EQUITY IMPACTS OF THE LONDON CONGESTION CHARGING SCHEME: AN EMPIRICAL EVALUATION USING SYNTHETIC CONTROL METHODS

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ABSTRACT

Congestion pricing has been long-believed to effectively regulate traffic in urban city centers. Practical implementations of such policies have been hindered by concerns that they would disproportionately and adversely impact low-income groups. This paper analyzes the impacts of two price increases to the congestion charge on different income groups in Central London, making use of the Synthetic Control method to leverage empirical data from the UK National Travel Survey. We estimate that the highest income earners contributed to more of the revenue than the lowest income earners, making the scheme progressive in the scale of its equity impact. Although high-income travelers appeared to drop more charge-eligible trips as the price increased, their total trips to Central London did not decrease, suggesting that they were able to substitute with non-chargeable modes of travel. Low-income travelers saw large declines across both chargeable and non-chargeable modes, revealing a much lower rate of substitution. The low-income group responded more to the 2011 price increase than the 2014 one, demonstrating the diminishing ability of subsequent price increases to regulate demand.

Keywords: Congestion Pricing, Equity, London Central Charging Scheme, Synthetic Control Methods

INTRODUCTION

Traffic congestion is a growing problem with high economic, environmental, and health costs to our cities. Congestion pricing, a policy of charging drivers in a congested area a higher price during peak times, has long been heralded as the solution. Yet, despite a hundred years of academic scholarship, only a handful of major cities have implemented true urban congestion pricing (*1*).

One of the main barriers to the implementation of congestion pricing is the concern that this policy would disproportionately burden already vulnerable groups. Taking into consideration differing levels of flexibility over travel behavior, such as high income workers having more flexible work hours or low income households needing to find affordable housing further away from the city center, it is natural to ask whether congestion pricing is a regressive policy, with low income drivers bearing the brunt of the burden (*2*). On the other hand, the current transportation landscape can itself be considered inequitable due to its auto-centricity, given the high cost of car ownership, and that people may be excluded from driving on the basis of age or disability (*3*). It has also been argued that there are important equity advantages to congestion pricing over classic transportation revenue schemes; while gas taxes apply to all trips, congestion pricing applies only to trips within certain geographic- and time-restrictions, and thus can be structured to be a more progressive policy (*4*).

Prior studies on the equity of congestion pricing, primarily using simulated data, indicate that the policy is not de facto regressive, but that the impacts depend on the scheme set up and revenue redistribution, as well as how fairness is measured (*5*–*8*). Yet the evidence is lacking with respect to empirical studies evaluating how different incomes groups actually responded to charging conditions. One of the major barriers to studying the impact of past congestion schemes from a distributional lens is the lack of data that continues demographic indicators; most congestion pricing schemes are monitored with count data and often only do in-depth monitoring for the first few years of implementation. Setting up comprehensive data collecting schemes is expensive and time consuming. Cities can be hesitant to start pilot projects without supporting evidence from existing congestion schemes. There is a need to find methods to use existing sources of transportation data to study the distributional impacts of congestion pricing and how impacts differ over time.

This paper makes use of the Synthetic Control Method in order to use data from the UK National Travel Survey to understand how travelers from different income groups responded to the 2011 and 2014 congestion charge increases in the London Congestion Charging Scheme (LCCS). This paper not only examines the heterogeneous responses of income groups to congestion charging, it also examines how those responses change over time.

The main findings of our analysis can be summarized as follows:

- The LCCS impacted high-income drivers the most, and as a revenue scheme can be regarded as mildly progressive, with the top 40% (by income) of drivers accounting for approximately 60% of the revenue.
- High income travelers (top 40% by income) drop more *chargeable* trips (i.e., trips that are subject to congestion charges) compared to low income travelers (bottom 40% by income).
- However, low income travelers drop more trips into Central London overall (25%, compared to 2%), suggesting that congestion charge-eligible trips reduced are increasingly forgone entirely instead of substituted to a non-chargeable mode or time of day.
- As the congestion charge continues to increase over time, the charge-eligible trips that

remain are increasingly inelastic and less responsive to the price increases. This raises an important equity consideration that must be addressed with income specific policies such as rebates or tax credits.

BACKGROUND AND PRIOR WORK

There are many different lenses in which the equity impacts of congestion pricing have been analyzed in the past. Earlier theoretical studies (*9*) (*10*) (*11*) revolved around formalizing the equity concerns. Simulation-based studies leveraged choice modeling and traffic simulation methods to overcome the lack of empirical data, and to examine the potential of future congestion pricing schemes. This method has been used to estimate the optimal tolls and impacts for two English towns (*12*), to estimate the impact of the Stockholm charge ahead of implementation (*8*) or to predict who would be most impacted by a proposal for congestion pricing in Beijing(*7*). Empirical studies are the most limited in scope due to the lack of available data. Both Karlström and Franklin (*13*) and Franklin (*14*) leverage data collected by the Stockholm trial to analyze the heterogeneous responses of travelers to congestion pricing in Stockholm. Karlström and Franklin (*13*) find relatively neutral welfare impacts from the charging scheme. Franklin (*14*) extends this by examining the contextual factors (such as home/work locations and time flexibility) that contribute to a group's response to charging. Ecola and Light (*15*) provide a full summary of the notions of equity applicable to congestion pricing and Levinson (*16*) summarizes past studies on this topic.

The London Congestion Charging Scheme (LCCS) is one of the most studied urban pricing examples. Most studies of congestion pricing in London have used aggregate data published by Transport for London (TFL) to examine overall changes in travel behavior, and to conduct cost-benefit analyses. Munford (*17*) studied how congestion charging impacted an individual's investment in social capital by measuring trips to friends and family before and after the Western extension. Controlling for age and employment status, the study found that employed persons took more trips. Santos and Fraser (*18*) analyzed the aggregate changes in travel behavior from the start of the LCCS, and found that the initial £5 congestion charge internalized the average congestion externality quite well. They also concluded that overall, the LCCS had positive impacts.

Givoni (*19*) revisited some of the initial results of the LCCS introduction released by TFL, and concluded that the impacts were not as significantly positive in the long run. In particular, this study noted that many of the traffic reductions were driven by complementary polices (for example, investments in bus services), and that national trend shifts that could have been achieved even without the scheme. Santos and Bhakar (*20*) focused on welfare impacts and changes to generalized travel costs, and advocated for a more general approach to estimating the value of time. Tang (*21*) analyzed the role of the London Congestion Charge (LCC) in influencing housing values. While a number of important aspects of the London Scheme have been analyzed, no one has yet to consider the distributional impacts of the charge and how travelers of different incomes reacted differentially to price increases; this paper aims to fill this gap in the literature.

In this paper, we consider the vertical equity of the LCCS, and analyze how the outcomes differ for people in different income groups. In doing so, we consider both the *scale of equity impact* (i.e., how the subset of people impacted is skewed relative to the general population), and the *magnitude of equity impact* (i.e., how different groups within the impacted population are impacted differently). The scale of impact is often determined by the structure and location of congestion pricing (area vs. cordon, hours of operation): for example, congestion pricing downtown may be more likely to impact high income drivers, making it progressive in terms of the scale of impact.

Much of the prior work on the equity of congestion pricing has focused on the scale of impact, based on the land-use and travel patterns of a region (*6, 8*). A policy may be progressive in terms of the scale of its equity impact while being regressive in terms of the magnitude. For example, while a downtown congestion pricing scheme may mostly impact high income drivers, the price-to-income ratio may be so low for them that they would not notice the burden or change their behavior, or they may have enough flexibility to adjust their departure times to avoid the charges. By contrast, even though fewer low income drivers may be impacted by a downtown congestion pricing scheme, the price-to-income ratio may be so high for them that they would be forced to either incur a significant burden or change to a travel mode with much longer travel times. The above example also illustrates how the magnitude of equity impact can be influenced by the pricing structure and the availability of alternatives.

DATA SOURCES AND CASE STUDY BACKGROUND

The Central London Congestion Changing Scheme began in 2003. It is an area pricing scheme in which drivers of chargeable vehicles operating within the zone between 7:00-18:00 on weekdays pay a flat fee for the day (as of July 2020 this has expanded to 7:00 am to 10:00 pm, seven days a week). The boundaries of the scheme are shown in Figure 1. The boundaries were briefly expanded between 2007 and 2010 to include Chelsea, Knightsbridge, and Bayswater as part of the Western Extension (*22*).

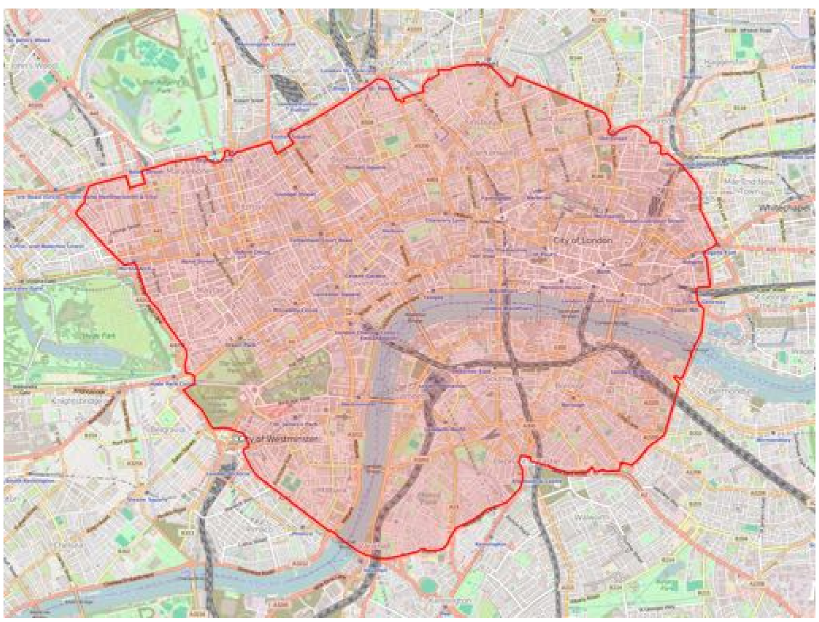

FIGURE 1 Central London congestion charging zone. Image from (*23*).

The congestion charge was initially priced at £5, and has since undergone five price increases; the current fee is £15. Cameras are used to read license plate numbers, which are checked against a database. Drivers can pay by telephone, text message, online, or by mail, before or on the day of travel. Auto-pay is also available. There are a small number of exemptions for licensed taxis and motorcycles, and discounts for Blue Badge holders and residents of the zone. TfL has also introduced a number of new transportation polices, many of them funded by congestion charge revenues, a timeline of these policies, along with key events, is shown in Table 1. TfL is legally required to re-invest any income left after operating costs in London's transport infrastructure (*24*)(*25*). Revenue from the congestion charge has been used to improve bus service, expand the network and improve the quality of roads, including safety, bicycle and pedestrian upgrades(*24*).

In order to monitor the congestion pricing scheme, TfL analyzed count data collected by the Automatic Number Plate Recognition (ANPR) cameras set up to charge cars entering and traveling within the zone. Additionally, from 2003 to 2008, TfL produced detailed annual Impacts Monitoring Reports, leveraging their traffic and transit data as well as data on air quality, accidents, economic activity and responses to a Social Impact survey, to track a range of key performance metrics. While this data painted a strong picture of the success of the scheme in reducing traffic and improving quality of life, none of this data was disaggregated based on any demographic indicators and the monitoring halted at the end of the five year period (*24*).

TABLE 1 Timeline of relevant transit policies and major events related to the LCCS.

Year	Events
2003	Congestion Charge begins at £5
2005	Congestion Charge increases to £8
2007	Western Extension added to Congestion Charging Zone, cut-off time moved from 18:30 to 18:00
2008	Introduction of initial phases of the Low Emissions Zone (LEZ)
2008	Economic recession
2010	Year of Cycling – increase in bike infrastructure
2011	Congestion Charge increases to £10, removal of Western Extension
2012	LEZ Phase 4 introduced
2012	Olympic and Paralympic Games in London
2014	Congestion Charge increases to £11.50
2017	T-charge put in place
2017	Mayor of London freezes public transit fares
2019	Private hire exemption reduced, charge now applies to Uber and ride-hailing companies
2019	Ultra Low Emission Zone (ULEZ) introduced and replaces T-charge
2020	Congestion, LEZ, and ULEZ charge suspended due to COVID-19
2020	All charges reinstated. Congestion charged increase to £15 and hours of operation expanded

Data Sources

This study uses data from the UK National Travel Survey (NTS) corresponding to trips into and out of Central London from 2007-2017 (*26*). This data is collected from face-to-face interviews and a 7-day self-completed written travel diary, allowing travel patterns to be linked with individual and household characteristics. Travel diary data is well-suited for equity analysis as it captures detailed information on trip purpose, time, and distance, as well as the mode and demographics of the traveler. In the case of the Stockholm trial, a specific travel diary survey was issued to monitor the pilot (*13, 14*).Standard annual travel diary data has the potential to be leveraged to study policy schemes, however it can require significant effort to standardize responses, and prepare the data for causal analysis.

Although the National Travel Survey included people in all age groups, we excluded observations for those under 16 years of age in our analysis as they cannot take independent car trips. The NTS employs a quasi-panel design, that is, half the sampling units are carried over from the previous year, and the other half are re-sampled (*27*). Consequently, we cannot trace the travel behavior changes of a specific household over time, but the sampling across groups is consistent enough that year-to-year comparisons can be made. While this data set does not encompass the initial introduction of congestion pricing in London in 2003, we believe it includes a sufficient number of trips (N=50,003) and time period (11 years) to evaluate how different income groups responded to congestion price increases both in the short- and long-run. Price-elasticity is not constant; as the congestion charge continues to increase it follows that those left on the roads represent increasingly the least elastic trips. Understanding who these inelastic groups are is critical to evaluating the equity of a policy in the long run. During this 11-year time period, the London charging scheme faced two price increases, and an overall price increase of over 43.75%. As a point of reference, inflation during this period averaged 2.4%, so the charge was increasing just ahead of inflation. To keep pace with inflation, 2011 price would have needed to be £9.6 (compared to £10 in reality), and the 2014 price increase needed to be £10.7, as opposed to the actual price of £11.50 (*28*).

It is important to note that this study is focusing exclusively on the congestion charge price increases. There are other pricing schemes in London (see Table 3 for full timeline), such as the LEZ or ULEZ. The LEZ was applied throughout London (not just Central London) on diesel-powered commercial vehicles, whereas the majority of trips reported through the NTS take place on personal vehicles. The T-charge was exclusive to Central London but was not implemented until April 2017 and only expanded to apply to more vehicles with the introduction of the ULEZ in 2019. Due to the constraints of our dataset these were not considered but could be grounds for future research to understand how the additive cost of both programs influenced behavior.

Tables 2 and 3 summarize the characteristics of the data set.

TABLE 2 Summary of NTS data analyzed in this paper for Central London.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Households	666	615	625	654	553	593	600	666	561	610	538
Trips	4,439	4,952	5,269	5,038	4,250	4,294	4,385	4,802	3,982	4,613	3,979

TABLE 3 Total number of Central London trips in each income quintile.

Quintile	1st (Lowest)	2nd	3rd	4th	5th (Highest)	Total
# Trips	5,398	5,191	7,114	9,929	22,371	50,003

SCALE OF EQUITY IMPACT

Our analysis finds that the scale of equity impact of the LCCS is progressive, consistent with the findings of (*7*), and (*8*), for the proposed schemes in Beijing and Stockholm, respectively.

Only 10.8% of the trips taken in Central London corresponded to travelers the lowest income quintile (the 1st quintile). The 2nd quintile was also underrepresented, with 10.3% of trips. A majority of trips taken to Central London were by wealthy individuals, with 44.8% of the trips taken by travelers in the top quintile. The skew decreases when we only consider chargeable trips; however, travelers from the lowest income quintile were still underrepresented with only 16.6% of chargeable trips, while the highest income quintile was over-represented with 38.6% of chargeable trips.

TABLE 4 Characteristics of Central London and Greater London travelers. All estimates were found to be statistically significant in the t-test comparison, with $p < 2.2$E-16.

	Central London	Greater London
Average age	37.2	42
Percentage male	42.2%	52.4%
Average quintile	3.8	3.2
Average no. of children in household	0.6	0.7
Percentage Blue Badge holders	2.8%	5.7%
Average number of vehicles	1.1	1.3

Table 4 summarizes the characteristics of travelers through the Central Zone and Greater London, as represented in the data set (2007-2017). Travelers in the Central London Zone were more likely to be male, wealthy, and young, than those in the Greater London area. They were also less likely to be Blue Badge holders [1], and had, on average, fewer children. The higher fraction of highest income quintile trips in our data set is both due to more such households traveling to Central London, and because households in the highest income quintile took more weekly trips on average.

The top two quintiles (i.e., top 40% of household income earners) took 57.3% of the charge eligible trips (charge eligible trips being auto-based trips taken during charging hours), while the bottom two quintiles only made up 30%. Assuming that all residents benefited equally from the revenue redistribution, this policy can be considered to be progressive. Considering the *net* effects and the fact that revenues were largely spent on public transit improvements (especially bus services, which low income households are almost 4 times as likely to take as high income households (*29*)), we conclude that this policy is, in fact, progressive in scale.

Even if the majority of the impacted population was high income, we still need to consider the level of burden faced by the impacted low-income travelers. Comparing travelers within Central London (Table 5), we find that drivers were more likely to be older, in a lower income quintile, and had more children, than non-drivers. The welfare impact of those who can easily adapt by switching to other affordable and convenient modes is very different from households who might have to drop the trip altogether due to the added financial burden. Understanding how different income groups responded to congestion pricing increases is crucial to evaluating the overall equity of a scheme.

[1] The Blue Badge is a program that eases parking/driving restrictions and grants access to designated parking space for persons with disabilities

TABLE 5 Comparison of Chargeable Travelers (with trips charged by congestion pricing) and Non-Chargeable Travelers (e.g., travelers using other modes of transport or changing departure times) within Central London. All estimates were found to be statistically significant in the t-test comparison, with $p < 2.2$E-16.

	Chargeable	Non-Chargeable
Average age	42.3	37
Percentage male	33.9%	42.6%
Average quintile	3.5	3.8
Average number of children in household	0.9	0.6
Percentage Blue Badge holders	11.6%	2.4%
Average number of vehicles	1.5	1.0

ANALYSIS USING SYNTHETIC CONTROL

The overall number of charge eligible trips decreased by 37% between 2007 and 2017 in the NTS data. Of course, not all dropped trips are a direct result of the price increases, there could be nation wide trends, for instance a growing awareness of climate change, that also contributed to a drop in auto-use during this time. Controlling for confounding factors and wider travel patterns is one of the biggest challenges of using more general transportation data to study an intervention such as congestion charge.

Many methods have been utilized in the past to add control and a lens of causality to aggregate data; Karlstrom and Franklin (*13*) used a propensity score matching estimator to match individuals impacted (driver's passing the cordon) by the Stockholm charge with similar, but non-impacted, individuals to better isolate mode shifts motivated by the charge. Difference-in-difference methods are also quite common, (*30*) use a difference-in-difference model to identify the impacts of the London congestion charge on road casualties. Most recently, (*31*) employed the synthetic control method to study the impact of Milan's road pricing on traffic flows across vehicle type.

Synthetic control is a method for doing causal inference on aggregate data. Whereas in previous methods, such as Difference-in-Difference, researchers use their best judgment to select one region/group to act as a control group, synthetic control uses a weighted combination of units to construct a synthetic control group that is most similar to the test group prior to intervention. This helps to overcome some of the selection bias at play in control group selection, as well as formalizes and adds transparency to the selection process. This method of control group synthesis can also be helpful in a case such as Central London where there is not one singular, obvious counterpart; instead by using a weighted compilation of a number of other cities/regions a more similar match can be created(*32*).

To examine how low and high income travelers responded differently to price increases in the London Congestion Charge we first constructed a synthetic control group using data from the NTS for other cities and travel regions in England. This data was supplemented with economic data from the Office of National Statistics to control for factors such as Gross Disposable Income per Household and Job Density(*33, 34*). Once the control group was defined we could then use this to compare how the number of charge-eligible (defined as auto-based trips taken between charging hours) trips differed after the price increases and compare this change in trips across income groups (using income quintiles are defined above).The goal is to assess how price increases in the congestion charge caused high- and low-income travelers to respond, and test to see if there was significant differences in how either group responded. Change in both charge-eligible trips within Central London and all trips within Central London was studied to see if driving trips "lost" to increases in the congestion price were being substituted back by either modal or temporal adjustments. By comparing changes in our "treated group", Central London, to changes that are expected from our "control group", a synthetically created Central London, this analysis can control for general travel trends and isolate shocks only present in the study region.

Match Specification

A weighted control group is chosen to most closely match Central London prior to the 2011 price increase. We match along the following demographic, trip-related and economic covariate factors: average age, # of kids per household, trips taken in cars, commute trips, job density and gross disposable household income. Due to the unique nature of Central London (much higher average incomes and more transit dependent than other regions), synthetic control helps to construct a better match than any one geographic unit alone would represent.

We used the "Synth" package in R to determine the composition of the synthetic control group this method utilizes the synthetic control procedure as defined by (*35*). It utilizes a optimization problem to select the optimal weighting of units from a "donor pool" (array of potential control units) such that the synthetic control closely resembles the test unit in pre-intervention characteristics. Matching is done both based on a matrix of pre-intervention covariates and pre-intervention outcomes (in our case the number of auto-based trips during charging hours). Weights, W, for each city are then chosen to minimize:

$$\|X_1 - X_0W\|_V = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$$

where X_1 is a vector of pre-treated covariates for the treated region, X_0 is the same for the donor region and W is the weight assigned to each donor region. V is a matrix that assigns weights to the importance of the variables in X_0 and X_1. *Synth* selects V to minimize the mean square error of the synthetic outcome estimator, that is the expectation of $(Y_1 - Y_0W)'(Y_1 - Y_0W)$ where Y represents the outcome,or number of auto-based trips during charging hours, for both the treated and untreated regions. (*32*) provides a full discussion of the theoretical properties of the method in which this optimization strategy is based on.

The donor pool consists of geographic regions from the National Travel Survey classification, only areas with full data are chosen, leaving 45 areas.These areas represent 88% of NTS recorded. Data is available from 2007 to 2017, aggregated to the half-year, leaving 22 time periods. Of these, eight time periods are treated as pre-intervention (pre-January 2011 price increase). From there the post-intervention period can be split into two, post-January 2011 containing seven time periods, and post-June 2014 price increase containing seven time periods.

Synthetic Group Generation

We chose to create six separate synthetic control groups and scenario.These six scenarios were selected to analyze changes in trip taking behavior across income groups and to compare changes to charge-eligible trips taken to overall trips in Central London. The differentiation between charge-eligible trips and total trips is important as drivers are faced with a number of different options under charging conditions. They can a) continue to take the trip as normal, b) switch to a non-charge eligible mode or take the trip during a non-charge eligible time or c) stop taking that trip into Central London. By separating out total trips and charge eligible trips we can compare how much of the drop in charge-eligible trips is due to options b) or c).

The six scenarios are as follows: all travelers charge-eligible trips (1) and overall trips (2); high-income (top 40% of income distribution) for both charge-eligible trips (3) and overall trips (4); and low-income (bottom 40% of income distribution) for both charge-eligible trips (5) and overall trips (6), see Table 6 for the full description. Traditionally, synthetic control is used to study the impact of an intervention, studying one case study across multiple time periods. But it can be extended to compare multiple cases; by using the same synthetic model specification across all scenarios we are able to isolate relative changes between income groups. In order to do this distributional analysis we must establish that changes across income groups are independent from one another. In our case independence is established as the travel patterns of drivers from one income quintile do not depend or differ with the travel patterns of another income quintile.

TABLE 6 Descriptions of scenarios.

	Outcome	**Population**
Scenario 1	Charge Eligible Trips	All Income Groups
Scenario 2	Total Trips	All Income Groups
Scenario 3	Charge Eligible Trips	High Income (top 40%)
Scenario 4	Total Trips	High Income (top 40%)
Scenario 5	Charge Eligible Trips	Low Income (bottom 40%)
Scenario 6	Total Trips	Low Income (bottom 40%)

Table 7 shows the weights applied to pre-intervention characteristics (X_0) and Figure 2 shows the weighting of geographic units from the donor pool. Table 8 shows the final matching between the treated group (Central London), synthetic control group and the overall sample mean for each scenario[2]. Here we can see that while the synthetic control group does a good job at matching along many parameters, the groups still differs in terms of number of household cars, commute trips, job density and gross disposable income index for a couple scenarios. All of these variables were selected as null weights in this scenario, meaning they had minimal predictive power for our outcome variable. This lack of a perfect match is mostly due to the fact that Central London is such an outlier when it comes to travel behavior in England, it is very difficult to generate a perfect control group representing the characteristics and travel behavior of Central London. This is one of the major downfalls of re-purposing travel data to study an intervention such as congestion pricing, there will never be perfect control of the data. However, understanding how people actually responded to past congestion price increases and in particular, being able to study these questions with a distributional lens, is crucial to the progress of policy going forward. Synthetic control allows us to get much closer to these answers than previously available.

[2] In order to handle the use of count data in synthetic control, the data is aggregated at the half year for each income group, hence why there are some differences between the means showed here and the tables in Section 4.1.

TABLE 7 Variables and the corresponding identified weightings. Weights sum to 1 for each hypothesis

	1	2	3	4	5	6
Age	0.004	0.127	0.159	0.066	0.002	0.186
Kids	0.067	0.181	0.027	0.009	0.002	0.008
Cars	0	0.015	0	0.099	0.003	0
# of Trips Taken on Automobiles	0.929	0.596	0.814	0.718	0.992	0.703
# of Commute Trips	0	0.08	0	0.106	0	0.103
Job Density	0	0	0	0.001	0	0
Gross Disposable Income Index	0	0	0	0	0.001	0

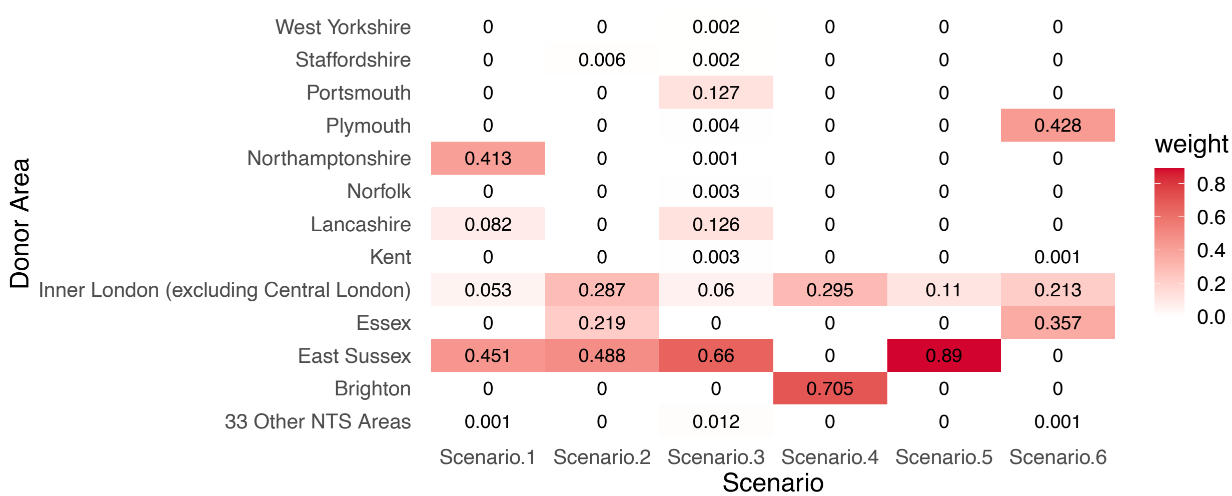

FIGURE 2 Geographic units and identified weightings. This table shows the weighting of each donor region across all six hypotheses. A higher weighting means that donor region was a better match, according to the variables shown in Table 6, and data from that donor region contributes more to the synthetic region.

TABLE 8 Comparison of the synthetic and treated means.

	Charge Eligible Trips			**Total Trips**		
	Treated	Synthetic	Sample Mean	Treated	Synthetic	Sample
All Incomes		(1)			(2)	
Age	41.51	42.98	43.77	41.51	42.75	43.77
Kids	0.50	0.50	0.561	0.50	0.53	0.56
Car_Ownership_HH	0.75	1.55	1.61	0.75	1.43	1.61
Non_Transit	111.83	115.32	580.40	111.86	322.09	580.40
Commute_Trips	614.53	98.35	220.4	614.53	413.11	220.40
job_density	61.88	3.94	2.26	61.88	18.21	2.26
GDHI	920.55	134.24	113.40	920.55	238.49	113.40
High Income		(3)			(4)	
Age	42.97	42.97	41.33	42.97	43.04	41.33
Kids	0.38	0.38	0.47	0.38	0.37	0.47
Car_Ownership_HH	1.09	1.95	1.91	1.09	1.37	1.91
Non_Transit	59.66	61.69	303.30	59.66	213.33	303.30
Commute_Trips	363.30	58.32	126.10	363.30	250.31	126.10
job_density	61.88	4.37	2.24	61.88	18.83	2.26
GDHI	920.55	141.70	113.40	920.55	232.01	113.40
Low Income		(5)			(6)	
Age	41.44	46.398	47.20	41.44	41.95	47.20
Kids	0.635	0.561	0.54	0.63	0.71	0.54
Car_Ownership_HH	0.588	0.936	1.222	0.588	1.364	1.222
Non_Transit	41.965	43.668	142.499	41.965	89.157	142.499
Commute_Trips	168.946	50.823	43.518	168.946	97.402	43.518
job_density	61.882	7.373	2.264	61.882	13.755	2.264
GDHI	920.55	173.244	113.404	920.55	185.689	113.404

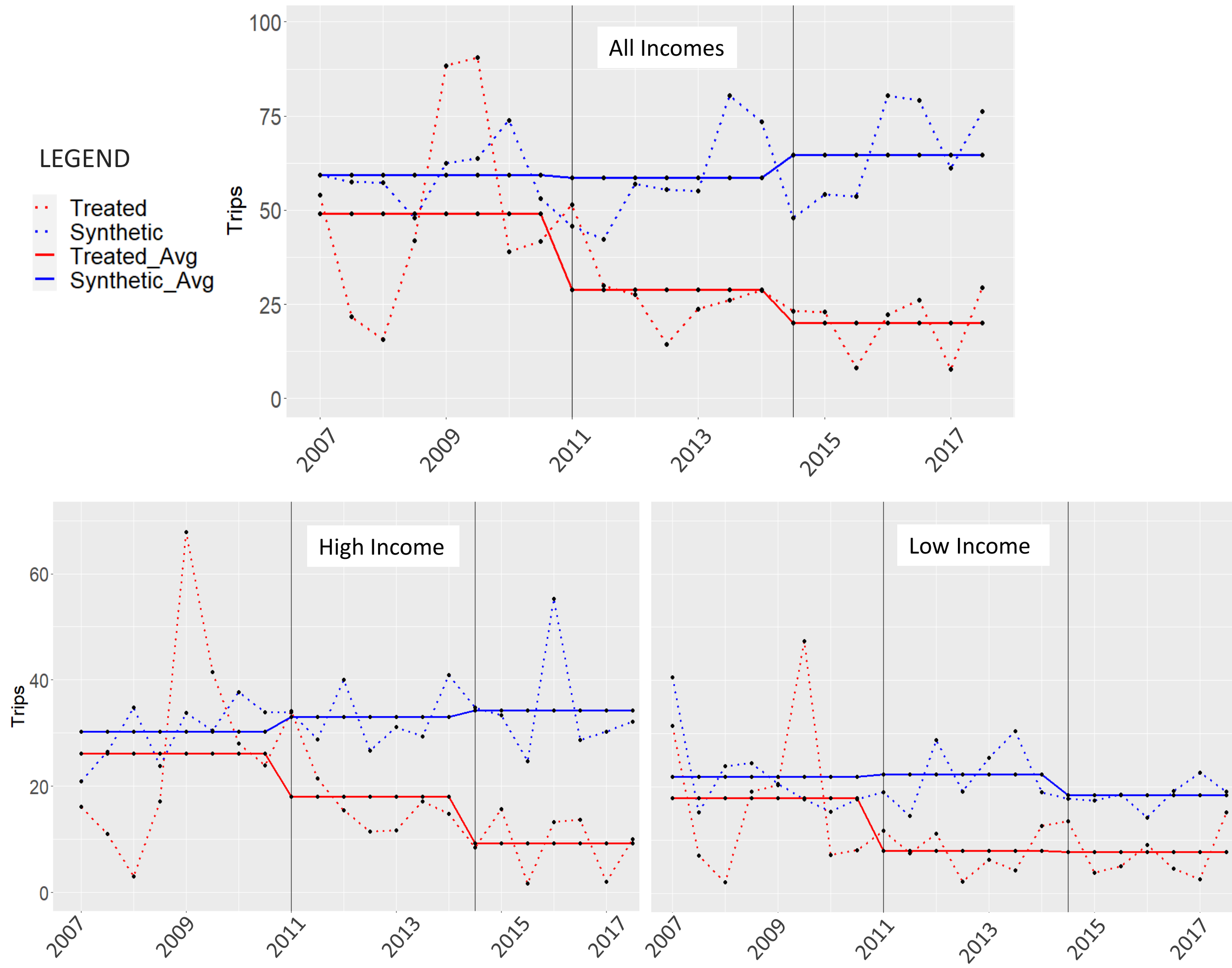

FIGURE 3 Charge eligible trips, for (top) all travelers, and (bottom) different income groups. The "Treated" series shows the number of trips actually recorded in Central London, whereas "Synthetic" represents the expected number based on the synthetically generated Central London.

High income drivers declined more in chargeable trips

Figure 3 shows the number of charge-eligible trips (auto based trips taken during charging hours) taken for both the actual and synthetically constructed Central London. Overall, we can see that while the line for the control group (synthetic Central London) remained stable, all three graphs show a drop in trips taken by the treated group (actual Central London) after each price increase. The average number of trips per time period dropped 59% from 2007 to 2017 in treated Central London (top graph). For high income travelers, this rate was slightly higher at 64% and for low income, slightly lower at 57%. Controlling for changes in average trips from the synthetic Central London, these adjusted rates are 68%, 78% and 41% for all travelers[3], high income and low income

[3] All future reported percentages are the controlled percentages; the rate of change for the treated group minus the rate of change for the synthetic group

travelers, respectively.

The large gap between high income and low income travelers response mainly stems from the third time period, post 2014 price increase, where low income drivers did not drop any further trips. High income travelers make up almost twice as many charge-eligible trips to Central London than low income travelers. With low income travelers already making up such a small portion of the population taking charge-eligible trips, it makes sense that those continuing to drive into Central London are less responsive to price changes. This can be a equity concern and we must consider whether this inelasticity is due to choice or constraint.

Due to the nature of London's congestion charge, there are three modes of substitution available to travelers: temporal shifts (taking trips outside charging hours), modal shifts (changing to a non-charged mode) or destination shifts (swapping destinations for something outside Central London). While willingness (and ability to pay) impact one portion of how elastic a person is to congestion pricing, ability to switch and access to these routes of substitution impact the other half. In the case of Central London and the available data, shifting destination equates to a "dropped" trip. One way to see if temporal or modal shifts were taken without having access to panel data is to compare cross-sectional data between total trips and charge eligible trips. If the total number of trips entering the Central London charging zones stays constant across the price increases, it suggests that trips that were once charge eligible have been adjusted to a non-chargeable alternative, such as transit trips or traveling in non-charging hours.

Low income travelers saw a larger decline in all trips to Central London

Comparing charge eligible trips (Figure 3) to total trips (Figure 4) we can see that this synthetic control model specification is able to generate a closer match for total trips. This again points to the unique nature of travel within Central London, already having a much lower rate of auto-based trips than any other comparable region, and highlights the challenge of studying congestion pricing with conventional transportation data. In this analysis however, comparing across income groups, the match between the treated and synthetic groups for both scenarios is the important indicator for this analysis, and is consistent. The goal is not to generate a perfect test isolating the treatment effect of congestion pricing but rather to control travel behavior to allow us to study relative changes between groups.

To understand what happened to the lost chargeable trips after the price increase we must look at the change in total trips in Central London, controlling for any changes in our synthetic control group. Looking at all trips taken we see that trips in the treated Central London did drop overall as the congestion charge price increased, However, when broken down by incomes this differs widely within the treated group. While the percent change for high income travelers is a 2% drop, for low income it is a 25% drop. In fact, for high income travelers, the adjusted number of total trips dropped is *less* than the adjusted number of chargeable trips dropped. This means that, on average, trips for the high income group that were once taken on car during charging hours have been substituted to either a non-chargeable mode or to a non-chargeable time of day.

In 2011 in particular, the low income group saw a large drop in charge eligible trips and an even larger drop in total trips. While we cannot map what happened to any specific trip, this data shows that, on average, trips "lost" to an increase in congestion price did not reappear elsewhere in Central London, they were either substituted to a non-Central London destination or foregone. Part of this could be due to the fact that low income travelers were already less likely to be making trips to Central London, and due to factors such as high housing costs in Central London and the

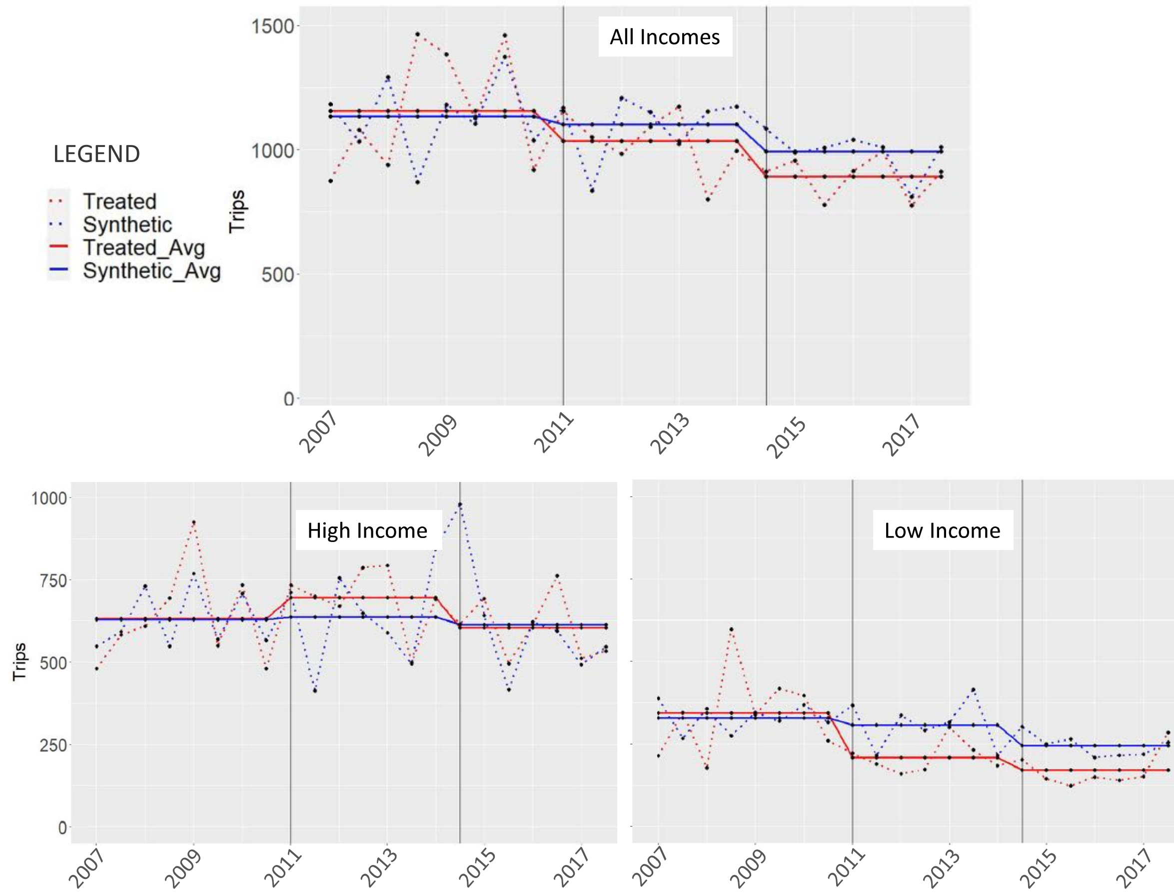

FIGURE 4 Total number of trips, for (top) all travelers, and (bottom) different income groups.

migration of low wage jobs to the outer core, lower income travelers may continue to seek out more destinations outside of the center of the city. However the stark difference between disappearing nature of trips, particularly considering these changes already control for travel patterns(such as the suburbanization of poverty) captured in the synthetic Central London , highlights the role of access to substitutes in congestion pricing equity.

Trends over time

As mentioned above, the heterogeneous responses to a congestion charge increase seem to diverge over time, as the price continues to rise. This is particularly salient for the low income group, who on average drop almost no trips despite a 15% price increase in 2014. This revelation is part of why we need more longitudinal studies on congestion pricing. It makes sense that over time, as the price continues to rise, the trips remaining on the road are increasingly the least elastic travelers of that group. Since the low income group was already smaller to begin with this inelastic portion has a larger and larger presence in the data.

IMPLICATIONS TO POLICY AND TOPICS FOR FURTHER STUDY

We set out to see if one could use readily available travel survey data to answer distributional impacts about congestion pricing. This is an important question as congestion pricing policy presents itself as an efficient solution to urban traffic issues but the further implementation of such schemes has been held back by fairness concerns and an unclear equity impact. While there are a number of implemented schemes around the world we can look to for answers, monitoring plans were initially set up to measure the efficiency of the scheme rather than the equity impact. Running pilot projects and collecting data at this level of granularity can be expensive and time consuming, thus finding a way to make use of existing data sources to understand the impact of past congestion schemes is imperative. This study finds that congestion pricing is not de facto regressive; the LCCS was slightly progressive in scale of equity impact with the top 40% (by income) of drivers accounting for approximately 60% of the charge eligible trips taken in Central London between 2007-2017. Using the synthetic control method to account for wider travel trends, we find that travelers to Central London continued to reduce charge eligible trips after both the 2011 and 2014 price increases. However, we find that low income travelers disproportionately dropped trips to Central London overall as the congestion price rose (a 25% drop in trips, compared to a 2% drop for the high income group). This suggests low-income drivers had a harder time making adjustments to those previously charge-eligible and choose/were forced to forgo the trip instead.

TfL currently uses scheme revenue to reinvest in local transportation infrastructure, which is in line with past studies recommendations on policies to enhance the equity of congestion pricing (*8*). Investments have been made in public transit, active transportation and street safety (*24*). While investments in non-driving alternatives are a critical policy to complement congestion pricing and expand routes of substitutions, as the price rises and remaining low-income drivers are more in-elastic the equity-enhancing nature of such policy diminishes. To continue to ensure a fair (but impactful) policy, scheme funds from price increases could be re-directed to more direct transfers for low-income drivers, such as the tax-credit included in the New York City legislation (*36*) for a downtown charging scheme. Income based discounts have been a large part of the policy discussion on congestion pricing in North America but have yet to make an appearance in any European schemes. Future research is needed on more direct mitigation policies, particularly considering the fact that, as London continues to battle with air pollution and congestion, not only does the congestion charge continue to rise in price, those driving older cars must also pay the charge for the ULEZ as well.

This analysis highlights the importance of not just studying congestion pricing as a point in time change, but understanding how distributional impacts change over time. In their review of the literature, Ecola and Light (*15*) cite the need for ongoing monitoring as a current gap within the policy paradigm. Comparing the two price increases, we see that while the 2011 price increase from £8 to £10 led to a decline in chargeable trips for both income groups, the low income group proved to be less responsive to the 2014 price change from £10 to £11.5. Conventionally, price elasticity is larger in the long run as people have time to adapt their behavior, yet, as the price continues increases we are increasingly left with the least elastic trips on the roads. This often means the trips left are those that are hardest to substitute to alternative modes or times of day. The distributional impact of how this plays out, particularly with high congestion charges like LCCS's current £20 charge, can pose very different cost burdens depending on the traveler's income. While charge-eligible trips are reducing, the small, but persistent, group of low-income drivers continuing to pay the charge (whilst others are dropping trips to Central London entirely) runs counter to what the TfL director in 2016 noted, saying, "the only private cars on the road are residents and rich people" (*37*). If we only study the equity of congestion pricing during the implementation period and fail to monitor as conditions evolve/the price changes, we would be overlooking critical impacts.

Finally, this analysis shows that readily available transportation data such as Travel Survey data can be used to study transportation interventions such as road pricing. Supplementing raw data with a synthetic control group allowed us to separate changes unique to Central London at the time of price increase. While we were not able to generate a perfect control group with the data to allow for a granular causal inference, this method enabled for much more precise estimate into the heterogeneous responses to price increases than previously possible. The application of synthetic control to travel survey data could open the door to a new cost- and time-effective way of studying transportation interventions post-facto.

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