WORKING PAPER

ITLS-WP-16-16

Electronic ticketing systems as a mechanism for travel behaviour change? Evidence from Sydney's Opal Card

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August 2016

ISSN 1832-570X

INSTITUTE of TRANSPORT and LOGISTICS STUDIES
The Australian Key Centre in
Transport and Logistics Management

The University of Sydney
Established under the Australian Research Council's Key Centre Program.

NUMBER: Working Paper ITLS-WP-16-16

TITLE: **Electronic ticketing systems as a mechanism for travel behaviour change? Evidence from Sydney's Opal Card**

ABSTRACT: Smartcard and other forms of electronic ticketing have become integral to modern public transport systems. While aggregate ridership figures have generally been positive, little is known about the drivers behind these changes because of a lack of travel information on individuals before and after implementation of such systems. This working paper presents analysis from a naturalistic travel behaviour study of inner-city Sydney residents that coincided with the phased introduction of the Opal smartcard system.

Using a differences-in-differences methodology, results indicate significant reductions in car use of around 10 minutes/day with commensurate increases in train use and incidental walking. This trend holds across income groups and is more pronounced for older residents. Results add further weight to the merits of simplifying ticket purchasing as part of a package of policy measures designed to increase public transport usage.

KEY WORDS: ***Smartcard ticketing; Public Transport; Travel Behaviour Change***

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DATE: August 2016

1. Introduction

Sydney's smart card ticketing system, the Opal card, was introduced in a phased approach from 2013 to late 2014, replacing Sydney's existing paper-based ticketing system as the primary ticketing system for the public transport system. The Opal card is similar in concept to those of other systems in use in public transport around the world including London's Oyster card and Hong Kong's Octopus cards but with some differences to the fare structure. In common with other smart card ticketing systems, the Opal card was in large part intended to improve the convenience of using public transport. This increased convenience was primarily achieved through removing the need to physically buy a paper ticket for every trip and by providing discounts for single fares compared to the equivalent paper tickets. However, although these objectives are frequently seen as motivations for introducing smart card ticketing systems, little research has been conducted to determine what effect they have on people's travel patterns and behaviour (as distinct from changes to aggregate patronage levels).

This paper uses data collected from residents of two inner-city areas of Sydney for one week in each of 2013 and 2014 to assess how the introduction of the Opal card influenced residents' use of both public transport itself, and other modes. Uniquely in this paper, the phased approach to the implementation of the Opal card system created the conditions for a natural experiment that coincided with an ongoing, but largely unrelated, study collecting data on residents' health and travel behaviour (Greaves et al., 2015). This allowed us to use variation in Opal card coverage as a source of exogenous variation in a differences-in-differences approach to identify the effect of interest.

After this brief introduction, the remainder of the paper is organised as follows. Section 2 describes Sydney's public transport ticketing system. Section 3 presents a literature review on smartcards ticketing systems as well as problems associated with measuring its effects. Section 4 describes the data and section 5 discusses the empirical strategy we adopt to identify the effect of Opal card on public transport behaviour. Section 6 and 7 presents results and discussion, respectively. Finally, section 8 concludes.

2. Sydney's public transport ticketing systems

2.1 Existing paper tickets and fare structure

Sydney's public transport system has used some form of automated and pre-paid ticketing system since the late 1980s (Byatt et al., 2007). The existing system in place when the initial phases of the Opal card were implemented was a system of paper tickets with a complex fare structure with hundreds of combinations of fares for each mode of public transport. This included single, return (peak and off-peak), ten-ride ("travel ten"), daily, weekly, monthly, quarterly and yearly tickets on a single mode of transport sold either between specific locations or for trips within zones. Also available were a selection of multi-modal tickets (known as "My Multi" tickets) that allowed for travel on multiple modes of transport within set zones. My Multi tickets were available for daily, weekly, monthly, quarterly and yearly durations. Sydney's single light rail line operated a completely separate fare structure and ticketing system although My Multi tickets have been accepted since June 2011.[1]

The longer duration tickets, travel ten and My Multi tickets were gradually phased out after the introduction of the Opal card although they were widely available at the time the data for this study were collected.

2.2 Overview of the Opal card

The initial work on a smart card ticketing system for Sydney's public transport system began in the mid-1990s with the intention of having an operational system by the 2000 Sydney Olympic Games. That system, which became known as the T-Card, was eventually abandoned without ever being fully rolled out and was replaced by the Opal card project (Mulley and Moutou, 2015).

2.2.1 Fare structure

The fare structure used for Opal is primarily based on the concept of single distance-based fares for trips on a single mode of transport. Pricing is calculated based on the distance from the origin to the final destination on the same mode but allowing for transferring between routes or lines within one hour, and a 30 percent discount for off-peak train travel. There is no off-peak discount for other modes, including buses. The discount for off-peak train travel meant that it became cheaper to take the train during off-peak periods than buses for some routes, a reversal of the relative pricing in place with the paper tickets. To replace the existing paper-based daily and weekly tickets, the Opal fare structure applies maximum daily and weekly fares of $15 and $60 respectively for all trips regardless of mode. A maximum cap of $2.50 applies for travel on Sunday.

One unique element of the Opal fare structure is that after eight "journeys" during a week[2], all remaining trips are free[3]. The mode-specific fares mean that in the Opal fare structure there is a

[1] The Sydney Monorail, operated by the same company as the Sydney Light Rail, was dismantled in June 2013 and never accepted My Multi tickets.

[2] The Opal week is a fixed week starting on Monday.

[3] From September 2016 this will change to a 50% discount instead of free travel.

distinction made between a "trip" (trips made on a single mode with one hour transfer times) and a "journey" (trips made on all modes with one hour transfer times). This means that people who commute to and from work by public transport every weekday can travel for free from Friday, or earlier in the week if they make additional trips. Both the daily caps and the free trips after eight journeys apply only to paid trips where the Opal card was used.

2.2.2 Roll-out and coverage

The Opal card was trialed on one of Sydney's ferry services in December 2012 before being introduced to the rest of Sydney's Ferries in mid-2013. The Opal card first became available on the train in the Central Business District's (CBD) City Circle line as well as the Eastern Suburbs line in June 2013 followed by a small section of the North Shore line in August 2013 (see Figure 1). By March 2014 the Opal card was available at all of Sydney's suburban railway stations. Although the Opal card was available on all ferries and at a small number of railway stations by August 2013 and the majority of railway stations by March 2014, the number of people using it remained very low with estimates of less than five percent of all trips taken using the Opal card by March 2014 (Saulwick, 2014).

The Opal card was rolled out to Sydney's buses in stages throughout 2014 with bus routes in the Inner West being among the last of the suburban bus routes to have the Opal card fully implemented. It was implemented on Sydney's light rail line in December 2014. By the end of 2015, the Opal Card was available on most public transport routes in the Sydney Greater Metropolitan Area, with the exception of some private ferry and coach services. The Opal card can also be used on some intercity trains within New South Wales (NSW).

3. Literature review

3.1 Smartcard ticketing systems

Although smart card technology has been around since the late 1960s, it was only in the late 1990s that it began to be used in public transport operations, with Korea's UPASS and Hong Kong's Octopus card in particular, leading the way. Since that time, smartcard systems have seen widespread adoption around the globe with hundreds of operational systems. Sydney has been somewhat of a laggard in adoption of the technology for reasons elaborated on in this paper. Most systems operate by users purchasing a smartcard, which can be used on any compatible public transport mode. The smartcard is typically prepaid and can be topped up automatically by linking to a credit/debit card or manually by paying online or in person at various outlets. In some cases, such as the Octopus card, the smartcard can also be used for a variety of other retail transactions.

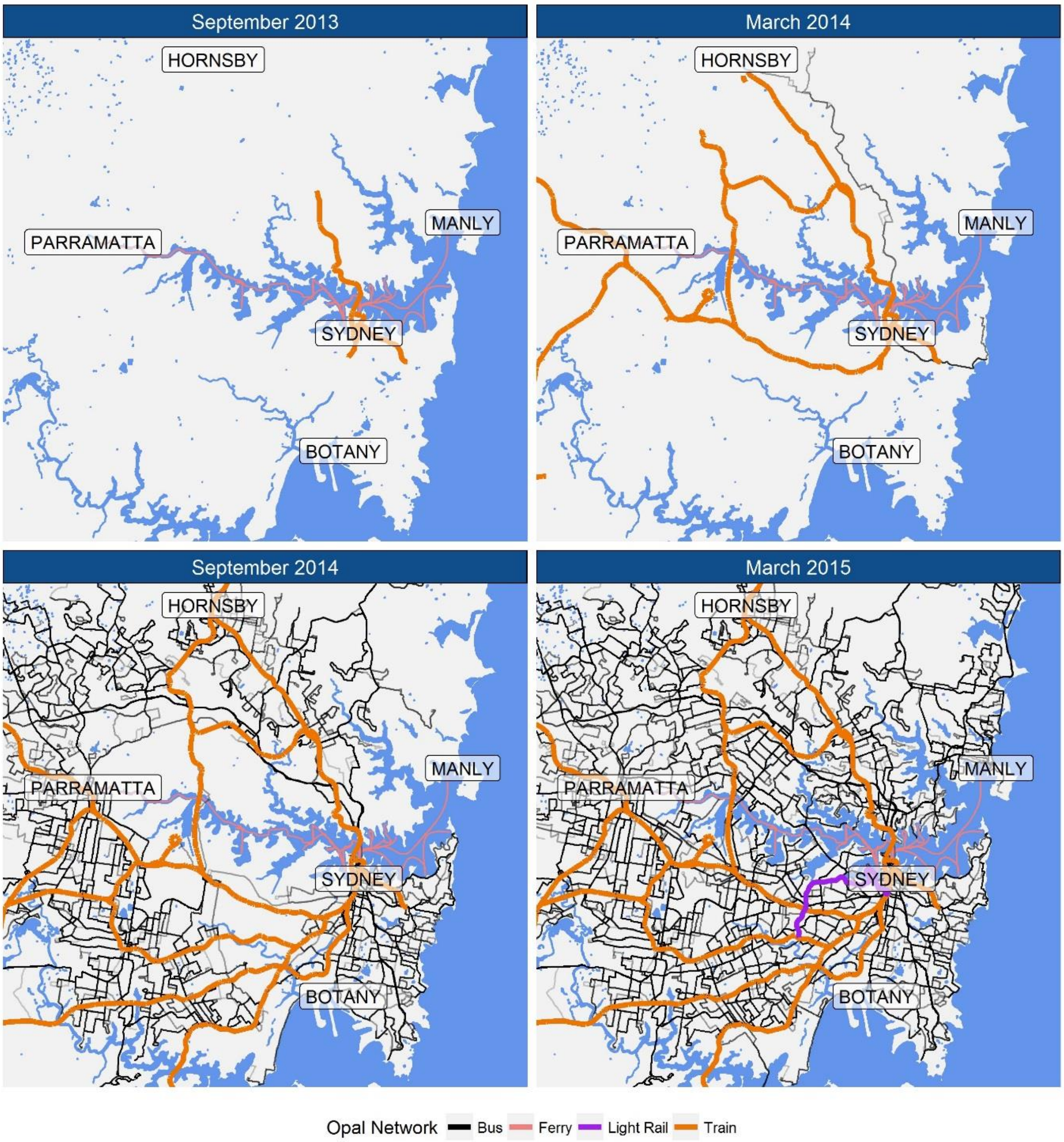

Figure 1: Opal Rollout

3.2 Benefits of smartcard systems

In a recent review of smartcard ticketing systems, Pelletier et al. 2011, summarise the purported benefits and challenges of public transport smartcard systems drawing on a wide range of implementation evidence. Smartcards clearly offer many potential benefits to both users and operators over paper ticketing, which is why their usage has grown world-wide. From the user perspective, they remove the need to physically buy a ticket and are much easier/quicker to use when boarding/alighting public transport. For instance, London's Oyster cards were reported to increase boarding rates in London by four times, while Queensland's GO card was reported to cut boarding times from 11 to 3 seconds (Tourism and Transport Forum, 2010). In turn, this has led to greater reported passenger satisfaction; for instance, following the introduction of the OPUS system in Montreal, overall satisfaction levels were reported at 90% with the technology (Société de transport de Montréal, 2009).

For operators, this expedition of boardings means less delay to services and a potential increase in service frequency. Additionally, although there is a large capital cost associated with installing card readers at stations and on vehicles, evidence suggests that over time, the maintenance costs are substantially less than paper-ticketing systems (Pelletier et al., 2011). These savings are likely greater when comparing the cost of manufacturing and distributing a one-off plastic smartcard versus disposable tickets. It is also suggested smartcard systems are better suited to deterring fare evaders because of the link with individual information (Tourism and Transport Forum, 2010). However, this would only appear to be the case where the smartcard is registered to a user – most systems also allow purchase on an ad-hoc basis.

An additional benefit is the wealth of detailed electronically-captured data on usage of public transport from a more substantial sample of the population than would typically be gathered from an on-board or household travel survey (Munizaga et al., 2014). In turn, these data can be utilised to map key performance indicators, patronage, travel patterns and network/service planning for operators.

3.3 Challenges of smartcard systems

Smartcard systems come with many challenges, particularly in the early stages of implementation where significant capital investment, software/hardware glitches, and buy-in of users are particular issues (Deakin and Kim, 2001). For instance, the much-lauded OPUS system in Montreal initially cost CDN$100 million and experienced many technical problems with readers (Pelletier et al., 2011). Hong Kong's Octopus system was found to have problems with its electronic top-up service, which had affected around 15,270 transactions dating back seven years, costing commuters more than HK$3.7 million (PriceWaterhouseCoopers, 2007). For users, while smartcard systems make travel easier once the card is purchased, they do require people to remember to swipe on and in most cases off to get the correct fare as well as keep their account in credit. In practice, people do forget, particularly to swipe off, which is one reason why the London Oyster scheme moved to flat rate fare for certain services so passengers only have to swipe on. Privacy is also an inevitable issue that arises, given the provision of detailed travel information that can be linked to the registered owner of a card.

3.4 Barriers to mode switching

Numerous studies have shown that certain mode characteristics are seen as barriers to switching modes, particularly from car to public transport. These include the perceived inconvenience of public transport, poor frequencies, the need to travel to multiple destinations (trip "chaining" our "tours"), the inability of public transport to accommodate adhoc decisions, etc. Arguably, several of these can be alleviated to some extent by the use of a smartcard ticketing system.

3.5 Impacts of smartcard systems on ridership and mode switching

While the general consensus appears to be that the benefits of smartcard systems outweigh the costs in comparison to paper ticketing options, the key question of interest here is whether this translates to increases in ridership. Evidence is largely positive, but is hampered by the fact that the smartcard implementation is typically accompanied by various endogenous (e.g., changes in fare levels and structures, service changes) and exogenous factors (e.g., changes in costs of other modes, economic changes) that have often accompanied introduction (Public Transport Executive, 2009). For instance, since the introduction of the Oyster card in London in 2003, bus patronage has risen by 56% and tube ridership by 21% (Thomas, 2013). However, over the same period, there have been major changes in transport operations, imposition of a congestion charge on cars, as well as significant socio-demographic changes that have all had an impact.

3.6 Quasi-experimental studies in travel

Quasi-experimental studies have become increasingly popular for studying the dynamics of change in a field/natural setting (Greaves et al., 2015). Such studies are based on the classical experimental design where participants are divided into treatment/placebo and control groups and observed before and after the treatment. In a field setting, there are clearly many more challenges around the actual measurement of the phenomena of interest as well as identification of a clear 'control' group, from which the impacts of the intervention can truly be assessed. The current study presented somewhat of a unique opportunity, because there was a natural treatment group where Opal was introduced and a natural control group, where it was not.

4. Data and sample

The data used for this paper were collected from 435 participants living in two areas of inner-city Sydney as part of a large study aimed at evaluating how changes in the transport system in Inner Sydney impact the general health, well-being and travel choices of residents. (Greaves et al., 2015). Although both areas are fairly similar to each other, as shown in Figure 2, only one had seen widespread implementation and adoption of the Opal card in 2014 when the second wave of data were collected. We refer to this area as the "intervention". The other area was among the last parts of Sydney to see the Opal card introduced on its buses and the light rail line and for this reason can be considered a "control". It must be acknowledged that participants in the "control" area were able to acquire an Opal card and use it on services in other areas (including all trains) by the second year of data collection. However, it must be emphasised that those living in the control area would need to pay twice if they changed from a non-Opal service (e.g., light rail) to an Opal service and would not get the benefit of free trips after eight journeys on trips made on non-Opal services. This, coupled with the widespread availability of multi-modal paper tickets at the time means it likely would have been more expensive for residents of the control area to use the Opal card than not use it. This is supported by estimates of the number of registered[4] Opal cards by area during the data collection phase that showed a considerably lower proportion of registered Opal cards sent to addresses in the control area relative to the intervention. As such, although it is not possible to say conclusively that the participants in the control were not using the Opal card, it is likely that few were using the Opal card during the time the second year of data were collected.

4.1 Sample and recruitment

The sample used for this analysis includes only participants who provided usable data for all seven days during both years of the study. Since the primary objective of the study on which the analysis in this paper is conducted was the effect of bicycle infrastructure, the sample was limited to people aged between 18 and 55 years old[5] and who did not have health problems that would prevent them from riding a bicycle.

The sample was recruited using a variety of methods to ensure a reasonable representation of the population including on key demographic variables (age, gender and location). These methods included market research panels, cold calling, leaflets and intercept events as well as specific recruitment methods targeting specific groups (students and cyclists in particular). The final sample was composed of a total of 435 participants across both the control and the intervention areas (Greaves et al., 2015). A summary of the demographic characteristics of the final sample is shown in Table 1.

[4] Opal cards can be ordered on the Opal website and sent to any address in Sydney. Towards the end of 2014 unregistered Opal cards became available from selected retailers.

[5] Pensioner Opal cards, available to those over 60 were not available at the time.

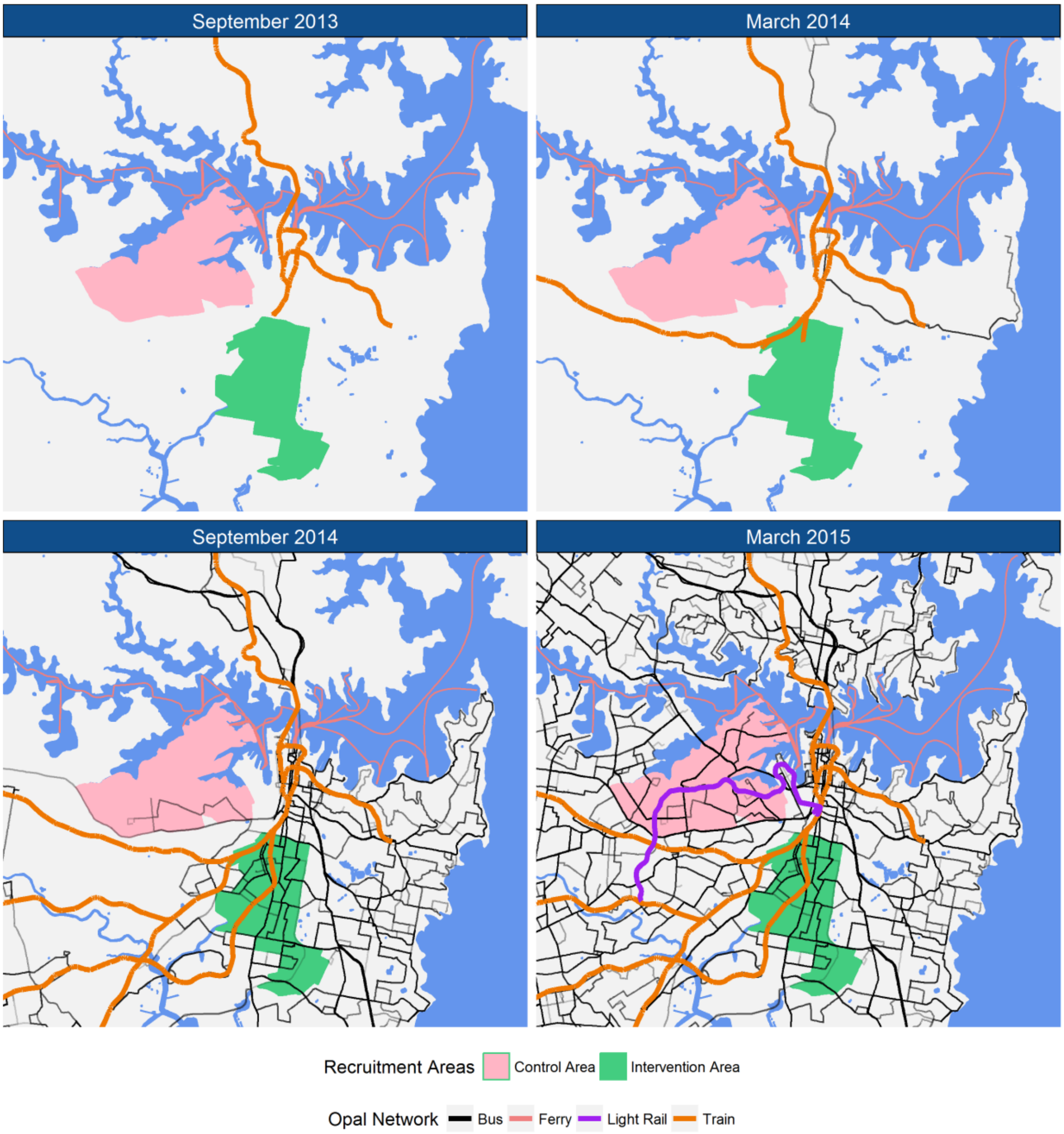

Figure 2: Recruitment areas and Opal network

4.2 Data

The data collected from participants included both data on health and their perception of their usual travel, and a seven day online travel diary that provided detailed data on where, when, why and how participants travelled to all activities during a one-week period[6]. Crucial for public transport, multi-modal trips were also recorded using the travel diary including access and egress modes and the time spent on each leg of the trip. For the purpose of this analysis, the total time and number of legs used for

[6] The reader is referred to Greaves et al. 2014 for full details of the data collection.

each combination of mode, purpose and day per participant are used. The mean number of trip legs by bus, car/motorcycle, train and walk as an access/egress mode per person per week are shown in Figure 3. Although there are differences between the control and intervention in terms of their original travel behaviour, the interest here is in the differences between the changes in the two groups. Given their relative proximity and similarities, notwithstanding the differences in the public transport modes available, it would be expected that the relative changes for both areas would be similar and yet walking as an access or egress mode increased in the intervention and went down (slightly) in the control.

Table 1: Summary of sample demographics

	Frequency	Proportion
Area		
Control	251	57.7%
Intervention	184	42.3%
Gender		
Female	277	61.1%
Male	176	38.9%
Age		
18-24	46	10.2%
25-34	93	20.5%
35-44	108	23.8%
45-55	206	45.5%
Income		
Less than $80k	130	33.3%
$80k - $140k	122	31.3%
More than $140k	138	35.4%
Not stated	45	

Note: Although the incomes appear high, the study area is populated by people with higher than average incomes and these categories split the sample into roughly equal thirds.

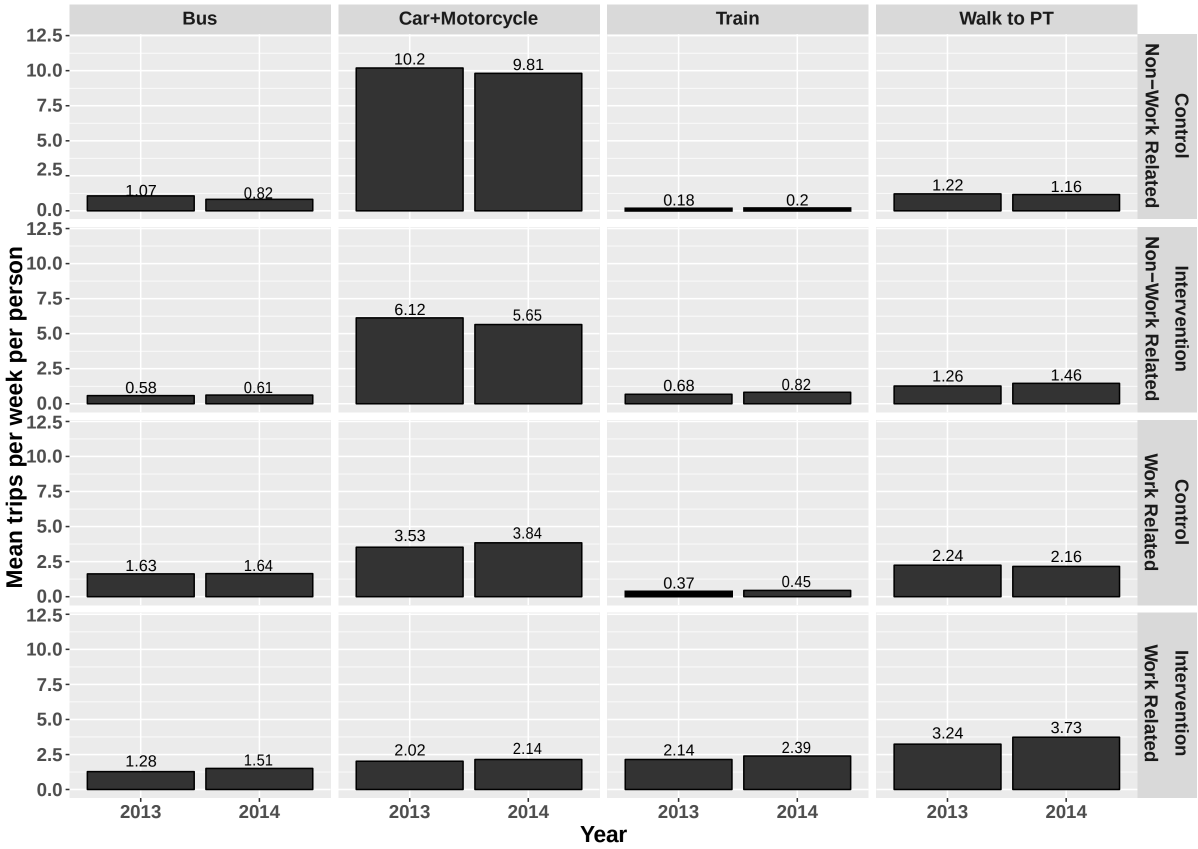

Figure 3: Mean number of legs per person per week by mode

5. Empirical Strategy

The focus of the analysis is to identify the average effect of the Opal Card on public transport use in inner-city Sydney. More specifically, we are interested in comparing outcomes related to car/motorcycle, bus, train, other public transport usage and active travel modes such as cycling and walking of individuals directly affected by the introduction of the Opal Card to what would have happened if the Opal card had not been introduced. Given outcomes for individuals in the intervention area (i.e. treatment group) in the absence of the Opal Card are never observed, this needs to be estimated. For this, consider the following simple difference-in-differences regression model:

$$y_{idtm} = \beta_{0m} + \beta_{1m} Opal_{idtm} + \delta_{im} + \delta_{dm} + \delta_{tm} + \epsilon_{idtm} \quad (1)$$

where y_{idtm} represents the outcome variable for individual i in day of week d during period (i.e. before or after the introduction of Opal) t for mode of transport m. $Opal_{idtm}$ is an indicator variable that takes a value equal to 1 if the individual i was in the area affected by the Opal Card in period t, and 0 otherwise. The parameters δ_{im}, δ_{dm} and δ_{tm} are, respectively, individual, day of week and year fixed effects, and ϵ_{idt} is an error term. The parameter of interest, β_{1m}, represents the effect of the introduction of the Opal Card on the outcome y for a given mode of transport.

The individual fixed effects (δ_{im}) included in the model control non-parametrically for unobservable individual-invariant characteristics, while the day of week fixed effects (δ_{dm}) and the year fixed effects (δ_{tm}) respectively control non-parametrically for day of week fixed differences in travelling behaviour and for yearly differences between outcome values (for example, fixed year differences within all individuals included in the sample). We interpret therefore the parameter of interest, β_{1m}, as the causal effect of the Opal Card on public transport use; i.e., this coefficient represents the difference between the average of the outcome of interest after the introduction of the Opal Card minus the average of this outcome before the introduction of the Opal Card for the intervention and control areas:

$$\Delta E(y_{idtm}|\delta_{im}, \delta_{dm}, \delta_{tm}, Opal)_{treated} - \Delta E(y_{idtm}|\delta_{im}, \delta_{dm}, \delta_{tm}, Opal)_{untreated} = \beta_{1m} \quad (2)$$

Our difference-in-differences strategy have until now used variation within time and unit of treatment to identify the parameter of interest, using individual level fixed effects in all regressions. However, one possible concern is that the impact of Opal on transport use may not be homogeneous across individuals, but rather may vary as a function of the characteristics of the individuals. For example, the impact of introducing Opal may matter more for more educated individuals or for older individuals. In this case, simple difference-in-difference estimates that we described so far may suffer from two additional sources of bias (Heckman et al., 1997). The first bias may arise when there are some individuals who belong to the treated Opal region, but no comparable individual in found on the untreated region with similar observable characteristics, to provide a reasonable comparison unit. The second bias may arise from different distributions of the vector of observable variables that affect transport usage within the two regions.

To account for that, we proceed in two ways. First, we estimate the models conditioning on important covariates, such as weekdays and weekends, work and non-work related trips, income, age and baseline self-reported main mode of transport used by the individual. Secondly, we match treated individuals (those with Opal) with untreated individuals (those in the control region) before treatment to balance a large set of observable attributes before implementing the differences-in-differences strategy. This is similar to the generalized difference-in-differences matching estimator proposed by Heckman et al. (1997) that extends conventional matching methods to longitudinal data and accounts not only for selection into treatment based on observable variables, given matching, but also accounts for selection into treatment on the basis of time-invariant unobservables, given individual level fixed effects.

To briefly present the matching method, let there be two potential outcome variables for individual *i*, along the lines of Rubin (1974), such that after treatment period we observe:

$$y_i = \begin{cases} y_{i1}, \text{ if } Opal_{idt} = 1 \\ y_{0i}, \text{ if } Opal_{idt} = 0 \end{cases} \quad (3)$$

where y_{1i} is the outcome under the presence of Opal and y0i is the outcome without Opal. The causal effect of the treatment ($Opal_{idt}$ = 1) relative to the control ($Opal_{idt}$ = 0) is defined as the difference between the corresponding potential outcomes β1i = y1i − y0i.

Here, we focus on the average treatment effect on the treated (ATT) which is defined as

$$\beta_{ATT} \quad = \quad E[\beta_{1i}|Opal = 1] = E[y_{1i} - y_{0i}|Opal = 1] \tag{4}$$

The problem in estimating equation (4) arises from the fact that comparisons of two outcomes for the same individual, when exposed and when not exposed to the treatment, is an unfeasible task, as the same individual can either be treated or not in the same time period (Imbens and Wooldridge, 2009). That is, we only observe one of the two potential outcomes given treatment status, $yi = y_{0i} + (y_{1i} - y_{0i})Opal_{idt}$.

The objective of the matching procedure, therefore, is to find different individuals (some treated and some not) such that after adjusting for differences in observed characteristics, or pretreatment variables, comparisons can be made (Angrist and Pishcke, 2009). In other words, the procedure will construct a control group such that observable characteristics are balanced in comparison to treated individuals (Oliveira et al., 2015). This is precisely the intuition behind the matching that, under the conditional independence (CIA) or unconfoundedness assumption (Rubin, 1974; Heckman and Robb Jr., 1985), imply that treatment assignment is independent of potential outcomes conditional on a set of covariates X or, as shown by Rosenbaum and Rubin (1983a,b), on the propensity score, p(X), defined as the conditional probability of being treated, $Prob(Opal = 1|X)$. In this case, the ATT is obtained by

$$\beta_{ATT} \quad = \quad E[\beta_{1i}|Opal = 1, p(X_i)] = E[y_{1i} - y_{0i}|Opal = 1, p(X_i)] \tag{5}$$

We will estimate the propensity score via a logit specification with the dependent variable being 1 for the treated region and 0 otherwise. Independent variables include several personal characteristics, such as age, income, education, and controls for transport usage before the introduction of the Opal card. After we obtain parameter estimates, we will use them to predict treatment probabilities or propensity scores for individual i belonging to the treated Opal region. Once propensity scores are available, we follow the approach carried out by Deng et al. (2012) and match each treated individual to a close untreated counterpart to obtain more reliable estimates of the effect of interest. Note that this implies significant reductions to sample size.

6. Results

The results of the estimated models are presented in the following tables. The estimates in these tables should be interpreted as the mean number of minutes per day that each person in the intervention group spent travelling (on a particular mode) relative to how the same person would have travelled had the Opal card not been introduced.

The estimates for work and non-work trips for weekdays and weekends are shown in Table 2. The results show that there was a statistically significant reduction in car use for both work and non-work travel on both weekdays and weekends. The reduction in car use was about 10 minutes per day per person during weekdays for work trips, and weekends for non-work trips. These reductions are offset by an increase of a similar magnitude to the total of both train and walking to public transport for work trips on weekdays. The effect of the Opal card on bus use were only significant for non-work weekend travel.

Table 2: Estimates for Work and non-Work related trips in the intervention area

Mode of Transp.	Weekdays		Weekends	
	Work	Non-work	Work	Non-work
Car/Motorcycle	-10.156	-5.962	-1.924	-9.646
	(1.997)***	(1.791)***	(0.976)**	(3.256)***
Bus	-1.691	0.906	-0.286	1.643
	(1.284)	(0.626)	(0.429)	(0.965)*
Train	6.306	2.315	0.141	2.980
	(1.303)***	(0.489)***	(0.240)	(0.763)***
Walk to Public Transp.	4.771	2.052	0.184	3.584
	(1.262)***	(0.642)***	(0.350)	(1.211)***
Other Public Transp.	-0.580	1.216	-0.189	0.775
	(0.421)	(0.387)***	(0.165)	(0.600)
Walk Only	3.295	-0.611	0.816	1.525
	(1.465)**	(1.335)	(0.567)	(2.250)
Bicycle	0.061	2.524	-0.131	5.086
	(0.917)	(0.748)***	(0.230)	(2.237)**
Other Transp.	-0.446	1.339	-0.203	1.591
	(0.441)	(0.442)***	(0.171)	(0.655)**
Year fixed effect	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes

Notes: Robust Standard errors in parentheses. ***, ** and * represent p<1%, p<5% and p<10% respectively.

Interpretation: Estimates represent mean number of minutes per day per person travelling on each mode relative to the same person if the Opal Card had not been introduced.

Table 3 presents results differentiated by income category. The reduction of car use and increase in train use and walk-access generally holds across the income groups with the largest effects on work-trips for those with medium incomes, and on non-work trips for those with high incomes. However, those with higher incomes were more likely to switch from car to train for work trips while those with medium incomes were also likely to switch to walking only (as well as trains).

Table 3: Estimates for work and non-Work related trips by income

Mode of Transp.	Work			Non-work		
	Low Income	Med. Income	High Income	Low. Income	Med. Income	High Income
Car/Motorcycle	-7.403	-9.776	-6.914	-3.578	-5.665	-8.464
	(2.809)***	(3.389)***	(2.131)***	(3.207)	(3.048)*	(2.925)***
Bus	-0.716	-2.771	-1.518	0.904	0.875	1.154
	(1.713)	(1.786)	(1.470)	(1.167)	(1.132)	(0.738)
Train	3.639	3.323	6.438	2.358	2.172	2.748
	(1.293)***	(1.544)**	(1.852)***	(0.971)**	(0.734)***	(0.626)***
Walk to Public Transp.	2.338	2.023	4.485	2.919	1.333	2.498
	(1.872)	(1.694)	(1.474)***	(1.434)**	(1.117)	(0.844)***
Other Public Transp.	-0.208	-0.665	-0.748	1.253	0.527	1.479
	(0.521)	(0.525)	(0.484)	(0.673)*	(0.643)	(0.530)***
Walk Only	0.978	5.814	1.354	-0.274	-0.596	1.432
	(2.152)	(2.409)**	(1.610)	(2.360)	(2.007)	(2.324)
Bicycle	-0.201	-1.023	1.371	2.894	2.482	4.925
	(0.793)	(1.287)	(1.263)	(1.401)**	(1.801)	(1.955)**
Other Transp.	-0.486	-0.304	-0.512	0.689	1.164	2.099
	(0.502)	(0.554)	(0.553)	(0.931)	(0.702)*	(0.559)***
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust Standard errors in parentheses. ***, ** and * represent p<1%, p<5% and p<10% respectively.

The results of the model estimating the effects of the Opal card based on age had more significant differences (Table 4). Because there are large similarities between adjoining age groups, the estimates shown here are only for those younger than 25 years old and 45-55 years old. The results show that those in the older age category had a statistically significant reduction in car use for both work and non-work trips. Participants aged younger than 25 years old made a significant switch between buses and trains for work trips but also an increase for train for non-work weekend trips. In contrast to age and income, the models for gender showed no significant differences in terms of the effect of the Opal card.

Table 4: Estimates for Work and non-Work related trips by Age

Mode of Transp.	Weekdays				Weekends			
	Work		Non-work		Work		Non-Work	
	18-24 yrs	45-55 yrs	18-24 yrs	45-55 yrs	18-24 yrs	45-55 yrs	18-24 yrs	45-55 yrs
Car/Motorcycle	-3.170	-10.279	-2.072	-7.587	-2.942	-2.340	3.969	-12.943
	(4.462)	(3.752)***	(3.503)	(3.518)**	(1.921)	(1.377)*	(7.953)	(5.060)**
Bus	-7.192	-1.986	-0.514	1.273	-4.715	0.167	0.223	-0.950
	(3.446)**	(1.752)	(1.905)	(1.159)	(2.609)*	(0.178)	(2.563)	(1.554)
Train	6.555	4.492	1.935	2.631	-0.230	0.329	5.165	1.674
	(2.759)**	(1.971)**	(1.241)	(0.841)***	(1.095)	(0.269)	(1.976)**	(1.282)
Walk to Public Transp.	2.963	4.980	1.010	3.173	-1.860	0.375	4.203	2.529
	(2.774)	(2.562)*	(1.678)	(1.153)***	(1.840)	(0.378)	(1.907)**	(2.477)
Other Public Transp.	-0.649	-0.656	1.715	1.078	-1.074	0.167	0.526	-0.347
	(0.894)	(0.677)	(0.945)*	(0.706)	(0.809)	(0.178)	(1.709)	(1.012)
Walk Only	1.012	6.393	2.164	0.522	3.647	-0.100	0.776	1.023
	(2.951)	(2.576)**	(3.273)	(2.343)	(3.317)	(0.251)	(3.341)	(4.058)
Bicycle	-1.143	1.962	2.569	2.331	-0.889	0.133	-0.493	4.620
	(1.430)	(1.876)	(1.244)**	(1.283)*	(0.862)	(0.326)	(2.512)	(3.821)
Other Transp.	-1.041	0.157	0.915	1.003	-0.759	0.067	-0.426	0.034
	(0.866)	(0.735)	(1.219)	(0.770)	(0.825)	(0.197)	(1.613)	(0.968)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust Standard errors in parentheses. ***, ** and * represent p<1%, p<5% and p<10% respectively.

A key issue is whether the changes in public transport use are occurring as a consequence of 'new' users taking advantage of public transport or if existing users are making greater use of the network. As expected, the results (shown in Table 5) for the effects of the Opal card by each participant's self-reported primary mode of transport to work/study before the Opal card differs both in magnitude and significance. The strongest effects were observed for individuals whose most common mode of travel to work was public transport before the intervention (column headings in Table 5). Specifically, less car and bus use and more train use was observed after the intervention relative to the before. This is corroborated by examining the proportions of public transport users in the intervention area before and after the introduction of the Opal card. Results showed that 58% of participants were existing users of public transport, 13% were new users, while 11% no longer used public transport. The remaining 17% of participants in the intervention area did not use public transport at all during the study. This suggests that the increased use of public transport is primarily being driven by existing users of the network.

Table 5: Estimates for weekday work and non-work related trips by original main mode of transport to work/study

Mode of Transp.	Work				Non-work			
	Pub. Transp.	Car/Moto	Bicycle	Walk	Pub. Transp.	Car/Moto	Bicycle	Walk
Car/Motorcycle	-3.870	-11.194	0.102	-7.570	0.858	-4.281	-2.703	-8.649
	(2.217)*	(5.598)**	(3.864)	(1.830)***	(2.226)	(4.949)	(3.733)	(3.321)**
Bus	-8.289	1.179	1.732	0.064	0.238	0.315	-1.646	0.624
	(2.630)***	(1.936)	(2.604)	(2.526)	(1.231)	(0.983)	(1.343)	(1.094)
Train	9.160	4.118	2.326	4.957	2.403	0.575	0.959	2.260
	(2.402)***	(2.396)*	(4.003)	(2.433)**	(0.934)**	(0.912)	(1.073)	(0.751)***
Walk to Public Transp.	5.214	3.022	0.013	4.474	2.456	0.377	-0.466	0.080
	(2.334)**	(2.238)	(2.584)	(2.169)**	(1.245)*	(0.938)	(1.174)	(1.116)
Other Public Transp.	-1.552	1.599	1.011	-1.163	0.751	0.344	0.838	1.099
	(0.854)*	(0.760)**	(0.846)	(0.677)*	(0.639)	(0.886)	(0.925)	(0.764)
Walk Only	-0.322	3.607	-0.084	4.446	1.128	0.809	2.252	-8.510
	(1.423)	(2.480)	(1.208)	(4.535)	(2.109)	(3.068)	(3.110)	(3.122)***
Bicycle	-0.845	0.992	4.105	-1.633	2.535	0.733	4.827	0.040
	(0.957)	(0.973)	(4.704)	(1.250)	(1.001)**	(1.144)	(2.843)*	(1.750)
Other Transp.	-1.625	2.010	1.144	-1.184	0.950	0.827	0.120	0.946
	(0.906)*	(0.731)***	(1.279)	(0.705)*	(0.723)	(0.992)	(1.737)	(0.773)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust Standard errors in parentheses. ***, ** and * represent p<1%, p<5% and p<10% respectively.

6.1 Propensity Score

We now move to our estimation of the propensity score. The purpose of this exercise is to determine how similar those in the intervention group are to the control group based on personal characteristics. We decided to include in the vector of controls all observed characteristics that may jointly determine both treatment (Opal) and outcome (time travelling on a particular mode). As argued in Section 5, this strategy may help in constructing a control group that is balanced in comparison to those in the intervention group in terms of observable characteristics.

Results for the propensity score logistic specification (logit model) are reported in table 6. Individuals in the intervention area are evidently younger, earn higher incomes and less likely to be students compared to those in the control area. However, they are quite similar in terms of gender, working status and education level. Our specification also includes variables related to baseline transport choices, to account for initial levels of public/private transport usage. Hence, we include for each mode of transport the time spent travelling before any intervention took place. As can be observed, coefficients are quite small, although statistically significant for a few modes. This highlights potential gains from using the matching approach we implement here. In this case, participants in the intervention group can be matched to similar participants in the control group thereby controlling for any remaining differences between the composition of the intervention group relative to the control group.

Before presenting the propensity score matching (PSM) results, however, we assess whether the implemented matching procedure has been effective in balancing observable variables. As emphasised by Dehejia and Wahba 2002, a matching procedure will be successful if members in the selected control group (matched sample) have similar observable characteristics (variables included in the vector of covariates) when compared to the intervention group.

Table 6 contains statistics that summarise the quality of the PSM implementation. In the second column of Table 7, which displays the pseudo R2 from the estimation of the conditional treatment probability (propensity score) on both raw and matched samples

(i.e., before and after matching), we first show that the model has significantly less power to explain treatment status after matching. Pseudo R2 presented a reduction of about 80%. This is confirmed by the Likelihood-Ratio (LR) test of the joint insignificance of all the regressors in column 3, which also suggests that the matched sample is well balanced in the observed variables. Finally, substantial reduction in mean and median absolute bias (intervention versus control differences in covariate means and medians before and after matching), as computed in Rosenbaum and Rubin 1985, is achieved (columns 4 and 5). Both present a reduction of about 70% and 65%, respectively. This means that the demographic characteristics of the matched sample do not predict the area (intervention or control) in which they live. This is good because it means the sample in each area are not characteristically different from each other and can, therefore, be reasonable compared.

We now analyse results for the propensity score matching (PSM) estimation in Table 8. As one may observe, results are quite similar to the ones presented in table 2, although coefficient estimates are slightly smaller and standard deviations are slightly larger (as expected, given smaller sample sizes[7]), making some of our parameters statistically insignificant. Empirical implications, however, are mostly left unchanged: car usage decreases for work related activities on weekdays and non-work related activities on weekends; total train and walk to public transport increases; and bus usage increases for non-work weekend travel. These results not only reinforce our conclusions regarding the policy, but also adds credibility to our empirical findings given both strategies deliver similar implications.[8]

Table 6: Matching logit: regression of Opal on all other covariates for intervention relative to control

Variables	Estimates	stand. dev.
Age	-0.050	(0.013)***
Male	0.411	(0.251)
Income less than $80k	-0.734	(0.323)**
Income $80k-$140k	-0.881	(0.301)***
Student	-1.164	(0.530)**
Part-time Worker	-0.241	(0.453)
Full-time Worker	-0.135	(0.432)
Tertiary Degree	-0.251	(0.730)
High School	0.015	(0.753)
Car/Moto - work related	-0.004	(0.001)***
Car/Moto - non-work related	-0.002	(0.001)**
Bus - work related	-0.004	(0.002)**
Bus - non-work related	-0.011	(0.004)***
Train - work related	0.005	(0.002)**
Train - non-work related	0.008	(0.006)
WalkPT - work related	0.001	(0.002)
WalkPT - non-work related	0.005	(0.004)
OtherPT - work related	-0.027	(0.012)**
OtherPT - non-work related	-0.028	(0.015)*
Constant	3.384	(1.051)***
N	435	

Note: *** represents p<1%, ** represents p<5%, and * represents p<10%.

[7] With a matched sample each person in the intervention area is matched to one similar person in the control area. Since there were slightly fewer participants in the intervention area (see table 1), non- matched individuals in the control area were dropped in the matched sample.

[8] Results via matching were also similar for tables 2-5, which we do not report to save space. They are however available upon request.

Table 7: Balance quality before (Raw) and after (Match) matching

Sample	Pseudo R^2	LR χ^2	Mean Bias	Median Bias
Raw	0.235	139.45***	26.2	19.9
Match	0.045	22.88	8.0	6.8

Note: *** represents p<1%. The mean and median bias serve as summary indicators of the distribution of the absolute bias and are calculated as treated versus control differences in covariate means and medians before and after matching.

Table 8: Estimates for Work and non-Work related trips - Matched sample

Mode of Transp.	Weekdays		Weekends	
	Work	Non-work	Work	Non-work
Car/Moto	-5.892	-1.358	-1.270	-4.008
	(2.265)***	(1.991)	(1.100)	(3.952)
Bus	0.150	0.022	0.234	1.898
	(1.370)	(0.745)	(0.355)	(1.090)*
Train	5.267	1.467	0.193	2.975
	(1.570)***	(0.579)**	(0.301)	(0.860)***
Walk to Public Transp.	5.259	0.833	0.328	3.883
	(1.491)***	(0.803)	(0.411)	(1.348)***
Other Public Transp.	-0.358	0.751	-0.149	0.793
	(0.483)	(0.444)*	(0.235)	(0.703)
Walk Only	1.777	-2.549	0.874	1.501
	(1.663)	(1.727)	(0.631)	(2.724)
Bicycle	-0.546	2.105	0.084	3.883
	(1.146)	(0.813)**	(0.276)	(2.595)
Other Transp.	-0.676	0.600	-0.076	1.697
	(0.535)	(0.582)	(0.238)	(0.761)**
Year fixed effect	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes

Notes: Robust Standard errors in parentheses. ***, ** and * represent p<1%, p<5%, and p<10% respectively.

7. Discussion

The results presented in Section 6 show that the effects of the Opal card on travel behaviour varies quite substantially by a number of different factors including the type of trip and the day of the week as well as some (but not all) personal characteristics. However, even at the aggregate level the introduction of the Opal system has coincided with significant changes in the use of most modes of transport. In particular, there is a strong and significant effect of people switching from cars (and motorcycles) to public transport, in particular to train travel. This travel is replaced with a similar amount of time spent using public transport and walking to access public transport. Although to be expected, the link between increases in public transport use and walking, either as an access/egress mode or as a stand-alone mode, is particularly positive given the health benefits of even relatively short amounts of walking (Pucher and Dijkstra, 2003).

The effects of Opal appear to be most pronounced for work trips on weekdays and non-work trips on weekends with reductions of around 10 minutes in car trips per day per person. In part, this is likely to be a result of the incentive of free trips after eight journeys that means those who commute to work by public transport during the week travel for free on weekends. Although many of these weekend trips are likely to be free for the user, there is undoubtedly a societal benefit from reducing car use for discretionary trips particularly since these trips have had relatively high car mode share in Sydney relative to commuting trips (Greaves et al., 2015).

For people whose stated main mode of travel to work (or study) was public transport, there was a significant shift in mode from bus to train for work trips. This was coupled with an increase in walking to public transport suggesting that people chose to walk further to access the train. There are two possible reasons for this effect. The first is that the Opal fare structure meant that for some trips in off-peak periods, the train became cheaper than the bus. However, since this effect was primarily for work trips, for which travel is largely during peak periods, this cannot fully explain the effect. Likely a more important reason for this effect is the removal of multi-modal tickets (the "My Multi" tickets). This means commuters who change modes pay two fares but these count for only one "journey" towards the eight required for free travel. This appears to have had the effect of commuters choosing to walk (on average further) to a railway station rather than first taking a bus then transferring to a train. Nonetheless, even for commuters whose primary mode of travel to work was public transport before the Opal card, the number of trips by car reduced (albeit only at the 0.1 significance level).

The differences in the effects of the Opal card between people of different ages and incomes provides further insights into the switching from car to public transport and from bus to train. The reduction in car use for those older than 44 years old in contrast to those younger than 25 who do not reduce their use of car suggests that the Opal card was successful in encouraging people who were previously less likely to use public transport to commute by train. Those older than 44 were as likely to switch to walking only as to the train. However, the switching from bus to train travel by those younger than 25 suggests that the effect of the Opal card on younger people (who are less likely to own a car) is one of switching between modes of public transport. That it is primarily age (rather than income) that is driving the effect of the Opal card on commuting trips is supported by the relative consistency of the effect by income for work trips (in contrast to the larger changes for those with high incomes for non-work trips).

It must be acknowledged that it is not possible in the context of this study to differentiate between the effect of the Opal card itself from the effect of the fare structure. However, it can be argued that a new (and frequently simpler) fare structure is an inherent feature of smartcard ticketing systems for public transport. Few, if any, major public transport systems retained the original fare structure (and pricing) of the system when the smartcard ticketing system was introduced. Nonetheless, the results in Section 6 and this discussion should be interpreted as the effects of the Opal card system as a whole including both the method of payment (i.e., the Opal card) and the accompanying fare structure. Furthermore, although the results presented here provide some evidence that the fare structure influences the exact effect of the smartcard ticketing system (e.g., by promoting or discouraging multi-modal trips), it is unlikely that changes to the fare structure would result in as large a switch from car to public transport for those who did not use public transport previously.

Placing these results in a wider context, this analysis adds to the generally positive view of Smartcard systems from cities that have implemented them. While much of the policy focus has been on improving service levels and coverage, reducing the barriers associated with complicated, cumbersome ticketing systems appears to be integral to encouraging ridership. It is true that despite the positives, Smartcard systems such as Opal still present many barriers particularly to the millions of annual visitors to Sydney. One obvious evolution is to provide greater flexibility in the use of personal credit cards (now operational in London) and mobile phone apps. A trial with contactless payment with credit and debit cards has been announced for 2017 (Transport for NSW, 2016). This may also make it easier to convert some non-users to incidental users meaning that someone may use public transport on an ad-hoc basis if it is more convenient than waiting for a lift or a taxi.

8. Conclusions

Smartcard and other forms of electronic ticketing have become integral to modern public transport systems around the globe testament to their touted benefits outweighing the challenges of implementation. However, while aggregate ridership figures have generally been positive, little is known about the drivers behind these changes because of a lack of travel information on individuals before and after implementation of such systems. Utilising a panel survey of inner-city residents that coincided with the phased introduction of the Opal smartcard system and associated changes in fare structures in Sydney, the current paper uses a differences-in-differences methodology to provide evidence of significant changes in mode choice. Of most note, is the changes appear to have encouraged people from private cars to public transport, although this is primarily towards the train as opposed to bus. In turn this has led to other positive outcomes, including an increase in (incidental) walking to access/egress public transport. That this switching is observed across income groups is particularly encouraging, because it suggests the changes have also spread to higher income groups, who are generally the most resistant to switch to public transport.

As with any study of this nature, there are acknowledged limitations. First, naturalistic field experiments such as this, invariably suffer from endogenous (fare structure, system changes) and exogenous (economic changes) effects over and above the intervention as identified in Section 3. The incorporation of a control area and the methodology employed attempted to deal to with the exogenous effects, while the endogenous effects are (arguably) an inherent component of smartcard introductions as discussed in the previous section. Second, it must be stressed, the sample were drawn from inner-Sydney, where multi-modal transport options are generally available – the situation is quite different in the auto-dominated middle and outer suburbs of the city, where significant public transport is needed above and beyond the improvement of the ticketing system. Finally, the extent to which the changes are sustained over time is clearly crucial, particularly in view of other planned system or fare changes.

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