CAUSAL ANALYSIS OF IMPACT OF EARLY-BIRD SCHEME IN HONG KONG USING TRAVELCARD DATA

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Introduction

The dearth of public transport capacities due to aberrant growth in ridership has become endemic for world's urban centres. Constrained by time and investment issues, transit operators have started resorting to demand management policies alongside traditional capacity expansion measures. These are aimed at utilizing the existing network capacities by spreading out peak-loadings, thus achieving a uniform diurnal ridership and avoiding off-peak underutilization. With similar objectives, Hong Kong Mass Transit Railway (MTR) launched its Early Bird Scheme on 1st September, 2014 offering 25% fare discount to trips culminating between 7.15a.m. to 8.15a.m. at twenty-nine designated stations.

The objective of this research is to study the causation for changes in trip-scheduling patterns of MTR users in response to this scheme. The previous research suggested a very small, though statistically significant aggregate-level impact on commuters (Graham et al., 2015). This research goes a step further by analysing the travel patterns on disaggregate i.e. origin-destination pair level and then mapping the identified impact with probable causalities.

Several travel surveys have been conducted in the past to understand the factors determining changes in commuters' travel behaviour in response to policies encouraging time-switching. Increasing peak and off-peak fare differentials have been found to substantially reduce train-overcrowding (Whelan & Johnson, 2004). Long-distance commuters paying higher fares and those commuters with higher income have shown greater time-switching tendencies as they might have less rigid work-schedules (Currie, 2010; Faber Maunsell, 2007). In this study, similar relationships have been established using travel patterns revealed in the smart-card dataset and aggregate-level population statistics.

The methodology used herein can be employed as an econometric evaluation tool in absence of travel survey data. It gives a fair assessment of equity of such transit demand management policies, which could save huge amount of resources put into travel surveys. The causal estimates established can be used by transit operators to identify and better target user-groups less respondent to such policies.

Methodology

The analysis uses difference-in-difference method, an evaluation tool often used for assessing transport policy impacts. This method can effectively control for both the errors due to confounding (when comparing control and treatment groups only) and biases due to general temporal trends and effects unrelated to treatment. These DID estimates have been further regressed with travel characteristics and aggregate-level socio-economics and demographics as explanators in generalised linear models to establish causal relationships.

In a simple DID analysis, observations on the variable of interest are made on the same unit in 'treatment' and 'control' groups for 'pre-treatment' and 'post-treatment' time periods. The average temporal growth between these groups are differenced out to get the average treatment effect. In this analysis, 'n' commuters, i = 1,2,…n, have been observed in two time periods, $T_i \in \{0,1\}$ with 0 indicating pre-treatment and 1 post-treatment period. With treatment defined in a binary form $D_i \in \{0,1\}$, the difference in average response that occurs in treatment group, D=1 relative to control group, D=0 is estimated.

$$\boldsymbol{\tau} = \mathrm{E}\left[\, Y_i(1) - Y_i(0)\right]$$

Where, $Y_i(1)$ and $Y_i(0)$ denote the response of interest for unit 'i' under treatment and control status respectively.

Critical to every DID analysis is the non-violation of parallel-trend assumption: in the absence of treatment, temporal responses of control and treatment group should be same. Furthermore, bias may occur due to certain fixed effects within groups when the same unit is repeatedly observed (William H., 2012).

To control these errors, the following DID model has been used (Graham et al., 2015):

$$Y_{i,1} - Y_{i,0} = \delta + \tau ID_i(1) + \beta Y_{i,0} + (\varepsilon_{i,1} - \varepsilon_{i,0})$$

where, β is a constant, δ captures the temporal variation and τ is the required DID estimate. ε_{it} is the random error term capturing the omitted variables. ID_i (1) is a dummy variable indicating the receipt of treatment i.e. for D_i=1, ID_i(1)=1; zero otherwise.

This requires $E[\varepsilon_{it}|Y_{i,0}]=0$ to be assumed for consistent estimates (Graham et al., 2015).

Results and Discussion

This analysis focuses on changes in mean arrival times of regular commuting trips due to the discount. The main objective behind the scheme was to reduce peak-hour loadings by encouraging MTR users to travel before the morning peak. Aggregate-level DID analysis suggests that there has been a very small although statistically significant reduction in mean arrival times. Disaggregate-level analysis on treated origin-destination pairs show that only 14% of treated pairs show significant changes in mean arrival times post-treatment. The shift is found to be more prominent in the vicinity of 8.15a.m. (end of discounting period). The scheme shows an even spatial coverage.

Travel costs, travel times and work-schedule flexibility have been found to be significant in shaping response, thus conforming to previous studies. Regular commuting trips involving harbour crossing and long distance trips, both costing higher have been found to be more sensitive. Higher income commuters have reported higher time shifts, as they might have more flexible work-schedule. Lastly, response has been higher amongst females, probably due to their lower pre-peak crowding level perception further incentivised by the discount.

As this analysis has been carried out for the second month after implementation of the scheme, medium-term growth effect (Passenger Focus, 2006) can be expected with travel patterns changing further over time. Also, with availability of diurnal crowding level information for the network and discrete level socio-economics and demographics, the reliability of these results can be enhanced.

References

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