be described in Section 3.3.3. They are also interrelated. For example, a program that has higher levels of acceptability may be more effective, and one that proves to be effective could increase levels of acceptability. Similarly, a program that is efficient in the way that it uses resources may gain higher acceptance levels by political leaders.
Effectiveness and Efficiency

A program that is effective is one that reaches its targets of changing demand patterns. Critical for effectiveness are changes to passenger flows, but there may be other relevant impacts to the customer experience. The distribution or equity of these impacts can also be considered. The relationship between these impacts and the financial impacts defines influence the efficiency of the design in the context of the agency (with metrics like cost per shifted user).

Efficiency can also be thought of in the broader economic sense: are resources being used for their most valuable purpose? By setting prices to reflect the full cost of providing service, including externalities like incremental crowding or environmental effects, economic efficiency can be increased. In the context of transportation systems, the marginal cost of an additional user is typically higher than the average cost over all users, because of the additional congestion that user causes. Therefore, one way to develop an efficient system is to reflect the greater burden of users in congested periods with higher prices. This could be done directly, by adding a surcharge to peak period travel, but other strategies may suggest this concept to users, like offering lower prices or additional benefits for off-peak travel.

If the program reaches its goals for effectiveness, and the agency wants to aim higher, it can either set more ambitious congestion targets or shift its focus to efficiency. With a better understanding of the impacts the program is having, the agency may be able to lower costs or use resources differently for the same system and customer impacts. Even if a program was not sufficiently effective or efficient, its results can suggest ways to improve the design. The magnitude of the policies may need to be revised if too few users are altering their behavior. The period can be reviewed if the time-shifting is not as expected as can the areas or modes that are covered. If possible, the types of customers that are or are not altering their behavior could be studied; if a certain type of user is contributing less to decreases in peak travel, marketing efforts or other strategies to appeal to these groups could be considered.

Acceptance

Measures that are considered to be more acceptable to customers and to agency or political decision-makers have a higher likelihood of being effective at managing demand and gaining the support needed to continue into the future. Acceptance is influenced by both the impacts of the program and the design itself—certain types of policy and parameters will be more popular even if they are not as effective as others.

Customer acceptability and its impact on TDM effectiveness are well researched, as was discussed in the literature review. Several key points for acceptance that can be derived from that work include:

- Integrating factors like social pressures and the personal benefits of participation
can improve acceptance through the significance of social norms and personal expectations.

- The particular factors (fairness, perceived freedom, etc.) that affect acceptability can vary based on the type of measure being used, so there may be benefits in evaluating the acceptance of different TDM policies separately.

- Acceptance is something that should be monitored over time to see how levels change as the program matures. People’s opinions often change once they have actually experienced a policy and its effects.

For some agencies, monitoring political support or the support of other government bodies may also be useful. Finding a set of strategies that are acceptable to higher-level decision-makers will depend largely on the local context, but considering aspects like cost efficiency and showing quantitative analysis on what the scheme’s impacts be can help the program be extended or expanded.

### 3.3.2 Sustainability of Changes

Underlying each of the three primary dimensions are questions of program sustainability. Monitoring should continue beyond just the initial evaluation to capture the medium and longer term changes that the strategy induces. There may be seasonal changes to its impacts on congestion relief, depending on factors like holidays and weather. Similarly, changes in costs might arise over time as could changes to public or political acceptance. For example, as discussed in the previous section, in the case of the Stockholm Congestion Charge System, Schuijtema et al. (2010) found that that people saw more positive outcomes and fewer negative outcomes than they had expected before it began.

### 3.3.3 Metrics for Evaluation

To measure the success of the program, a number of impacts can be considered. Here they are organized into system impacts, which directly relate to congestion-reduction goals; customer impacts, which reflect other changes users might see in service as a result of system impacts and how they perceive these effects; agency impacts, reflecting finances and resource usage; and social impacts that capture broader effects to the region.

**System Impacts**

This set of impacts are most closely related to effectiveness and can help answer the most critical question: did demand conditions actually improve? Given the baseline figures that were developed when initially characterizing congestion, new measurements can be compared. The various factors that cause congestion should be considered: modes, temporal and spatial scales, and how these may differ for different user groups. Depending on the motivating factors for TDM, important metrics could include:
Station Passenger Flows. If people are altering their travel patterns as desired, rates of passenger movements through stations should decrease (at least in peak periods or on congested routes). This can be measured in terms of entries or exits, depending on the direction of flow in the time period considered. In addition, one can measure whether total demand is constant and people are just redistributing themselves over time, or if the spatial coverage of the design may be leading to people traveling to different stations.

Link Flows or Vehicle Loads. When vehicle crowding is identified as an issue, similar analyses can be done for flows between stations. Again, one can consider whether users are just shifting their departure time or if the policy is actually affecting route choice. If actual vehicle (or even train car) loads are unavailable, passenger flows along each link can be used as a proxy.

Customer Impacts

In addition to those changes that directly relate to crowding, there may be related changes to the customer experience. As a result of crowding reductions, customer may experience changes to comfort levels, being more likely to find a seat or not needing to stand so close to other passengers. This can occur either while waiting on platforms, moving through stations, or traveling on vehicles. Even though individuals have different tolerances for crowding, a measurement of the typical number of passengers per area or number of standees can provide insight into the impact of comfort.

Similarly, changes to crowding levels may have an impact on average travel times and reliability. With less demand, train dwell times and run times may also decrease, perhaps improving reliability as well. If passenger journey times are known (e.g. from AFC records), changes in the full journey time could also reflect reductions in denied boardings. If more people can get on the first train to arrive, the time they spend waiting after tapping into the system will be reduced.

A final type of customer impact is how their attitudes toward the agency may be affected by the TDM policies. Regardless of actual impacts, do they feel that their travel experiences have improved and that the agency’s efforts are worthwhile? This can have strong implications for acceptance levels and willingness to take advantage of policies.

Agency Impacts

In addition to changes in the customer experience, the impacts the agency faces in running the program are important to evaluate. In most cases, particularly for the many agencies that either operate under a tight budget or must answer to shareholders, changes to costs and revenues will be of particular interest. Establishing the program will have costs associated with it in terms of staffing, acquisition and installation of new technologies, promotion, etc. In addition, if fare differentials are part of the program, revenues may change. The program may also attract new customers or cause existing customers to
switch to another mode, leading to additional revenue gains or losses.

Changes in resources allocation is another dimension to consider. In some cases, it may be possible for the agency to run fewer vehicles on a route or have lower staffing levels if demand is better managed, allowing these resources to be used more effectively. If one strategy involves transit mode shifts, there could also be a need to improve service levels and use more staff and vehicles on certain routes, taking it a step beyond simply demand management. If the agency had also been considering shorter term infrastructure improvements (e.g. additional rolling stock), reduced demand may allow them to at least delay these purchases, leading to savings in capital costs.

**Societal Impacts**

This set of impacts speak to broader social issues, including the impacts the program may have on people who are not directly involved. Depending on the scope of the changes being proposed, the level of evaluation needed in these areas will vary.

One dimension to evaluate is the distribution of effects on different types of riders. A strategy that overwhelmingly benefits or disadvantages certain segments of society should probably be reconsidered for one that instead affects users more equally or fairly. Some groups of interest could be those based on age, income, race, or other previously defined environmental justice communities. Areas to consider in the evaluation could include:

- Does a fare surcharge cause undue hardship for low income users? Previous research has found that higher income commuters typically have more flexibility in their start time (Faber Maunsell, 2007), meaning that those who already have more money can more easily avoid higher fares, should they decide it is high enough to shift their behavior.

- Does the TDM policy lead to an uneven spatial distribution benefits, such that certain populations receive additional benefits or face more disadvantages? It could be problematic if certain traditionally underserved groups are more likely to face a fare surcharge, not receive a discount or otherwise not enjoy the benefits of a TDM program because of the zones chosen to be included in it.

- Do certain groups lack access to necessary technologies? If enjoying the benefits of the TDM policies require using technologies that certain income or age groups do not have the ability to use, the accessibility of the program could be reconsidered to try to ensure it can serve a larger population.

Given the size of the demand problem and scope of the TDM policies, there may also be broader, macroeconomic benefits that can be considered in an evaluation of the program. For example, if workers have more comfortable commutes, they may be more productive at work (Meyer, 1999). If the TDM program makes it easier for people to travel, it could increase both the customer or employee base for a business. TDM policies that have a longer term focus, particularly those that integrate land development changes, may also
lead to economic changes from additional centers of employment that are easier for people to reach.

Some TDM programs may also evaluate their impacts on the environment, including pollution or greenhouse gas emissions. If demand management measures lead to people choosing to take transit rather than driving or reduce vehicle dwell times, there could be reductions in these emissions. However, this area is likely not a major goal for agencies and transit-focused measures probably have a lesser impact than ones targeting car traffic. Thus this element is not as critical to consider unless transit demand management is as part of a broader set of policies that include other modes.

3.4 A General Approach for TDM Redesign

The process of redesigning policies or adding measures to a demand management program bridges the design and evaluation steps of this framework. As touched on in the previous section, after performing the evaluation, their effects can inform what additional strategies could be successful as well as provide more detailed information for forecasting the impacts of a proposed policy. It can also give policymakers additional insight into which design dimensions and evaluation metrics are most important in their systems.

Individual responses to TDM policies may only become available after initial measures have been implemented, so one dimension that may be particularly interesting to consider at this stage are the targeted users. This aspect can be approached by conceptualizing a "willingness to change" characteristic; customers would be willing to travel outside the peak with some type of incentive (though it might be unrealistically extreme). If this characteristic were known for everyone, along with the marginal benefit of removing each additional user from peak periods, the agency could use price discrimination to give each user his or her personally optimal incentive. This would allow it to remove the largest number of users from the peak at the lowest cost, either until crowding standards are met or budget expended. Figure 3-7 shows a representation of this relationship. Very low-cost measures will reach few users. Full-scale policies have the potential to influence more users. At some point, the marginal cost of each additional user will start to rise because only those with a high willingness to respond are left.

Determining this characteristic for each user, as well as actually implementing such discrete incentives, is probably not technically or politically feasible. However, dividing users into more homogeneous groups may be one way to proxy this characteristic. Groups
could capture price sensitivity, such that a fare differential influences enough groups for
the desired level of impact. They could also reflect constraints on travel that can be ad-
dressed similarly. Customer groups can be identified before the promotion begins then
be followed to see what their responses were. The opposite approach could also be taken:
grouping users based on their responses to the promotion, and then developing an un-
derstanding of each group’s socio-demographics and typical travel patterns before the
promotion began.

By focusing on particular sets of users, an agency can be more effective or cost efficient. If
it is able to actually give an incentive only to some users, knowing they are highly likely
to alter their behavior, the agency can either spend less money (only providing benefits to
the users who will respond) or spend the same amount, but spur more behavior change.
Even with users identified to various groups, it may still be politically and practically
unfeasible to give different incentives. Instead, the agency can frame their policy design
process as trying to meet the specific needs of a group, better matching their desire for
lower crowding with a group’s particular characteristics. It can also rely on self-selection,
requiring users who are likely to respond to opt into getting an incentive.

Figure 3-8 shows a potential structure of the redesign process, focusing on user groups.
First, strategies (S_i) are matched to particular groups. In the initial strategy, S_0, all groups
are targeted with the same incentive, I_0, but in newly proposed policies, this need not be
the case. As an example here, S_1 targets two groups using the same incentive, S_2 targets
only one group, while S_3 targets two groups, but uses a different strategy for each one.
Of course, though a policy might target a certain group, others still could be eligible to
take advantage of it. These strategies can be developed by considering the shortcomings
of the initial policy, in terms of its effectiveness, efficiency, or acceptance. For each set of
policies, the expected effect for several key measures (e.g. cost, system impacts, equity,
privacy, etc.) can be explored, if not fully quantified, to determine which is the best option
to implement.

3.5 Data and Methods of Analysis

Once the key areas for goal-setting, design, and evaluation have been determined, the
actual methods for doing any supporting analyses have be decided. The scope and meth-
ods will depend on what data is available to the agency, as well as the technical expertise
of its staff. Beyond the most basic evaluations—did congestion decrease?—a number of
complexities can be introduced for a more thorough analysis. This section describes some
of the data sources that can be used for analysis and how they can be used to support each
step.

3.5.1 Data

The information used for the evaluation of a TDM program’s impacts can come directly
from users via surveys, staff-collected data, and/or automatic data collection sources
Figure 3-8: Developing new demand management policies

(ADCS). In addition to AFC (fare collection data), other sources include automatic vehicle location data (AVL) and automatic passenger counts (APC). Other sources, like company financial records, broader economic data, or inputs for environmental analyses, can also be beneficial for certain studies.

For studying aggregate changes in ridership, ADCS will typically offer the most complete set of information. They allow analysis of discrete time periods and particular parts of the network (preventing temporal or spatial averaging from hiding some of the true impacts). In particular, APC data can be used to study how passenger loads change on each link before and after the program begins. Depending on the design of the system, AFC data can be used to study how passengers’ system entry times and locations change. AFC data can also be used to see how average passenger journey times and reliability are affected by the program. Vehicle location data may also supplement these travel time impacts, particularly if crowding had a large impact on dwell times. Looking at how passengers’ chosen fare media changes could also be relevant: do new incentives change the relative number of cash or single journey ticket entries in relation to those paid for with a smart card, or does the number of travel passes vs. pay-per-use fares change when the program begins?
What ADCS typically cannot provide, however, are people’s opinions about the program, why they are or are not participating, and their socio-demographic characteristics. Surveys are one way to fill this gap. Possible survey questions could elicit information on:

- Reasons for shifting behavior
- Nature of changes to:
  - Departure time
  - Route(s) or station(s) used
  - Mode(s) used
  - Frequency of travel in peak hour
- Trip characteristics
- Socio-demographic characteristics

For systems where ADCS is not fully available, surveys can help provide information about ridership changes. In addition, surveys can be used to gather information about a yet-to-be-implemented program or potential alteration. A major shortcoming of using surveys for this purpose, of course, is that the results may be biased if people respond differently than they would actually act.

If possible, information about changes to other modes (like increases in walking, bicycling, or driving), could be used to understand users’ broader travel behavior and to estimate cross-modal elasticities. Data on the financial impacts of the program, including development and implementation costs and revenue impacts can provide useful information for more detailed cost-benefit analysis.

3.5.2 Analysis

Depending on the goals the agency has for its TDM program, there are several methods of analysis they can pursue.

Before and After Analysis

Before and after analyses can be used to understand changes in ridership patterns on an aggregate scale. By comparing the number of users who travel through a particular station, OD, or link of the system before and after the program goes into effect, one can estimate the impact it has on crowding levels. If the goal of a program is to spread the peak, looking at differences by time period will be critical, as will looking at how spatial patterns change if certain parts of the network are more congested than others. Aggregate elasticities can also be estimated. ADCS would be the ideal data source for this type of analysis, particularly where detailed fare or passenger count systems are available.

However, when carrying out this type of analysis, several things are important to keep in mind. First, representative baseline figures need to be determined for the "before" characterization. This is especially important for transportation, given both seasonal fluctuations and longer term increases or decreases in use. Thus a month like August, with many
tourist users and residents on summer holidays, is perhaps not comparable to September when people tend to have more typical travel routines. Possible confounding factors should also be considered; service, fare, or network structure changes could alter travel patterns in addition to the TDM strategies.

If detailed AFC or survey data is available, some of these shortcomings can be dealt with through a panel analysis, in which a group of users is followed over a period that spans the introduction of the promotion. Because the same group of users is tracked through both periods, changes that are not due to the demand management policy can be more easily controlled for. This analysis also allows for more disaggregate study of changes in travel behavior.

If a fully individualized panel analysis is not possible but an aggregate study cannot provide the level of detail required, an analysis using customer segmentation is a promising alternative. Customer segmentation (i.e. grouping passengers into classes according to their travel patterns) removes some of the heterogeneity in the full user population to provide information about each group’s responses. A starting point can be the effect on people using different fare types. If AFC records are connected to surveys or socio-economic data, further questions of equity can be addressed. AFC data also allows users to be grouped into classes representing their system usage, such as commuters, tourists, leisure users, etc. These groups may provide a better sense of how general travel patterns affect one’s likelihood of changing their behavior. For example, commuters may have less flexibility than those who travel frequently but mainly for personal purposes, (so a smaller differential may be enticing).

Models

Models can be used to help understand why people made the shifts they did and predict what changes would be expected in the future. They are also often used before a TDM program is estimated to estimate its effects and make adjustments to the design. In particular, revealed or stated preference (RP or SP) surveys can be used to estimate discrete choice models. For example, an SP experiment for trains to London found how passengers value crowding and displacement time, both overall and given their specified level of flexibility (Liu and Charles, 2013). This was extended by Douglas et al. (2011) who used a "rooftop" model to estimate specific departure time choices given trains’ generalized costs (including values of displacement time, user characteristics, and fares). Other modes and ticket types can also be incorporated (Whelan and Johnson, 2004). Finally, route choice under different incentive strategies can also be modeled, as in Li and Wong (1994). Some types of large-scale programs can also be evaluated by more complex demand forecasting and urban planning models.

Cost-Benefit Analysis

A final type of analysis that can be conducted is to compare the benefits realized by the TDM program with its costs. This analysis supports the evaluation of a program’s effi-
ciency. These might include:

- Increased or lost fares from either new fare policies or new or lost customers
- Changes in travel time and reliability
- Environmental impacts
- Costs to design and implement the program
- Costs or savings related to changes in resource allocation
- Broader economic impacts

At an agency-specific level, a cost-benefit analysis establishes whether it makes financial sense for the agency to begin or continue a program; will it reduce their profits too much or require them to take on additional subsidies? Cost-benefit analysis can also be performed from an economic point of view, taking into account broader societal impacts are appropriate for large scale projects. An example of this type of analysis can be found in Eliasson (2009) for the Stockholm Congestion Charge System.

### 3.6 Summary

The chapter presented a framework to guide the development of demand management policies. Four key steps were identified: motivations, design, evaluation, and redesign. An overview of how agency staff can approach each of these steps was provided, though given a desire for generality, not all of these details may be relevant for a particular system and there could be other, specific concerns to be addressed. The goal of the framework was not to develop an unyielding protocol, but rather to provide a starting point and help structure the process. Given staff and time constraints, it may be difficult to cover all of these steps. The remainder of this thesis will apply the framework to MTR, providing an example of how its steps can be utilized.
4 Motivating MTR’s Demand Management Program

The initial steps of the framework proposed in Chapter 3 are to develop the motivations for the TDM program then design policies that address these issues. However, in applying the framework to MTR, this section will take the reverse approach and begin with the design. MTR had already proposed its TDM program when this research began, so the initial design process was outside the scope of this thesis. After a general introduction to MTR’s need for demand management, their policies will be described. The remainder of this chapter goes deeper into the demand patterns that necessitated TDM, connecting the policies to system conditions. Section 4.2 describes aggregate passenger flows through stations and links. Section 4.3 addresses the travel patterns of individual customers, developing groups of users who travel on MTR in similar ways.

4.1 The Need for Demand Management

As MTR’s overcrowding has worsened over the past several years, congestion has become a topic of concern among the public, the Hong Kong government, and MTR itself. At the beginning of 2014, the government’s Legislative Council Panel on Transport released a report describing current loading-to-capacity ratios and the actions MTR has taken to reduce loads (Subcommittee on Matters Relating to Railways, 2014). Because capacity standards had recently been lowered from 6 passengers/m² to 4 passengers/m², the East Rail and Tseun Kwan O Lines were found to be at or above peak hour capacity. Several other lines were just below the standards. While the panel recognized MTR’s past actions to control loads through increased frequencies and platform attendants, as well as the future expansions (described in Chapter 1), they also invited MTR to investigate other short-term measures, including off-peak incentives.

In May 2014, MTR announced their first major TDM strategy since the 1990’s. The Early Bird Discount Promotion is a pricing strategy that offers a 25% discount for adult card users who exit certain stations in a pre-peak hour. It began on September 1, 2014 and will run for a trial period of nine months, ending on May 29, 2015. Internal goals were to shift about 3% of peak hour trips to the pre-peak hour. At this point there are plans to evaluate its impacts to decide how or if it should be continued beyond May. This policy is
a simplified descendant of the previous pricing strategies that were described in Chapter 2. It does not require a pass or incorporate any route-based pricing; any adult user who exits an eligible station can get a discount. Following the design framework presented in Chapter 3, the parameters for this promotion are as follows:

**Type of Measure:** As a fare differential policy, the Early Bird Promotion is an economic, structural measure targeting the system’s pricing structure. It reduces the price of traveling before the peak, making it a pull measure to attract people to travel earlier. Finally, it is customer-based since it does not directly involve employers and is not dependent on broader government policies.

**Users Targeted:** No particular user types are being targeted in this promotion, though only adults, who get no other concession, are eligible. MTR hopes any adult who travels in the peak hour will take advantage of the discount.

**Magnitude of Program:** The discount offered is 25%, which was chosen based on estimates of fare elasticity in similar cities and their desired level of impact. Because fares vary based on distance, this is equivalent to about HK$1-12, or US$0.13-1.5.

**Temporal Coverage:** As will be discussed in Section 4.2, the peak hour of train loads in the morning is approximately 8:00 to 9:00, with the peak of the peak from about 8:30-8:45. Rather than choosing 7:30-8:30 for the promotion, exactly an hour before the peak of the peak, staff shifted it 15 minutes earlier to 7:15-8:15. This was meant to be sufficiently earlier so that the peak itself did not just shift earlier, but not so much earlier that no peak hour travelers were willing to shift their departure time. Though Section 4.2 will show that different links and stations reach their peaks at different times, there was no link between temporal and spatial coverage; the same period applies at 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 customers can’t remember the details of the promotion, they may not respond in a way that actually induces this potential effectiveness.

**Modes Covered:** Only the heavy rail system is covered; the light rail, Airport Express, and buses are not. Though there is anecdotal evidence of overcrowding on the light rail system, it lacks the same ADCS as heavy rail. Attention is turning to the system as the New Territories grow, and the lessons learned through the Early Bird Promotion may be useful to the light rail in the future. Future incentive designs might also consider the interplay between these systems and how additional incentives on one mode could enhance the impacts on others.

**Spatial Coverage:** 29 key urban stations are covered by the promotion, highlighted by the gray box in the map in Figure 4-1. Though on-board congestion over certain links motivation for this promotion, it was simpler to apply a discount on the basis of stations. MTR staff thus attempted to match trips that used the most congested links to the user’s exit station. Their analysis found that 80% of trips that traveled
over a congested link exited at one of these stations. While not all of them face similar levels of congestion, having one contiguous zone again recognizes the need for simplicity; selecting all stations within a boundary is easier for users to understand.

**Practicalities:** With the Octopus card fare system, this discount was simple to implement; the rules of fare calculations just needed to be adjusted to have a temporal component. Because fares are distance based and only known on exit, it was logical for the promotion to be exit-based as well. A potential concern of exit-based systems has been that delays and disruptions may prevent someone from getting the discount even if they started a trip with enough time in normal conditions. Entry times and stations are also recorded, and an entry-based system may actually help avoid these logistical challenges; someone’s chosen departure time is not dependent on atypical MTR service levels. In addition, MTR staff expected that some customers would complain if their clock showed they exited on time but the fare system’s clock did not. MTR compensated for this by adding a few minutes of buffer time before and after the official boundaries of the discount period. Though the buffer times were chosen using professional judgment, using a reliability metric such as the RBT (reliability buffer time, described in Wood, 2015) could be a more systematic way to
set it. It is meant to cover minor delays and clock discrepancies. For more major disruptions, other company policies take priority.

**Marketing and Information:** MTR initially announced the promotion on May 27, 2014 through press releases which were posted on its website and picked up by the media. As September approached, they continued to publicize it through advertising and social media. When the promotion began, they released a series of humorous videos about the benefits of traveling earlier.²

This program addresses a number of the factors mentioned in Chapter 2 as supporting the effectiveness and acceptability of TDM programs. Of the three dimensions for effective pricing (Steg, 2003), it does have immediate consequences and is relevant to the desired behavior; evaluation will show whether the level is correct. It also allows people to set specific goals—finish a trip by 8:15—which they are more likely to reach. One area that it may fall short in, however, is the issue of fairness. Users who travel in the pre-peak anyway still get a discount. The saliency of the pricing mechanism may also be limited for two reasons. First, by paying with a smart card, people are already more distanced from the act of paying then they would be with cash. Also, the distance-based pricing structure makes people less familiar with the prices for a given trip, so they may also not be fully aware of what "25%" corresponds to. It is unclear how people might respond to the program in the long term, but further addressing internal factors may be another way the program could be improved.

Beginning on October 6, 2014, MTR also began a second program in conjunction with the KMB bus company. MTR monthly pass holders became eligible for free trips on KMB bus routes that served similar origins and destinations as their pass. Two to four trips on each of six bus lines (four along the West Rail Line corridor and two along the East Rail Line, departing between 7:15 and 7:45am) were eligible for free trips. The goal of this promotion is similar to the Early Bird Discount, shifting users to earlier departure times, but is more spatially focused on these two lines. This promotion is perhaps more interesting for both is cross-modal and cross-agency characteristics, and what it could reveal about how people perceive travel costs when using a pre-paid pass. However, no data is available for bus services and political activities disrupted MTR demand in October, so it would be difficult to get a full picture of its effects. The remainder of this section describes the data sources that are available in more detail.

### 4.1.1 Data Sources

Automatic Fare Collection (AFC) data from Octopus smart card transactions was the primary source used in this chapter and the rest of the thesis. For MTR’s nine urban rail lines, transactions are recorded on entering and exiting the system, giving the complete record of a trip. Some stations on the Airport Express Line station do not have fare gates, so their trips are not included in analysis. (Inference was deemed unnecessary because

²https://www.youtube.com/watch?v=HjGKTYh64vE
these trips are few in number and are not important in the context of congestion.) Table 4.1 summarizes the transaction data fields relevant to this research. Entry and exit records were linked by matching transactions of type "entry" and "usage" by card ID (the same), entry station (the same), business date (the same), and transaction number (sequential, though not necessarily consecutive if someone made in-station purchases).

Table 4.1: Relevant octopus card data fields

<table>
<thead>
<tr>
<th>Octopus Card Field</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Card ID</td>
<td>Anonymized from actual ID</td>
</tr>
<tr>
<td>Business Date</td>
<td>From 5:00am to 4:59am the following day</td>
</tr>
<tr>
<td>Transaction Time</td>
<td>Actual date and time to the second</td>
</tr>
<tr>
<td>Transaction Type</td>
<td>Entry or &quot;Usage&quot; (i.e. exit)</td>
</tr>
<tr>
<td>Fare Type</td>
<td>As described in Chapter 1</td>
</tr>
<tr>
<td>Transaction Location</td>
<td>Station code</td>
</tr>
<tr>
<td>Train Entry Station</td>
<td>Same as transaction location for entry transactions,</td>
</tr>
<tr>
<td></td>
<td>previous location for usage transactions</td>
</tr>
<tr>
<td>Transaction Number</td>
<td>Increases with each usage transaction</td>
</tr>
<tr>
<td>Modal Discount Value</td>
<td>Discount from eligible transfers or Fare Saver system</td>
</tr>
<tr>
<td>Transaction Value</td>
<td>Fare, less any discounts; charged on usage transactions</td>
</tr>
<tr>
<td>Card Value</td>
<td>Remaining value on card</td>
</tr>
</tbody>
</table>

MTR also generates passenger flow data, an indicator for train crowding, using AFC records and route choice information. This data is available in 15 minute intervals for both directions on each link in the system. It was be used for link-level analyses.

4.2 Spatio-Temporal Congestion Patterns

As was introduced in the framework, congestion can be quantified using both spatial and temporal patterns of demand. The basis for this analysis will be normal weekdays in previous Septembers, as to make later comparisons with September 2014 when the promotion is in place. Because of data availability, September 2012 will be used the link-level analysis, while September 2013 will be used for the remainder.

4.2.1 System-Wide Temporal Patterns

While different parts of the system experience peaks at different times, looking at the entire system gives an overview of when the system is most heavily used. The top graph in Figure 4-2 shows the proportion of entries and exits that happen in five minute intervals over the course of an average weekday, with the peaks of each marked. MTR has high crowding in both the AM and PM peaks. The spikes reach similar levels of demand.
in both periods, though the morning exit peak and evening entrance peaks are slightly sharper and higher than their counterparts, likely the influence of commuters with similar work schedules. In the afternoon, demand grows more slowly and is elevated for a longer time, about two hours on either side of the peak compared to one hour in the morning.

The bottom of Figure 4-2 shows the system-wide accumulation: the difference between the number of trips that have started and finished (beginning at 5:00am to exclude trip that began the previous day). When accumulation is high it means there are many people using the system, either on trains or waiting on platforms, so crowding is elevated. The peak accumulation periods are about equidistant between the peak entries and exits, but otherwise its trends are similar to the entry and exit distributions.

The peak five minutes of entries is about a half hour 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 7:45-8:45 for entries and 8:20-9:20 for exits, and in the afternoon, 17:50-18:50 for entries and 18:20-19:20 for exits. MTR’s policy, which runs from 7:15-8:15 does then align with
the pre-peak hour of exits and is slightly earlier than the peak 15 minutes of accumu-
lation, at least at the system-wide level. However, should an entrance-based system ever
be considered, the policy’s period should be adjusted accordingly.

4.2.2 Link Level Spatio-Temporal Patterns

While MTR does face crowding in its stations, the major bottleneck to service is crowd-
ing on trains; overcapacity trains called for MTR restarting a TDM program. Because
many users are headed toward the CBD in the morning, the critical links tend to be in the
"down" direction (south or west). MTR does already employ platform attendants at key
stations to control boarding and alighting, as well as encourage users to spread out over
the length of a train. While uneven train loading does happen, in the most peak periods
all cars are crowded.

Exploring spatio-temporal patterns in depth is well-suited to interactive displays that
show how crowding develops over time. Figure 4-3 gives a snapshot of these patterns for
both directions in both peak periods. The first element of this graphic is the width of each
link, which corresponds to the passenger flow in the AM and PM hours with the highest
flows system-wide (8:00-9:00 and 18:15-19:15, the peak accumulation times). The most
crowded link is from Tai Wai to Kowloon Tong on the East Rail Line. Even though East
Rail Line cars can carry the most passengers, this section still operates at capacity. There
are also high levels of crowding all down Nathan Road and from the eastern harbor cross-
ing into the CBD. These patterns are mimicked in the PM peak (though in the opposite
direction). However, the PM peak’s down links face higher crowding than the up direc-
tion in the morning because non-commuters begin to travel after work and school in the
afternoon. The TDM policy does target these congested regions in Kowloon and Hong
Kong Island. However, a policy that considers direction might better target the critical
links. Especially once the new extensions open, MTR might also consider route-based
incentives again to try to get people to travel on less congested links (e.g. in the current
network, the Tung Chung Line instead of Tsuen Wan line).

The color of each link marks the 15 minute period that it actually has its highest passenger
flows. The downward movement of passengers is evident; the peaks near Central are later
than those farther north. Graduated temporal coverage on links would be complicated
to implement, but TDM policies should consider when the 15 minute peaks on the most
critical links occur when setting a time period.

4.2.3 Station Level Spatio-Temporal Patterns

Station-level patterns provide insight into the origins of link congestion, as well as where
there might be congestion in stations. MTR stations tend to be quite large, especially the
concourse levels, and their bottlenecks are often the escalators and stairs between levels.
Transfer stations also experience high levels of crowding on the platform.
Figure 4-3: Peak hour demand and peak 15 minutes at each station

(a) AM peak

(b) PM peak
Figure 4-4: Peak hour demand and peak 15 minutes on each link

Figure 4-4 is the station equivalent of Figure 4-3 from the previous section. Here, the size of each circle represents the demand at that station, with larger circles representing more transactions (though for legibility, a log scale was used). Again, demand is measured in the peak hour (as identified in Section 4.2.1, except AM exits which are measured from 8:15-9:15 to correspond to the Early Bird Discount) over all stations. While
entries are fairly distributed throughout the network in the morning, key exit stations are
Hung Hom (where many people transfer to cross harbor buses), and those near many
offices (Central and Wan Chai on Hong Kong Island, and Kowloon Bay and Kwun Tong
in Kowloon). The same stations have high entry levels in the afternoon, while Causeway
Bay, Tsim Sha Tsui, and Mong Kok attract the highest proportion of users because of their
nearby restaurants and shopping attractions.

The actual AM and PM peak 15 minute periods, indicated by a station’s color, typically
fall within the peak hour (shown with the black box over the legend), but not always.
The key observations from these plots are that the AM peak entry period gets later as one
approaches the CBD, but there is a major split in peak exits; a sizable group of stations
peaks at 7:45, while most peak an hour later. This is likely because these two groups of
stations have activities that follow different schedules around them. Afternoon peaks do
not show quite such distinct patterns, though there is some reversal of the morning en-
tries, with stations farther from the CBD having their exit peaks later.

An important implication from these results for revising TDM strategies in the future is
that if station crowding becomes a motivation, a single time window for the whole net-
work may be not appropriate because peaks differ across the network. It also suggests
that exit-based TDM strategies could be more effective in the morning and entry-based
ones in the afternoon when those types of transactions are more spatially concentrated.

These observed station and link patterns are driven by the users’ OD matrix. Because
MTR has over 6000 OD pairs, Figure 4-5 instead shows zonal OD pairs with stations
grouped roughly by Hong Kong district. In this representation, the length of each arc
around the circumference represents the number of trips whose destination is in that zone
and the width of each chord’s end represents the inflow to that zone. The chords are color
coded based on the zone with the larger inflow (and the colors themselves correspond to
the primary line serving that zone).

Again, western Hong Kong Island (detailed in Figure 4-6a) and Central Kowloon (pri-
marily Hung Hom; Figure 4-6b) attract the largest number of trips, but their trips’ origins
are distinct. Most trips to KOW-C come from the northern part of the East Rail Line (in
particular, Tai Wai to Hung Hom the morning’s most common OD) and trips to HKI-W
come from Nathan Road, Tsueng Kwan O or other parts of Hong Kong Island. There
are also some zones that have many trips within them, rather than to other parts of the
network. In fact, two of the three most common ODs fall into this group: Sheung Shui to
Lo Wu on the East Rail Line (largely from "parallel" traders going to Shenzhen) and Tin
Shui Wai to Tuen Mun at the end of the West Rail Line (see Figure 4-6c).

Overall, the Early Bird Discount Scheme does address many of the congestion patterns
that have been described here, including the peak period and key exit stations. The major
area that is not is covered is the Kwun Tong Line in eastern Kowloon; Kowloon Bay and
Kwun Tong are major destinations for AM peak travelers and the links leading to them
are fairly congested. In addition, most stations on the Tung Chung Line did not have
many users exiting them in the morning (most users of this line take it all the way to Hong Kong Station). These discrepancies can be explained by the need for simplicity, which can encourage acceptance and make it easier for people to take advantage of the promotion. The actual impacts the promotion has had on these patterns will be covered in Chapter 5.
4.3 Customer Classification

The demand patterns described above emerge from the way individual customers use the MTR system. Four "User Dimensions" that affect congestion were discussed in the Motivation Framework, and this section concentrates on the second: travel behavior. Though this concept can be quite broad, a fairly narrow focus of users’ travel patterns on MTR is taken here. Of the other three dimensions, limited information about user socio-demographics is available through AFC data, and essentially no insight about users’ attitudes and constraints can be gained. (Internally, MTR does have additional information...
in these areas from surveys and MTR Club members.) The more aggregate travel patterns captured through the network OD matrix were considered in the previous section.

The concept of customer classification, introduced in Chapter 2, will be applied to uncover the general types of behavior exhibited by MTR customers. MTR maintains a large database of AFC transactions that allow the travel patterns of nearly any user to be measured in detail over long periods of time. This allows long-term travel patterns to be captured in a way that traditional survey data does not. Though customer classification, the specific impact each group has on network traffic can be measured. In the next chapter, these groups will also be used to understand the different responses to the Early Bird Discount.

There are several inherent shortcomings in this analysis. First, though Octopus cards can be used on all transit modes in Hong Kong, only MTR trip records are available. Only MTR travel behavior could be measured, though the way someone uses other modes can provide context for his MTR use. In addition, the fairly strong assumption that one card corresponds to one user must be made. In reality, some users may have multiple Octopus cards that they switch between, while some cards may be shared between several people (e.g. family members or office staff). The former is thought to be relatively more common in Hong Kong than other cities because Octopus cards can be used for many types of purchases, but trying to match multiple cards to a single user could be a project in itself. Finally, the so-called "window effect" from having data from only one particular period influences the results. As an example, an ID that only becomes active in the last week may be assumed a short-term user even if they are actually a new commuter. By only being able to observe one period, the classification implicitly assumes that the behavior in the period is fully representative of behavior overall.

4.3.1 Methodology

User behavior groups were developed using data clustering methods. A set of transit-use characteristics was developed for a sample of users, and the k-means algorithm was applied to segment users based on their behavior.

Sample Selection

To measure long-term behavior trends, a sample of users was chosen from a 12 month period for which continuous AFC data was available: August 2012-July 2013. This data set included approximately 3 billion transactions, corresponding to 1.5 billion trips, made by 17.8 million distinct Octopus IDs. (These IDs are anonymized from actual card numbers and no further identifying information was provided to ensure privacy concerns are met.) Performing a clustering analysis over all of these users would have been highly data intensive, so a sample of users was selected for the analysis. With a 2% sample, a number of aggregate trends followed similar distributions to the population, as seen in Figure 4-7. Though some differences between the two were statistically significant given the large sample sizes, they were not deemed important for the purposes of this analysis.
There is also a very high correlation between the two data sets for the share of trips on each origin-destination (OD) pair: 0.997. Figure 4-8 shows the proportion of trips taken on each of the top 200 ODs among all users in September 2012, ordered by their ranking, as well as the proportion of trips taken by sample members on the same ODs. These two distributions follow each other quite well, and users take about the same number of trips to these ODs in aggregate: 28.39% among all users versus 28.44% among sample members. This implies that the sample is not spatially skewed toward any part of the network.

The final sample had 386,610 IDs, representing just over 30 million trips. While cards of any fare type had been included initially, some preliminary analysis showed non-revenue cards (primarily for staff) were found to display outlying behavior. They were removed so only IDs coded as Adult, Senior, Child, Student, or Disabled types were included in this final group.

**Time Period**

The primary results use the entire period under consideration: August 2012 to July 2013. As discussed, such a long period was used to capture longer term behavior patterns that may not be observable over a shorter time. However, this does introduce additional "noise" to users’ behavior and also may span legitimate changes in behavior (e.g. someone gets a new job in the middle of the period or has a child). To check group and individual stability, data from two 2 month periods—October-November 2012 and March-April 2013—were also analyzed. These periods were chosen to span months that would share more similar seasonality patterns, so the actual stability of the groups would be measured rather than changes due to outside influences.

**Variables**

Primary characteristics of transit use are how often someone travels, when his or her trips are, and where in the network he or she visits. The variables used to quantify these characteristics are listed and described below.

**Frequency Characteristics**

1. **Range of Travel**: Though a year’s worth of data was considered, the majority of cards are not active over the whole period. The difference between a user’s first and last day on MTR gives context for how regularly and frequently he or she uses the system. Range can also suggest how people might respond to TDM measures. Those with a long range are more likely to be in Hong Kong regularly. They are likely more familiar with MTR’s publicity campaigns and its congestion problems.

2. **Number of Weekdays/Weekends Traveled**: In conjunction with range, these variables provide a measure of frequency. The number of distinct days with at least one completed trip were totaled, though weekdays and weekends were counted separately. Different usage patterns would be expected for these different parts of the week, and the types of days that users travel is useful in describing their behavior.
(a) Number of trips taken in Sept. 2012 for clustering sample and all users

(b) Departure time distribution

(c) Fare type

Figure 4-7: Comparison of clustering sample and all users for Sept. 2012
3. **Number of Weekday/Weekend Trips** Again in conjunction with range, these variables provide a measure of frequency of use. Considering both the number of days traveled and the actual number of trips also gives a sense of the intensity with which someone uses the system: do they take many trips over only a few days, or just one or two trips on many days?

4. **Gaps in Travel: Number and Minimum/Maximum Gap Length**: The days that someone does not travel can also inform their intensity and regularity of travel. Gaps can be short or long, regular or irregular, and suggest someone’s travel regularity more generally. Regularity likely plays an important role in responses to a TDM measure; if someone already exhibit high variability, changing his or her travel may be less onerous. Someone was considered to have a gap in travel if they go at least one day without using MTR; the length of the gap is the number of days in a row that someone goes without traveling on MTR. From all the gaps in travel, the minimum, maximum, and average gap lengths were calculated.

**Temporal Characteristics**

1. **Median Start Time for First Trip of Day, Weekday/Weekend**: The time users take their first trip of the day is critical for understanding how their travel relates to the AM peak. The median was found to be more representative of someone’s typical travel time than the mean because of its lower of sensitivity toward outliers. For users who did not travel on weekdays or weekends at all, the median time was set to be the mean value for all other users’ median times. This is a simple imputation method, but comparing results from either clustering only users who did travel on both types of days or excluding these variables entirely suggested it was sufficient.

2. **Median Start Time for Last Trip of Day, Weekday/Weekend** Similar to the first trip of the day, the last trip of the day can again be important to distinguish users who
travel in the peaks or not. In addition, the combinations of first and last trips can
give a sense of the duration of a users’ activities, or if they only use MTR in one
direction of a round trip.

3. Number of Days Started within 30 min of Median Start Time: This variable was
included to try to account for someone’s temporal regularity. Days with a start time
within 30 minutes of the median start time were counted, with weekdays compared
to weekday median, and weekends to weekend median. Users with less variability
in their departure time may be less susceptible to TDM programs that encourage
shifting departure time.

Spatial Characteristics

1. Number of Distinct ODs Traveled: Some users travel on only a few origin-destination
pairs, while others have records throughout the MTR network. The number of ODs
can suggest someone’s dependence on MTR versus other modes as well.

2. Number of Trips on Most Common OD: This variable attempts to capture spatial
regularity. It is defined as the greatest number of times someone used a particular
OD pair.

3. Number of Distinct Origins for First/Last Trip of Day The number of different
stations someone starts and ends their days at can also be used to measure spatial
variability. People who only use MTR to travel to and from work may have fewer
distinct origins than someone who uses MTR to travel around Hong Kong.

4. Number of Days with First Trip at Border Crossing: Cross-border travel to and
from China is very common, and the users who travel using border crossing sta-
tions tend to have distinct travel patterns compared to people who primarily use
MTR within Hong Kong. This variable was calculated by finding the number of
days where a user’s first origin of the day is at Lo Wu or Lok Ma Chau, with the
assumption that if a day’s first trip is from the border someone is less likely to be a
Hong Kong resident (who would more likely enter a border crossing station as their
last trip after a day in China). While many visitors do arrive by air, sea, or other
surface modes like bus, train, and car, no data is available for non-MTR Octopus
trips and few tourists use Octopus cards for Airport Express Line trips. This makes
more detailed visitor analysis difficult.

Because the magnitudes of many of these characteristics are influenced by the same un-
derlying behaviors, there was correlation between several sets of variables. As shown in
the correlation matrix visualization in Figure 4-9, particularly those related to the amount
traveled, start and end times, and the gap variables showed correlation. Such correlations
could suggest that some variables may be unnecessary, but in this case, removal does lead
to noticeable differences in the results so all were included.

These correlations effectively gave some factors extra weight over variables that were
more independent. To control for this, principal component analysis (PCA) was used to
define a set of uncorrelated vectors and reduce the dataset’s dimensionality. PCA lin-
early transforms a matrix into its eigenvectors, which define a new basis for the data. The
eigenvectors, or principal components, are perpendicular and uncorrelated, and ordered
by the amount of variance explained by each. The first principal component lies along the axis with the greatest variation, the second principal component along the axis with the next most variation, etc. Often, a subset of principal components captures most of the variability and can be analyzed instead of all of the original dimensions. More detail can be found in Jolliffe (2002).

The chart on the left of Figure 4-10 shows how much variability is explained by each principal component. It is typically recommended to choose enough clusters to account for at least 85% of the variability or where there is a break in the cumulative variability explained. In this case, the first six components explain about 85% of the data’s variability, and the first eight over 90%. The results that will be presented are based on clustering these first six components. After six principal components, each additional one explains less than 5% additional variability and caused little difference in the results. The characteristics associated with each principal component are shown in the right-hand plot, which visualizes how the principal components are correlated to the original data (shown in the same order as in Figure 4-9). The first is 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, again suggesting that six principal components are the optimal number for this data set.
components are sufficient for the remainder of the analysis.

Clustering Algorithm

There are several broad types of clustering methods, and a number of distinct algorithms within each. Supervised algorithms, like least squares regression and $k$-nearest-neighbor rules, require training samples with known classifications that can be used to develop rules for classifying additional data. On the other hand, unsupervised methods do not use training samples and group data using only its own characteristics. This category includes hierarchical methods, which build a nested structure of groups based on their similarity, and partitional methods, which assign individuals to groups in order to optimize an objective function. More details about these methods in the context of transportation data and behavior can be found in Ortega-Tong (2013).

The partitional $k$-means algorithm (Hartigan and Wong, 1979) was chosen in this analysis. Because there was no data with which to train a model, supervised methods could not be used, and the high computational complexity and noise sensitivity of hierarchical methods makes them ill-suited in this context. The $k$-means algorithm attempts to minimize the sum of differences between points $(x_{ij})$ and the centroid $(c_j)$ of their assigned cluster $j$:

$$\min \sum_{i=1}^{n_k} (x_{ij}^{(k)} - c_j^{(k)})^2$$
k, the number of clusters, is a parameter that must be set by the researcher; the optimal number of clusters is not known in advance. The algorithm begins by randomly partitioning the data and calculating the centroid of each. It then iterates between assigning each point to the cluster with the nearest centroid and recalculating the centroids. Once the assignment converges and each point remains in its current cluster, the process is complete. One of the shortcomings of this algorithm is that the initial assignment is random. This not only slows down the clustering process, but can also lead to a result representing only a local minimum. The MATLAB\(^2\) implementation used here compensates for these problems by actually implementing the \(k\)-means++ algorithm. Introduced in Arthur and Vassilvitskii (2007), this algorithm selects cluster seeds that are spread farther apart, which reduces the time for the clustering to converge and helps ensure a global minima.

Another characteristic of \(k\)-means that can be problematic is its sensitivity to outliers. The \(k\)-medoids algorithm, which assigns a particular data point as the center of a cluster, is more robust against outliers, but is also computationally more complex. In this case, the results will show that there was a small but distinct group with outlying behavior and it was better captured by \(k\)-means.

4.3.2 Results

After a discussion of the specific parameters used for \(k\)-means clustering, the primary groups that emerged for a year’s worth of data will be described. Comparisons with other periods conclude this section.

Parameters for \(k\)-means

To develop a set of customer groups using \(k\)-means clustering, two parameters need to be set: the distance measure and the number of clusters. Established distance measures include squared Euclidean distance, correlation measures, and cosine-based measures of the angles between points. In this analysis, the squared Euclidean distance was found to work best.

There are several metrics that can be used to define the optimal number of clusters, but interpretable and meaningful results also provide guidelines. To determine the number of clusters that should be used, both the Silhouette Criterion and Gap Statistic were considered (L. and Rousseeuw, 1990 and Tibshirani et al., 2001, respectively). Silhouette values measure how similar a point is to the others in its cluster versus how similar it is to points in other clusters. For each point \(i\), a value \(S_i\) is defined as:

\[
S_i = \frac{b_i - a_i}{\max(a_i, b_i)}
\]

Where \(a_i\) as the average distance from point \(i\) to the other points in its cluster and \(b_i\) is the minimum of average distances to points in each other different cluster. In other words,

\(^2\)MATLAB 2014b
$b_i$ is the average distance to the cluster closest to $a_i$, where $a_i$ would be assigned if its current cluster were not available. Silhouette values for each point range from negative one to one with a higher value corresponding to better structure. The silhouette value for all points is averaged to get the silhouette criterion.

The Gap Statistic formalizes the "elbow" approach of choosing $K$ based on when the largest decrease in squared error occurs. Rather than visually inspecting a plot of $K$ vs. SSE for the "elbow" in the plot, it uses the following metric:

$$\text{Gap}_n(K) = E_n\{\log(W_K)\} - \log(W_K)$$

with: $W_K = \sum_{r=1}^{k} \frac{1}{2n_r} D_r$

$W_K$ measures the pooled within-cluster dispersion for either the actual data or a reference distribution, $K$ is the number of clusters, $n_r$ is the sample size in cluster $r$, $D$ is the sum of all pairwise distances (here the squared Euclidean distance) for points in cluster $r$. The optimal number of clusters corresponds to the cluster with the highest gap statistic.

Figure 4-11a shows the silhouette values for $K=2$ to $K=9$, and suggests that the optimal number of cluster is just two. On the other hand, the gap statistic values in Figure 4-11b suggest that nine is the best option. Considering the actual characteristics of the clusters from these results, the characteristics of the groups found with $K \leq 4$ are highly dependent on only the first principal component and do not really capture other behaviors that are evident with higher $K$. Focusing on the higher $K$, then, the optimal number of clusters seems to be seven from the Silhouette plot. Though the gap statistic suggests $K=8$ or $K=9$ are better, the groups that are added beyond seven provide little additional insight to behaviors. On the other hand, the new groups that are added from five to six to seven are fairly distinct. $K=7$ best balances these two metrics and was selected for this analysis, but this question will be readdressed at the end of the next section.

**Group Characterizations**

The seven groups of MTR users can be characterized with the following descriptions. Justifications and further descriptions of these groups’ travel behavior will make up the remainder of this section.

1. **Short Term Users**: Largely characterized by a short range, these users also tend to travel later in the day 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.

2. **Long Gap Users**: This group generally had similar characteristics to Group 1, but are distinct because their cards are used for two or three short periods over the year,
separated by several weeks or months of disappearance. They could be tourists who keep their Octopus card between visits (a hypothesis that is further strengthened by this group’s relatively high proportion of days that begin at a border crossing station) or use one Octopus card very irregularly.

3. **Occasional Cross-Border Travelers**: These users have a fairly long range, but relatively infrequent use and a higher proportion of days that begin at a border crossing station. 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.

4. **Cross-Border Commuters**: This group has a longer range and relatively high num-
ber 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.

5. Intermittent Hong Kong Users: Generally similar to Group 3, these users have a lower proportion of trips beginning at the border and slightly more frequent use of MTR (about twice per week). Their trips are also somewhat less concentrated in commercial areas and spread throughout the network. They could be Hong Kong users who primarily rely on other modes, but also users that switch between several Octopus cards.

6. Casual Hong Kong Users: These users have a long range and more frequent travel than Group 5 plus even fewer trips from the border. They may use MTR in conjunction with other modes or only for non-commute trips. Indeed, their trips are typically later in the day, e.g. going out after work.

7. Hong Kong Commuters: With an average range of almost the whole period and the most frequent travel, these are the heaviest users of MTR. They also take most of their trips in the AM and PM peaks, so this group can assumed to include those commuting within Hong Kong.

The proportion of IDs in each group can be seen in the pie chart on the left of Figure 4-12. Over 40% of users are classified as Group 1, the short term users, while an additional 25% fall into the other visitor or cross-border groups. While it might be surprising that only 6% of IDs are classified into the Group 7, the commuters, the pie chart on the right of Figure 4-12 showing the proportion of trips taken by each group (based on all trips taken over the year) better fits expectations. In fact, the proportions are nearly reversed: commuters take 43% of trips and Groups 1-4 take a combined 12% of trips. These results match well with internal MTR estimates of tourist usage that put the percent of visitor trips at 13%. Clearly, the fact that most trips are made by a minority of users should have implications for TDM design. While the current design has not made it a point to target specific users, more focused marketing or incentives may have value in the future.

The simple explanation for this discrepancy is that a single commuter is responsible for trips over the whole year, while a short term user is seen only for a few days. Figure 4-13 shows the percentage of users from each group in a single day. These proportions align much more closely with the overall trip proportions than the overall ID proportions; however, there is within-week variation. Groups 4 and 7 make up a smaller percentage of users on weekends, following their commuter classification, while Group 5 in particular makes up a larger percentage, one reason they were described to use MTR mostly for non-work trips. The proportion of trips taken by Groups 1 and 2 is also higher on Saturday, but the difference is not so large, which could suggest that these short term visitors are likely to be in Hong Kong throughout the week. In addition, the difference for Group 3 is larger, which makes sense as cross-border travelers may be more likely to come to Hong
Figure 4-12: Proportion of IDs (L) and trips taken by group (R)

Figure 4-13: Proportion of users from each group on different days of the week
Table 4.2: Group means for selected characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<tr>
<td>Users in Group</td>
<td>165,354</td>
<td>17,143</td>
<td>76,535</td>
<td>870</td>
<td>67,378</td>
<td>36,245</td>
<td>23,085</td>
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<td>Range (Days)</td>
<td>13.1</td>
<td>218.33</td>
<td>211.04</td>
<td>323.91</td>
<td>277.41</td>
<td>337.81</td>
<td>353.58</td>
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<td>Distinct ODs</td>
<td>5.72</td>
<td>6.31</td>
<td>10.08</td>
<td>39.02</td>
<td>26.67</td>
<td>67.3</td>
<td>71.25</td>
</tr>
<tr>
<td>Wkdays Traveled (Days)</td>
<td>2.88</td>
<td>2.16</td>
<td>7.9</td>
<td>145.63</td>
<td>27.9</td>
<td>105.06</td>
<td>211.49</td>
</tr>
<tr>
<td>Wkends Traveled (Days)</td>
<td>1.19</td>
<td>1.25</td>
<td>3.48</td>
<td>38.95</td>
<td>12.7</td>
<td>37.36</td>
<td>60.46</td>
</tr>
<tr>
<td>Max Gap (Days)</td>
<td>5.22</td>
<td>195.96</td>
<td>99.6</td>
<td>21.79</td>
<td>53.02</td>
<td>20.41</td>
<td>9.79</td>
</tr>
<tr>
<td>Avg. Gap (Days)</td>
<td>3.21</td>
<td>175.34</td>
<td>46.63</td>
<td>3</td>
<td>13.07</td>
<td>3.36</td>
<td>1.83</td>
</tr>
<tr>
<td>% Days from China</td>
<td>20.22</td>
<td>35.68</td>
<td>26.46</td>
<td>79.9</td>
<td>7.76</td>
<td>2.23</td>
<td>0.76</td>
</tr>
<tr>
<td>Avg. Daily Travel Time*</td>
<td>52.3</td>
<td>66.3</td>
<td>48.9</td>
<td>59.3</td>
<td>39.0</td>
<td>40.8</td>
<td>47.6</td>
</tr>
<tr>
<td>Avg. Fare</td>
<td>11.81</td>
<td>16.12</td>
<td>12.91</td>
<td>19.79</td>
<td>9.32</td>
<td>7.84</td>
<td>7.15</td>
</tr>
</tbody>
</table>

*Total minutes spent traveling on days that users did travel

Kong for leisure trips on non-work days.

The principal evidence for the characterizations above comes from the distributions of the variables listed in Section 4.3.1. The mean values for several key characteristics are shown in Table 4.2 for each group. Two additional characteristics, not used in the clustering analysis are also shown here. The first, the average time that users spend traveling each day (in minutes, and only including days when an individual was seen) shows that the groups that are thought to be cross-border travelers do have longer journey times. They also pay more per trip on average, in line with the higher cross border fares. Groups 5 and 6 spend less time traveling than Group 7, likely a result of taking fewer trips on the days they use MTR (the higher average fares imply that they are not taking shorter trips).

More tangible evidence of their different travel patterns is presented in in the rest of this section. First, the range, days traveled, and gap patterns for each group can be seen in Figure 4-14, which visualizes the days traveled by individual users in each group. Each row represents one user and each column a single day of the year; a blue square indicates a user traveled that day, while a gray one means he or she did not. Users are ordered by their group (signified by the color of the leftmost column) and the first day their card was used. It is easy to see that most of Group 1’s use is concentrated near their first day of travel, and that users in Group 2 have sparse use over a longer range. Nearly all users in Groups 6 and 7 have begun traveling by the end of the first month. Group 7’s travel is even dense enough to highlight weekends and holidays. The relatively lighter area near Day 200 is the Lunar New Year, while Easter occurred around Day 240. With vacation, these users are less likely to travel, though the increase in new Group 1 users around the same time suggests that visitors are more likely to traveling in Hong Kong. Some of the "window effect" impacts of using a pre-defined period are also evident near the end of
the year. Travelers whose first days are later are less likely to be classified as Group 6 or 7 because their range is shorter. If had a different year-long period had been chosen, their results could change.

The bi-variate kernel density distributions of each groups’ members’ weekday median first and last median entry time are shown in Figure 4-15. These contour plots show the relative number of users who had a particular median first and last entry time; yellower contours represent the peaks of the distribution while bluer ones bound combinations that are less common. The gray boxes indicate the pre-peak hour, 7:15-8:15.
Figure 4-15: Distribution of median start time of the first and last weekday trip for each group (gray box indicates pre-peak hour)

The diagonal sections seen in Groups 1-3 represent users whose first and last median entry times were the same (primarily people who traveled only once or only ever in one time period). The other parts of these distributions show a wide range in start time, particularly the last trip. For all three groups, the peak for the first trip is between 10:00 and 12:00 (slightly later for Group 3). Of these three groups, Group 1 tends to have its last trip the latest and Group 3 the earliest, perhaps because Group 1 is staying in the city while Group 3 is more likely to travel back across the border at the end of the day. Commuting patterns are strong for Groups 4 and 7, with first trips around 8:00 and last trips around 18:00, though Group 4 has a secondary peak that implies some members come into Hong Kong for the afternoon. Groups 5 and 6 transition from the midday/evening patterns of the first three groups and commuting patterns. Both groups have a peak around 18:00, implying that they only use MTR after work or school (or use it only to return home, but not in the morning).

All groups except the fourth have peak entries after the pre-peak hour—they are not even starting their travel until after they would had to have exited. Group 4 was entering during the pre-peak, but few of their trips are to stations that would become eligible for a discount. Even still, a major target for AM congestion relief is clearly the commuters, who take both first and last trips in the peaks, and potentially the casual users for similar reasons. However, in the PM peak, other groups are also more likely to be traveling, so strategies in terms of users to target should differ in these different periods.
Finally, Figure 4-16 on the facing page shows the spatio-temporal patterns for the trips made by each group. Here, the relative number of trips started at each station in each hour of the day is shown for the seven groups. Yellower squares again correspond to more common entry points (among trips by that group). Stations are in order of their numerical code (see Appendix A for details and note that some numbers are skipped). Key station codes are 1, 2, and 26-28 (CBD, including Central and Causeway Bay); 3-6 (Nathan Road Corridor, including Tsim Sha Tsui and Mong Kok); and 76 and 78 (border crossings). The 29 stations that became eligible for the Early Bird Discount are indicated with gray boxes or black lines.

Group 7 shows the peaking patterns that characterize system usage as a whole: many entries are around 8:00-9:00 or 18:00-19:00 and fewer trips start in the middle of the day when people are presumably at work or school. The trips are also spread throughout the network, with morning entries typically at stations that are in more residential areas (and are not covered by the discount), and evening entries in business districts (at stations that are covered). This is what would be expected for Hong Kong residents who live and work throughout the city.

Group 1 has more trips in the middle of the day, and the locations of these trips are more concentrated. There are many entries at Lo Wu, Tsim Sha Tsui, and Mong Kok in the morning, and touristic or shopping destinations like at Central, Tsim Sha Tsui, Mong Kok, and Causeway Bay in the evening. There is also a relatively high number of entries at Disneyland (55) in the evening, as well as at Tung Chung (43; near the Big Buddha cable car and outlet mall). There higher number entering at Hong Kong Station (39), could reflect people who were visiting Central, or visitors who transferring with the Airport Express. Groups 2 and 3 show fairly similar patterns, though both are even more concentrated along the end of the East Rail Line, CBD, and Nathan Road. In particular, the higher number of morning entries at border crossing stations suggests these repeat visitors are more likely to be coming from the mainland while the single visit users include customers of more variable backgrounds.

Group 4, the very frequent cross-border users, are indeed traveling from the border in the morning, but their entry stations later in the day show that they seem to confine themselves to the end of the East Rail Line. They take only a small number of trips elsewhere in the system. Thus while they may be taking a relatively high number of trips, they are only using a relatively isolated subset of the whole system.

Group 5, the intermittent Hong Kong users, have peak entries only in the evening and mostly from commercial centers, but also from border crossing stations. This pattern is more characteristic of someone from Hong Kong visiting Shenzhen for the day then a Mainland resident visiting Hong Kong for the day. Like Group 1, travel ramps up as the day goes on, with most trips taking place in the evening, after work, but there is more travel from less touristic parts of the network. Group 6 falls between 5 and 7. Its peaks happen in commercial centers in the evening, but cross-border travel is less common and a somewhat higher proportion of trips take place in the morning peak.
Figure 4-16: Relative number of entries at each station in each hour of the day by group (with early bird scheme stations indicated)
These patterns provide some additional insight to the results of Section 4.2. The sharp morning peak is largely due to commuters, while the more gradual evening peak is a result of all groups were traveling. While TDM policies may be useful in both peaks, these different types of travelers along with the longer duration of high demand in the afternoon means that different policies may need to be used in each.

Finally, it is useful to return to the assumption that seven was an appropriate number of clusters. With six clusters, Groups 4 and 7 were combined, but as has been shown, they display quite different spatial patterns, which can be important for determining how to best target users for demand management. Groups 2 and 7 are fairly constant over all numbers of clusters. This is expected since the "amount" traveled and gap characteristics are embedded in the first two principal components. Otherwise, the clusters change primarily on the basis of frequency of use. For example, with K=4, the resulting clusters are essentially Groups 1+3, Group 2, Groups 5+6, and Groups 4+7, while with K=9, Groups 1 and 3 redistribute to form four groups: one with a shorter range than Group 1 and three that are primarily distinguished by their entry times (morning users, mid-day users and late afternoon users). While more discrete time divisions could be useful for TDM uses, these new group’s trips are still not in the AM peak, and represent few trips. Given the even lower silhouette values, this finer level of frequency which was deemed unnecessary to gain an understanding of the main types of users.

**Temporal Stability**

To see how sensitive these results are to the period used in the analysis, two periods of two months were also analyzed. Using only two months of AFC records is less data-intensive, making it perhaps more realistic for an actual implementation. It also can be more useful when trying to analyze behavior change, since considering a whole year can hide changes that are observable in more discrete periods. By analyzing two separate periods, the stability over different times of year could be tested along with the stability over different lengths of time. The two periods chosen were October-November 2012 and March-April 2013.

In general, the results were very similar between the two month periods, and quite similar to the 12 month results (taking period length into account where appropriate) as shown in Table 4.3. The primary difference is that, over only two months, there was no long-gap group—such long gaps were not observable. Thus Group 2 collapses into Group 1. Otherwise, the characterizations of each group for two months matches the characterizations for 12 months. Therefore, if the long gap group is not of major interest, two months would be sufficient to capture most of the longer term trends found with 12 months.

On an individual level, there were many users who were classified in the same way in all three cases, but also some whose classification differed. This is not surprising; their behavior could legitimately be different in different seasons of the year. Figure 4-17 shows how users were classified differently over the year compared to just March and April. For example, among users who did travel in March and April, 13.24% were classified as
Group 1 for their two month travel patterns, but as Group 3 over the entire year. For clarity, the 55% of users had the same classification in both periods are not shown. The largest differences are among Groups 1, 3, and 5. When someone is classified as Group 1 over two months, but 3 or 5 over 12, he or she probably just traveled very infrequently in March and April compared to other months. The discrepancies between Groups 3 and 5 are related to someone’s cross-border mode choice. The primary difference between Groups 3 and 5 was how frequently they started their day at a border crossing. However, if someone varied what mode they used to cross the border (taking a bus or car, for example) or how often they traveled to China in March and April compared to the rest of the year, they could get classified in a different group.

Figure 4-17: Comparison of cluster membership over two months and 12 months, excluding users with the same classification (Values indicate percent of users falling into that group)
<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Oct-Nov</td>
<td>3.32</td>
<td>1.43</td>
<td>1.54</td>
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<td>12.78</td>
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<td></td>
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<td>1.41</td>
<td>0.7</td>
<td>12.73</td>
<td>16.31</td>
<td>0.96</td>
<td>0.83</td>
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<tr>
<td>12 mo</td>
<td></td>
<td>15.47</td>
<td>2.48</td>
<td>3.19</td>
<td>1.31</td>
<td>12.42</td>
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</tr>
<tr>
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<td>1.45</td>
<td>1.78</td>
<td>0.9</td>
<td>12.87</td>
<td>15.66</td>
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<tr>
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<td>Mar-Apr</td>
<td>38.02</td>
<td>1.47</td>
<td>1.62</td>
<td>1.08</td>
<td>12.8</td>
<td>15.77</td>
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</tr>
<tr>
<td>12 mo</td>
<td></td>
<td>230.3</td>
<td>4.3</td>
<td>6.7</td>
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<td>3.77</td>
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<td>15.48</td>
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<td>6.03</td>
</tr>
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<td>6</td>
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<td>9.71</td>
<td>18.13</td>
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<td>9.81</td>
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<td>7.82</td>
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<td>35.85</td>
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<td>2.91</td>
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<td></td>
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<td>59.92</td>
<td>35.31</td>
<td>36.67</td>
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<td>17.88</td>
<td>3.52</td>
<td>1.62</td>
<td>0.77</td>
</tr>
<tr>
<td>12 mo</td>
<td></td>
<td>352.81</td>
<td>191.16</td>
<td>211</td>
<td>59.07</td>
<td>9.11</td>
<td>18</td>
<td>10.16</td>
<td>1.87</td>
<td>0.73</td>
</tr>
</tbody>
</table>
4.3.3 Implications for MTR

The existence of these groups will be useful for travel demand management applications, but could also inform other agency activities. Some of the possible uses are:

1. **Travel Demand Management**: MTR can evaluate policies on a group-based level, which can give a better sense how different types of travelers respond differently to TDM policies. Staff can also try to improve how it markets its policies, for example, putting more or different notices on certain trains and stations. Through the MTR Club, they could even appeal directly to members of different groups in ways each would be most likely to respond to. For example, for users who are less accustomed to traveling in the peak, like Group 5, the lower crowding levels of the pre-peak could be stressed, while the higher reliability and regular cost savings could be communicated to commuters.

2. **Commercial Activities**: Knowing which types of customers are using each stations can inform the commercial activities within the station, including which advertising to display and which shops will be most popular. Even time-dependent displays could be considered given the different temporal patterns of these groups. It could also inform broader commercial interests, particularly in MTR malls around stations.

3. **Customer Information**: Depending on his or her travel patterns, a customer may find different types of information more useful. For example, commuters may be more interested disruption alerts or maintenance schedules, while occasional cross-border travelers might find special tourist promotions useful.

4. **Long Term Planning**: Better characterizations of demand can also help in longer-term planning decisions. One applications could be demand forecasting; if a major new business locates near an MTR station, most new demand will follow the commuter group patterns, while if tourism is expected to grow, stations that see many visitors are likely to see higher increases than other stations.

Finally, these results can be considered in the context of the Early Bird Promotion and aggregate congestion patterns. MTR faces congestion in both the morning and evening with much of the traffic to or from the CBD, where many of Hong Kong’s jobs are located. The significance of users with commuter characteristics in these results is thus not surprising. In deciding whether to take advantage of the Early Bird Promotion, these users will face a trade-off between flexibility and incentives. As frequent travelers, the total discount they receive will be large, but the low flexibility of commute trips makes earlier trips more burdensome. Other groups, like the intermittent and casual users, may have fewer constraints in when they travel, but if they do not often use MTR in the morning, only 25% off may not entice them to travel even earlier. Touristic groups are also not negligible, especially in the PM peak, but effective marketing campaigns and information will be important to ensure they are aware of these potential discounts. These relationships will be explored further in the following chapter, which will discusses the impacts of the promotion at the system-wide, group, and individual levels.
Early Bird Promotion Analysis

The framework in Chapter 3 laid out three dimensions for evaluation: effectiveness, efficiency, and acceptability. This section will focus on effectiveness, developing an understanding of the promotion’s impacts and the factors affecting users’ responses. As with the analysis in Chapter 4, AFC data and link flow data will be the primary sources used. While the data does provide very detailed records of how users responded to the promotion, both on an aggregate scale and an individual one, it is still not enough for evaluating acceptability and efficiency in depth. These dimensions require, respectively, more detailed survey data to measure perceptions of the TDM program or additional supply-side and financial information. Assessment of long term changes will also not be covered here. Political protests disrupted normal demand patterns from October to December 2014 and 2015 data became available too late for inclusion in this thesis.

Therefore, the primary metrics considered were system impacts: passenger flows through stations and links. These can suggest further customer impacts, particularly crowding levels. No data is available to consider broad economic impacts, and given Hong Kong’s already high dependence on transit, the environmental impacts of this promotion are likely minimal. While socio-economic data would be interesting to consider for a true equity analysis, it was not possible to tie this information to Octopus card IDs.

The focus of the analysis is a before-and-after study: how did the time that people travel change once the Early Bird Promotion went into effect? Rather than performing this analysis at just one level of customer aggregation, three different levels are considered. The first, in Section 5.1 does consider all customers, but Section 5.2 examines which types of users responded to the promotion in more detail with the customer behavior groups identified in Chapter 4. Finally, Section 5.3 uses a customer panel to track how individual users altered their behavior once the promotion began, providing more detail about the factors that led users to shift out of the peak (or not).

Throughout this 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. MTR has experienced annual growth of about 4% over the past several years (Figure 5-1 on the next page) and because it introduced this program at the
beginning of September, seasonality differences are relatively strong. People are transitioning from summer holidays in August to more typical work and school patterns in the fall. A final factor, unique to this context, is that Hong Kong people began widespread demonstrations in the last week of September 2014, protesting the Hong Kong electoral system. A major part of these protests was sit-ins on major roads in central parts of the city (Admiralty, Causeway Bay, Mong Kok, Tsim Sha Tsui), which disrupted bus services and dramatically increased ridership on MTR. This can also be seen in Figure 5-1, with the most affected months marked in red.

5.1 Aggregate Analysis

A first step in understanding the effects of this—or any—promotion is to consider all users, without any control for heterogeneous behavior. This is useful from an operational perspective since it is most directly related to service quality and the experience typical users will have on their trip. For agencies with less detailed fare collection data, this might also be the only type of analysis that is possible. Section 5.1.1 discusses a general approach for this level of analysis and how to deal with the issues raised above. The remainder presents the system-wide impacts as well as changes on both a station and link basis.

5.1.1 Approach

With the promotion beginning on September 1, a period of a month is used as the basic unit of analysis, though week-long or multi-month periods could be informative in other contexts. The months analyzed are September 2012, September-October 2013, and July-
October 2014. Only non-holiday weekdays were included, as no discount was given on weekends and public holidays\(^1\). Days with major typhoons were also excluded; over the months considered in this analysis, there were two\(^2\) typhoons significant enough to affect if and when people traveled. Finally, all records from September 28, 2014 through the end of October were deemed unsuitable for most analysis. Because the demonstrations prevented many bus routes from operating, monthly ridership was up nearly 10\% from the previous year, much higher than the regular 4\% trend. There were particularly large ridership increases in the pre-peak period, almost certainly driven by mode shifts or the more extreme crowding in the peak, not the promotion.

To deal with the annual and seasonal impacts, most analysis was done on a relative basis. The AM commuting period was defined as 7:00-9:30am to encompass the MTR defined pre-peak (7:15-8:15) and peak (8:15-9:15) hours, plus 15 minutes on either side. Comparing the percent of these AM trips that took place in various subperiods for different months can show whether the promotion spurred any changes in the distribution of exit times. Such patterns might not be obvious if considering only the absolute number of trips.

### 5.1.2 System-Wide Results

The most aggregated comparisons that can be made are for the whole system: all users at all stations. Figure 5-2 compares the entry and exit transaction distributions and the system-wide accumulation for September 2014 with those presented in the previous chapter for September 2013 (again using an interval of five minutes). The AM peak does decrease for all three, and there is also a minor decrease in the PM peak for exits and accumulation. In the pre-peak hour, the distribution for September 2014 is higher than in 2013, continuing this pattern.

Figure 5-3 focuses on the AM peak and presents the exit time distributions for several past months. This includes only trips that would have been eligible for a discount: made by adult Octopus cards to one of the 29 eligible stations. All the months before the promotion follow a similar pattern, but beginning in September 2014, there are more trips in the pre-peak period and fewer in the peak. The small peaks at either end of the promotional period are also characteristic of this type of promotion; early morning travelers wait in the paid area until it goes into effect at 7:15, while people who traveled in the peak hour shifted their travel by as little as possible to get the discount right before it ends at 8:15. In addition, October 2014 is shown to demonstrate the effects of the protests. The shift toward the pre-peak is more extreme, though there were actually about 12\% more trips per day in the peak hour compared to September 2014.

Trips that would not have been eligible for the discount can be used as a control group to check if there were any more general shifts in ridership in September 2014. Trips made by

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\(^2\)Sept. 23, 2013, Sept. 16, 2014
Figure 5-2: Transaction distributions in 2013 and 2014

Figure 5-3: Morning exit time distribution for adult cards at early bird-eligible stations
Figure 5-4: Morning exit time distributions for non-eligible trips

adult cards to non-eligible stations or by non-adult cards to eligible stations should have minimal changes, and as Figure 5-4 shows, this is the case. For adult cards, the summer months show slightly different distributions, but the fall months are nearly the same. For other cards, the summer months are affected by school holidays (students do not need to travel so early to get to school on time), but September 2014 does not show any patterns that could mistakenly be associated to the promotion.

The differences among eligible trips are further quantified in Table 5.1, which lists how the percent of trips in the pre-peak (7:15-8:15) and peak hours (8:15-9:15) compare. These
values are again changes in the proportion of all trips from 7:00 to 9:30 that took place in that hour, e.g. if 50% of trips were in the peak hour in August and 45% in September, the change would be -5%.

The values in September 2014 are distinct from those in prior months, decreasing about 2.5% in the peak hour and increasing about 3% in the pre-peak hour (as some users are also shifting from the early morning period into the pre-peak). It is important to note that these values are only for people who could have received a discount—the effect is diluted if other stations and fare types are included. There is a pre-peak exit increase of only 1.4% and peak trip decrease of 1.3% among all cards to any station in September 2014 as compared to September 2013 or 2012.

In addition, as suggested by the five-minute distributions in Figure 5-3 shows that the peak-of-the-peak is experiencing a smaller decrease than the first 15 minutes of the peak hour. Though MTR is judged on hourly capacity standards, more discrete periods better describe how customers actually experience the system at different times of day. This suggests that a different policy design may be necessary to really target peak crowding, since most people do not seem willing to shift over 30 minutes for just 25% off.

### 5.1.3 Station-Level Changes

Chapter 4 showed that stations differ in the demand they face during the system-wide peak hour as well as when their particular peak 15 minutes is. Correspondingly, the promotion’s impacts also varied at different stations. For a station-level comparison, rather than presenting exit time distributions for all 29 stations, the peak–pre-peak trip ratio was selected as a single metric to use for station comparisons. This metric is simple, but has been used in past peak spreading evaluations⁴, to capture the relative imbalance between periods. Though traditionally it uses the number of trips taken in each hour, here a relative version based on the percent of AM trips taken in each hour was used:

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Figure 5-5: Change in peak/off-peak ratio from Sept. 2013 to Sept. 2014

A smoother peak would have a lower ratio, with the peak and pre-peak more balanced, so a peak smoothing promotion like the Early Bird Promotion should cause the ratio to decrease. Figure 5-5 shows these ratios for each station in both 2013 and 2014 along with the associated percent change. Those with the largest changes tended to be near major business districts, including Sheung Wan (26), Wan Chai (27), and Quarry Bay (32), while those with smaller changes tend to lack major employment draws, like near the Nathan Road Corridor (e.g. 7-Shek Kip Mei, 17-Sham Shui Po) and in in West Kowloon (53-Nam Cheong, 40-Kowloon, 111-Austin). In addition, there is a weak correlation ($R^2=0.26$) between stations’ 2013 ratios and their percent decreases, meaning the promotion was having a stronger effect at the stations that need it most (and removing two outlier stations nearly doubles the $R^2$).

A potential effect of the promotion’s spatial characteristics is that stations at the border of the coverage area may see increases in ridership. If someone’s final destination is between two stations, one covered and one not, he or she may choose to exit at the one that gets them a discount. However, no such edge effects were evident. The covered stations and their neighbors tended to follow the same trend; for example, the proportion of trips (taken between 7:00 and 9:30) ending at Kowloon Tong and Lok Fu both increased while the proportions to both Tai Koo and Sai Wan Ho decreased.
5.1.4 Impacts on Link Flows

Though MTR’s TDM program is based on station-level transactions, it is truly trying to target overcapacity passenger flows. To understand link-level impacts, relative values were used again, as in Section 5.1.2. Here the proportion of passengers on a link in a particular period is calculated against the total number that pass over that link from 7:00-9:30am. Though data for September 2013 was not available, the same September 2012 data that was presented in Chapter 4 could be compared to September 2014. Since the relative demand at the station level was similar in September 2012 and 2013, the same should be true at the link level.

Figure 5-6 shows how the percent of AM loads on each link in the down direction (i.e. toward Central) changed from September 2012 to September 2014. The loads include all fare types and even non-Octopus card users. The color indicates both the magnitude and direction of change: redder links seeing increases, greener ones decreases, and darker ones minimal change. The width of each segment also reflects the magnitude, with wider links seeing a larger change. The figure does show that the promotion had the desired impact, with more links increasing in traffic in the pre-peak hour and more decreasing in the peak hour. In particular, the areas that tend to be more congested are seeing relief, like along the Island Line, Nathan Road Corridor, and harbor crossings. The magnitudes are on the low end of the targeted changes. However they are in line with the changes observed in the previous two sections.

Looking at flows on key links in more temporal detail further suggests that the promotion
is having an impact. Given that most trips in this period are going to the CBD, many links are most affected at the time associated with such trips. For example, the link between Tin Hau and Causeway Bay, just outside the CBD, has heavier loads before 8:00 and lighter loads around 8:15-8:30. The link between Shek Kip Mei is higher between 7:15 and 7:45 and lower from 8:00 to 8:30, which aligns with the 20 minute trip from Shek Kip Mei to the CBD. However trends in other parts of the network, particularly in the New Territories, do not follow any explainable patterns. Though this might be evidence that weakens the previous conclusions, it could also be reflective of the OD matrix presented in Chapter 4; most users in the New Territories are not traveling to eligible stations so they have no reason to respond to the promotion.

MTR’s own measurements for passenger flow show few improvements as a result of the promotion. These flow values, found in reports from the Subcommittee on Matters Relating to Railways (2014) and Tang and Cheung (2014), are based on the peak hour (designated as 8:15-9:15) frequency of each line, and the trains’ capacity. Two crowding standards—six and four people per square meter (ppsm)–are shown because MTR has recently reduced their standard from six to four ppsm. The 2014 values in Table 5.2 are for the same “normal” days in September 2014 that have been used throughout, while the 2013 values are taken from the LegCo report and their exact dates are unspecified. The capacities are the same in both years.

### Table 5.2: Peak hour capacity and 2013 and 2014 critical link loading

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<thead>
<tr>
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</thead>
<tbody>
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<td>East Rail Line</td>
<td>82,500</td>
<td>0.71</td>
<td>0.71</td>
<td>58,700</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>West Rail Line</td>
<td>49,200</td>
<td>0.70</td>
<td>0.74</td>
<td>35,000</td>
<td>0.99</td>
<td>1.04</td>
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<tr>
<td>Ma On Shan Line</td>
<td>26,800</td>
<td>0.57</td>
<td>0.57</td>
<td>19,100</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>Tseung Kwan O Line</td>
<td>62,500</td>
<td>0.70</td>
<td>0.70</td>
<td>44,500</td>
<td>1.01</td>
<td>0.98</td>
</tr>
<tr>
<td>Island Line</td>
<td>80,000</td>
<td>0.66</td>
<td>0.67</td>
<td>57,000</td>
<td>0.93</td>
<td>0.94</td>
</tr>
<tr>
<td>Kwun Tong Line</td>
<td>71,400</td>
<td>0.67</td>
<td>0.67</td>
<td>50,800</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td>Tsuen Wan Line</td>
<td>75,000</td>
<td>0.70</td>
<td>0.70</td>
<td>53,400</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>Tung Chung Line</td>
<td>37,500</td>
<td>0.60</td>
<td>0.57</td>
<td>26,700</td>
<td>0.84</td>
<td>0.80</td>
</tr>
</tbody>
</table>

While some may suggest that the lack of a reduction in the loading means the promotion was a failure, this perspective fails to take ridership growth into consideration. In fact, from 2013-September 2014, overall ridership likely grew 3-6%, yet peak loading remained mostly constant. In addition, by only reporting peak hour flows, no consideration is given to how the distribution of loading over the morning changed; the promotion could have helped avoid further peak congestion if new growth took place pre-peak hour instead of causing even higher loads in the peak. Another discrepancy with these comparisons is that the Early Bird period (8:15-9:15am) does not actually correspond to the hour with peak loads (8:00-9:00am). Since the station analyses showed that most shifting was happening in the earlier part of the peak hour, using a later period of analysis may not capture
the impacts of the promotion. This suggests that MTR may have underestimated the true impacts by using a common peak period for analysis.

Unfortunately, the available data sets make it challenging to come to more detailed conclusions. Lacking complete 2013 data makes it harder to observe long term trends and, while fully-aggregated fare type data does better reflect crowding conditions, it makes identifying promotion-related changes more difficult.

5.1.5 Summary of Aggregate Results

Analysis of changes to travel patterns over all users shows that the Early Bird Promotion had a small but non-negligible impact. In general, the links and stations that had the highest levels of crowding also saw larger changes. However, these conclusions are based on the distribution of trips across time periods. Increases in ridership means it may have helped slow peak period congestion rather than actually reversing it. These aggregate results also do not give a good picture of which customers are responding to the promotion. The following section will explore this issue using the customer classification analysis introduced in Chapter 4.

5.2 User Group Analysis

While an aggregate analysis is useful to determine what the effects of the promotion were, it does not provide much insight into why or how these impacts came about. This section will tackle the question of how different users groups responded to the promotion: what travel behaviors are more susceptible to peak-spreading demand management? From these results, the groups that MTR should focus its future strategies toward are identified. The analysis will focus on groups defined by their general travel patterns rather than developing groups based on users’ specific responses to the promotion.

5.2.1 AM Travel by Group

The same methodology presented in Chapter 4 was used to develop groups for this analysis; however, rather than assigning classifications based on 12 months, two month periods were used instead. This was done in part because of a lack of continuous data, as well to more accurately capture behavior in each period. Separate samples were taken from September-October 2013, July-August 2014, and September-October 2014. While groups with longer ranges could have the same members over all three periods, short term visitors typically only show up in one. Using three separate samples ensured that all groups would be represented in each period. The clusters of this analysis follow the same characterizations as in Chapter 4 and have similar centroids to the two month groups presented there. Again Group 2 (the long gap group) is not captured because two months is too short to observe its distinct behavior; these users get absorbed by Group 1.
To review, the groups that are included are:

1. Short Term Users
2. Repeat Cross-Border Users
3. Cross-Border Commuters
4. Intermittent Hong Kong Users
5. Casual Hong Kong Users
6. Hong Kong Commuters

The characterizations in Chapter 4 showed that the plurality of trips are taken by Group 7, and in the mornings (again 7:00-9:30am), they actually take a supermajority of the trips to stations eligible for the discount. Figure 5-7, based on in September 2014 records, also shows the other Hong Kong based groups take a non-negligible 18% of trips, but the remaining three groups together only make 3% of these trips. For Groups 1 and 3, this is likely due the fact that few members of these groups travel at all at these times. For Group 4, it is partly a factor of the small size of the group, but also because its members tend to be traveling on the north end of the East Rail Line, not in Kowloon or Hong Kong Island.

The stations that these groups visit can also be considered. While the pie chart above reflects only trips to EB stations, Figure 5-8 shows what percent of morning trips each group actually makes to these stations versus non-eligible ones. Most of Group 4’s trips are still only to Mong Kok East and Hung Hom, so they really only contribute to East Rail congestion. Each of the other groups travels relatively equally to the 29 stations versus the rest of the network, with no stations or OD pairs making up a particularly high proportion of trips. Their contribution to on-train congestion is probably similar to the proportion of trips made by each.

Finally, Figure 5-9 shows the distribution of exits for each group over the morning (in 10 minute intervals because some groups have very few trips). Because Group 7 makes up the majority of trips, their distribution is closest to that of all users, peaking around 8:55 and then declining. Groups 5 and 6 also show some peaking at this time, but it is not as strong. The two visitor groups do not show strong peaks and make increasingly more trips as the morning proceeds, while Group 4 shows peaks at both 7:30 and 8:20.
5.2.2 Group-Specific Responses

The groups differed in how they responded to the promotion. The exit time distributions for Groups 1, 5, 6, and 7 (which had enough trips for legible figures) are shown in Figure 5-10. Group 7 shows the pattern that was observed in the aggregate analysis. On the other hand, Group 6 shows almost no change in September, and only reduces its peak travel in October when the demonstrations began. 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, they switched to MTR instead, and whether because of their typical bus schedules or peak crowding, they were more likely to travel in the pre-peak hour. Future analysis should look at whether this group has maintained its pre-peak MTR use now that the promotion is over.

Groups 1 and 5 each show smaller changes, though these are more difficult to make out in the figure. Table 5.3 summarizes the differences in peak and pre-peak travel for each group, comparing September 2014 to August 2014 and September 2013. The groups with the largest decreases in peak hour travel compared to the previous September are Groups 3, 5, and 7. These groups have larger increases in pre-peak travel as well. On the other hand, while Group 4 does exhibit changes, they are not in the expected direction; peak travel increases and pre-peak travel decreases from the previous September. These changes are likely due to unrelated changes to cross-border travel patterns.

Figure 5-10: Exit time distributions for several groups
Table 5.3: Percent of travel in pre-peak and peak hours by group, with changes in September 2014

<table>
<thead>
<tr>
<th>Group</th>
<th>% AM Travel</th>
<th>Pre-Peak Hour (7:15-8:15)</th>
<th></th>
<th></th>
<th>Peak Hour (8:15-9:15)</th>
<th></th>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 1</td>
<td>% AM Travel</td>
<td>23.9%</td>
<td>22.3%</td>
<td>21.8%</td>
<td>57.0%</td>
<td>57.9%</td>
<td>56.9%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>1.6%</td>
<td>2.2%</td>
<td>-0.8%</td>
<td>0.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 3</td>
<td>% AM Travel</td>
<td>23.3%</td>
<td>19.7%</td>
<td>22.8%</td>
<td>54.8%</td>
<td>60.9%</td>
<td>59.5%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>3.5%</td>
<td>0.5%</td>
<td>-6.1%</td>
<td>-4.7%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 4</td>
<td>% AM Travel</td>
<td>35.1%</td>
<td>37.3%</td>
<td>33.8%</td>
<td>54.2%</td>
<td>51.6%</td>
<td>51.6%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>-2.2%</td>
<td>1.4%</td>
<td>2.6%</td>
<td>2.6%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 5</td>
<td>% AM Travel</td>
<td>28.2%</td>
<td>26.3%</td>
<td>25.5%</td>
<td>54.0%</td>
<td>56.4%</td>
<td>57.5%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>1.9%</td>
<td>2.7%</td>
<td>-2.4%</td>
<td>-3.5%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 6</td>
<td>% AM Travel</td>
<td>21.8%</td>
<td>22.0%</td>
<td>21.5%</td>
<td>60.5%</td>
<td>60.4%</td>
<td>60.4%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>-0.2%</td>
<td>0.4%</td>
<td>0.1%</td>
<td>0.1%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group 7</td>
<td>% AM Travel</td>
<td>27.7%</td>
<td>25.0%</td>
<td>24.5%</td>
<td>58.2%</td>
<td>60.5%</td>
<td>60.9%</td>
</tr>
<tr>
<td></td>
<td>Sept. 2014 Change</td>
<td>2.7%</td>
<td>3.1%</td>
<td>-2.4%</td>
<td>-2.8%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.2.3 Potential for Peak Spreading

The results of the previous section have implications for which types of users MTR should be targeting for effective TDM program. Table 5.4 breaks down the overall change in peak trips by group, weighting the change by the proportion of peak hour trips taken by each group:

\[ P_{14} - P_{13} = \sum_{i=1}^{7} T_{14,i} \times (P_{14} - P_{13})_i \]

Where \( P \) is the percent of morning trips in the peak hour in either September 2013 or 2014 and \( T \) is the percent of trips taken by Group \( i \) in September 2014. Since the commuters are responsible almost 80% of eligible AM trips and showed a fairly high response to the promotion, the vast majority of the overall decrease was because of them.

Table 5.4: Contribution to early bird impacts by group

<table>
<thead>
<tr>
<th>Group</th>
<th>% of Peak Hour Trips</th>
<th>Change*</th>
<th>C (=A*B) Absolute Contribution</th>
<th>D (=C/\sum C_i) Relative Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.00%</td>
<td>-1.60%</td>
<td>-0.032%</td>
<td>1.43%</td>
</tr>
<tr>
<td>3</td>
<td>0.26%</td>
<td>-3.50%</td>
<td>-0.009%</td>
<td>0.40%</td>
</tr>
<tr>
<td>4</td>
<td>0.67%</td>
<td>2.20%</td>
<td>0.015%</td>
<td>-0.65%</td>
</tr>
<tr>
<td>5</td>
<td>5.47%</td>
<td>-1.90%</td>
<td>-0.104%</td>
<td>4.62%</td>
</tr>
<tr>
<td>6</td>
<td>12.29%</td>
<td>0.20%</td>
<td>0.025%</td>
<td>-1.09%</td>
</tr>
<tr>
<td>7</td>
<td>79.31%</td>
<td>-2.70%</td>
<td>-2.14%</td>
<td>95.29%</td>
</tr>
<tr>
<td>Total</td>
<td>100.00%</td>
<td>—</td>
<td>-2.25%</td>
<td>100%</td>
</tr>
</tbody>
</table>

*Difference between the percent of AM trips (7:00-9:30) taken in the peak hours of Sept. 2013 and 2014

Table 5.5 summarizes how much of an impact these groups could have under similar strategies in the future, taking into account:

- **The proportion of users in each group.** By targeting groups with more members, MTR can reach a broader audience with the same TDM design.

- **The proportion of trips made by each group.** Just considering the size of each group may not be enough, particularly in cases like this where a small number of users make the majority of trips. In fact, focusing on smaller groups that make an outsized number of trips could be more effective at changing demand patterns.

- **The average fare paid by each group.** Because the discount is a percentage of a passenger’s fare, those who pay more will get a higher benefit. This may make them more likely to shift their travel.

- **Response to Early Bird Discount.** Each group’s change in peak travel in September 2014 may be indicative of their general willingness to peak-shift, including the impact of more latent characteristics that cannot be captured by AFC data alone.
Red boxes in Table 5.5 indicate a likely low impact while green boxes highlight properties that suggest the group could be important to TDM measures. Commuters are obviously important: they take a large number of trips and seem to be responding to the fare differential. Perhaps programs that work with major employers could be considered in the future, as Singapore is currently doing as part of its Travel Smart program. However, Group 5 could also be important, 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 more flexible users. Though there does seem to be some evidence of Group 3 changing behavior, it may not be worthwhile to target these users. They, as well as Group 1, make few trips and seem to be less likely to live in Hong Kong, making them harder to reach. Inter-modal incentives may be more effective for Group 6, and more East Rail Line-specific promotions may be better suited for Group 4.

### Table 5.5: Potential impact of each group

<table>
<thead>
<tr>
<th>Group</th>
<th>% of Cards (Sept. 2014)</th>
<th>% of AM Trips (Sept. 2013)</th>
<th>Avg. Fare (Aug. 2014)</th>
<th>Change in Peak Trips (9/13 → 9/14)</th>
<th>Impact on Peak Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36.0%</td>
<td>2.0</td>
<td>8.12</td>
<td>-0.80%</td>
<td>Low</td>
</tr>
<tr>
<td>3</td>
<td>5.5%</td>
<td>0.24</td>
<td>8.24</td>
<td>-6.10%</td>
<td>Low</td>
</tr>
<tr>
<td>4</td>
<td>0.4%</td>
<td>0.50</td>
<td>29.77</td>
<td>2.60%</td>
<td>Very Low</td>
</tr>
<tr>
<td>5</td>
<td>27.7%</td>
<td>4.9</td>
<td>9.29</td>
<td>-2.40%</td>
<td>Moderate</td>
</tr>
<tr>
<td>6</td>
<td>16.8%</td>
<td>11.2</td>
<td>8.39</td>
<td>0.15%</td>
<td>Low</td>
</tr>
<tr>
<td>7</td>
<td>13.6%</td>
<td>81.2</td>
<td>7.52</td>
<td>-2.40%</td>
<td>Very High</td>
</tr>
</tbody>
</table>

### 5.3 Panel Analysis

The goal of the panel analysis is to disaggregate users even further by looking at the travel behavior of individuals over time. By tracking the same users before and after the promotion begins, it is possible to study how the changes seen at the aggregate and group levels relate to the behavior of each customer. Some of the changes that may be possible to detect and measure through a panel analysis include:

- **Changes to Frequency:**
  - All-morning system usage could be constant (if people just shift when they travel) or could increase (if the discount induces trips or mode shifts)
  - Pre-peak travel should increase, perhaps with related decreases in the peak hour
  - Users might change which stations they use, choosing to exit at eligible stations more frequently. (Since no evidence of this was found at the aggregate level, it was not a focus of this analysis.)

- **Changes to Exit Time:** Among people who start traveling more in the pre-peak hour, there should be a corresponding change in their typical exit time, with it shifting earlier toward the pre-peak hour.
• **Changes to Fare Type**: Users may switch between paying for each trip and having a pass, though this was not a primary concern in this analysis.

With these expectations, the following questions were used to guide the analysis:

1. Can the users that changed their behavior in response to the promotion be identified?
2. How often did they travel in the pre-peak before and after the promotion begins?
3. How much are these users shifting their departure time?
4. How do factors like entry and exit station, trip distance, duration, departure time variability, etc. impact someone’s response to the promotion?

A panel analysis does help alleviate some of the problems associated with aggregated results. Because the same users are followed over time, there is less of an impact from ridership growth due to new users and seasonality. However, it is still important to recognize that AFC data does not reveal the motivations behind a user’s actions. Though there was strong evidence that the panel as a whole did begin to travel in the pre-peak hour more often once the promotion began, it is possible that some individuals who are recognized as having responded to the promotion may have done so because of other lifestyle changes.

### 5.3.1 Panel Selection

Rather than selecting users from the entire population, the panel instead focused on high frequency, peak hour users. This ensured that members would have taken enough trips to give some context to trends in their usage. Also, since this type of user takes the majority of trips, understanding the factors that influence their response to the promotion can have significant benefits for updating the promotion design.

In particular, panel members were selected on the basis of their August 2014 travel; they had to have an adult fare type, and have traveled at least 15 times in the peak hour (8:15-9:15) to one of the 29 eligible stations. These are users who were likely to continue traveling into September and would have received relatively high monetary benefits from the promotion. Panel members should correspond to Group 7 of the cluster analysis, but the even stricter parameters here necessitated a larger pool to choose from (only a sample was used in the group analysis) so the entire population was considered. 124,306 of the 8,784,932 distinct August card IDs, or 1.4%, met this criteria and 20,000 were selected for the panel. Because of this selection methodology, the focus of the analysis was how existing peak hour customers changed their behavior; users who shifted from the early morning to the pre-peak hour or did not previously use MTR were outside its scope.

As with the previous two sections, the time periods used for the panel analysis were September-October 2013 and July-October 2014. This ensured that behavior in Fall 2014 could be compared both to recent months and to months that may be more similar in terms of seasonality. Still only weekday trips were considered, so holidays and days that were majorly affected by typhoons were again excluded. The days that saw the most disruption from the political demonstrations were kept, but recognized.
5.3.2 General Characterization of Panel Members

To give a general sense of how these users differ from the users presented in the previous sections, Figure 5-11 compares their exit time and frequency distributions. In terms of temporal patterns, the panel has much sharper peaks and fewer midday trips than the population. The AM peak is particularly sharp for the panel (due to how they were selected), while evening trips are more spread out. Most panel members take 30-50 weekday MTR trips per month. The overall population’s distribution is skewed strongly to the right, though there is still a small second peak at 42 trips. On average, the population took 12.6 weekday trips in August while the panel took 42, putting their per-day mean at two trips. In addition, approximately 98% of their morning trips (defined as prior to 10:30am for this section) are to early bird-eligible stations. As intended, the panel is mostly commuters who use the stations of interest.

![Graph](image)

(a) Weekday exit time distribution (5 minute intervals)

![Graph](image)

(b) Weekday frequency distribution

Figure 5-11: Comparison of panel and population characteristics in August 2014
Figure 5-12: Comparison of weekday station use

Figure 5-12 compares station usage in August, with the size of each station representing the difference between each group’s proportion of entries or exits there, and the color representing whether the panel was more (green) or less (red) likely to use the station than the population. From the entries, panel members are more likely to be starting their trips on Hong Kong Island and the Nathan Road Corridor, as well as some stations farther afield. The exits are more skewed because of the criteria used to select panel members; nearly all of their trips are to stations eligible for a discount.

Finally, Figure 5-13 compares how often panel members traveled in the pre-peak hour in different pairs of months. This comparison is based on what percent of a user’s AM trips (<10:30am) were in the pre-peak hour. A negligible number of users had the same percentage in both month, except in the case of 0%. Most users did not travel in the pre-peak hour in either month, while others began to travel more or less frequently from one month to the next. As expected, when one month is before the promotion and the other is after, there were more users who increased how often they traveled in the pre-peak. The types of changes are essentially balanced when both months are before and, though not shown, the magnitude of change is more likely within the range of normal variability. In contrast, when one month is after the promotion, the increases are often by more than more 30% while most of the decreases are less than 10%. This further suggests that the increases into September 2014 are due to the promotion rather than external factors.

5.3.3 Identifying Shifters

To understand the extent of behavior change and if any particular factors were associated with responding to the promotion, change point detection was used to identify "shifters," users who exhibited a behavior change that could be associated to the promotion. Change point detection is a type of time series analysis that aims to find when the distribution of a data series changed. It could include searches for changes in mean, variance, or correla-
Figure 5-13: Comparison of direction of change to percentage of morning trips eligible for early bird direction

In this case, the focus was changes in mean—did someone’s typical exit time change in a way that could be associated with the promotion? Looking for these more significant changes means that typical monthly variation should not be captured, only more major behavior changes.

This analysis had two parts. First, a set of change points was determined for each user, then those whose changes corresponded to the promotion were identified.

1. Individual Change Point Analysis: A time series dataset was set up for panel members with one exit time on each day traveled. The methodology was as follows:

   • Users: Users who never traveled in the pre-peak hour during September were excluded. In addition, any users who were identified as "pass-dependent" in September 2014 were not considered. Though MTR’s Octopus data does not have a field that explicitly records whether a card has a pass associated to it, pass-holders will not be charged a fare on any trip covered by their pass. Since non-pass holders are also occasionally not charged a fare and pass-holders are charged on some ODs, "pass-dependent" users were defined as those who were not charged on at least 2/3 of their trips. This level ensures users with moderate numbers of no-fare trips are still included; they still could have been influenced by the promotion, either because they regularly make two trips in the morning (one with pass followed by one without) or just make enough non-pass trips. 4,591 users were ultimately included.

   • Dates: Only the four months of continuous data were included: July-October 2014. For the purposes of a time series dataset, weekends and other excluded days were
assumed to not exist, i.e. Days 1-3 were July 2-4, weekends July 5-6 were excluded, Days 4-8 were July 7-11, etc.

- **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. Again "AM Trips" were defined as those that finished before 10:30am. Because the panel was selected such that most of their morning trips were between 8:15 and 9:15am before the promotion started, the number of exits was small and relatively constant after 10:30. These were assumed to no longer be regular commute trips (in many cases users who did travel after 10:30 were making their second trip of the day or taking an anomalous trip), plus it would be very unlikely for someone to shift their departure time by more than two hours for a 25% discount.

  Of this set of AM trips, the most logical variable would have been a single exit time on each day. However, some users travel multiple times each morning, either taking two successive trips or taking one trip in the pre-peak or peak hours and another the mid-morning. To deal with this, a user’s first exit time after 7:15 to an eligible station was selected as the time series data point for each day. Taking the median AM exit time of each day was also considered, and while the results were not greatly different, it did disguise some pre-peak trips when the user also traveled later.

The analysis was carried out the **breakpoints** function from the **strucchange** package developed for the open source software R (Zeileis, 2015). It begins with a standard linear regression for the time series:

\[ y_i = x_i \beta + u_i \]

Given parameters for minimum segment size (h) and maximum number of breakpoints (n), breakpoints are selected to minimize the sums of square residuals among possible segments. Each segment is fit using ordinary least squares regression. For the simple change in exit time desired here, a one-dimensional model was used, essentially just finding the best intercept, or mean, for each segment. This type of change point analysis is also known as step detection. More complex methods include accounting for day-of-week effects and seasonal effects, accounting for auto-correlation, or taking a Bayesain approach to calculate the probability of a change having occurred at each point.

After some experimentation, the minimum segment length was set at 10 days and the maximum number of segments at three. (These are just constraints for the optimization—users could still have longer segments or fewer breakpoints, and most did.) 10 days, equivalent to two workweeks, ensures that no minor fluctuations in exit time are mistakenly identified as time shifting behavior. It does also mean that users who tested out the promotion for a few days and quickly reverted to their previous behavior are not identified, though it would be more difficult to confidently associate these changes with the promotion anyway. Allowing a maximum number of segments of three fills a similar role. Only 5% of users had even three breakpoints, as Figure 5-14 shows, and given the time span of the data, three is the maximum number of reasonable breakpoints assuming no other behavior changes: one at the beginning of August (when the panel selection criteria
go into effect), one at the beginning of September (for the promotion/beginning of fall), and one in October (demonstration-induced changes).

This stage provided a set of up to three breakpoints for each individual, as well the regression results for each segment. Figure 5-15 shows kernel density distributions of when each breakpoint fell. The first day along the x axis is 11, i.e. the first possible date for a change point with the 10 day minimum, and the three vertical lines mark the beginning of August, September and October for context. Figure 5-15a aggregates all breakpoints (whether someone’s first, second, or third). The y axis value corresponds to the percent of breakpoints falling on a particular day among all the breakpoints of all users. Figure 5-
15b shows separate distributions for when people’s first, second, and third breakpoints were (among users with at least that many breakpoints, i.e. BP2 includes the second breakpoints of users with two or three breakpoints). Among all breakpoints and first breakpoints, the largest peak is just before the beginning of September, corresponding to the start of the promotion though also the end of the "summer season". The second and third breakpoint distributions also show peaks around the beginning of October when the protests began. This matches with expectations, many users changed their behavior when the promotion began or holidays ended, any further changes were likely brought upon by the demonstrations.

Figure 5-16 shows an example of what the results look like for two individuals. The one on the left has a large drop in their exit times at Day 42 (August 28) which can be associated to the promotion, but the one on the right has a slightly later exit times in August and September compared to July and only begins traveling earlier at the end of September when the demonstrations began. The next stage dealt with aggregating these results to determine which individuals had likely responded to the promotion.

2. Aggregation of Individuals To identify the users who may have a change 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 the hour of the promotion. Four criteria were used:

- **Date:** The user has a change point between the end of August and middle of September. Earlier breakpoints are unlikely to be related to the promotion while those at the end of September or into October may be due to the demonstrations. The boundaries were set at Tuesday August 19 and Friday September 19 (i.e. -1.5/+3 weeks from September 1). This interval helps capture users who may have not responded to the promotion right at the beginning and accounts for noise in the data, which can
lead to a breakpoint being identified few days before or after a change is actually initialized or completed.

- **Direction**: The mean at a change point in the range above should decrease—the user should begin exiting stations earlier in the morning rather than later.

- **Magnitude**: The mean after a change that meets both of the above criteria should be before 8:25am. This ensures that most days’ earliest trips are before 8:15. It was important to have some buffer after 8:15 (even users who had a fairly strong response to the promotion would not be expected to travel in the pre-peak hour every day). A later boundary included too many users who just regularly exited between 8:15 and 8:30. For example, changing it to 8:30 increased the number of shifters by 15%, although most rarely traveled in the pre-peak hour.

- **Number of Trips**: Users had to have at least four trips after any breakpoint that met the above criteria to better control for breakpoints more associated with frequency changes (especially as this tended to increase noise in the data) than exit time changes.

Based on these three 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 peak to pre-peak changes, both of which were about 2.5-3%. As discussed in the introduction to this section, it is possible that some of these users may have other lifestyle changes that influenced their travel patterns. The promotion might, however, 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. No matter the factors that led to this behavior change, these are the users who personally benefited from the promotion and who contributed to system-wide benefits. Future research might consider a panel analysis done in conjunction with a survey to better understand the impacts of external lifestyle characteristics and socio-demographics. Having acknowledged these limitations, the following section will explore how various characteristics differ between these users and the rest of the panel.

### 5.3.4 Comparison of Shifters to Rest of Panel

Differences between these groups could come from two sources. The shifters and the rest of the panel may have had different characteristics to begin with or the shifters may have changed their previous travel patterns more dramatically. The following sections will explore differences in frequency, exit times, exit time variability, and trip characteristics like station use, distance, and duration. Throughout this analysis it is important to remember the strict criteria set for the August travel of panel members. This means that the differences between August and other months could be somewhat artificial; comparison to July 2014 or months in 2013 may be more representative of someone’s typical travel than their trips in August.
Frequency

If the promotion induced demand for pre-peak travel, there may be increases in how often panel members used MTR. Panel member’s MTR use was compared over three time spans: the whole day, the morning (again before 10:30), and the pre-peak hour. If travel is induced, there may be increases overall or in the morning, but if users are just shifting when they travel, only the pre-peak frequency should be different. The average number of trips taken by a user per weekday in these periods for three different months is summarized in Table 5.6. In addition, the distributions for morning trips are shown in Figure 5-17.

Table 5.6: Average daily travel frequency over different periods for shifters and full panel

<table>
<thead>
<tr>
<th>Period</th>
<th>Group</th>
<th>September 2013</th>
<th>August 2014</th>
<th>September 2014</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Std. Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>All Day</td>
<td>Shifters</td>
<td>1.89</td>
<td>0.71</td>
<td>2.05</td>
</tr>
<tr>
<td></td>
<td>Non-Shifters</td>
<td>1.79</td>
<td>0.72</td>
<td>2.04</td>
</tr>
<tr>
<td>AM</td>
<td>Shifters</td>
<td>0.89</td>
<td>0.39</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>Non-Shifters</td>
<td>0.80</td>
<td>0.36</td>
<td>0.97</td>
</tr>
<tr>
<td>Pre-Peak</td>
<td>Shifters</td>
<td>0.22</td>
<td>0.34</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>Non-Shifters</td>
<td>0.05</td>
<td>0.15</td>
<td>0.02</td>
</tr>
</tbody>
</table>
In general, frequency was lower in September 2013 than in 2014, even having excluded users who did not travel in a given month. In August, the period from which users were chosen, there is essentially no difference between the frequency distribution of the two groups for all trips and AM trips. In addition, the average frequency over the whole day and the morning is nearly the same for the shifter group from August to September, though it does decrease among other users. In terms of pre-peak usage, the shifters were already making more trips than the other group, though many fewer than in September 2014. The other group also begins to travel more in the pre-peak, but the increase is much smaller. As mentioned before, it is difficult to attribute this difference to fall/summer seasonal travel patterns or the promotion causing a reversal of longer term drift. However, comparing September 2014 pre-peak travel to September 2013 also shows an increase, though smaller, which implies the gains on August are not just due to seasonality.

**Shifts in Exit Time**

Having established that most “shifters” are actually shifting their exit times from the peak to the pre-peak hour, rather than just adding new trips, the time that these users traveled before the promotion began can be compared with when they traveled after. First, the aggregated trip exit time distributions are shown in Figure 5-18. This plot shows these distributions only for the mornings; the differences between groups and between months were minimal in the rest of the day. In the morning, the shifters have a sharper distribution in all three months, but while the mode of their distribution is at the same time in September 2013 and August 2014, it shifts noticeably earlier in September 2014, from 8:20 to 8:10. There is no such change for the other group, who also tend to be traveling later and more evenly over the peak hour. Among shifters, the proportion of AM trips that take place between 8:45 and 9:00—the peak of the peak—decreases from 9.3% in September 2013 and 11% in August 2014 to just 3.0% in Sept. 2014.

![Figure 5-18: Exit time distribution (10 minute intervals)](image)
Next, Figure 5-19 shows the median travel times of individual users in six different months. Only AM trips (before 10:30am) were considered when calculating the median. The shifters tended to travel on the earlier side of the peak even before the promotion began. In Fall 2013, 18% of the shifters had a median exit time before 8:15, compared to 3% of non-shifters, while the number is nearly zero for both groups over summer 2014 (because of the panel selection criteria). In Fall 2014, over 50% of shifters have a median that falls in the pre-peak hour. That not all their trips are in the pre-peak means that they still have some variability in when they choose to travel—even users who were influenced by the promotion to travel more often in the pre-peak still take some later trips. (This was also demonstrated in Table 5.6, where shifters’ pre-peak travel frequency was only about half of their AM frequency in September 2014.) In contrast, only 2% of non-shifters have a median in the pre-peak hour after the promotion begins.

Figure 5-19: Median exit time distribution for several months
Figure 5-20 shows the distribution of the changes in median exit times. The difference between each individual’s median exit time in September 2014 and his or her median in two prior months, August 2014 and September 2013, shows how much earlier users were actually willing to travel in order to take advantage of the promotion. The differences are greater with August—shifters begin to travel earlier by an average of 19 minutes, and median of 14 minutes—but even compared to September 2013 the mean shift is 13 minutes. For the non-shifters, the average change is less than one minute from both previous months. However, the range of their changes is nearly the same as the shifters, it is just more concentrated around zero and more balanced between earlier and later. Non-shifters with large changes also tended to be traveling in the late morning prior to September 2014; even after they begin traveling much earlier, they do not reach the pre-peak hour.

The implications of these results for reducing peak hour travel are significant. If nearly all of those who shifted to the pre-peak hour are coming from the 8:15 to 8:30 period, the actual peak of the peak is seeing very few reductions. This is consistent with the aggregate results presented in Section 5.1. There, the exit time distributions of September 2014 versus prior months were most different at the beginning of the peak hour. Different incentives may be needed to actually target users traveling at the most congested times.

Exit Time Variability

The variability a user shows in his or her exit times might be a proxy for the flexibility he or she has in traveling. Standard deviation of exit times in the morning (for all stations) was used as a measure of variability. Figure 5-21 shows the distribution of these standard deviations for the shifters and non-shifters in August and September 2014. There is indeed a slight difference between the two groups; the shifters’ mean standard deviation
Figure 5-21: Comparison of distributions of exit time variability before and during the promotion

is higher in both cases, even more so once the promotion starts. This could imply that policies that promote flexible working hours could allow more users to shift their travel time, or that some intervention is needed to disrupt the patterns of habit-led individuals.

Spatial Patterns

The extent to which shifters use entry and exit stations in comparison to the rest of the panel can suggest the types of trips people are making, their broader transportation patterns, as well as how the promotion might be tailored to different stations. (Focus has been given to station, rather than OD pairs because of the size of the panel.) Figure 5-22 compares where these two groups start and end their trips by calculating the percent of entries and exits that take place at each station for each group and taking the difference between groups. Larger circles represent a larger magnitude difference and the color represents the direction of the difference (red=fewer shifters relative to the full panel and green=more shifters).

These results indicate that more who have shifted their behavior are coming from Kowloon and the lower New Territories, while fewer are coming from the Hong Kong Island and the northern New Territories. In particular, stations along the Kwun Tong Line have relatively more users taking advantage of the discount. This could mean that while users who are making longer trips would get a discount worth more money, having to leave even earlier than they already do is not worthwhile. Looking at destinations, the biggest differences are at Hung Hom and Wan Chai. Because Hung Hom has many users who transfer to buses, this could imply that people making multi-stage journeys are less likely to participate in the promotion because they would have to change their routine even more. On the other hand, Wan Chai (and Admiralty) attracts many commuters, which corresponds
to the higher impact seen among commuter-like users in the Group Analysis. At stations that are not eligible for the discount there is little difference, largely because so few users are traveling to those stations anyway.

Figure 5-23 compares the distributions of trip duration and straight-line trip distance between the groups. Shifters are more likely to be taking mid-length trips, as measured both by journey time and the distance between stations. This matches the spatial patterns above, with origins in the New Territories less common than in Kowloon. These patterns are the same before and after the promotion begins, though the differences are greater in September. In that month, the mean distance traveled by shifters is 7.7 km, slightly less than the 9 km of non-shifters. The differences for duration are similar: 23.9 min for shifters and 25.9 min for the rest of the panel.

5.4 Overall Conclusions

Through the three analyses of this chapter, a relatively comprehensive picture of the Early Bird Discount Scheme has been presented. From the panel analysis, the prototypical shifter is someone who uses MTR every morning to travel between Kowloon and the CBD, and while likely making a commute trip, he does have some variability in when he chooses to arrive to work. User frequency and temporal characteristics, as well as the most affected stations, all highlight the importance of commuters, but the potential influence of intermittent users, likely with higher levels of flexibility, should not be understated. All three analyses also stress the need for MTR to consider how it can better target users who actually travel in the peak of the peak, rather than right after the promotion ends. The relatively low proportion of shifter trips to Hung Hom also suggest that additional cross-modal partnerships or incentives could be beneficial. Finally, though most of the analysis focused on relative changes to demand, MTR’s absolute link flows show that
these changes are less reducing congestion than preventing it from getting even worse. The relative changes are similar in magnitude to MTR’s annual growth rate, so the discount seems to be helping to prevent peak hour ridership from growing as much, instead encouraging growth in the pre-peak hour.

Analysis of costs associated with the promotion are beyond the scope of this analysis. However, the cost per shifted user is probably quite high because of lost revenue from users who already traveled in the pre-peak hour; relatively few users shifted from the peak compared to the number who were traveling in the pre-peak anyway. Developing a better understanding of the policy’s acceptance, as well as differences among socio-economic groups, would have been well-suited to a user survey. Associating survey results to Octopus cards would be particularly insightful.

Unfortunately, the protests prevented analysis of long-term behavior change. Even data from January 2015 and beyond, when demand returned to normal, would have been difficult to ascribe to the promotion; did someone take longer to adjust her lifestyle to earlier departures or did the protests necessitate a change in habit? However, if confounding factors could be accounted for, it would also be interesting to try to further analyze whether TDM promotions or major, long-term disruptions to service (like the high demand caused by demonstrations) are more effective for long-term behavior change.

The next chapter will take these lessons and return to the design of the strategy. Continuing the analyses presented here, elasticities for each of the three customer levels will be developed and applied to improvements for the current scheme. Other potential strategies will also be discussed.
While the program evaluation in Chapter 5 showed that the Early Bird Discount Promotion has led to changes in ridership patterns, the analysis also suggested how MTR’s policies might be improved or expanded. Building on the redesign framework in Chapter 3, this chapter takes a group-level approach where possible. Section 6.1 continues the analysis of Chapter 5 with the specific intent of improving the Early Bird Program. Changing the time period, coverage area, and magnitude of discount is considered through the development of elasticities and a discrete choice model. A broader view of MTR’s demand management options is taken in Section 6.2. It proposes several new types of policies for MTR that may better target congestion and discriminate between users with different characteristics.

### 6.1 Improvements to the Early Bird Discount Scheme

Taking the type of program as fixed, the main design dimensions engaged by the Early Bird Discount Promotion are:

- Discount magnitude
- Spatial coverage
- Temporal coverage

While there may be practical or political limitations to offering different fare incentives or coverage areas/periods to different users, any of these dimensions could be adjusted for all users.

The first sections below cover the question of the level of discount to offer. Typical methods for optimizing fares use fare elasticities, which measure customers’ price-sensitivity. If users are more price sensitive and thus their elasticity greater, a smaller fare change is needed for a particular change in demand. The actual value of the elasticity reflects the percent change in demand associated with a 1% change in fare. As with most products, transit fare own-price elasticities are typically negative. To provide an example, when \( E = -0.5 \), a 1% fare increase for a service leads to its demand decreasing by -0.5%. The signs of cross elasticities—which measure changes to demand as a result of price changes...
to another service—depend on whether the other service compliments (also negative) or competes (positive) with the first. Most empirical measurements of transit elasticity show changes in demand to be less than changes in fare, i.e. inelastic demand (-1<\(E<0\); Linsalata and Pham, 1991). This is particularly true during peak periods. For MTR’s pre-peak discount, this implies that while demand will increase in the pre-peak hour, the agency will see less revenue as a result. Several methods for calculating elasticity for the MTR case are discussed below.

6.1.1 Aggregate and Group Elasticities

Though agencies that lack detailed data often rely on the Simpson-Curtin rule for elasticity (the average fare elasticity is -0.33; Linsalata and Pham, 1991), more accurate measurements can account for context- and user-specific price sensitivities (Cervero, 1990). In particular, focusing on different market segments with more homogeneous characteristics can allow agencies to account for how users’ characteristics and needs affect their purchase behavior and/or responses (Elmore-Yalch, 1998). These groups can be defined by socio-demographic characteristics, like age, income, and employment status; fare type or media; or system usage. The same customer classification groups used in Chapters 4 and 5 will be studied in this section in addition to the population as a whole.

A number of methods exist to calculate elasticity. The simplest method for calculating elasticity is a shrinkage ratio—using the percent differences of fare and demand before and after a change—but this method is only accurate for small changes because it is very sensitive to the initial demands and fares. Midpoint elasticities, on the other hand, are less dependent on initial conditions and often more accurate. They are an approximation of arc elasticities, which represent elasticity as a series of incremental changes. Midpoint elasticities are more common in transportation applications because they do not use logarithms so they are applicable in free-fare situations. The formula for each of these elasticities and how to calculate an updated demand are:

Shrinkage Ratio:  
\[ E = \frac{(Q - Q_0)/Q_0}{(P - P_0)/P_0} \]
\[ Q = Q_0 + EQ_0\frac{(P - P_0)}{P_0} \]

Arc Elasticity:  
\[ E = \frac{\log(Q) - \log(Q_0)}{\log(P) - \log(P_0)} \]
\[ Q = Q_0\left(\frac{P}{P_0}\right)^E \]

Midpoint Elasticity:  
\[ E = \frac{(Q - Q_0)(P + P_0)}{(P - P_0)(Q + Q_0)} \]
\[ Q = Q_0\left[\frac{P_0(E - 1) - P(E + 1)}{P(E - 1) - P_0(E + 1)}\right] \]

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.

Unfortunately, the values measured through the demand and fare changes brought upon by the Early Bird Promotion do not represent a "pure" elasticity. For many users, the discount is only available alongside a change in departure time. Though a model-based
elasticity could help control for this issue, there is not enough data to develop a demand model for all users or for most user groups. Therefore, the elasticities that will be presented here are better represented as elasticities of proportions than of demand. They capture the fact that changes in demand could be due to existing users who shift between the peak and pre-peak hours as well as new customers, without distinguishing between these different types of new trips. The elasticities were calculated using the midpoint formulation and the following assumptions:

**Demand.** Relative trip values have been represented as percentages, similar to what was used in the previous chapter. Again the AM period is defined from 7:00-9:30am, so the "demand" in the pre-peak or peak hours is:

\[
\%\text{Demand} = \frac{\text{Avg. Trips}_i^j}{\text{Avg. Trips}_{9:30}^{7:00}} \times 100\%
\]

Where \(\text{Avg. Trips}_i^j\) is the average number of trips between \(i\) and \(j\) for a particular month, with \(i=7:15\) and \(j=8:15\) for the pre-peak and \(i=8:15\) and \(j=9:15\) for the peak. By setting the base period from 7:00-9:30, both hours of interest plus 15 minutes on either side are included. Extending the period later introduces more seasonality differences, while very few trips are completed before 7:00. Using percentages, the demand value captures whether users shifted from the peak to the pre-peak or if the pre-peak experienced greater growth than the peak, without impacts from exogenous ridership growth.

The aggregate values are presented as the daily average number of trips, while the groups are monthly averages (because some groups were so small). Again, only normal weekdays have been included in these averages. For the aggregate elasticity, several months are presented to show a likely range, and to be useful for planners making comparisons from different parts of the year. The group elasticities are shown for July, which has values in the middle of this range and does not have any confounding fare effects (discussed below).

**Fare.** For each group and overall, the average adult fare for AM trips to early bird-eligible stations was calculated in each month (excluding free fare trips and trips that received other discounts). The percent differences were approximately 25% for each group, but there was some small variation depending on the most common ODs in the before and after periods (i.e., if there were more longer, expensive trips in August than September, the fare difference would be slightly greater than 25%).

For the overall elasticities made with comparisons to 2013 or 2012, the results are also confounded by annual fare increases (about 3% per year). These fare increases are not applied to OD pairs uniformly, and other fare concessions were also introduced or retired over this period. Because accurate results could not be assured even with corrections, none were made in the elasticities that are presented. However, given the magnitude of the annual increases, elasticities that do control for them would be expected to have slightly lower magnitudes.
For the early bird discount, both own-price and cross elasticities can be calculated. The own-price elasticities consider how fare changes in the pre-peak hour affect demand in the \textit{pre-peak} hour, while the cross elasticities measure how pre-peak fare changes affect \textit{peak} demand. In this context, the own-price elasticity should be negative, with the fare decrease leading to higher demand as people begin traveling in the pre-peak hour. The cross elasticity, however, should be positive because it is a competing service for most users. With lower pre-peak fares, the demand in the peak hour should also decrease as some users will begin traveling earlier.

Overall elasticities are presented in Table 6.1 using the demand from several months as the base case (i.e. \(Q_0\) and \(P_0\)). The values are in line with elasticities found in other cities—typically -0.1 to -0.2 in the peak hour and -0.3 to -0.5 in the off-peak (Cervero, 1990). With a cross elasticity of about 0.14 and MTR’s desired 3% change in peak hour loads, a 25% discount was in fact appropriate at the aggregate level. However, this calculation considers only eligible trips, which make up just 44% of all AM trips. In order to see a 3% decrease throughout the network, the discount would have to be higher: over 40%, probably too high of a financial burden on MTR.

However, not all groups responded in the same way, as shown in Table 6.2. This table presents elasticities using July 2014 for the base demand and fare. As demonstrated by

<table>
<thead>
<tr>
<th></th>
<th>Pre-Peak</th>
<th>Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sept. 2014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand (Q)</td>
<td>27.5%</td>
<td>57.8%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare (P)</td>
<td>7.01</td>
<td></td>
</tr>
<tr>
<td>Aug. 2014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand</td>
<td>23.9%</td>
<td>60.6%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.51</td>
<td></td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.46</td>
<td>0.16</td>
</tr>
<tr>
<td>Jul. 2014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand</td>
<td>24.2%</td>
<td>60.4%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.60</td>
<td></td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.40</td>
<td>0.14</td>
</tr>
<tr>
<td>Oct. 2013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand</td>
<td>25.0%</td>
<td>60.2%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.41</td>
<td></td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.32</td>
<td>0.14</td>
</tr>
<tr>
<td>Sept. 2013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand</td>
<td>24.9%</td>
<td>60.0%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.39</td>
<td></td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.33</td>
<td>0.13</td>
</tr>
<tr>
<td>Sept. 2012</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of AM Demand</td>
<td>24.7%</td>
<td>60.5%</td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.52</td>
<td></td>
</tr>
<tr>
<td>Elasticity</td>
<td>-0.35</td>
<td>0.15</td>
</tr>
</tbody>
</table>
the aggregate elasticities, July’s seasonality differences are generally less extreme than August, plus it does not have the fare increase complications brought on by comparisons to 2013. Because Group 7 makes up most of the users in the morning, its elasticities are closest to those of the population. Group 5 has similar values, with the difference in pre-peak elasticity due mostly to a lack of users shifting from the early morning.

Table 6.2: Midpoint elasticities for specific user groups

<table>
<thead>
<tr>
<th>Group</th>
<th>% of AM Demand</th>
<th>Avg. Pre-Peak Fare</th>
<th>Elasticity</th>
<th>Pre-Peak Own Elasticity</th>
<th>Peak Cross Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>21.1%</td>
<td>23.3%</td>
<td>56.2%</td>
<td>57.6%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>11.12</td>
<td>7.10</td>
<td>-0.22</td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>Group 3</td>
<td>17.7%</td>
<td>23.3%</td>
<td>60.3%</td>
<td>55.2%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>10.66</td>
<td>7.06</td>
<td>-0.68</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td>Group 4</td>
<td>36.7%</td>
<td>36.3%</td>
<td>51.6%</td>
<td>53.8%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>31.97</td>
<td>24.86</td>
<td>0.04</td>
<td>-0.17</td>
<td></td>
</tr>
<tr>
<td>Group 5</td>
<td>25.5%</td>
<td>27.6%</td>
<td>57.8%</td>
<td>55.1%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>10.17</td>
<td>7.52</td>
<td>-0.26</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>Group 6</td>
<td>22.2%</td>
<td>21.8%</td>
<td>60.2%</td>
<td>60.8%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.84</td>
<td>7.25</td>
<td>0.06</td>
<td>-0.03</td>
<td></td>
</tr>
<tr>
<td>Group 7</td>
<td>24.0%</td>
<td>27.1%</td>
<td>61.8%</td>
<td>59.1%</td>
<td></td>
</tr>
<tr>
<td>Avg. Pre-Peak Fare</td>
<td>9.05</td>
<td>6.73</td>
<td>-0.42</td>
<td>0.15</td>
<td></td>
</tr>
</tbody>
</table>

The other groups are quite different. Group 3 has very high values, but also very few trips taken, meaning these results may not be particularly reliable, but also that this group is not particularly important for congestion relief. Group 1 has negative own and cross elasticities. This group includes many tourists who tend to travel more often in the post-peak during the summer. Comparisons to the previous fall (not shown here) do show the correct sign. Future analysis focusing on tourist response to TDM measures will need to recognize their stronger seasonal differences. Groups 4 and 6 show unexpected signs for both elasticities, but for Group 6, the magnitudes are small enough to essentially imply that this group just did not respond to the promotion. In the initial group characterization, Group 4 was found to have relatively distinct travel patterns from the other groups, especially spatially, so its elasticities further suggest that its travel patterns are being guided by other trends. This means that changing the discount a moderate amount will likely
not inspire members of these two groups to change their behavior. Other strategies will be needed instead.

### 6.1.2 Modeling the Panel’s Response

By being able to identify which users responded to the promotion, a more detailed approach can be used to quantify the panel’s fare elasticity, as well as other marginal effects and values of time. The analysis in Chapter 5 identified which members of the panels were shifters. Therefore, a binary logit model could be estimated for users’ decision of whether respond to the promotion or not.

This type of model is based on random utility theory, so the utility specification (U) includes a systematic utility term (V) as well as an error term (ε). V is linear in parameters, with a coefficient (β) for each variable xᵢ. A utility is specified for each combination of alternative i and user n using the appropriate variable values. However, though users are assumed to choose the alternative with the highest utility, not all factors can be quantified in V. The error term accounts for this discrepancy, as well as measurement error, etc. The utility formulation used here is the following:

\[
U_{\text{Shift},n} = V_{\text{Shift},n} + \varepsilon_{\text{Shift},n} = \beta_0 + \beta Z_{\text{Shift},n} + \beta S_n + \varepsilon_{\text{Shift},n}
\]

\[
U_{\text{NoShift},n} = V_{\text{NoShift},n} + \varepsilon_{\text{NoShift},n} = \beta Z_{\text{NoShift},n} + \varepsilon_{\text{NoShift},n}
\]

Where variables have been divided into attributes of the alternative, Zᵢₙ, and attributes of the decision-maker Sₙ. β₀ is an alternative specific constant. In this case, the constant and the user-specific variables are only included in the shift utility.

Assuming that the errors follow extreme value distribution, the probability that a user makes a particular choice can be calculated using the logit model. (Further details of this method are available in Ben-Akiva and Lerman, 1985.)

\[
P(\text{Shift}) = \frac{e^{V_{\text{Shift}}}}{e^{V_{\text{NoShift}}} + e^{V_{\text{Shift}}}}
\]

### Model Specification

Two alternatives were considered in this model: shift or no shift. Only AFC data was available for specifying the model, so important factors like socio-demographics or employment could not be included. Though some proxies were developed, the fit of the model would likely improve with other explanatory variables. The variables that were considered are:

**Attributes of Alternatives**

- **Fare**: Users’ fares for AM trips in September 2014 were reconstructed as if they had been taken in the peak or pre-peak hours, with no other discounts given. A users’
median peak fare and pre-peak fare for their September AM trips were used for the two alternatives. The sign of the coefficient should be negative, reflecting that as the savings of traveling in the pre-peak increases (i.e. the fare difference becomes more negative), the utility of shifting increases.

- **Required Displacement Time:** This variable is a measure of the inconvenience of starting a trip earlier. Users who are already traveling closer to the pre-peak hour were found to be more likely to have responded to the promotion in Chapter 5. For the no-shift option, this variable’s value is zero since users can continue to travel as they did before. For the shift option, it was calculated by taking the difference (in minutes) between a user’s median travel time in August 2014 and 8:15am.

**User and Trip Characteristics**

- **Trip Duration:** The median journey time on each OD in the AM period was extracted from the full set of September 2014 Octopus records. The expected travel times for each individual’s AM trips were reconstructed so that this variable reflects the duration a user would expect for their trips. Because duration was found to have different effects depending on whether the trip was of moderate length or long, a piecewise linear specification was used:

  \[
  \text{Duration1} = \begin{cases} 
  \text{Duration}, & \text{if Duration} < 25\text{min.} \\
  25, & \text{if Duration} \geq 25\text{min.}
  \end{cases} 
  \]  
  \( (6.1) \)

  \[
  \text{Duration2} = \begin{cases} 
  0, & \text{if Duration} < 25\text{min.} \\
  \text{Duration-25}, & \text{if Duration} \geq 25\text{min.}
  \end{cases} 
  \]  
  \( (6.2) \)

The coefficient of the first term is expected to be positive, while the second should be negative, following the comparison of distributions (in Chapter 5.3). 25 minutes was selected by comparing each groups’ distribution of journey times. Other boundaries, from 15 to 35 minutes, were found to produce less significant model parameters. This variable was used as a user characteristic to describe the nature of the trips an individual takes rather than the potential travel times saving from traveling in one period or another. Peak and pre-peak journey times tend to be similar with differences due primarily to longer headways in the pre-peak rather than operational or crowding delays in the peak.

- **Exit Time Variability:** Users who show more variability in when they make their first trip each morning may have more flexibility, making it easier to shift to the pre-peak hour. This variable was calculated by taking the standard deviation of when an individual’s took their first trip each morning in August. Its coefficient is expected to be positive: more variability leading to a higher likelihood of shifting.

- **Days with Modal Discount Value:** Octopus data includes a field that records whether a user got any non-MTR discounts applied to their fare. There are two kinds of discounts, one from transferring from certain bus routes (worth HK$0.3-2.8, most are less than HK$1) and another from tapping an Octopus card at a “Fare Saver” reader (these are located in malls near MTR stations and provide a HK$2 discount). The majority of discounts seem to come from the Fare Saver discounts, and users who
make a point to use these terminals likely have a higher price sensitivity or higher likelihood of seeking discounts. The number of days a user received a discount in September was used for this variable, and it should have a positive coefficient to show the positive relationship between seeking discounts.

- **Transfers**: Intra-MTR transfers can impact someone’s trip in several ways. First, this trip characteristic may be a good proxy in-vehicle or station crowding; many of the most crowded links are around transfer stations, and transfer stations tend to have more crowded platforms. Someone who experiences more crowding may be more likely to want to travel earlier to improve their trips. On the other hand, it might also reflect the utility users get from a one seat ride. Having to transfer adds complexity and uncertainty to a trip, and users might not want to further complicate their journey by traveling at a different time. Finally, it could simply relate to the network’s physical structure and spatial coverage of the promotion. This variable was defined as the percent of a user’s MTR trips that had a transfer. Depending on which of the above impacts dominates, the sign could be positive or negative.

- **Exit Station Dummies**: Two exit station dummies were used to account for particular types of trips. If a user took a majority of trips (>50%) to one of these sets of stations, the corresponding dummy variable has a value of one, otherwise his value was zero.
  - Hung Hom: where many users transfer to buses to cross the harbor; should have a negative sign to reflect inconvenience of rescheduling multi-modal trip
  - CBD (Admiralty through North Point): location of many office jobs that attract commuters; expected to be positive based on prior findings about commuter trips

Other formulations of these variables were found to be less significant, as were other variables, like attempts to include crowding more explicitly. Only users who were not previously classified as "pass-dependent" (>2/3 of AM trips charged no fare) were included when estimating the model parameters.

**Results**

The R package **mlogit** (Croissant et al., 2012) was used to estimate the model. The results are shown in Table 6.3. The base choice is not shifting, so the intercept and all user characteristics are included in the utility for shifting. All variables have the expected sign and nearly all are significant at the p=0.05 level. Interestingly, one of the few that is not is fare. This could reflect that, once a fare differential exists, the actual magnitude of the savings is less important to customers than these other factors. The required exit time shift is negative and extremely significant. Users who travel farther into the peak are much less likely to have responded to the promotion.

Otherwise, the intercept is negative, reflecting users’ disinclination to change their behavior. Duration is not very significant in the low range, but as trips get longer, people are less likely to respond to the promotion. As discussed previously, there are several possible explanations for this. It may relate to the duration itself, and how users making long trips may not want to leave even earlier, but could also be a proxy for the socio-
economic and employment characteristics of users who live farther away from the city center. Users who already showed more variability in when they traveled were more likely to shift. This could mean that different incentives are needed to influence users with strict routines (e.g. TfL’s habit-led users, Section 2.2), as well as implying the importance of flexibility in getting people to shift out of the peak. Users who received other discounts more often were also more likely to shift, with very high significance. Since most users who received these discounts were using Fare Saver terminals rather than transferring, one explanation is that users who are already more price sensitive and discount seeking were more likely to also take advantage of this incentive. Finally, the two station dummies have the expected signs. This implies a multi-modal transfer penalty on shifting (at Hung Hom). The positive sign for CBD destinations, in conjunction with the duration variable and flexibility variable, suggests that higher income office workers, who live closer to Hong Kong’s urban core and have some flexibility in their work hours, are more likely to have changed their behavior.

Table 6.3: Model estimation results

|                          | Estimate | Std.Error | t-value | Pr(>|t|)   |
|--------------------------|----------|-----------|---------|------------|
| Intercept                | -1.630   | 0.166     | -9.833  | <2.2e-16   *** |
| Fare (HK$)               | -0.054   | 0.053     | -1.019  | 0.308      |
| Displacement Time (min)  | -0.089   | 0.003     | -26.565 | <2.2e-16   *** |
| Duration (<25min)        | 0.007    | 0.008     | 0.822   | 0.411      |
| Duration (>25min)        | -0.017   | 0.006     | -2.727  | 0.006 **   |
| Variability (min)        | 1.342    | 0.294     | 4.557   | 5.18e-06   *** |
| MDV (days received)      | 0.036    | 0.007     | 4.959   | 7.08e-07   *** |
| Transfers (% of AM trips)| 0.192    | 0.091     | 2.100   | 0.035 *    |

Exit Dummies (>50% of trips)

|               | Estimate | Std.Error | t-value | Pr(>|t|) |
|---------------|----------|-----------|---------|----------|
| Hung Hom      | -0.183   | 0.158     | -1.156  | 0.248    |
| CBD           | 0.192    | 0.088     | 2.173   | 0.030 *  |

L(β): -2777.9
L(c): -3268.7
Likelihood ratio test: chisq = 981.65 (p.value = <2.22e-16)

Figure 6-1 gives a sense of how fare savings and a user’s required displacement time impact their likelihood of shifting to the pre-peak. All other variables have been given values of a typical user. As the savings increase or the time decreases, users become more likely to shift. However, the discount has a much strong effect when the time is low; almost no users whose displacement times are over 25 minutes are expected to respond to the promotion.

While the overall fit of this model is not very high—the adjusted McFadden R² is 0.147—this is not uncommon in disaggregate models. One way the explanatory power could be improved is through the addition of socio-demographic data. People’s travel decisions,
Figure 6-1: Likelihood of shifting as a function of displacement time and fare savings

particularly in the AM peak, are highly influenced by factors like employment status and job type, family structure, and income. If this data does become available in the future, it would be interesting to incorporate it into the model and see what additional insight it brings to these trip attributes.

Elasticities and Values of Time

The coefficients of this model can be used to calculate further characteristics of the panel members. Fare elasticity, as well as other marginal effects, can be calculated from the estimated logit model. Because models can differentiate between the factors that affect demand, these elasticities also control for some of the effects unintentionally captured in the midpoint elasticities (time shifting, trip characteristics, etc.). This formulation of elasticity is a more accurate point elasticity that uses the instantaneous rate of change between fares (P) and demand (Q):

\[ E = \frac{dQ}{dP}/Q = \frac{P \; dQ}{Q \; dP} \]

Using a logit model, the disaggregate elasticity (for a particular individual n) of the change in the probability of choosing alternative i (\( P_n(i) \)) in regard to a change in attribute k (\( x_{nk} \)) is given by:

\[ E_{x_{nk}}^{P_n(i)} = (1 - P_n(i))x_{nk}\beta_k \]

The aggregate elasticity of demand for alternative i over all users can be calculated using a weighted average. Each individuals’ elasticity is weighted by the probability that he or she will choose that alternative.
In addition to elasticities, the logit model also provides estimates of how users trade off between attributes. Because the coefficients of the model convert each attribute to a comparable unit, the ratio of a pair of coefficients provides insight into how users value one compared to another. For example, the value of displacement time is given by the following formula:

\[ \text{VoT} = \frac{\beta_{\text{Fare}}}{\beta_{\text{DispTime}}} \]

Table 6.4 summarizes two calculated elasticities for the panel and the value of displacement time. These values are in line with expectations, though one caveat is necessary to mention. First, two of these values depend on the fare coefficient, but it has a p-value of only 0.22, which is not highly significant. Even still, the fare elasticity is in line with the overall (and Group 7) elasticity when comparisons are made with previous Fall months. The elasticity for time shifting is elastic (<-1) which is consistent with previous evaluation results; people were much more likely to shift when they traveled close to the end of the eligible period. The value of displacement time (i.e. required shift) is slightly higher but not out of line with values (e.g. $3.60/hr in Henn et al., 2011).

Table 6.4: Elasticities and attribute tradeoffs

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fare Elasticity</td>
<td>-0.34</td>
</tr>
<tr>
<td>Time Shift Elasticity</td>
<td>-1.38</td>
</tr>
<tr>
<td>Value of Displacement Time</td>
<td>HK$36.60/hr</td>
</tr>
<tr>
<td></td>
<td>US$4.80/hr</td>
</tr>
</tbody>
</table>

### 6.1.3 Other Early Bird Recommendations

In summary, the aggregate elasticity implies that MTR has set its fare differential at the appropriate level to see their desired change among eligible users. However, should they want to see this level of change among all users (reduce peak hour exits by 3% systemwide), the discount would need to be twice as high. Since there is quite a bit of variability among groups, MTR might need to consider other strategies, like those that are discussed in Section 6.2, to engage users who seem uninclined to travel earlier for a fare discount. The panel model also showed an elastic response to displacement time, which means that moving the promotion’s time period later could help better target the peak of the peak. However, since demand is higher as the peak progresses, this means MTR would also be rewarding more people who do not actually change their behavior. Further analysis is needed to evaluate the strict financial implications of the promotion.
Finally, if the spatial coverage area does not need to be one contiguous zone, the stations that make the most sense to add are Kowloon Bay and Kwun Tong. They see many morning exits and the links around them see the highest loading in the up direction (refer to Figures 4-3 and 4-4). However, they are surrounded by many stations which do not see high exit demand and which tend to peak earlier in the morning. The typical origin stations for users exiting at these two stations (Figure 4-5) also mean that few are traveling over the system’s actual critical links. Of the stations currently covered, the ones that might make sense to exclude are those in West Kowloon: Nam Cheong, Austin, Olympic, and Kowloon. These stations have relatively few exits and experienced smaller responses to the promotion (refer to Figures 4-4 and 5-5). Plus, the majority of trips on the critical segment (Olympic to Kowloon) continue on to Hong Kong Station. Mei Foo, upward Nam Cheong and Austin attracts more users and did have a larger response, so the tradeoff between having a contiguous zone, the station’s impact to load reductions of critical links, and the cost savings of excluding it should be further analyzed.

6.2 Potential Strategies for MTR

Figure 6-2 lists several new types of strategies MTR might consider once the Early Bird Discount Promotion ends in May 2015. They are organized into four categories: targeted information, pricing structure, pricing basis, and inter-institutional policies. The motivation for each in the context of MTR is discussed below, along with their potential drawbacks and the technologies or relationships that would need to be developed to bring them to fruition. The discussion here will focus largely on how the Early Bird Program could be adapted to or be supported by these different types of measures. The new TDM program could include policies from multiple categories and even abandon the Early Bird discount altogether. The approach described in the framework from Chapter
3 should be used to fully analyze and quantify the potential impacts of each alternative design, including the focus on different user groups.

### 6.2.1 Targeted Information

Though MTR ran a publicity campaign for the Early Bird Program, it consisted largely of mass marketing. However, it should consider using its available customer data to tailor messages for individual users, empowering them to make decisions that improve both their own experience and system conditions. Though shifting users away from the peak has system-wide benefits, most users care far more about their personal experience than abstract network conditions. Therefore, these messages should stress how someone’s trip would be improved in the pre-peak and convey information that relates directly the benefits important to that user. Several strategies MTR could employ are:

1. **Station Advertisements:** Station-level advertising campaigns can reflect when and to where the stations’ users tend to travel. Messages should highlight the station-specific periods with lower train crowding or lower likelihood of denied boarding (particularly at major transfer stations like Admiralty or Kowloon Tong). Stations where several routes to major destinations exist should recognize the less crowded options. The typical groups that frequent a station can also inform these messages. Stations with high use by tourists, the elderly, commuters, etc. could post the messages that best meet the needs and sensitivities of these groups.

2. **Journey Planner Upgrades:** The journey planner MTR provides on its website and mobile app can be used to reach certain customer groups. According to data (collected by Li, 2014), about 8% of customers use this tool when planning a trip. About one quarter of these customers changed their original travel plan based on its suggestions and an additional 27% had no original plan, relying completely on the planner. The current planner has no temporal dimension and just reports the average travel time and fares for each ticket type on a given OD pair. Letting people specify when they want to travel would let MTR more widely publicize the fare discount, and also include more time-specific journey time and crowding data. This would allow users to better assess the potential benefits of alternatives.

3. **MTR Club Enhancements:** Currently, users who register their Octopus Cards with the MTR Club receive occasional emails and can participate in surveys, events, and promotion through the MTR website. This program is a strong starting place for providing even more personalized information.

   - **Emails:** Since Fall 2014, MTR Club emails have been used for conveying messages about service additions, the opportunity to purchase MTR-themed products, or surveys about MTR shops\(^1\). Instead, emails should take advantage of MTR’s ability to link contact information to trip histories (through the registered card number). It is also a fairly low cost option for further promoting demand management policies and how they can benefit individuals.

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\(^1\)Examples are from MTR Club emails directed toward the author since Fall 2014.
Relevant user characteristics include travel patterns, but also more latent characteristics like price-, crowding-, or time-sensitivity. AFC reveals some of the travel dimensions through observed travel patterns, use of discounts, etc. As was discussed in Chapter 5 and the previous section, groups did respond differently to the Early Bird Discount and better conveying particular benefits to them may encourage higher shifting rates. User classification as in Chapter 4 can differentiate users based on general travel behavior, but other segmentations, like most used stations or socio-demographics (available for MTR Club members) are also relevant.

- **Travel Dashboard**: Fully individualized information can be provided through the MTR website’s MTR Club section. Since not all users are members of the MTR Club, this is a method of differentiation that provides a benefit only to those likely to respond, e.g. not tourists and occasional cross-border users. It is also less intrusive than emails because users must take the initiative to use it. One option is to add a trip history dashboard to the website. This section would let people see their recent MTR trips and need not be specifically for demand management. Self-tracking is becoming increasingly popular for health, personal finance, and even location and travel, which would be supported by this section.

  In the example shown in Figure 6-3, users can see their MTR trips from the previous week, a heatmap of their most used stations and a plot showing long term trends in travel. Depending on their usage, suggestions for better travel experiences are made. Here, the cost-savings associated with earlier travel, as well as expected lower crowding and route choice suggestions are provided. Following the suggestion from the literature reviewed in Chapter 2, the dashboard could even allow users to set travel goals to engaging goal-setting response. Such an addition would have to ensure customer privacy and security concerns are met. Rolling it out first as a pilot project can help MTR staff determine the types of information that are most useful to customers and beneficial to system conditions. It would be particularly interesting to study the behavior changes among users who do have access to this dashboard compared to those who do not.

### 6.2.2 Pricing Structures

The Early Bird Promotion has a single fare discount percentage over the whole pre-peak hour which is applied immediately at tap-out. By altering any of these characteristics, MTR may be able to induce more behavior change.

1. **Flat Discount**: By changing how users experience the discount, its salience may be increased. Salience—that users are aware of how much they are paying—can be influenced by pricing structure, presentation, or payment method. More complex
Good Evening, Anne!

Your Trips Last Week:

<table>
<thead>
<tr>
<th>Day</th>
<th>Origin</th>
<th>Destination</th>
<th>Cost</th>
<th>Tap In</th>
<th>Tap Out</th>
<th>Duration (min.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>Tsuen Wan</td>
<td>Wan Chai</td>
<td>$13.20</td>
<td>8:22</td>
<td>8:57</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>Wan Chai</td>
<td>Tsuen Wan</td>
<td>$13.20</td>
<td>18:02</td>
<td>18:39</td>
<td>37</td>
</tr>
<tr>
<td>Tu</td>
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<td>Wan Chai</td>
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<td>8:13</td>
<td>8:47</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Wan Chai</td>
<td>Tsuen Wan</td>
<td>$13.20</td>
<td>18:02</td>
<td>18:39</td>
<td>37</td>
</tr>
<tr>
<td>W</td>
<td>Tsuen Wan</td>
<td>Wan Chai</td>
<td>$13.20</td>
<td>8:16</td>
<td>8:52</td>
<td>36</td>
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<tr>
<td></td>
<td>Causeway Bay</td>
<td>Mong Kok</td>
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<td>18:12</td>
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<tr>
<td></td>
<td>Mong Kok</td>
<td>Tsuen Wan</td>
<td>$7.70</td>
<td>21:53</td>
<td>22:13</td>
<td>20</td>
</tr>
<tr>
<td>Th</td>
<td>Tsuen Wan</td>
<td>Wan Chai</td>
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<td>15:22</td>
<td>15:57</td>
<td>35</td>
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<tr>
<td>F</td>
<td>Tsuen Wan</td>
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<tr>
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<td>Total</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>5 Hrs and 20 Min</td>
</tr>
</tbody>
</table>

Travel in the Pre-Peak!

> If you had finished your morning trips before 8:15 you would have saved: $16.50 (13% of your travel costs!)
> Do you take the Tsuen Wan Line? Travel before 8:15 for 45% less crowding on trains or try transferring to the Tung Chung Line

Special Alerts for Your Preferred Trips

> Current incident at Mei Foo Station: Expect 10 minute delays
> Escalator maintenance at Wan Chai through May 21
> Rugby Sevens is almost here! Take the Citybus shuttle from Admiralty and expect high demand at there from March 28-30

Where do you travel?

How much do you travel?

Click HERE or use the menu on the left to change your preferences.

Figure 6-3: Mock-up of MTR Club portal with trip history dashboard
policies and automatic payment systems tend to reduce saliency, so users may not be fully conscious of discounts that depend on the base fare and which are only specified on the small screen of the fare gates.

One way to increase salience could be to simplify the discount further, making it HK$2 or HK$3 for all trips (about 25% of the average fare). Ultimately, MTR is most concerned with loads in particular parts of the network, so a user who takes a short trip just over an overcapacity link places a similar burden on the system as someone whose long trip goes over one congested link as well as less crowded ones. MTR could also consider extending this type of policy with zones, charging, for example HK$1-2 for each critical link a user is expected to travel over. It could also be combined with the OD or link-based discounts discussed in Section 6.2.3. One potential concern is that users who had been receiving a larger discount may feel unfairly targeted (especially since those taking longer, more expensive trips are more inconvenienced by having to travel even earlier and tend to have lower incomes).

2. **Fare Rebate:** Another option for changing salience is to give users a single, larger weekly credit that includes all the benefits they earned the previous week. This structure would be well-suited to be introduced with the targeted information discussed in above—customers could receive a weekly email informing them of their credit. By timing the email appropriately (e.g. Monday morning before the first trip of the day), MTR will remind users of the discount as they start the week and may be more open to new routines.

3. **Tapered Discounts:** The Early Bird evaluation and panel model showed that users who traveled closer to the pre-peak hour already were more likely to change their behavior. A tapered structure controls for this by offering a larger discount for periods farther from the peak. This gets both time-sensitive and cost-sensitive users to shift earlier. An example is shown in Figure 6-4, where a larger discount is given for exiting between 8:00-8:20 than from 7:20-8:00. One benefit is that the covered period can be closer to the peak of the peak and thus make people more willing to travel earlier, but the revenue losses per user shifted will be lower. The model in Section 6.1.2 showed users had an elastic response to time shifting, so even small changes in time period could get many more people to begin traveling earlier. However, the time periods still need to be set such that not too many people get a discount without actually changing their behavior. Tapered discounts would be easy to implement, since they are just an extension of the current policy.

4. **PM Discounts:** As Figure 6-4 also shows, MTR could direct a pricing strategy toward the PM peak. The addition of a new discounted period will almost certainly increase MTR’s costs, so financial considerations will be critical in determining what time period and discount to use. Several lessons from the morning period can inform the design of this strategy. The evening does have a longer period of elevated demand because more non-commuter type users are traveling. This means a policy like the Early Bird Promotion will give discounts to more users who make no changes to their behavior. Better targeting users may be one way to only reward behavior change, like the employer policies that will be discussed in Section 6.2.4.
Figure 6-4: Tapered discounts in the AM and PM peaks

post-peak policy is the example here because users have more flexibility after work; they can eat dinner or run errands before getting on the train. Also, though entry-based policies will be discussed below for the AM peak, such policies are actually better applied to the evening since entry demand is concentrated in congested parts of the network. MTR could even try linking AM and PM behavior. Someone could only become eligible for an incentive (or become eligible for a larger incentive) if they travel in a peak shoulder in the morning and evening.

5. **Lotteries:** There are two advantages to using lotteries as an incentive instead of just fare-based incentives. First, people tend to overweight small probabilities (see Prospect Theory in Section 2.2). Many users will think they have a larger chance of winning than they really do, and thus be more likely to participate to potentially win a reward. However, by requiring some sort of extra step to participate in lottery scheme, MTR can also use it as a method for self-selection. Only users who are more price-sensitive or interested in participation will enter, meaning fewer people who do not change their behavior are rewarded.

MTR did experiment with lotteries at a small scale in the past, using the MTR Club. However, few people registered to participate, so the impacts were limited. Therefore, though there should be some barrier for entry (both for the self-selection reasons discussed above and to have some way to contact winners), it needs to lower. One option is to automatically enroll MTR Club members and another is to make the rewards greater, spurring higher participation rates. This could also incentivize more users to join the MTR Club, giving staff more data about their users. Additional steps to become eligible for the discount could include having to tap your card at an additional origin, transfer, or destination station location, or
making users log on to the MTR Club website or app to re-enter regularly.

Assuming the same revenue loss for a lottery program as the Early Bird Promotion, MTR could also offer much higher rewards to more customers than their previous iterations of lotteries. As an example, MTR might assume that if they ran an effective lottery, they would only have to reward half as many people. This assumption stems from the types of users who will participate in the lottery. The first group is users who actually do shift because the lottery makes them willing to change their behavior. The second are users who were already traveling in the pre-peak, but chose to take the extra steps to get this discount. Users who travel in the pre-peak but are not sensitive to the lottery do not have to be rewarded as they were with the Early Bird discount. Keeping the same total payout, rather than offering approximately HK$2 to 135,000 users per day, MTR could reward 675 users per day with HK$400 (giving those who enter a 1% chance of winning).

6.2.3 Pricing Basis

For the morning commute, an exit station and time based pricing structure is effective because demand is concentrated both spatially and temporally toward Hong Kong’s business districts. Users throughout the city begin traveling at whatever time will allow them to exit by the start of work, usually 9:00. However, it also introduces uncertainty into the trip decision-making process. Users may think they will exit in time to receive a discount, but could be denied boarding or face disruption delays while riding (hence the current buffer time MTR includes on either end of the time period). An exit station system also does not directly target train congestion problems. Several alternatives MTR could use are:

1. **Entry or OD Based Incentives**: Entry time-based pricing alleviates some of the uncertainty with exiting on time. Through MTR’s own journey time estimates and AFC records, the typical travel time on every OD is known. Each station could be associated with a particular entry time, so that if someone taps-in during the appropriate period AND exits at an eligible station, he or she will receive a discount. Theoretically each OD pair could have its own time period, but the complexity of such a system would be too high. This concept could also be extended to particular links. The peak period on each link is known, as is the time it takes for anyone to reach a particular link from their origin and then continue on to their destination. Though route choice will come into play for some OD pairs, it would be possible to set OD-specific entry-based time periods such that users are incentivized to travel early (or late) enough to avoid key links during their peaks.

Figure 6-5 shows one example of how an entry-based scheme could be designed with three zones. Users who travel within the most central part of Hong Kong—which are the eligible exit stations in this scenario—must enter between 7:15-8:00. With intra-zonal travel times between 5 and 30 minutes, most users will still exit between 7:30 and 8:15. The journey times from the next ring of stations to the eligible ones are largely between 10 to 35 minutes; it is covered for entries between 7:00
and 7:45. Finally, the Islands and New Territories, where most trips to the eligible stations take 25-55 minutes, are covered from 6:45-7:30. If certain links were more critical than others, this scheme could be adapted for travel times to specific links.

2. **Route Based Incentives:** Another type of policy could engage route choice directly. This is done in London, where users who avoid crowded Zone 1 can tap their cards at a transfer station to receive a discount, and was previously attempted at MTR. Not all MTR lines are crowded to the same degree and in some cases, it may not be unreasonable for users to take the less crowded option. A primary example in the current network is routes that go from northern/western Hong Kong to Hong

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**Figure 6-5:** A possible scheme for entry station discounts
Kong Island. Users who start on the West Rail Line in the New Territories or the end of the Tsuen Wan line can take either the Tsuen Wan line (directly or transferring at Mei Foo—see Figure 6-6), or the Tung Chung Line (transferring at Lai King or Nam Cheong). According to route choice data (Li, 2014), more users take the Tsuen Wan line option, choosing to avoid the long transfer between Hong Kong and Central Stations instead of higher crowding on the Tsuen Wan Line.

Offering a discount to users who chose less crowded routes (or easing transfers) can balance demand across the network spatially. A major hurdle for such a scheme is the technology that enables recording route choice in an unobtrusive way. When MTR offered discounts for using the Tsing Kwan O Line in the 1990’s (see Chapter 2), platform crowding caused by users queuing to swipe cards became an issue. With current smart cards, users could more quickly tap their card on transfer station platforms. Another option would be to explore new advances in transit fare technology, like the use of NFC (near field communication) enabled smartphones to replace smart cards, which are currently being piloted by the Octopus Corporation. With an app that allowed customers to record their location, users could just be prompted with a notification some time after they tap in, or even allow the app to do it automatically. As MTR expands its network and has more ODs with viable route choices, such a scheme could become even more worthwhile.
6.2.4 Inter-Institutional Policies

Finally, a number of conclusions in the evaluation pointed toward the impacts of constraints on departure times, including work start times and transfers with non-MTR transit service. Possible solutions to address these constraints are listed below:

1. **Employer Programs**: Having to be at work at a specific time is a major constraint on when people travel in the morning. Many stores and services are not yet open, so users who do want to travel before the AM peak have limited options besides going into work early. However, office culture may prevent these employees from also leaving earlier, so they just end up working more.

   One approach to take is to encourage companies to develop their own TDM policies, as the LTA in Singapore does. This could involve helping companies understand the impacts their employees have on travel congestion and developing solutions that meet their particular needs, whether allowing employees to time shift their hours or telecommute. In Singapore, companies can win grants to help them hire transportation consultants or implement their own promotions, incentives, or policies. Ideally, these policies (the LTA’s suggestions include subsidizing morning activities, supporting bicycling, and getting management buy-in for flexible hours) can better encourage the adoption of new habits, targeting people’s beliefs, attitudes, and values more than a temporary fare decrease. However, they do require high financial investments by the agency that provides funding, particularly if many companies are to be involved. Therefore, as in Singapore, it could be beneficial to partner with the Hong Kong government for financial support and to assert the legitimacy of both the congestion problem and this solution.

   MTR could also consider engaging employers with policies similar to the Early Bird Discount, but with the benefit only given to enrolled users. For example, MTR could offer a special pass to employees of participating companies that give a discount for either pre- or post-peak travel in exchange for the company setting flexible work hours. In theory, the discount could even be customized to match with the employers’ policies; pre- or post-peak, AM or PM, all stations or just those nearest the office. Since most of the travelers in the morning and most of the shifters are commuters, this would be a way to better target users who actually changed their behavior without giving discounts to people who would travel off-peak anyway. It would be particularly useful for implementing PM peak discounts, since there are many other types of users who travel in the evening. Such a program would likely have institutional challenges in terms of working with employers and would have to consider equity when recruiting employers to participate. There may also be technical considerations, though these passes could be similar to MTR’s current travel passes, just with fewer eligible stations and a temporal component.

2. **Inter-Agency Programs**: The lower shifting rate of panel members traveling to Hung Hom, and Group 6’s major behavior change when the demonstrations began suggest that users who rely on buses in addition to heavy rail may have been less likely to respond to the Early Bird Program. Lack of bus data been makes it difficult
to understand the effectiveness of MTR’s second demand management strategy (offering pass-holders free trips on certain KMB bus routes). Nevertheless, MTR could consider ways of easing these transfers or engaging other agencies further so multi-modal travelers are willing to travel outside of the peak. For example, rather than only allowing pass-holders these inter-modal discounts, fare policies could be more closely linked so that both agencies offered similar discounts or instituted a pre-peak transfer benefit. Obviously it could be institutionally difficult to find a policy that all parties think will benefit their service without being a financial hardship.

6.3 Final Remarks

A number of possible demand management policies and tools for their design have been presented in this chapter. These strategies, as well as some of their key advantages and disadvantages are summarized in Figure 6-7. As MTR moves forward with their program, a final dimension to consider is how its policies can be integrated with the system’s expansions. Spatial and temporal considerations need to be made if policies like the Early Bird Discount continue to be implemented:

- How will system demand patterns be affected by new lines and stations?
- Will the time period need to change?
- Will new stations be covered?

Dealing with increasing demand will be a concern in the next several years as MTR expands it catchment area, but as lines that introduce more route choice are completed, it

<table>
<thead>
<tr>
<th>Examples</th>
<th>Advantages</th>
<th>Disadvantages</th>
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<tbody>
<tr>
<td><strong>Targeted Information</strong></td>
<td>Station Marketing Journey Planner MTR Club Emails + Dashboard</td>
<td>Provide info that best suits needs Differentiate between time/price/crowding sensitivity</td>
</tr>
<tr>
<td><strong>Pricing Structure</strong></td>
<td>Flat Discount Fare Rebate Tapered Discounts PM Coverage Lottery</td>
<td>Price saliency More targeted congestion relief Differentiate between time/price/crowding sensitivity</td>
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<tr>
<td><strong>Pricing Basis</strong></td>
<td>Entry/OD Based Route Based</td>
<td>Reduce delay impacts on getting benefit More targeted congestion relief</td>
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<tr>
<td><strong>Inter-Institutional</strong></td>
<td>Employer Policies Inter-Modal</td>
<td>Reduce constraints on travel time Simplify multi-modal trips</td>
</tr>
</tbody>
</table>

Figure 6-7: A summary of suggested designs with advantages and disadvantages
will have to contend with more complex and multi-directional passenger flows. Different policies may be appropriate in these two stages. Developing strong policies now can help users appreciate the benefits of demand management and lead to changes in long-term attitudes and values rather than just short-term adjustments.
This final chapter reviews and summarizes the work presented thus far. One of the key contributions of this thesis is a framework for how transit agencies can use demand management. The steps this framework proposes are reviewed in Section 7.1. Specific findings and recommendations derived from the MTR case are described in Section 7.2. While no two agencies face exactly the same problems, this analysis and the issues it raised can help guide other agencies as they prepare their own policies. Finally, Section 7.3 describes several ways to continue or expand this work in future research.

7.1 Research Summary

Because TDM was developed for car traffic, best practices for using these techniques in the transit context are still emerging. Therefore, one of the primary goals of this thesis was to develop a methodology that agencies can use to guide their demand management activities. Through a review of academic literature and previous real-world experiences, a four part framework was developed and presented in Chapter 3. The steps suggested were:

1. **Motivation**: The specific context and conditions that a transit agency faces must influence how they approach TDM—what works in one city may not be appropriate for another. Policymakers should consider three areas as they set particular goals: current system conditions, involved stakeholders, and time frame. By quantifying the interplay between fixed service levels and the characteristics of their users, agencies can get a better sense of spatial and temporal congestion patterns. The feasibility of particular policies is strongly influenced by whether the TDM program will be agency-led or will also involve other government or community groups. Finally, appropriate policies will depend on whether TDM is being used for a short-term influx of demand, as a medium-term measure to improve conditions until capacity increases are complete, or to shape long-term demand patterns.

2. **Design**: The primary design aspect to determine is the type of measure, which itself can be framed in several dimensions. Depending on their policy goals, decision-makers may choose push or pull, hard or soft, or market or regulatory measures.
A final dimension to consider is which stakeholders the policy engages: the customer directly, their employers (or schools, etc.), or the region as a whole. Other aspects to recognize are which users the policy is targeting, the magnitude to which it is implemented, its temporal and spatial coverage, and its treatment of different modes. Once the policy itself is designed, its feasibility should be ensured. Developing a strong marketing and publicity program for the new policy can also help it be effective at causing behavior change.

3. **Evaluation**: Important factors in policy evaluation include effectiveness, efficiency, and acceptance. A number of metrics can support the evaluation of each of these. System metrics quantify changes to passenger flows. Agency impacts can be used to understand how the policy affects costs, revenues, and resource utilization. Customers may also experience changes to comfort, reliability, and travel times, as well as to their attitudes toward transit service. Finally, there may be broader economic, environmental, or equity impacts. Regular monitoring will inform how these impacts change over time and if adjustments are needed to the TDM program.

4. **Redesign**: At some point, TDM policies will have to be reconsidered, either to keep up with changing system conditions or because they did not have the desired results. The results of the preliminary evaluation and subsequent monitoring provide additional data for the design process. Decision-makers can consider policies with a user group focus, since these more heterogeneous policy responses may not be known in the initial design process. Impacts can be forecasted for key evaluation metrics based on responses to the initial program. Preferred policies can be refined using the design framework, implemented, and re-evaluated.

A final aspect included in the framework was how a more data-driven approach can be used to support these steps. The proliferation of automatic fare collection systems is particularly advantageous for demand management applications because they allow for such detailed temporal and spatial resolution. In addition, when transactions are associated to a user ID, travel patterns of individual users can be studied and tracked to understand how use evolves over time. Though this thesis focused on how AFC data can be used for evaluating demand management policies, some impacts (like acceptance levels and the impact of socio-demographic characteristics) are better captured through surveys. A key method for using either of these data sources is a before and after analysis, which compare conditions before the TDM program begins with those after. This data can also be used in models to further quantify user response and forecast the effects of future policies and in cost-benefit analysis to determine whether the program is efficient.

### 7.2 Summary of Findings and Recommendations

Findings from the case of the MTR Early Bird Discount Program are described in the following sections. Associated recommendations, both MTR-specific and more general, are highlighted.
7.2.1 System Demand Patterns

Chapter 4 examined MTR’s demand patterns at the system-wide level, but also from link, station, and OD perspectives. Spatial and temporal characteristics were considered in tandem since they do not always align; peak 15 minute periods vary across the network. Since so much traffic is directed toward the CBD, more central links and station entries tend to peak later, 8:45-9:00, compared to areas farther from the city center (e.g. around 8:00 on the Ma On Shan Line). Stations exits tend to peak either at 7:45-8:00 or 8:45-9:00, depending on the types of trips directed there. Such patterns are less strong on links and at stations in the evening, when commuters are less dominant. The OD matrix for trips taken during the morning commute period identified the most common pairs, as well as the areas that have high levels of intra-district demand.

Understanding these demand patterns was particularly useful in Chapter 6 to generate new strategies for MTR. An interactive tool for creating visualizations like those presented in Chapter 4 would help facilitate future analyses of demand. It would support detailed analysis of changes in demand patterns that might get lost with the data just in tabular form. With a database of AFC records, MTR could automate graphs like those shown in Chapter 4, make it easier to transition between different times of day and durations (e.g. yesterday, last week, this month last year).

7.2.2 Customer Groups

A clustering analysis found seven customer groups among MTR’s passengers each with distinct frequency, spatial, and temporal travel patterns:

1. Short Term Users
2. Long Gap Users
3. Repeat Cross-Border Users
4. Cross-Border Commuters
5. Intermittent Hong Kong Users
6. Casual Hong Kong Users
7. Hong Kong Commuters

These different groups were used for evaluating the promotion (Section 7.2.4). Identification of different user groups and their specific needs will help the agency provide better customer information, select more relevant advertising and shops in stations, or assist with long term planning. Particular areas for extending this work are described in Section 7.3.

7.2.3 System-wide Impacts

Reviewing the aggregate impacts of the promotion shows that about 3.5% of eligible peak trips shifted to the pre-peak hour, representing about 2.5% of all demand in the AM commuting period (7:00-9:30). Changes were particularly evident at either end of the pre-peak
hour since many users tried to shift their behavior as little as possible from the early morning or peak hour. Minimal changes were seen among trips to non-eligible stations or by cards with non-eligible fare types. Stations in the CBD area of Hong Kong generally saw particularly high response rates, and link-level passenger flows in the downtown also saw higher reductions in the peak hour. However, all of these comparisons were made using proportional values to control for seasonal and annual ridership levels. Absolute numbers show that the promotion did slow peak hour growth but whether it actually reversed it is questionable.

The own-price fare elasticity with respect to demand found for the population in Chapter 6 ranged from about -0.33 (for comparisons to previous fall month) to -0.43 (for comparisons to summer months), while the cross elasticity with the peak hour was about 0.15 in all cases. Elasticities are useful for refining the current strategy or the designs of future ones. In particular, though the relative decrease among eligible users was in line with their goals, only about 80% of users traveling to the 29 incentivized stations and 44% of trips among all users and all stations between 7:00 and 9:30 were eligible. A slightly higher discount is necessary if the scope is kept to the eligible stations, but to reach this level of decrease throughout the network, a discount of over 40% would be necessary.

### 7.2.4 Group-Level Effects

Each of the groups derived in Chapter 4 was explored in more detail in Chapter 5 to understand how they contributed to AM congestion and responded to the promotion. The majority of eligible trips were taken by the commuter group (80%), while tourist-like Groups 1-3 took only about 2%. While Group 3 appeared to have a high response to the fare discount, the small number of trips taken by the group makes these results unreliable. Given that it may be more difficult for MTR to inform tourists of demand management policies, it will be more important for them to focus their policies on Hong Kong residents. However, these groups contribute more to the PM peak and should be further analyzed if the promotion is extended.

Groups 5 and 7 are more promising. Group 5, the intermittent users, had a relatively high response rate and since they tend to use the system less regularly, may have more flexibility when they travel. Group 7, the commuters, benefit from the regular fare discount to their frequent trips. MTR may see these groups continue to respond if they change the parameters of the current promotion, but could also consider other policies, like those described in Section 7.2.6. Groups 4 and 6, which showed essentially no response to the early bird promotion could also perhaps be targeted through these other strategies.

The elasticities calculated for each group in Chapter 6 follow these results. Group 7 had an elasticity that was nearly the same as the population, and Group 5’s was slightly lower in magnitude. Group 3’s was quite high, though based on very few trips. Groups 1, 4, and 6 showed very small elasticities or ones that were highly dependent on the season. MTR can use these elasticities to focus on the response rate of a particular group. However,
expanding the choice model introduced in Chapter 6 to include less frequent users may be a more robust method for forecasting their responses.

### 7.2.5 Panel Response

The customer panel followed a sample of high-frequency users from the months before the promotion began to those after. Change point analysis was used to determine if and when a user’s typical exit time changed. Those whose behavior changes could be associated to the promotion were identified as "shifters" and their characteristics compared to the rest of the panel. About 4% of the panel were classified as shifters, which is in line with the aggregate and Group 7 results. They were found to be more likely to take two morning trips, have higher variability in their exit times, and be more likely to take mid-length trips, particularly from Kowloon to Hong Kong Island.

These relationships were further quantified using a discrete choice model. The fare elasticity of (relative) demand was -0.34, slightly lower than Group 7 and the whole population. However, users were found to be very sensitive to the displacement time required for shifting from the peak to the pre-peak. This highlights the importance of what period is eligible for a discount. Other variables found to be highly significant in explaining shifting behavior include the variability users show in when they travel and how discount-seeking they are outside of this promotion (measured through how often they seek other inter-modal or promotional discounts).

As discussed above, MTR could explore the modeling opportunities of this promotion with additional data. They might also consider running a regular customer panel that integrates AFC records with survey data. This panel would allow for a better longitudinal analysis of the promotion, but also allow MTR study other customer travel patterns and opinions.

### 7.2.6 Other Recommended Strategies

Several other strategies were proposed for MTR’s demand management efforts in Chapter 6. Their feasibility depends on the complexity their customers tolerate, partnership opportunities, as well as financial implications.

- **Customer Information**: Providing more individualized information will allow users make better travel decisions, ideally helping them to recognize the benefits of off-peak travel. Possible strategies include:
  - Station-specific marketing campaigns
  - Adding a temporal dimension to the online journey planner, allowing it to display time-specific fares and crowding data
  - User-specific marketing through the MTR club emails
  - Expanding the MTR Club’s web presence to include a trip history dashboard, with suggestions for off-peak travel, relevant alerts, and other personal travel data
• **Pricing Structure:** In addition to the possibility of incentives for the PM peak, MTR could also consider several other ways to revise its current discount structure:
  
  – The discount could be simplified to a single flat value so users have a better idea of how much they are saving.
  – Structuring the incentive more as rebate rather than a discount, providing a single, large payout once per week, may be appealing to users. It makes the benefits of early travel more obvious to users than a small regular discounts that could be easily overlooked.
  – A tapered discount (higher farther from the peak) would help better discriminate between time- and cost-sensitive users.
  – **Lotteries** would allow MTR to be more efficient with its payouts, incentivizing participation through the potential of a larger reward, but taking advantage of user self-selection by making users take an extra step for eligibility.

• **Pricing Basis:** Rather than providing a discount based only on exit station, the promotion could target entrance stations, OD pairs, or alternative routes. These options would better manage uncertainty with travel time, in-vehicle congestion, or the need to start a trip earlier, respectively. However, MTR’s current information technology may need to be upgraded to support these systems, perhaps through the integration of new smartphone and location services.

• **Inter-Institutional Policies:** This could include working with employers to implement flexible hour policies or developing employer passes. MTR might also consider cooperating with other transit operators to better integrate their fare policies, particularly the tease of transfers.

### 7.3 Future Work

There are a number of opportunities to continue or extend this research:

• **Other impacts.** An obvious area for additional work is to flesh out the evaluation, looking at dimensions other than effectiveness. With financial records and a better characterization of MTR’s operational and organizational structure, agency-level efficiency could be studied. Broader efficiency studies, including macroeconomic or environmental impacts, could also be carried out, though given the policy’s impacts, the findings of such an analysis will probably be limited. Socio-demographic data could support an equity analysis, but even a more detailed spatial analysis could allow for some understanding of the program’s equity implications. It seemed New Territory residents, who tend to have lower incomes, responded less than users who lived more centrally. If there is a systematic bias against their ability to receive the discount, it should be addressed.

• **Long term impacts of promotion.** In this thesis, analysis was mostly focused on September 2014 data because of the protests that began in October. With these having ended, further research could consider demand patterns after several months.
The panel would be particularly useful to understand what changes were due to the promotion and which were not, since MTR has also expanded its network in the past few months. Three new stations have opened since September 2014, but unless panel members’ home or work locations moved, they probably are relatively unaffected by these changes. The change point analysis could be continued to determine if (and when) users reverted to their previous behavior. Finally, if the program is not continued past its current end date in May 2014, it would be interesting to study any lingering impacts once the fare discount ends. Was it successful at changing people’s habits or will most people start traveling earlier again without this incentive?

**Survey integration.** One of the key shortcomings of the program evaluation presented here was the lack of socio-economic data and information which can help better understand users’ behavior. Transport for London, with its Travel Demand Survey asks participants to provide their Oyster Card number, providing a direct link between socio-economic characteristics, general travel patterns, and transit usage for users who consent. This provides a much richer data set for planning purposes. The analysis presented here would also benefit from incorporating a panel into future policy evaluations. MTR could perform an initial survey to understand users’ perceptions of the program, then follow their travel patterns (with Octopus data) and attitudes (with additional surveys) to understand how each evolves as the program progresses. They could also further the modeling efforts begun in Chapter 6 with these additional data sets to actually forecast expected impacts of their policies.

**Applications of innovative technologies.** Several of the strategies proposed in Chapter 6 would be challenging to implement with current Octopus card technology. One area for future work is to review technological advances and consider how they could be applied to the transit context. For example, they could work with the Octopus Corporation to expand and improve the program for NFC-enabled smartphones (letting people use their phone to enter and exit the system). Phone applications that provide information or support tasks based on typical travel patterns and recent transactions would be useful. One application is route-based pricing with users’ locations recorded through their phones rather than having to visit a fare terminal. Users could also receive route-specific information about delays on the line they currently use. Research would have to focus on what technologies are available, both for customer-facing interfaces and back-end support, and how these could be integrated with MTR’s current technology infrastructure.

**Further customer classification.** The customer groups presented in this thesis take a very general perspective of a user’s travel patterns, but for other applications different methods may be preferable. In particular, a hierarchical approach may be useful—starting with a general segmentation to determine short-term, occasional, and frequent users, then examining each with different foci. Questions that could be addressed include:

- Which short-term users seem to be international tourists, cross-border users, or Hong Kongers who only used the card once?
– How much regularity do occasional users show in their travel patterns?
– How can frequent travelers be grouped by typical station use and time traveled?

Chapter 4 listed several areas where customer classification can be beneficial, including long-term planning, commercial applications, and customer information. Operational applications, like short-term demand management in the case of incidents or station closures, could also benefit from analysis of when certain types of users patronize parts of the network.
### MTR Line and Station Codes

#### Table A.1: MTR Lines and Abbreviations

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<th>Line Abbreviation</th>
<th>Line</th>
<th>Color</th>
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Figure A-1: MTR map with station codes (from Fall 2014)


LegCo Panels on Transport and Finaial Affairs (1999). How public views collected in relation to fares are taken into account by the MTR corporation.


