How Card Acquisition Fee Affects New Transit Card Purchase Patterns: Evidence from New York City and Washington, D.C.

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Abstract

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1 Introduction

The provision of an efficient and effective public transport is an important component to successfully integrate transport and land use in cities. Transit authorities in many cities have introduced automated fare media by expanding fare payment to electronic, magnetic-stripe contact cards and more recently to smart cards. Most transit smart card come with a refundable or non-refundable one-time acquisition fee to cover the card costs and ensure uninterrupted transit service in case of negative value on card. For instance, there is a one-time $3.00 acquisition fee for a Clipper card, a reloadable contactless card used for automated public transit fare collection in the San Francisco Bay Area. So far, most empirical studies on optimal fare structures of public transportation system focus on the demand elasticity of rides in response to base fare changes or differential pricing (rush v.s. non-rush hour fares). The effect of the ubiquitous new transit card fee is not clear, largely due to the scarcity of reliable disaggregate card data.

With novel data sets from the Washington Metropolitan Area Transit Authority (WMATA) and the New York City Metropolitan Transportation Authority (MTA), I address this gap in the literature by adopting a causal inference approach, a difference-in-difference (DID) model, to examine the effects of a new card acquisition fee on new transit card purchases.

For New York City, the Metropolitan Transportation Authority (MTA) system has used MetroCards to collect subway and bus fares since 1998. Riders can add cash amounts to MetroCards and swipe these cards when they ride a subway or bus. A MetroCard itself used to be cost-free. But a $1 non-refundable acquisition fee, tacked on when someone buys a new MetroCard, went into effect on March 3, 2013. Riders do not pay this fee when they refill MetroCards or purchase single-ride tickets. Also, the acquisition fee does not apply to MetroCards purchased out-of-system through MTA extended sales merchants.

For Washington D.C., the Washington Metropolitan Area Transit Authority (WMATA) began using SmarTrip for payment on Metrorail in 1999. It was later extended to other public transit systems throughout the region. Riders load SmarTrips with cash amounts that they choose and tab these cards when they ride a Metrorail or bus. Before September 2012, there was a one-time non-refundable \$5.00 acquisition fee for a new SmarTrip. From September 2012 to September 2013, the cards still cost \$5, but the WMATA offered \$3 rebates to riders who registered their new SmarTrips online after first use of the card. Subsequently, from October 2013 on, the rebate program was discontinued and the price of the card was reduced to \$2. In September 2015, Washington Metro begun upgrading existing fare vending machines to dispense SmarTrip cards rather than paper farecards, and discontinued all sales of paper farecards when the last machine on the system was upgraded by January 2016.

Using these policy changes, I examine the demand elasticity of new transit card purchases in response to changes in acquisition fee. In New York City, the overall demand for new MetroCards dropped by over 52 percent upon the imposition of the acquisition fee in March 2013 (Figure 2). In Washington D.C., the sales of new SmarTrip cards stayed constant when the rebate program was introduced in September 2012. Similarly, the reduction of new card fee from \$5 to \$2 only slightly increased the purchase of new SmarTrip cards. In contrast, the elimination of paper farecards prompted riders to go paperless and caused a significant increase in the overall demand for new SmarTrip cards.

The response of new MetroCard and SmarTrip card sales to these policy changes may suffer from confounding biases, which emerge due to temporal trends. For example, the difference in new SmarTrip card sales between 2015 and 2016 may not be solely due to the discontinuity of paper farecards because there may be an intrinsic (temporal) decrease in demand over years. Moreover, other effects unrelated to the policy changes such as weather and festival events may further exacerbate the issue of confounding bias. Thus, the estimates derived from a simple before-after comparison may not reflect the true policy effects. We address these potential estimation biases by adopting a causal inference approach, a difference-in-differences (DID) model. Specifically, for new transit card sales, we use the average daily transit rides as the control group: new card sales are likely to be proportional to transit ridership and the volume of people riding the subways and buses, unless these are systematic changes in rides patterns.

Using the DID model, we first estimate the impacts of different policy changes at the network (aggregate) level. The granularity of station-level data also enables us to analyze the spatial variations in new MetroCard and SmarTrip card sales at each subway station (disaggregate level). We observe substantial variation in new card sales across different neighborhoods. To identify the factors that influence new transit card sales, we allow the treatment effect to vary with observed baseline census tract characteristics (e.g., median household income and unemployment rate). These estimates of heterogeneous policy effects provide insights into how transit agencies can better target the less responsive rider groups and make such policies more effective.

This study contributes to a number of existing literatures in transportation research. First, this study contributes to a large literature on optimal pricing policies for public transit system. So far, most empirical studies on optimal fare structures focus on the demand elasticity of rides in response to fare increases (Vickrey, 1955, 1963; Palma and Lindsey, 2007; Small and Verhoef, 2007; Tirachinia and Henshera, 2012; Jong and Gunn, 2001; Chen et al., 2011; Davis, 2021). This paper examines the causal effect of a surcharge fee (card activation fee) on transit card purchase and use patterns. We show that a new card fee induced riders to reuse existing transit cards more instead of buying new ones.

Second, this study also contributes to an emerging literature on public transport payment preference. Despite the availability of, and benefits associated with, prepaid reloadable fare cards, many transit riders continue to select traditional single ride or round trip tickets for payment of their fares (Weinstein et al., 1999). Lu et al. (2019) shows that, in Manila, light rail (LRT-1) riders with lower education level, lower income, or with unstable job prefer to use single journey ticket rather than use smart card. At the same time, a lot of public transit riders do not reuse their prepaid reloadable transit cards. For example, in New South Wales (NSW), state of southeastern Australia, many public transit riders simply ditch free transit cards (Opal cards) with a zero or negative balance and then start afresh with a new card (Coyne, 2017). Each Opal card costs the state more than $2 to produce and distribute. These discarded cards add up to a loss of millions of dollars to the NSW government. Complementing prior studies, this paper shows that a large portion of public transit riders treat prepaid reloadable transit cards as single ride or round trip tickets when it costs nothing to get new transit cards. In contrast, a surcharge fee on new transit card prompts riders to substitute to refill existing cards.

Third, this work connects with a growing strand of the literature that has used smart card data for transport evaluation. Data generated by cards are used widely in trip pattern analysis and planning (Wei, 2022; Shin, 2021; Wang et al., 2021). Pelletier et al. (2011) thoroughly reviewed studies on trip pattern analysis using transport smart card data and categorized the existing research into three areas: strategic, tactical, and operational levels. Meanwhile, a large volume of research has used large-scale smart card data to explore the responsiveness of public transit riders to different pricing policies (Hussain et al., 2021; Liu et al., 2019; Zhao and Zhang, 2019). Extensive reviews can be found in Halvorsen (2015) and Liu and Charles (2013). While prior studies have largely focused on transit fare policy assessment and travel pattern analysis, this paper reveals that smart card data can be used to assess the effectiveness of different policies to increase use and reuse of automated fare cards as well.

The remainder of the paper is organized as follows. Section 2 gives a brief introduction to SmarTrip cards and the main policy changes of interest. Section 3 describes the main features of data sets used in the empirical analysis. Section 4 discusses the specification of the DID model. Section 5 presents the main findings about changes in new MetroCard and SmarTrip card sales in response to different policy changes. Section 6 performs robustness tests. Section 7 summarises the results of heterogeneity in new MetroCard and Smartrip card purchase patterns across different subway stations. Section 8 concludes the paper.

2 Background

2.1 SmarTrip

A SmarTrip card is a rechargeable plastic farecard that can hold up to $300 in value to pay for WMATA transit services (Metrorail, Metrobus, and DC Circulator), bus systems in Virginia (ART

(Arlington Transit), CUE (Fairfax City), DASH (Alexandria Transit Company), Fairfax Connector, and Loudoun Commuter Bus Service) and bus systems in Maryland (Maryland Transit Administration, Ride On (Montgomery County Transit Services Division), TheBus in Prince George's County, and PRTC (Prince William County, Manassas and Manassas Park)). SmarTrip was the first contactless smart card for transit in the United States when WMATA began selling SmarTrip cards on May 18, 1999. New SmarTrip Cards can be purchased using either a card or cash at Metro stations, Metro sales offices, retail outlets, and commuter stores. Riders could also add value to their SmarTrip cards by trading in paper farecards (paper tickets with a magnetic strip).You need to use the same SmarTrip card or paper farecard to enter and exit the system, and you must have one per person or Metro will charge you the maximum fare. Since March 6, 2016, Metro eliminate the use of paper farecards and SmarTrip cards become the only payment method accepted on Metrorail and Metrobus.

2.1.1 Policy Changes

Initially, there was a one-time non-refundable $5.00 acquisition fee for a new SmarTrip card. Starting September 1, 2012, Metro began offering $3 rebates to riders who registered their new SmarTrip cards online after purchase. The cards still cost $5, but a $3 credit was refunded to the card five days after first use. Effective October 1, 2013, the acquisition fee of new SmarTrip card was reduced to $2 and the rebate program was discontinued. In September 2015, Metro begun upgrading existing fare vending machines to dispense SmarTrip cards rather than paper farecards, and discontinued all sales and uses of paper farecards when the last machine on the system was upgraded by January 2016.

2.2 MetroCard

The MetroCard is a stored ride fare card for the New York City Subway rapid transit system; New York City Transit buses, including routes operated by Atlantic Express under contract to the Metropolitan Transportation Authority (MTA); MTA Bus; Nassau Inter-County Express systems;

the PATH subway system; the Roosevelt Island Tram; AirTrain JFK; and Westchester County's Bee-Line Bus System. It is a thin plastic card on which a rider electronically loads fares. Riders can put up to $100 in value on the card. A rider can purchase new or refill existing MetroCards at a subway station MetroCard vending machine (MVM) or at a station's manned booth (teller). MetroCards can also be purchased out-of-system through the MTA extended sales merchants, users of EasyPayXpress cards, transit benefit organization riders who get their MetroCards directly from employers or their benefit providers, or riders who purchase a combination railroad/MetroCard ticket (including merchants and tax-benefit providers).

2.2.1 Policy Changes

A new Metrocard itself used to be cost-free. But a $1 surcharge fee, tacked on when someone buys a new metrocard, went into effect on March 3rd, 2013. The fee applies to each new MetroCard purchased at a MetroCard Vending Machine, station booth, or commuter rail station. Riders can avoid this fee by refilling their MetroCards. The MTA will issue a new MetroCard at no charge if a card is expired or damaged. The new $1 charge did not apply to single journey tickets or to MetroCards bought by reduced fare riders (seniors and riders with disabilities). Also, the card fee does not apply to MetroCards purchased out-of-system through the MTA extended sales network (including merchants and tax-benefit providers).

3 Data

In this section, we present the main features of data sets used in this paper. This paper documents changes in new MetroCard and SmarTrip card sales in response to different policy changes using five data sets: monthly new MetroCard sales data, monthly new SmarTrip card sales, average daily Metrorail ridership of the WMATA system, average daily subway ridership of the MTA system, and American Community Survey census tract data.

3.1 Monthly-level new SmarTrip Purchase Data

The SmarTrip card monthly sales data from August 2010 to December 2019 include information on the number of new SmarTrip card purchases made by riders in each month. Before September 2015, SmarTrip cards can only be purchased at Metro sales offices, retail outlets, and commuter stores. Starting September 2015, the new card sales data are broken out for each metro station as Metro updated fare vending machines to dispense SmarTrip cards rather than paper farecards.

Table 1 provides the summary statistics of monthly new SmarTrip card sales and the average number of daily Metrorail rides made each month across different time periods. Before the implementation of the rebate program in September 2012, the monthly sales of new SmarTrip cards was 0.27 million cards. After Metro began offering $3 rebates on new SmarTrip card purchases, monthly new SmarTrip card sales increased slightly from 0.27 million to 0.31 million. Similarly, after the acquisition fee of new SmarTrip card was reduced to $2 and the rebate program was discontinued October 2013, monthly new SmarTrip card sales merely increased from 0.31 million to 0.32 million. In contrast, demand for new SmarTrip cards shifted dramatically after all sales and uses of paper farecards were discontinued in September 2015. The monthly new SmarTrip sales increased from 0.32 million to over 0.65 million and stayed high.

Table 1: Summary Statistics of Daily Ridership and Monthly SmarTrip Card Sales in Washington Metropolitan Areas

	(1) Aug 2010-Aug 2012	(2) Sep 2012-Sep 2013	(3) Oct 2013-Aug 2015	(4) Sep 2015-Dec 2019
New SmarTrip Sales	270.90 (67.86)	314.56 (118.95)	319.59 (109.54)	658.55 (256.98)
Daily Average Ridership	24.06 (1.41)	23.38 (1.61)	22.58 (1.54)	20.33 (1.53)

All numbers are in thousands. Standard deviation in parentheses.

3.2 WMATA Metrorail Rides Data

This data set includes the average number of daily Metrorail rides made each month from August 2010 to December 2019 as riders entered each station of the Metrorail, broken out for each metro station. As shown in Table 1 and Figure 2, the Metrorail delivered about 24 thousand rides per weekday when the acquisition fee of new SmarTrip card was $5. The daily average ridership on Metrorail stayed relatively stable after Metro began offering $3 rebates on new SmarTrip card purchases in September 2012. Similarly, the daily ridership on Metrorail only decreased slightly after the acquisition fee of new SmarTrip card was reduced to $2 in October 2013 and all sales and uses of paper farecards were discontinued in September 2015, respectively.

3.3 Monthly-level new MetroCard Purchase Data

The MetroCard monthly sales data from January 2011 to June 2015 include information on the number of new MetroCard purchases made by riders in each month, broken out for each subway station and out-of-system through the MTA extended sales network. Table 2 provides the summary statistics of monthly new MetroCard sales and the average number of Metrorail rides per weekday across different time periods. Demand for MetroCards fell drastically after the imposition of the $1 new card fee. The monthly new MetroCard sales dropped from over 7 million to about 2 million and stayed low.

Table 2: Summary Statistics of Daily Ridership and Monthly MetroCard Sales in New York City

	(1) Jan 2011-Feb 2013	(2) Mar 2013-Jun 2015
New MetroCard Sales	7.65	2.3
(Total in-system)	(0.58)	(0.36)
Daily Average	4.51	4.77
Ridership	(0.21)	(0.21)

All numbers are in million. Standard deviation in parentheses.

3.4 MTA Subway Rides Data

This data set includes the average number of daily subway rides made each month from January 2011 to June 2015 as riders entered each station of the New York City subway system, broken out for each subway station. As shown in Table 2 and Figure 3, the subway delivered about 4.5 million rides per weekday when new Metrocards themselves were cost-free. The daily average ridership on subway stayed relatively stable after the imposition of the $1 new card acquisition fee.

3.5 Census Tract Data

We utilize data from the American Community Survey (ACS) to obtain the 5-year-average (2011–2015) median household income, percent of Hispanic, percent of African American, and unemployment rate for each census tract in the Washington metropolitan area (all of Washington, D.C. and parts of the states of Maryland, Virginia) and each census tract throughout the five boroughs of New York City. The ACS is a statistical survey conducted by the US Census Bureau that samples a small percent of the US population every year to provide demographic, social and economic data on various communities in the US. ACS provides 1-, 3- and 5-year rolling data but the 5-year ACS data are based on larger survey samples and are considered more reliable. Census tract data are then matched to each geocoded metro station record for heterogeneity analysis.

4 Methodology

This section discusses the specification of the DID model, followed by the choice of dependent variables to quantify the impacts of policies on new MetroCard and SmarTrip card purchase patterns. We then discuss the classification of control and treated groups in the DID model.

4.1 The Difference-in-differences Regression Model

In this analysis, a difference-in-differences (DID) approach is adopted to estimate an average treatment effect (ATE), the difference in response that would occur under treatment status ($Treat$=1) relative to control status ($Treat$=0), averaged over the population. A simple before-after comparison of new transit card sales may suffer from confounding biases. For instance, the difference in the number of new SmarTrip card sold between 2015 and 2016 (Figure 2) may be due to a temporal increase in demand over years. Similarly, a plain comparison of post-treatment outcome for treated and control groups may be subject to confounding effect of other factors, such as weather and special events. Using information of both treated and control groups in both pre- and post-treatment periods, the DID estimator addresses such confounding problems (Wooldridge, 2010).

The empirical difference-in-differences model takes the following form:

$$Y_{it} = \theta_0 + \theta_1 \textit{Post} + \theta_2 \textit{Treat} + \theta_3 \textit{Post*Treat} + \lambda X_i + \beta T + \epsilon, \tag{1}$$

Where θ_0, θ_1, θ_2, θ_3, and λ are parameters to be estimated. $Treat$ is a dummy variable representing assignment of the treatment, *Treat*=1 for treated group, zero otherwise. *Post* is a dummy variable indicating whether the observation was from the post-treatment period of the policy change. *Post*=1 for time periods after the implementation of the policy, zero otherwise. ϵ is a potentially autoregressive error with mean zero in each time period (Wooldridge, 2010).

The parameter θ_0 relates to the expected pre-treatment response of the control group. The parameter θ_1 measures the difference between the expected post-treatment and pre-treatment responses of the control group. The parameter θ_2 measures the difference between the expected pre-treatment responses between the treated and control groups. The effect of the treatment is captured by the parameter θ_3, which provides the sample average outcome for treated units in the time periods when the treatment occurs. We introduce X_i, station-specific fixed effects, and T, a time effect common to all subway stations in period t, in the above equation to capture any unobserved heterogeneity in outcome dynamics between treated and control groups.

We first estimate this model at an aggregate level, that is, at the network level. The granularity of station-level sales data also enables us to estimate the spatial variations in new MetroCard and SmarTrip card sales at each subway station (disaggregate level). Besides, we estimate heterogeneity in new card sales across different neighborhoods. In this specification, we allow the treatment effect to vary over observed socioeconomic characteristics (γ_i) such as median household income, percent of Hispanic, percent of African American, and unemployment rate at the station level:

$$Y_{i,1} - Y_{i,0} = \theta_0 + \tau_0\gamma_i + \tau_1 Treat + \tau_2 Treat.\gamma_i + \lambda.X_i + (\epsilon_{i,1} - \epsilon_{i,0}). \tag{2}$$

The results of this model provide empirical insights into how the effect of the policy varies across riders with different socioeconomic characteristics.

4.2 Dependent Variable in the DID Model

We choose the number of new MetroCard and SmarTrip card sold as the response variable Y_{it} to capture the impacts of different policy changes on new transit card purchase patterns.

4.3 Selection of Control and Treated Groups

We use monthly new SmarTrip card sales from August 2010 to September 2013 for the rebate program analysis. This time window comprises both the pre-treatment and post-treatment periods. We use the average weekday rail entries as the control group since more new SmarTrip cards are likely to be sold when more people choose to ride the Washington Metro system. We conduct robustness test to check the sensitivity of results relative to the time period used in Section 6.

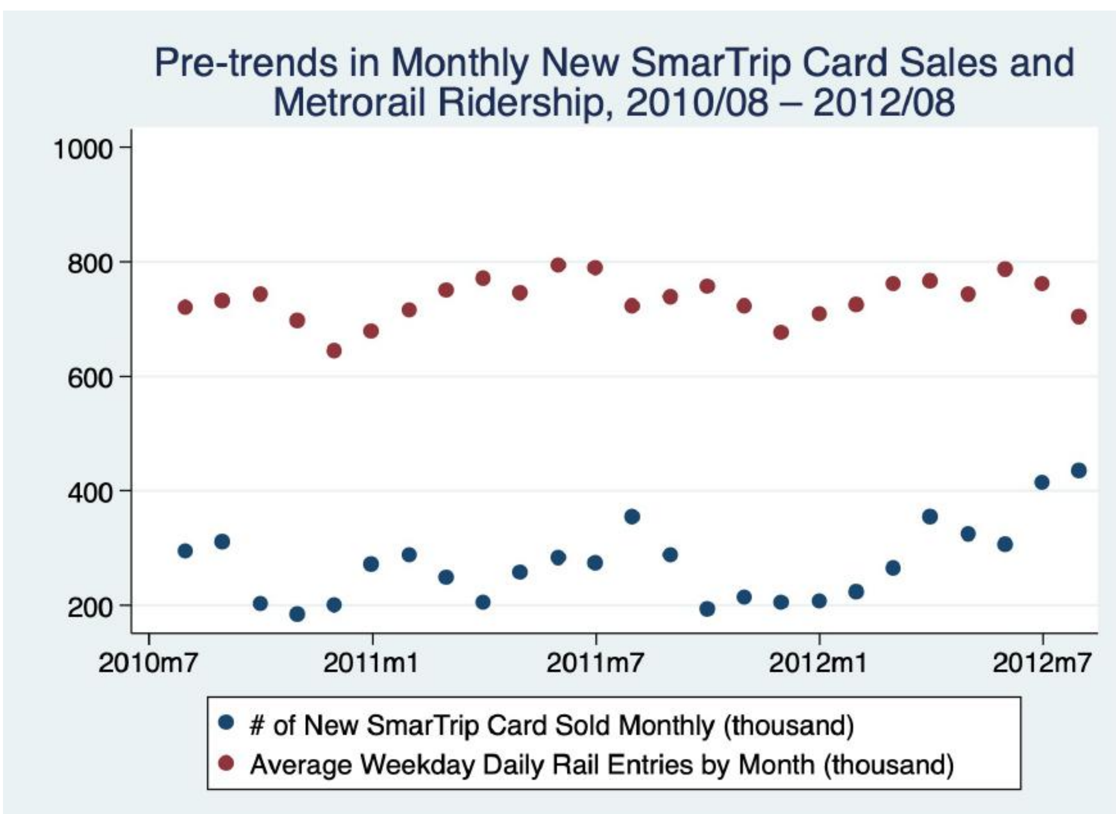
We use monthly new SmarTrip card sales from September 2012 to August 2015 for the new card fee reduction analysis. This time window comprises both the pre-treatment and post-treatment periods. Similarly, we use the average weekday rail entries as the control group and conduct robustness test to check the sensitivity of results relative to the time period used in Section 6.

We use monthly new SmarTrip card sales from October 2013 to December 2019 for the elimination of paper farecards analysis. This time window comprises both the pre-treatment and post-treatment periods. Again, we use the average weekday rail entries as the control group and conduct robustness test to check the sensitivity of results relative to the time period used in Section 6.

We use monthly new MetroCard sales from January 2011 to June 2015 for the introduction of the \$1 new card fee on MetroCard analysis. This time window comprises both the pre-treatment and post-treatment periods. Likewise, we use the average weekday subway entries as the control group and conduct robustness test to check the sensitivity of results relative to the time period used in Section 6.

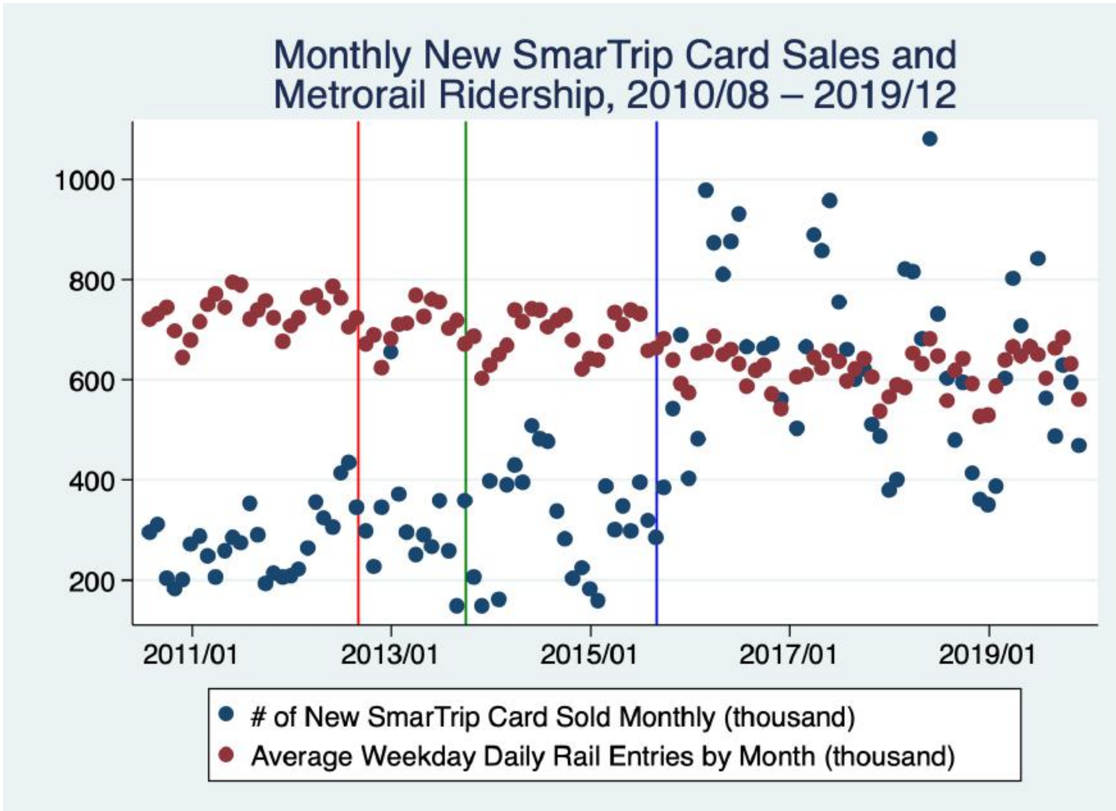
The key assumption in DID estimation is a common-trends assumption that treated groups would have followed the same time trend as untreated groups had they not been treated. Under this assumption, the difference in the rates of change between treated and untreated groups equals the true treatment effect. One way to gauge the validity of this assumption is to compare the time trend before any treatments occur (that is, the "pre-trend") for groups that are treated with the pre-trend of control groups that are never treated. Figure 1 and 4 shows similar pre-trends in the control (daily average subway ridership) and treated (new transit card sales) groups in the pre-treatment period for both New York City and Washington, D.C. areas, which suggests that the common trend assumption is satisfied.

Figure 1



Note: Figure 1 plots the number of new SmarTrips sold monthly from August 2010 to August 2012.

Figure 2

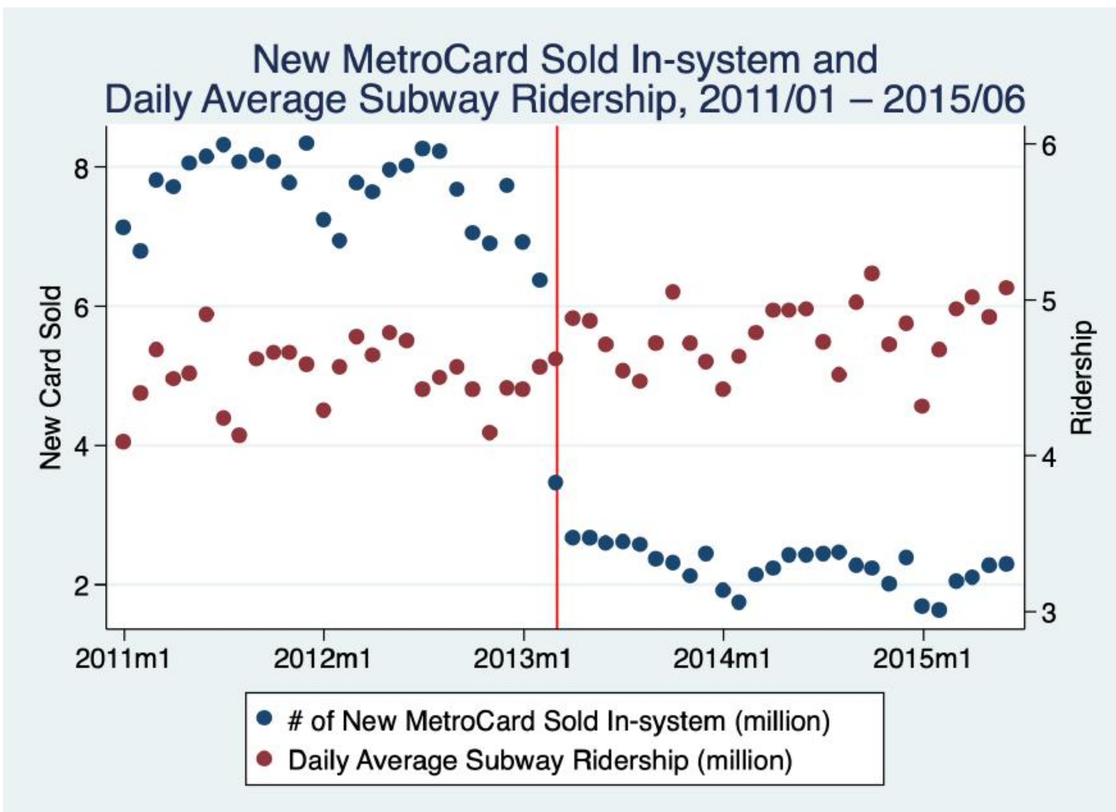


Note: Figure 2 plots the number of new SmarTrips sold monthly from August 2010 to October 2017. The first vertical line marks the month when the rebate program was implemented. The second vertical line marks the month when the price of new SmarTrip card decreased from \$5 to \$2. The third vertical line marks the month when the paper farecards were eliminated.

5 Results

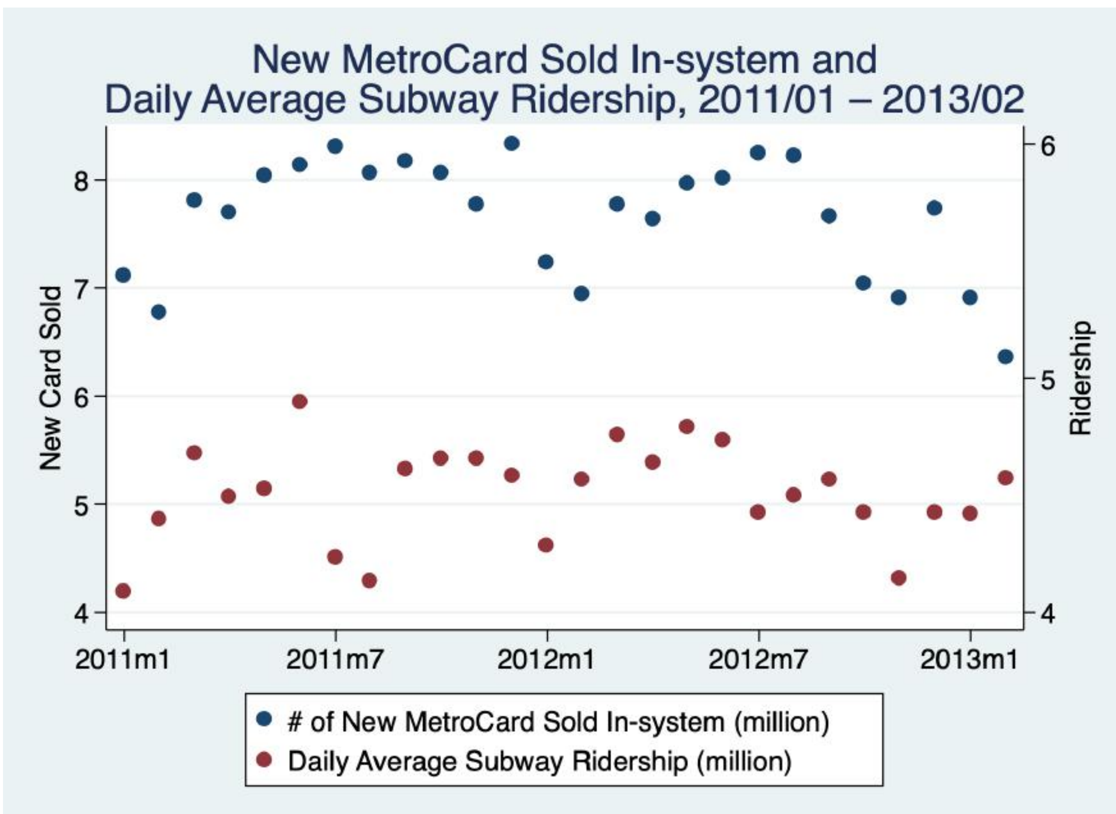
This section has four subsections. The first subsection reports the summary statistics of new SmarTrip card sales before and after policy changes. The second subsection summarizes the main implications of the aggregate (network-level) DID estimates. The third subsection performs validation tests to check the robustness of the DID estimates. The spatial variations of the station-level SmarTrip card purchase patterns are presented in the last subsection.

Figure 3



Note:

Figure 4



Note:

5.1 Main Results of the DID Estimates

5.1.1 Aggregate-level

Table 3 presents results for the effect of the rebate program on the number of new SmarTrip card sold, using different control variables in each DID specification. The model in column 1 controls for time period, card type, and the interaction of card sales and card sales in the post-period only. The results show that the introduction of $3 rebate program caused no change in new SmarTrip card sales.

Table 3: The Impact of Rebate Program on New SmarTrip Card Sales

	(1)	(2)	(3)
Pass	-23.31	-21.97	-17.83
	(13.15)	(11.02)	(35.47)
Treat	-461.9***	-461.9***	-461.9***
	(15.57)	(13.89)	(14.06)
Pass*Treat	66.96	66.96	66.96
	(37.68)	(37.59)	(38.30)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	76	76	76
R^2	0.917	0.935	0.936

Outcome variable: SmarTrips sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. ** p < 0.05, ** p < 0.01, *** p < 0.001*

If riders card purchase patterns are different across different months of the year or if different types of riders purchase at different times of the year, any variations in the time of data collection could affect the regression results. To account for this possibility, my preferred specification in column 3 includes month and year fixed effects. As with the other control variables, the inclusion of these fixed effects has little impact on the estimated effect of the rebate program. Using the same sets of control variables, table 4 present results for the effect of the price reduction on new card sales. Similarly, the price reduction from \$5 to \$2 caused no statistically significant change in new SmarTrip card sales, with or without month and year fixed effects.

Table 4: The Impact of Price Reduction on New SmarTrip Card Sales

	(1)	(2)	(3)
Pass	-34.15*	-32.16**	-101.7
	(14.05)	(11.91)	(60.17)
Treat	-394.9***	-394.9***	-394.9***
	(34.22)	(36.43)	(38.82)
Pass*Treat	68.82	68.82	68.82
	(42.75)	(44.67)	(46.46)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	84	84	84
R^2	0.782	0.803	0.810

Outcome variable: SmarTrips sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Using the same sets of control variables as in Table 3, Table 5 summarizes changes in new SmarTrip card sales in response to the elimination of paper farecards. In contrast to the effects of the rebate program and the fee reduction, the monthly new SmarTrip card sales increased drastically after the discontinuity of paper farecards. This increase in sales is very robust across different specifications: the monthly sales of new SmarTrip cards increased by more than 0.4 million after the Washington Metro eliminate paper farecards from the system.

Table 6 presents results for the effect of the \$1 acquisition fee on new MetroCard sales, using the same sets of control variables in each specification as in Table 3. Consistent with Figure 3, the number of new MetroCard sold fell drastically after the introduction of \$1 acquisition fee on new MetroCard purchases. This drop in sales is very robust across different specifications: the monthly sales of new MetroCard decreased by more than 5.6 million after March 2013, with or without month and year fixed effects.

Table 5: The Impact of Paper Farecards Elimination on New SmarTrip Card Sales

	(1)	(2)	(3)
Pass	-58.78***	-69.55***	-89.09
	(10.85)	(12.95)	(91.04)
Treat	-326.1***	-326.1***	-326.1***
	(25.35)	(26.46)	(26.52)
Pass*Treat	393.6***	393.6***	393.6***
	(46.28)	(44.51)	(44.25)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	150	150	150
R^2	0.391	0.500	0.530

Outcome variable: SmarTrips sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. ** p < 0.05, ** p < 0.01, *** p < 0.001*

Table 6: The Impact of $1 Acquisition Fee on New MetroCard Sales

	(1)	(2)	(3)
pass	0.265***	0.209**	0.414
	(0.0569)	(0.0643)	(0.318)
treat	3.141***	3.141***	3.141***
	(0.117)	(0.0931)	(0.0936)
passXtreat	-5.615***	-5.615***	-5.615***
	(0.141)	(0.115)	(0.115)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	108	108	108
R^2	0.966	0.980	0.981

Outcome variable: MetroCard sales on monthly basis at network (aggregate) level (in millions). Robust standard errors in parentheses. ** p < 0.05, ** p < 0.01, *** p < 0.001*

6 Validation Tests

In this section, we perform several validation tests to check the robustness of the DID estimates.

6.1 Time Window Selections

We capture the sensitivity of DID estimates relative to sample selection by analyzing two subsamples of the original time windows: nine months before and after each policy change (December 2011 to May 2013 for the rebate program on SmarTrip cards, January 2013 to June 2014 for SmarTrip card price reduction, June 2015 to November 2016 for the discontinuity of paper farecards in Washington D.C., and June 2012 to November 2013 for the Imposition of New Card Fee on MetroCards) and six months before and after each policy change (March 2012 to February 2013 for the rebate program on SmarTrip cards, April 2013 to March 2014 for SmarTrip card price reduction, September 2015 to August 2016 for the discontinuity of paper farecards in Washington D.C., and September 2012 to August 2013 for the Imposition of New Card Fee on MetroCards).

Table 7, 8, and 9 summarize the DID estimates of these two time window for SmarTrip cards and MetroCards, respectively. These estimates are consistent with those of the original time window. Meanwhile, we observe that the narrower is the time window, the smaller is the magnitude of the aggregate DID estimate, that is, the less in the magnitude of change in new card sales. This decrease in the magnitude of response makes sense because riders, who purchase and use transit cards in days closer to the implementation of policies, have less time to change or adjust their card purchase and use patterns.

6.2 No Jumps (or Discontinuity) in Ridership Before versus After Policy Changes

One concern with interpreting changes in behavior as a response to the policy changes is that there may be fluctuations in subway ridership that could conflate the effect of different policies. Figure 2 and Figure 3 shows monthly average metrorail rides in Washington, D.C. and subway rides in

Table 7: Impacts of Different Policies on New SmarTrip Sales

	(1) Rebate Program	(2) Price Reduction	(3) Paper Farecard Elimination
Pass	3.323	-34.34	-47.01
	(30.45)	(38.00)	(36.76)
Treat	-433.2***	-404.8***	-237.4***
	(32.79)	(52.68)	(52.06)
Pass*Treat	74.76	58.80	391.8***
	(58.22)	(65.72)	(64.00)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	36	36	36
R^2	0.907	0.872	0.794

Outcome variable: SmarTrips sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. * *p < 0.05*, ** *p < 0.01*, *** *p < 0.001*

Table 8: Impacts of Different Policies on New SmarTrip Sales

	(1) Rebate Program	(2) Price Reduction	(3) Paper Farecard Elimination
Pass	50.97	29.74	-52.23
	(175.6)	(97.14)	(81.77)
Treat	-404.4***	-476.7***	-169.3*
	(34.72)	(25.73)	(67.18)
Pass*Treat	94.98	102.2	379.0***
	(70.83)	(52.57)	(76.56)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	24	24	24
R^2	0.918	0.966	0.862

Outcome variable: SmarTrips sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. * *p < 0.05*, ** *p < 0.01*, *** *p < 0.001*

Table 9: Impacts of $1 Acquisition Fee on New MetroCard Sales with Different Time Windows

	(1) 9-month	(2) 6-month
pass	0.0513	0.153
	(0.183)	(0.169)
treat	2.985***	2.674***
	(0.203)	(0.216)
passXtreat	-5.119***	-4.592***
	(0.256)	(0.270)
Month FE	Yes	Yes
Year FE	Yes	Yes
Observations	36	24
R^2	0.973	0.982

Outcome variable: MetroCard sales on monthly basis at network (aggregate) level (in thousands). Robust standard errors in parentheses. * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

New York City, respectively. It does not show a jump or discontinuity in ridership before versus after the policy changes. This suggests that changes in new SmarTrip card and MetroCard sales are unlikely to be caused by rides variations.

6.3 Factors Influencing Responsiveness to the Policy Changes

We use census tract socioeconomic characteristics such as median household income and unemployment rate that are obtained from American Community Survey data for heterogeneity analysis. Census tract data are then matched to each geocoded metro station record to identify factors that influence the new transit card sales.

6.3.1 Spatial Analysis of SmarTrip Sales Patterns

Figure 5 plots the spatial distribution of the new SmarTrip card sales across different subway stations after Washington Metro begun upgrading existing fare vending machines to dispense Smar-

Trip cards and eliminated paper farecards in September 2015. Metro stations in lower income neighborhoods and hub stations (major transfer station or the main downtown station) are associated with larger sales of new SmarTrip cards.

6.3.2 Spatial Analysis of MetroCard Sales Patterns

Figure 5 plots the spatial distribution of the new MetroCard sales across different subway stations after the $1 new card fee went into effect in March 2013. Different from the observed purchase patterns of SmarTrip cards, subway stations in higher income neighborhoods and hub stations (major transfer station or the main downtown station) are associated with larger sales of new MetroCards.

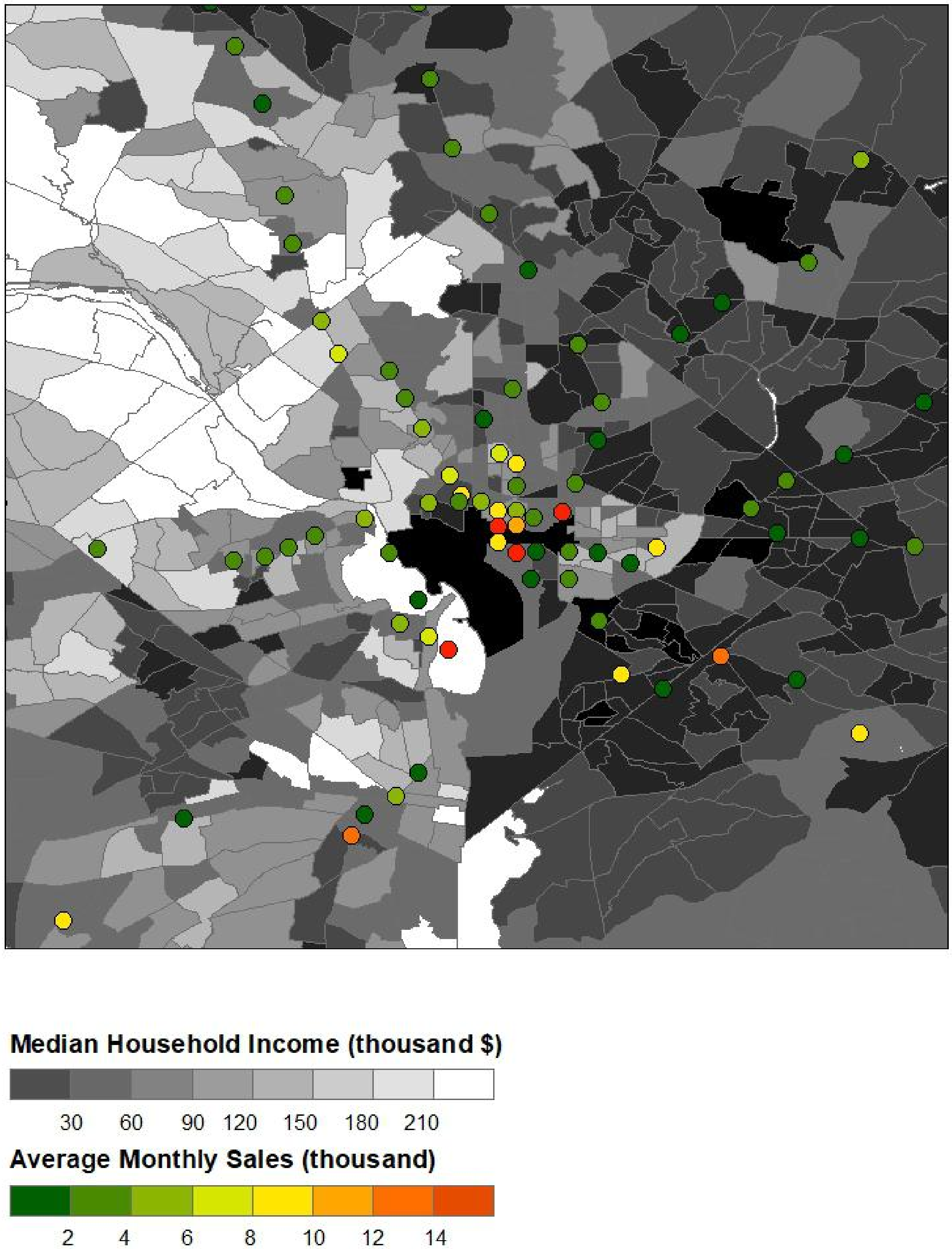
Table 10: New York City

	(lnSales)	(lnSales)	(lnSales)
lnIncome	-0.261**	-0.261**	-0.261**
	(0.0830)	(0.0830)	(0.0830)
lnPop	-0.155	-0.155	-0.155
	(0.188)	(0.188)	(0.188)
lnHHS	0.660***	0.660***	0.660***
	(0.155)	(0.155)	(0.155)
UnemployedRate	-1.345	-1.349	-1.349
	(0.870)	(0.870)	(0.870)
LineNumber	0.247***	0.247***	0.247***
	(0.0206)	(0.0206)	(0.0206)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	2467	2467	2467
R^2	0.115	0.117	0.117

Outcome variable: SmarTrips sales on monthly basis at station (aggregate) level. Robust standard errors in parentheses. * *p < 0.05, ** p < 0.01, *** p < 0.001*

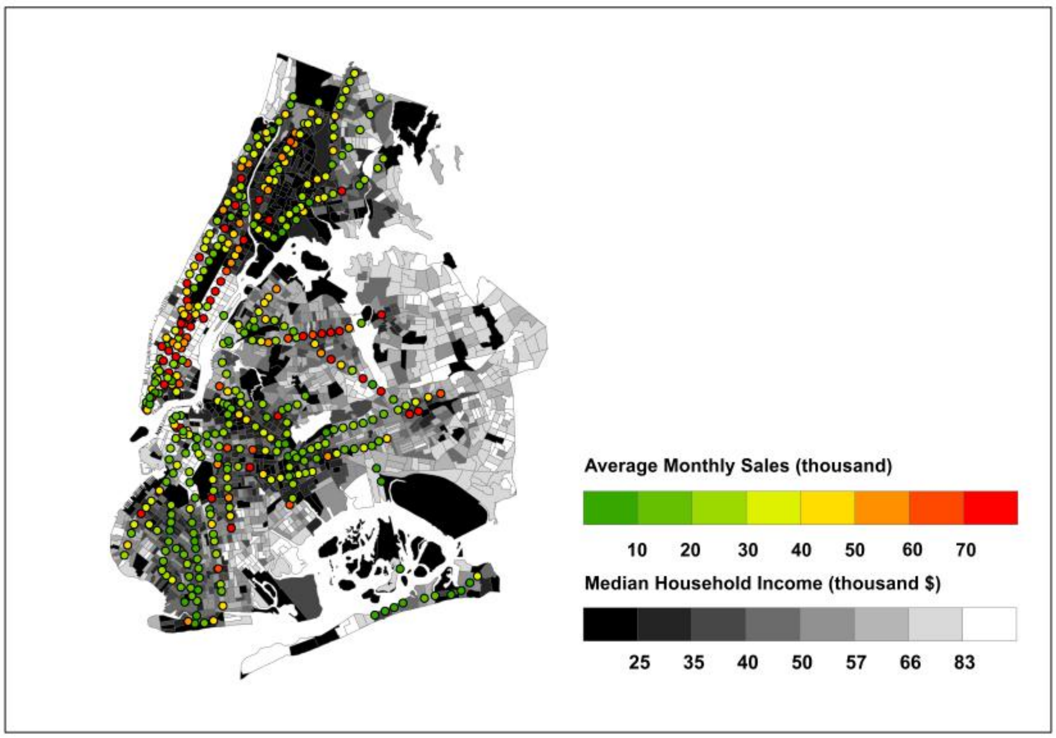
Table 11 summarizes results of the impacts of socioeconomic characteristics on new SmarTrip card purchases with different specifications, using monthly SmarTrip sales from September 2015 to December 2019. We find that neighborhoods with higher median household incomes are as-

Figure 5



Note: Figure 5 plots the number of new SmarTrips sold monthly in each metro station from January 2017 to December 2018.

Figure 6



Note: Figure 6 plots the number of new SmarTrips sold monthly in each metro station from January 2017 to December 2018.

Table 11: Washington DC

	(lnSales)	(lnSales)	(lnSales)
lnIncome	0.517***	0.517***	0.517***
	(0.127)	(0.124)	(0.124)
lnPop	-0.361**	-0.361**	-0.361**
	(0.130)	(0.124)	(0.124)
lnHHS	0.319***	0.319***	0.319***
	(0.0668)	(0.0599)	(0.0598)
UnemployedRate	-5.578***	-5.578***	-5.578***
	(1.048)	(1.025)	(1.025)
LineNumber	0.0671**	0.0671**	0.0671**
	(0.0234)	(0.0223)	(0.0223)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	1729	1729	1729
R^2	0.195	0.261	0.263

Outcome variable: SmarTrips sales on monthly basis at station (aggregate) level. Robust standard errors in parentheses. * *p* < *0.05*, ** *p* < *0.01*, *** *p* < *0.001* sociated with fewer new SmarTrip card sold. 1 percent increase in the median household income in a neighborhood brings about 0.3 percent decrease in the number of new SmarTrip card sold. Similarly, neighborhoods with higher share of Hispanics or African Americans are associated with fewer new SmarTrip card sold. 1 percent increase in the share of Hispanics in a neighborhood brings about 2 percent decrease in the number of new SmarTrip card sold. 1 percent increase in the share of Hispanics in a neighborhood brings about 0.4 percent decrease in the number of new SmarTrip card sold. In contrast, unemployment rates or poverty rates do not affect the magnitude of new SmarTrip card sales.

7 Discussions and Conclusions

Using a novel data set from the Washington Metropolitan Area Transit Authority (WMATA) system, this paper examines the impacts of different policies on new transit card (SmarTrips) sales. Specially, we assess the effects of rebate program versus price reduction versus paper farecard elimination on SmarTrip purchase patterns. As a simple before-after comparison may suffer from confounding biases and not reflect the true policy effects, we adopt a causal inference approach, a difference-in-differences (DID) model, to address potential estimation biases.

Using the DID model, we first estimate the impacts of different policy changes at the network (aggregate) level. The granularity of station-level new SmarTrip data after September 2015 also enables us to estimate the spatial variations in new SmarTrip card sales at each metro station (disaggregate level).

Disclosure Statement

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8 Temporary Table

Table 12: Washington DC

	(1)	(2)	(3)
lnIncome	-0.215*	-0.215**	-0.215**
	(0.0853)	(0.0831)	(0.0833)
Unemployment	-3.415***	-3.415***	-3.415***
	(1.012)	(1.001)	(1.005)
Race_Black	-0.308*	-0.308*	-0.308*
	(0.134)	(0.130)	(0.131)
Race_Hispanic	-1.951***	-1.951***	-1.951***
	(0.285)	(0.276)	(0.275)
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	2070	2070	2070
R^2	0.039	0.104	0.105

Outcome variable: SmarTrips sales on monthly basis at station (aggregate) level. Robust standard errors in parentheses. * *p < 0.05, ** p < 0.01, *** p < 0.001*

Table 13: New York City

	(1)	(2)	(3)
lnIncome	0.523***	0.523***	
	(0.0531)	(0.0531)	
Unemployment	-0.170	-0.170	
	(0.590)	(0.590)	
Race_Black	0.262***	0.262***	
	(0.0679)	(0.0678)	
Race_Hispanic	0.819***	0.819***	
	(0.0927)	(0.0926)	
Month FE	No	Yes	Yes
Year FE	No	No	Yes
Observations	2509	2509	
R^2	0.038	0.039	

Outcome variable: MetroCard sales on monthly basis at station (aggregate) level. Robust standard errors in parentheses. * *$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

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