The effect of an unconventional fare decrease on the demand for bus journeys*

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Abstract

We analyse the effect of a change in the fare structure for bus journeys in London on different demand measures using a regression discontinuity design. We utilise data obtained from Transport for London following the implementation of a new bus price policy in September 2016, in which a follow-up journey made within the hour of first paying for a journey became free. Drawing on millions of individual paid and unpaid journeys, we estimate the effect of this price policy on the number of paid bus journeys, follow-up journeys and bus passenger numbers. We find that the policy significantly increased the number of bus trips by 5% and follow-up journeys by 8%. Passenger numbers increased by 4%. We also find that the increase in demand was not only driven by new customers, but also by more intensive demand by existing customers.

Keywords: public transport, demand, travel choice, regression discontinuity design

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1. Introduction

To encourage the use of public transport and combat the effects of climate change transport policy makers invoke different transport demand management measures including hard and soft techniques (see Offiaeli and Yaman, 2021a). Transport providers can therefore influence transport decisions through their pricing policy which may have some effects on the generalised costs of travel. Transport for London (henceforth TfL), which oversees the transport network in London, implemented one such policy in 2016, namely the Bus Hopper Policy. A follow-up bus journey formerly paid for became free on the 12th of September as long as it was undertaken within the hour of paying for the first one;[1] akin to a 'buy one get one free within the hour' price promotion. Most of the extant literature on the effects of public transport fare changes on demand are based on fare increases. Perhaps the most pertinent literature is the work by Brechan (2017) who performs an analysis of the results from a trial involving 15 projects of price reduction and 9 projects of service increase on some transit corridors in Norway. However, the trials included in this meta-analysis took place in small cities (population<150,000), where the public transit system consists almost exclusively of buses.

Urban public transport offers a good laboratory to gauge the price effects on demand. Firstly, it is consumed at the point of purchase so that a journey purchase truly reflects demand. Goods, on the other hand, can be purchased when prices are low for future consumption, leading observers wrongly to conclude that a price decrease increased demand. Secondly, while changes in fares are communicated to the public, non-profit transport providers typically do not try to 'lure' customers into buying their service by combining fare changes

[1] In 2018 free journeys were extended to all follow-up journeys by bus or tram within the hour of the first one. We do not consider this extension here.

with other marketing tactics which further confound the estimation of price elasticities (see Offiaeli and Yaman, 2021b).

Our research is unique in several ways. Firstly, our research is set in London with a large population and many modes of transport including trams, trains, subways, bicycles, cars, taxis, buses, cable car, etc. Unlike previously studied cases, London passengers have a choice of alternative modes in a highly integrated transport system. The ease with which passengers could switch modes means that there are available substitutes which would have some effects on individual choice and behaviour. Secondly the Bus Hopper policy represents a tangible reduction in fares. Prices are often sticky in the downward direction and doubly so in public transportation. Scenarios where fares become nominally cheaper are very scarce in practice. Our paper is set apart because we examine a rare situation in London where journeys that were hitherto paid for became free.

Thirdly the policy provides a case study for an atypical change in fare policy. It is more akin to a ‘buy one get one free’ promotion than an actual price change. It is an economic truism that when prices drop more goods are demanded, but would this classical economic theory hold true when prices change in a rather unconventional manner?

This paper adds to the body of literature on the effects of price policy changes on demand and travel behaviour by using data obtained on bus demand before and after the policy implementation. We have a rare situation in public transportation where the price of a mode of transport is reduced subject to certain conditions and we analyse how passengers respond to the price reduction. Our identification relies on estimating how passengers react to the sudden change in price after the implementation date compared to before. We thus only consider the immediate impact of the new fare structure.

We estimate the average treatment effect using a sharp regression discontinuity design (RDD) as it enables the exploitation of a discontinuity in the treatment assignment to identify a causal effect (see Angrist and Pischke, 2009). An RDD is appropriate when a single continuous forcing variable (in this case time) is used to determine whether a trip is in the control or treatment group.

Our analyses show that the London Bus Hopper price policy had significant effects on the number of initial trips (by 5%) as well as follow-up journeys (by 8%). It also led to an increase of passenger numbers by 4%. Bus journeys per passenger also increased, so that the total increase in bus usage was driven both by more intensive use by existing customers as well as new customers choosing to use the bus.

2. Literature Review

2.1 Effects of fare changes on transport demand.

The demand for public transport is a derived demand, which is generally driven by variables such as; service levels, socio economic factors, fares, quality of service, trip purpose, time of travel, journey time, and income, amongst others (Chen et al., 2011; Currie and Delbosc, 2011; Paulley et al., 2006), with varying effects on an individual's demand function (see Nijkamp and Pepping, 1998; Bonnel and Chausse, 2000; Bresson et al., 2003; Canavan et al., 2018). These variables however, should not be considered in isolation from each other as their effects on public demand functions can be complex and intertwined (Balcombe et al., 2004; Paulley et al., 2006).

Fares and patronage are inversely related in that an increase in fares leads to a decrease in patronage and vice versa, by a proportion that is determined by the prevailing elasticity. The effect of fare increases or decreases is usually measured in elasticities. The response to a fare increase may not be the opposite of the response to a fare decrease; that is, they may be asymmetrical. Fare elasticities are dynamic and may be affected by the magnitude of the fare change. They vary over time (peak or off-peak), across journey purpose and periods (short, medium, or long runs), as well as across modes and locations (Dargay and Hanly, 2002; Paulley et al., 2006). In the UK for example, off-peak fare elasticity values are about twice the peak values. Peak values for bus, metro and suburban rail are estimated to be -0.26, -0.26 and -0.34 respectively while the off-peak counterparts are -0.48, -0.42 and -0.79 respectively (Balcombe et al., 2004). Monthly information on the different factors that influence public transport ridership, like fuel prices, unemployment rates, population and traditional bus fares, were used by Guzman et al. (2020) to estimate the effects of a nominal fare increase in Colombia's Bogotá. They find that the elasticity's absolute value decreases from -0.565 (1 week) to -0.408 after a month and that low-income users, as expected, are more sensitive to fare changes.

In estimating the response of transit demand to fare changes Nijkamp and Pepping (1998) compare 12 studies from 4 European countries (Finland, the Netherlands, Norway and the United Kingdom). They conclude that the range of elasticity values is quite wide, from as low as -0.15 in the UK to as high as -0.8 in the Netherlands. Canavan et al. (2018) estimate elasticities of demand for metro services with respect to fares, income, quality of service, population and network length using a dynamic panel data model specification. They find a statistically significant negative fare elasticity of -0.25 in the long run for a passenger kilometre specified model and -0.4 in the long run for a passenger journey specified model. But it should be pointed out that the study only used a proxy for metro fares estimated through dividing annual revenue from fares by the annual number of passengers, not actual fare information.

Anciaes et al. (2019) show that manipulating price structures by reducing the complexity would lead to a substantial reduction in demand (11% to 45%, depending on route segment). By contrast, increasing complexity by adding new flexible or advance tickets (valid on the services immediately before or after the chosen service) would increase demand by anything from 4% to 15%. In the same vein Sharaby and Shiftan (2012) use data from Israel's city of Haifa's new fare policy to evaluate travel behaviour. Haifa's new and integrated fare policy changed the historically complex per-boarding system to a simple five-zone fare system with free transfers, reducing fares for many passengers thereby making it very similar to London's Bus Hopper policy. They show a significant increase in single ticket sales of up to 25% over the first year following the launch of the reform, while the survey they carried out points to an increase of 7.7% in passenger trips and 18.6% in boarding numbers. It should be stated Haifa's public transportation system is 81% by bus; 17% by *sherut*, privately owned, fixed-route, communal transport services; and 2% by Israel rail, with a population of about 1million (Sharaby and Shiftan, 2012). In contrast, London offers multiple modes of transportation has a population of 9million.

Variations in elasticity also depend on location. People who live in urbanised and high population density areas tend to rely more on public transport while those in low populated areas depend more on their cars and therefore have higher fare elasticities. The effects of fare changes on competing modes depend on the transport network integration; the greater the interchange ability the lower the fare elasticity. Aside from ticket fares other pricing methods such as congestion charges, parking charges and emission charges could also be implemented to encourage public transport ridership. Chen et al., (2011) use trip and fares data for travel between and New Jersey and New York to conclude that a rise in transit fares leads to a decrease in demand while a drop in fares has no significant effect on demand. We note that they consider only real prices from which they calculated price decreases using inflation index rather nominal or actual price changes.

Brechan (2017) performs an analysis of the results from 15 projects involving price reduction and 9 projects involving increased service frequency on some transit corridors in Norway. The results show that both price reduction and increased service frequency generated public transport demand, in particular, the average effect for the price reduction projects is reported to be 30%. Again, all the route and fare trials included in this meta-analysis took place in smaller cities (population<150,000), where the public transit system consists of almost exclusively buses, which probably accounts for the magnitude of the elasticity obtained. Our research differs from Brechan (2017) in that our data is set in London where passengers have a choice of alternative modes in a highly integrated transport system. The ease with which passengers could switch modes means that there are available substitutes which would have some effects on individual choice and behaviour, making our research significantly different. Prices are generally sticky in the downward direction and particularly so in public transport. Our data set is unique and presents an appropriate setting to explore the responses of demand to an actual decrease in price rather than an inflation indexed decrease used in most, if not all, the existing literature.

3. The Bus Hopper Policy

Buses are by far the most used mode of transport in London, accounting for slightly over 2.2 billion passenger journeys in 2018 compared to just over 1.5 billion mustered by London Underground and Light Railway combined (TfL, 2019). On the 12th of September 2016, the Mayor of London, through TfL, introduced the Bus Hopper Policy. The policy was announced by press release a week prior to its stars, on the 5th of September. The policy was introduced for two broad reasons. Firstly, it enables millions of passengers to save on their generalised costs, in terms of fares and time, on the London transport networks. It benefits travellers on lower income who mostly use the bus network. The idea is that passengers could switch modes since travelling by bus would become cheaper. Secondly as a positive externality of the cheaper travel policy visitors and Londoners alike are encouraged to use public transport instead of cars to help reduce both congestion and pollution. By agreeing a 'Low Emissions Bus Zone' and only buying hybrid or zero-emission double-decker buses the Mayor of London, working with TfL, aims to reduce vehicle emissions within London significantly. At its introduction the Bus Hopper Policy allowed passengers to make one follow-up journey on London's bus network for a nominal fare of £1.50 within one hour from the first paid journey. Once a passenger touches in using a valid payment method the Hopper fare is automatically applied to the journeys of anyone who uses the same card or mobile device to pay as they go. In other words, passengers could 'hop' from one bus to another at no extra cost as long as it was done within the hour. This represents real savings for millions of people who live, work in, or visit London. More than 450,000 bus and tram trips were made every day using the Hopper fare. Since its launch 160m journeys were made using the hopper fare (London Assembly, 2018).

4. Data

The data are from TfL's ODX database which records every bus journey on London's network. Only paid weekday journeys are considered. We obtained individual journeys made between the 14th of June 2016 and the 11th of December 2016, which represent data for 3 months either side of the policy implementation date amounting to 6 months in total. To validate that changes in 2016 are driven by the new policy rather than other (seasonal) factors we also obtained the same data for the year 2015. For each passenger-day combination, we have data on the number of bus trips, distinguished by 'First trips' (subject to payment under the Hopper policy) and 'Hops' (not subject to payment, see also below). We also obtain the daily total number of distinct people travelling on the buses in the study period (Passengers). Each passenger is identified by a unique number, the total number of distinct passenger numbers are then summed to get the total passengers. Since the policy was introduced on the 12th of September, time (measured in days) presents the forcing variable. Payment for bus journeys are made by tapping a payment card on the on-board fares collection equipment.

The analysis of the effect of the Hopper fare is complicated by a peculiarity in the data collection. Customers could tap in when entering a bus by using a so-called Oyster card. This card contained pre-paid credit and had to be topped up when the existing credit did not cover the fare. This was still the predominant payment method in 2017. Alternatively, customers could pay by tapping in their bank debit card. These payments were introduced in 2012 but started to be registered on TfL's ODX database only in August 2016, which unfortunately is just before the Hopper policy became effective. We therefore restrict our analysis to bus journeys which were paid for by Oyster card only. As such, our analysis does not cover the entire demand for bus travel unless we assume Oyster card users to behave the same as customers paying by bank card.

We consider the following variables:

First Trips and Hops

First trips are trips which would be paid for under the Bus Hopper Policy. We apply this terminology irrespective of whether the Hopper policy was in place or not. Every first bus journey on a day counts as a *first trip*. A bus journey which is undertaken within an hour of a *first trip* is a *hop* (e.g., would be free under the Hopper policy). A bus journey that is undertaken after a *hop* is a *first trip* (since the Hopper policy allows for ONE free follow-up journey). A bus journey undertaken after a *first trip* which was more than an hour ago, is again a *first trip* (since the follow-up journey must be undertaken within one hour). If more people use the bus, then *first trips* should increase. If people use the bus more frequently, then both variables should increase. It is also possible that in response to the Hopper fare people time their trips such that they substitute a *hop* for a *first trip* (e.g., finishing their shopping quicker to take advantage of a *hop*).

Passengers

Passengers represent the daily aggregate number of distinct people using the bus network. As stated earlier, the data contains unique travel information of each individual passenger. A passenger may have one *first trip* and two *hops* or may have four *first trips* and nine *hops* within the day. In either case we would count this as one passenger. We expect an increase in the number of *passengers* since certain bus journeys became cheaper with Hopper fare. All things being equal, we expect a positive effect on *passengers* as more people would likely switch modes to enjoy the 'free ride'.

First trips per passenger, hops per passenger, hops per first trip

First trips per passenger and *hops per passenger* are informative about the intensive margin of demand for bus journeys. For example, if the increase in *first trips* is driven entirely by new customers, then we would expect no or little effect on *first trips per passenger*. On the other hand, if *first trips* is driven by existing customers who use bus services more often, then the increase in *first trips per passenger* should be similar to the increase in *first trips*. A similar reasoning applies to *hops per passenger*. Finally, *hops per first trip* is an alternative measure of the intensive margin of bus journey demand. If people switch to buses in anticipation of benefiting from the Hopper fare, or if people substitute *hops* for *first trips*, then this measure should increase.

[Table 1 approximately here]

Table 1 presents summary statistics on our outcome measures, divided by year and time period (before vs. after the 12th of September). We observe that in 2016 *first trips*, *hops*, and *passengers* increased by approximately 4%. However, compared to 2015, the most striking increase is in *hops* – this variable increased only by 0.3% in 2015, but by 3.9% in 2016 when the Hopper fare started. Similarly, while *hops per passenger* dropped in 2015 by 3.4%, it did so in 2016 by only 0.3%. We also observe that bus use in 2016 is lower than in 2015. This could be due to lower demand for public transport in general, or can perhaps be explained by an increasing uptake of paying by bank card which is not included in our data (see section 3).

5. **Model Specification**

We estimate the effect of the Hopper policy on impact, that is upon its launch, using a Regression Discontinuity Design (RDD). RDD has become increasingly popular in economics since its introduction by Thistlethwaite and Campbell (1960). RDD requires relatively mild assumptions compared to other non-experimental approaches to econometrics (Angrist and Lavy, 1999; Angrist and Pischke, 2009; Lee and Lemieux, 2010). Treatments are assigned to units above or below a threshold; in this case the 12th of September is the cut-off (treatment) date. Since time perfectly sorts our observations into treatment and control days, the RDD is sharp. An RDD is appropriate when a single continuous forcing variable is used to determine whether a trip is in the control or treatment group. While the RDD produces an impact estimate which can confidently be interpreted as causal, it can identify this effect only in a narrow window around the forcing variable. In our case, we can estimate the impact of the Bus Hopper policy when it was introduced – and arguably no other change occurred which could cause a discontinuous change in bus travel demand. However, we do not attempt to uncover its medium- or long-term effect on bus travel demand.

In this analysis the forcing variable used is date while the threshold is determined by the date of the implementation of the Bus Hopper policy (12^{th} September 2016). If a trip is made on or after the 12^{th} of September 2016 then it is classed as treated (subject to the Hopper policy), while those trips made before the 12^{th} of September are in the control group.

Our general econometric model is of the following functional form:

$$Y_t = \beta_0 + \beta_1 \, Post_t + \beta_2 X_t + f(t) + \mu_t$$

Where $Post_t = \begin{cases} 1, & t \geq c \\ 0, & t < c \end{cases}$

The receipt of treatment or participation in the policy, *Post*, at any time t, is determined by the threshold c (=the 12^{th} of September, which we set to 0). β_1 is the immediate effect of the treatment on outcome Y. X is a vector of dummies for the day of the week, and $f(t)$ is a polynomial function of time t, on either side of the threshold c, which captures the trend in Y over the sample period. The random error term μ is assumed to be normally distributed and has mean 0. The equation represents a *sharp* RDD because treatment assignment is deterministic and discontinuous at the cut-off: all observations with $t < c$ do not receive treatment and all observations where $t \geq c$ are treated.

[Figure 1 approximately here]

[Figure 2 approximately here]

[Figure 3 approximately here]

Figures 1-3 show the log of daily averages of *first trips*, *hops*, and *passengers* in 2015 and 2016. The cut-off date of September 11 – the day before the Hopper policy became effective – is marked by a vertical line. On both sides of the cut-off date, we also fit a third-degree polynomial. All graphs indicate that bus use drops off towards the end of July, marking the beginning of the summer school holidays, and picks up again in September. Judging from the polynomial fit, there does not seem to be a significant change in bus usage just around the cut-off date. However, the polynomial is misleading. We see clearly from the scatter plot of *hops* in 2016 (Figure 2, right hand panel) that *hops* are more frequent after September 12 than before. Yet, in trying to fit the unusually high number of *hops* just before the cut-off date, and the unusually low number of *hops* just after, the polynomial function increases sharply before and again after the cut-off.

[Figure 4 approximately here]

[Figure 5 approximately here]

[Figure 6 approximately here]

Figures 4-6 replicate the figures after leaving out the five days just before and just after the cut-off. The data series now look smoother and the upward jump in the polynomials around the cut-off date in 2016 now point towards the expected effect of the Hopper policy. In 2015 there is no sudden change around the same cut-off date. Thus, the changes observed in 2016 seem unlikely to be explained by seasonal and other factors, since we should observe these effects also in 2015.

6. Results

Table 2 reports the estimated 'treatment' effects on the dependent variable. Since the dependent variables are in logs, the estimated β_1 translate into $(100*\beta_1)$% changes in the dependent variable. All our models include day-of-the-week fixed effects to control for any changes in daily demand within the week. Standard errors are calculated as heteroskedasticity robust standard errors.

[Table 2 approximately here]

The results indicate that the number of *first trips* (panel 1) increased by 5.2% after the introduction of the Hopper policy in 2016 – an estimate significantly different from zero at the 5% level. In the previous year, there is no discernible difference in *first trips* around the 11th September. If the effect in 2015 constitutes a valid counterfactual scenario to what would have happened to demand if there had not been the Hopper policy, then the difference between the estimated effects for 2016 and 2015 can be given a causal interpretation. This difference is also 5.2%, but the difference is not as precisely estimated and thus insignificant.

Not surprisingly, the strongest effect is found for *hops* (panel 2). *Hops* increased by 8.1% after the Hopper policy, and the difference to previous year's increase was 6.3%. *Passengers* (panel 3) increased by 4.1% (4.3% compared to 2015).

The results for our measures of the intensive margin of demand (panels 4 to 6) also suggest positive effects of the Hopper fare. A typical passenger undertook 1% more *first trips* (0.9% compared to 2015), and 4.1% more *hops* (2% compared to 2015). Finally, 2.9% more *hops* were undertaken for every *first trip*.

7. **Conclusion**

We have evaluated the performance of the London Bus Hopper policy by examining the effects on 6 key variables: number of *first trips*, number of *hops*, number of *passengers* and the measures of the intensive demand margin *first trips per passenger*, *hops per passenger*, and *hops per first trip*. Our results show that the London Bus Hopper price policy had significant effects on bus usage on all of those dimensions, with the strongest effect on the number of hops. We conclude that the policy was effective and worked as intended upon its launch.

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Figures and Tables

Table 1: Summary Statistics (Daily average)

	2015			2016		
	Before	After	% change	Before	After	% change
First Trips (in 1,000)	3,465	3,579	3.29	3,177	3,300	3.87
Hops (in 1,000)	1,274	1,278	0.31	1,133	1,177	3.88
Passengers (in 1,000)	1,797	1,869	4.01	1,660	1,731	4.28
First Trips / Passenger	1.93	1.92	-0.67	1.91	1.91	-0.42
Hops / Passenger	0.71	0.68	-3.39	0.68	0.68	-0.29
Hops / First Trip	0.37	0.36	-2.72	0.36	0.36	0.28
Number of days	57	60		58	60	

Averages of daily outcomes by year and period. Before is the period from mid-June to September 11. After is the period from September 12 to mid-December. % change is the percentage change from Before to After.

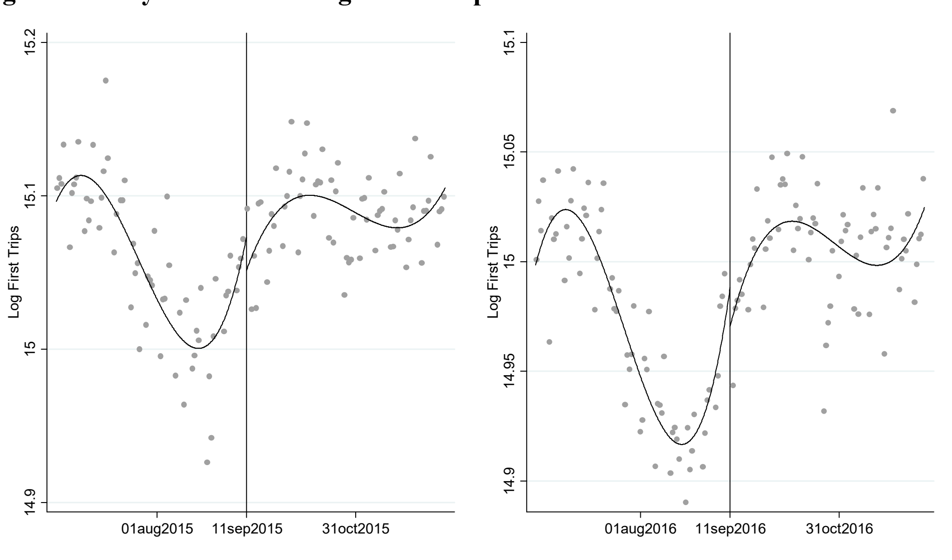
Table 2: RDD estimates for 2015 and 2016

	(1) First Trips			(2) Hops			(3) Passengers		
	2015	2016	Difference	2015	2016	Difference	2015	2016	Difference
Coefficient	0.001	0.052**	0.052	0.018	0.081***	0.063	-0.003	0.041**	0.043
Standard error	(0.028)	(0.020)	(0.035)	(0.050)	(0.030)	(0.058)	(0.021)	(0.016)	(0.026)

	(4) First Trips per Passenger			(5) Hops per Passenger			(6) Hops per First Trip		
	2015	2016	Difference	2015	2016	Difference	2015	2016	Difference
Coefficient	0.003	0.012**	0.009	0.021	0.041**	0.020	0.018	0.029**	0.011
Standard error	(0.009)	(0.006)	(0.011)	(0.033)	(0.017)	(0.037)	(0.026)	(0.013)	(0.029)

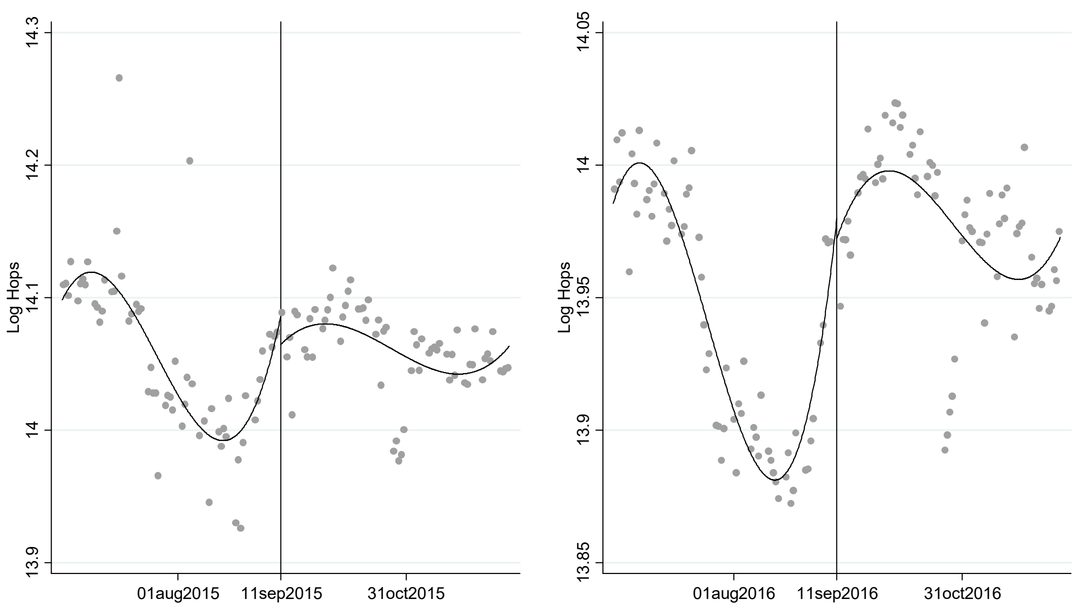
Estimated effects of the September 12 cut-off (β_1) on bus demand measures. All measures are in natural logs. Coefficients are semi-elasticities (β_1*100 percent change). The Bus Hopper was introduced on September 12, 2016. First trips are trips that would be paid for under the Bus Hopper fare. Hops are trips which would not be paid for under the Bus Hopper fare. Passengers are the number of distinct passengers on a day. All regressions include day-of-week dummies and third degree polynomials of Date on either side of the cut-off date (see also Figures 2 to 7). Standard errors are in parentheses. * $p < 0.1$ ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Daily values of the log of first trips



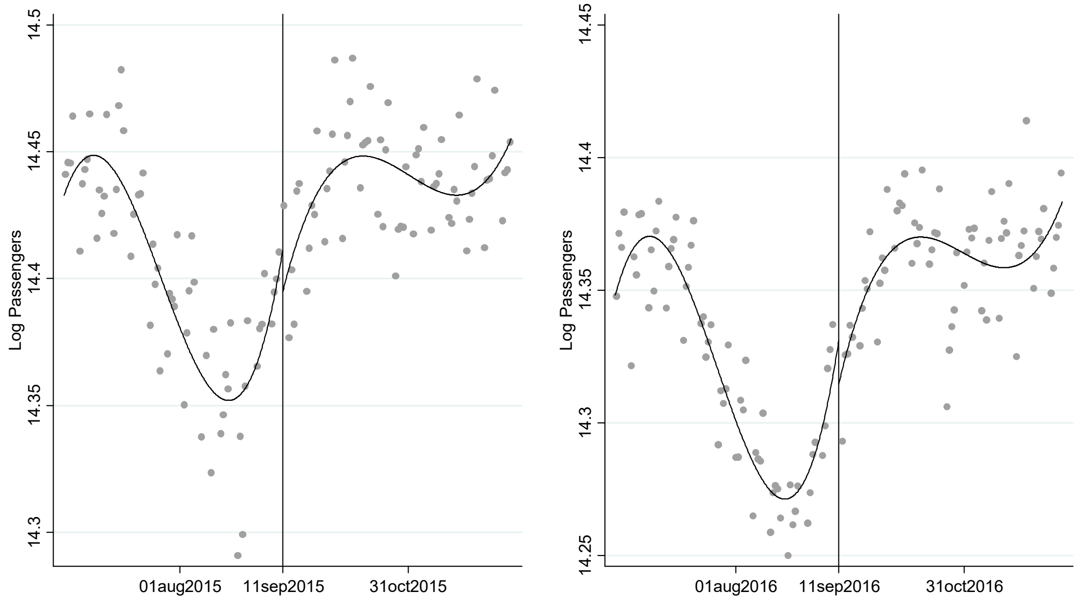
Scatter plot of daily first trips (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 2: Daily values of the log of hops



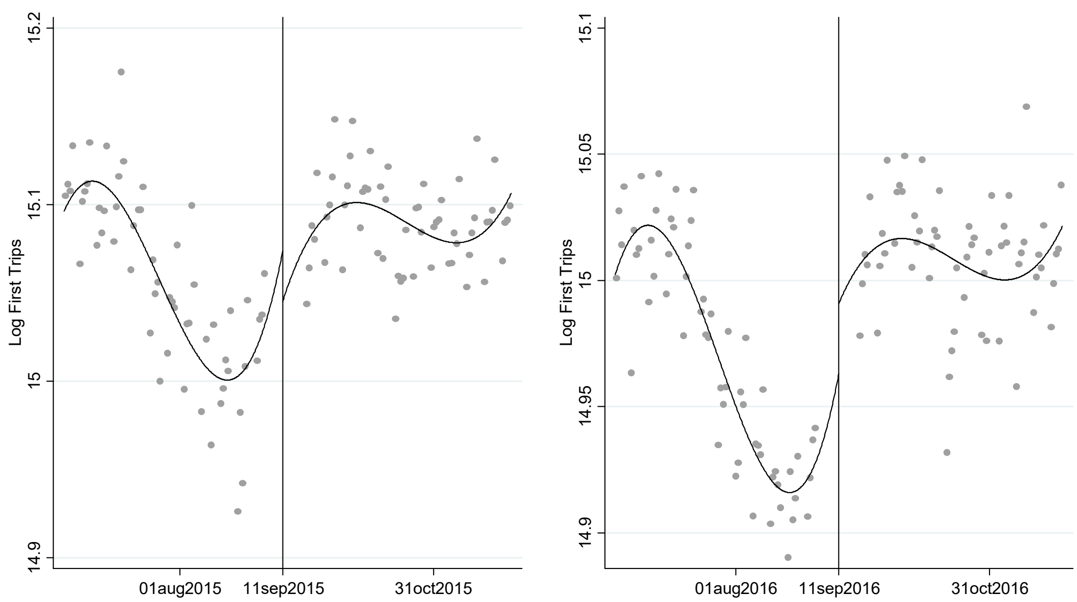
Scatter plot of daily hops (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 3: Daily values of the log of passengers



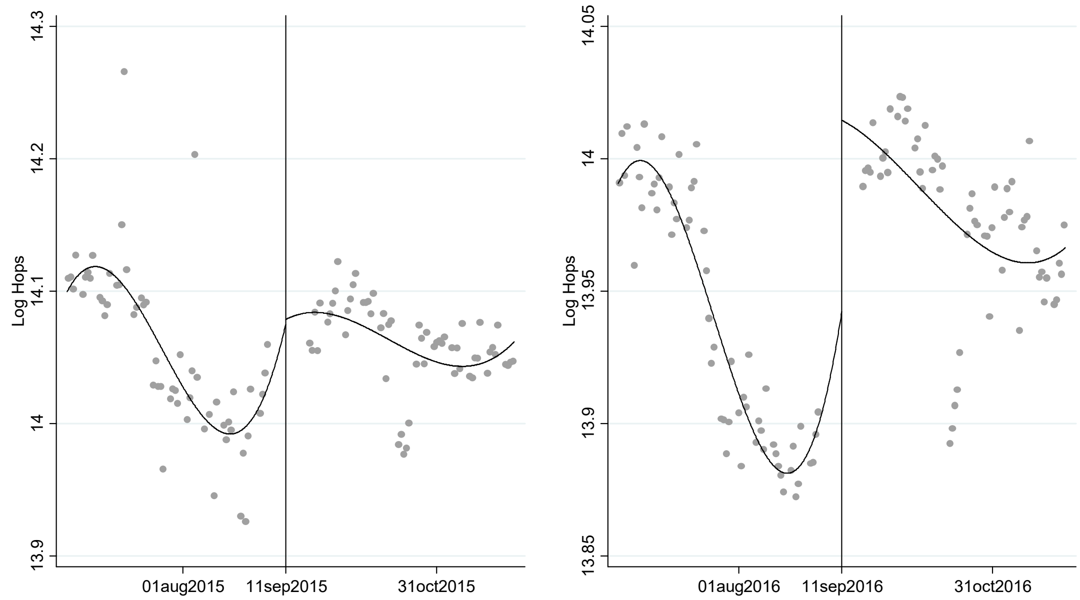
Scatter plot of daily passengers (in natural logs) in 2015 (left) and 2016 (right). The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 4: Daily values of the log of first trips (smaller sample)



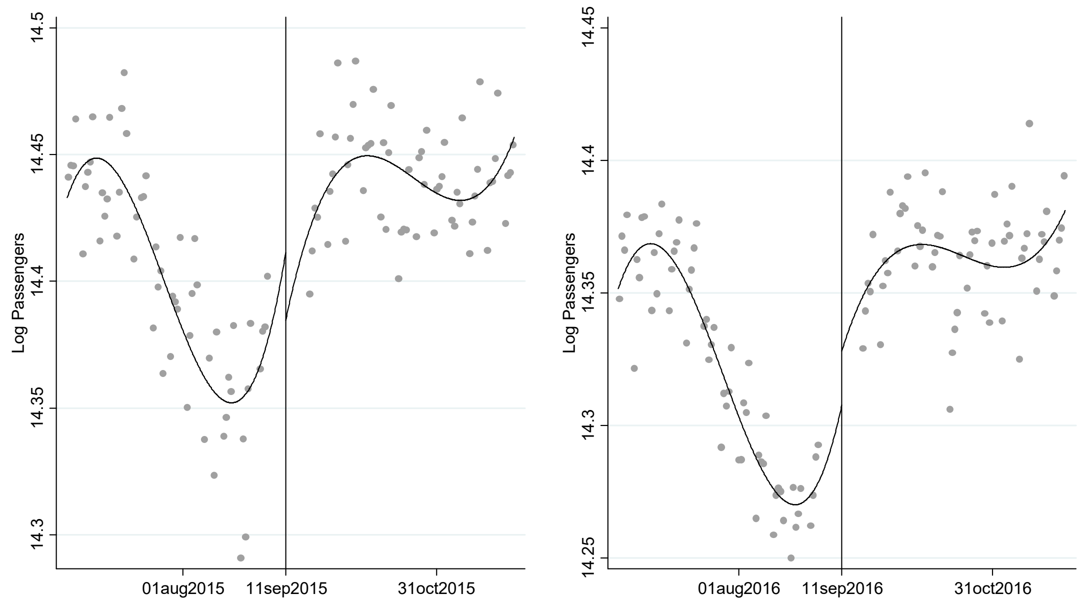
Scatter plot of daily first trips (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 5: Daily values of the log of hops (smaller sample)



Scatter plot of daily hops (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.

Figure 6: Daily values of the log of passengers (smaller sample)



Scatter plot of daily passengers (in natural logs) in 2015 (left) and 2016 (right) after removing the five days before and after the cut-off date. The vertical line is the 11th of September (the day before the Hopper fare became effective in 2016). The smooth lines are third degree polynomial fits for the periods before and after the 11th of September.