UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Master Degree Project in Economics

Do Gothenburg's Car Drivers Care About Congestion Charges?

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Master Degree Project No. 2016:94
Graduate School

ACKNOWLEDGEMENTS

We would like to thank our supervisor Håkan Eggert (associate professor of environmental economics at the University of Gothenburg) who made every meeting interesting and boosted our energy to complete this paper. We also had great help from Karin Björklind (head of analysis and models at the municipality of Gothenburg) and Jonas Maran (business developer at the Swedish transport agency) in providing us with the necessary data. Both answering all our emails, telephone calls and being very supportive throughout the whole process.

ABSTRACT

This paper analyses the effect of the controversial congestion charge in Gothenburg – both the implementation in 2013 and the increase of the congestion charge in 2015. Our focus lies on the commuters; therefore the study is limited to peak-hour traffic which suffers from the most severe congestion. The data sets that we use are divided since The Municipality of Gothenburg handled the data before and after the implementation on the 1st of January, 2013, and The Swedish Transport Agency collected data after the implementation and after the charge increase on the 1st of January, 2015. The models used are log-linear OLS models with streets and months identified as fixed entities. The results show that the implementation of the congestion charge had a negative effect on traffic demand but that it diminishes with time. The price increase did not affect traffic demand significantly; however it might have slowed down the otherwise rapid increase in traffic flow in Gothenburg. The main contribution of this study is deeper knowledge about the peak-hour traffic demand in response to the congestion charge in Gothenburg.

1. Introduction

Traffic congestion is not only a nuisance to the private commuter but has numerous negative effects in terms of pollution, accidents, capital wear and time inefficiencies. The introduction of road pricing is an attempt to reduce the number of cars by increasing the private cost of driving. In 2013, the city of Gothenburg implemented a congestion charge with time-differentiated charges where the peak hours were charged higher than off-peak hours with the purpose of reallocating traffic. The aim was to incentivize commuters to change travelling time or to reallocate travel behavior. The effectiveness of such a policy depends on the elasticity of driving, i.e. how much people responded to the increased cost by driving less. The aim of our thesis is to find whether there was a response and to evaluate the elasticity of driving in response to the charge. By further comparing the implementation phase of 2013 to the increased charge in January 1, 2015, we found the temporal effect where drivers seemed to differ from the classical *homo economicus* and found that behavioral aspects lead to a diminishing effect in the long run.

The congestion charge in Gothenburg aims at improving the environment, lower the congestion, and partly finance the infrastructural project *Västlänken (*The Municipality of Gothenburg, 2016*)*. In this study we focus on the aspect of congestion. The type of congestion urban areas experience is the recurrent form of bottleneck passages that create queues during peak hours, where each vehicle imposes an incremental time delay for all drivers (Vickrey, 1969). In order to address the problem of peak hour queues Gothenburg's congestion charge vary accordingly, depending on time and day of the week. The passage is free of charge during weekends, while weekdays are charged at varying prices during 6.30-18.30. The peak hours are 7:00-8:59 and 15:00-16:59 when the majority of commuters travel. During these periods the average speed on the motorways decreases from 90 km/h to 50km/h which creates recurrent queues (Hasselblom, 2010). On holidays and in July the passages are also free of charge so as not to discourage the commercial sector of the city (The Swedish Transport Agency, 2016).

Imposing a price on a previously free good, such as congestion, raises a lot of debate and has been a politically unpopular policy. It also requires additional investments in infrastructure to monitor the charge, and enforcing the policy may both be unpopular and costly. All these aspects probably result in the few examples of congestion charges in the world (Singapore, Oslo, London, Stockholm and Gothenburg) (The Guardian, 2016). The implementation in Gothenburg did create a lot of discussion and controversy, and is still going on (Sweden's Television, 2016 & Göteborgs-Posten, 2016). Critics claim that it is merely a revenue mechanism for the municipality, while proponents maintain that it will both create revenue and improve the transport situation in the city. The actual outcome depends on the price elasticity of demand. If drivers are perfectly inelastic, the congestion charge will only collect revenues, but if drivers are somewhat price sensitive the charge will also lower the traffic congestion.

The purpose of this thesis is to investigate whether the congestion charge in Gothenburg has an impact on the amount of traffic during peak-hours. We also assess the responsiveness to a monetary cost increase. Further, we evaluate whether time elapsed since the implementation of the congestion charge had an effect. Particularly, we examine the alternative hypothesis that either drivers will explore alternatives to driving in the long-run, or that they will grow accustomed to the policy and become less sensitive to the charge over time. By answering our research questions below we will get a deeper understanding of the impact of the congestion charge and on its intended purpose – to decrease the number of cars on the streets of Gothenburg.

We focus on three research questions:

1) Have the congestion charges had a significant effect on peak-hour traffic (7:00-8:59 and 15:00-16:59)?
2) How price sensitive are the drivers, i.e. is the demand curve for driving during peak-hours elastic?
3) Does the elasticity diminish over time (from January to December)?

We study both the period of 2012-2013 (the implementation) and 2014-2015 (the increase of charge levels) and answer the research questions accordingly. We investigate these periods separately due to incompatible datasets, but we also discuss the differences in results and potential reasons between the introduction of a policy and a change in the level.

There are two time aspects detectable regarding congestion; between the hours of the day and the development over time (months and years). This study addresses the dimension over time as its implications for the policy efficiency in the long run are interesting for policy implications. By doing this we intentionally focus on one group of passengers – commuters – by limiting ourselves to study the inflow of cars in the morning peak-hours and the outflow in the afternoon peak-hours. We restrict our focus to the impact of congestion charges on reaching the set up congestion goal from the municipality, and refrain from discussing cost-benefit aspects such as the impact on the business community. By delimiting our study to these aspects the analysis is more focused and more clearly captures the answers to our research questions.

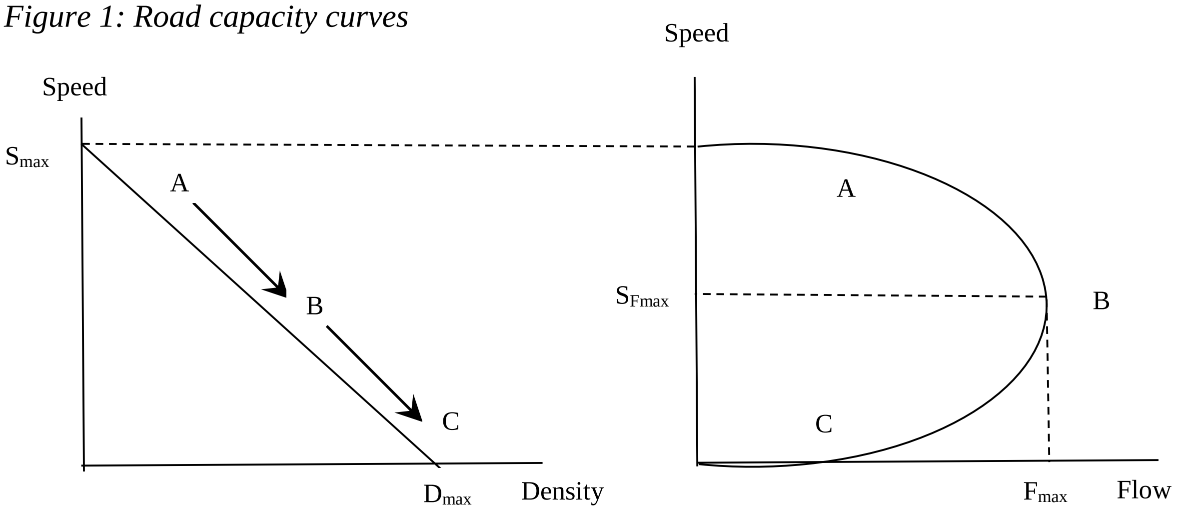
The structure of our thesis is as follows; we begin by giving a theoretical background, supported by a body of previous research, regarding traffic congestion and transport elasticity. The following sections describe the data and methodology. In the result section we perform the same steps of econometrics for both periods but parallel in both calculation and presentation. This is followed by the discussion part where we tie the results together and the implications of the results on long-term effects of the policy. Finally, the conclusion gives the overall summary of the results.

2. Theory

Congestion occurs because the traffic demand is higher than the traffic supply i.e. the capacity of the roads is not enough for the total amount of cars. When the number of cars increases on a certain road (with a fixed capacity), speed and traffic flow will decrease severely. Passing the maximum point, every additional motorist will reduce the flow of vehicles per lane (Knights, 1924). This event is what is defined as a backward-bending curve (Morrison 1986). The relationship between speed and density is negatively sloping, i.e. the lower the density of the cars, the faster we can drive. Imagine yourself driving before rush-hour where there are just a few cars on the road and you might drive at the speed limit, in figure 1 this is at point A. As the peak-hour approaches, traffic starts to increase, density goes up and the average speed decreases - as we are approaching D_{max} which is the maximal density (Morrison, 1986).

In the curve to the right the relationship between speed and flow is displayed where the optimum lies at point B where $S_{Fmax}=F_{max.}$ At this point there are many cars around you but not to the point where your speed is decreasing. This is an optimum stage where flow and speed are at symbioses. Beyond this point additional vehicles will lower the speed and the flow of traffic since the space between each car is decreasing (between point B and C). Looking at the curves together we see that as the density approaches maximum both the flow and the speed approach zero – the situation of congestion at the level where there are long queues and bottleneck passages. This is a common situation in rush hour traffic and is costly, both through the amount of emissions released and the time that could be spent in an activity creating utility (Morrison, 1986).

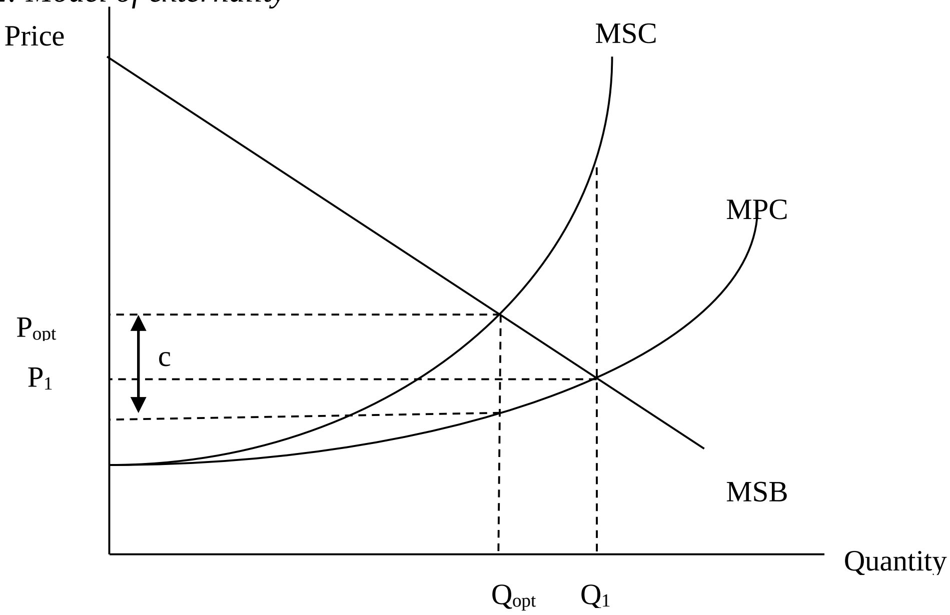
Figure 1: Road capacity curves



The economic theory behind traffic congestion is based on the theory of externalities which was developed in 1920 by Arthur Pigou. Externalities arise when the private cost of the good or service, i.e. the price, does not equal the social cost and a third party is affected but not compensated. Drivers only face the user cost of the car (gasoline etc.) while there are external costs that are not paid for by the driver (e.g. pollution). This means that the price is too low for optimal market allocation and there will be an overdemand. Drivers can drive more since the price is not equal to the marginal social cost and overconsumption is a fact (Button and Verhoef, 1998). The supply side of the traffic is the infrastructure which is inflexible in nature as it is neither easy nor quick to expand the capacity of the roads. Thus, it is more manageable in the short-run to impact the level of undersupply by trying to alter the demand pattern (Hau, 1998).

In figure 2 the model of externalities is displayed; the marginal private cost (MPC) does not equal the marginal social cost (MSC) and the difference between them is the externality. Due to this inequality the actual price (P_1) is lower than the optimal price (P_{opt}) making the actual quantity demanded (Q_1) higher than the optimal amount (Q_{opt}). This type of externality is a negative, consumption externality as congestion is created by the drivers imposing pollution, accidents and time delays on third parties. The MSC and the MPC curves are not parallel since there is no congestion at very low levels of traffic and as the number of cars increases the externality increases (Button and Verhoef 1998).

Figure 2: Model of externality



Arthur Pigou argued that an externality can be dealt with through imposing a tax with a monetary value equal to the cost of the side effect - the Pigouvian tax. By adding to the user cost this incentive instrument internalizes the externality and if the new cost equals the MSC this will bring optimal allocation. Pigou used congestion as an example where the drivers should be charged their marginal external cost c (figure 2) of driving in areas with congestion traffic – road pricing. In the simple model of road pricing (also presented by figure 1) all vehicles are identical in all senses except for their willingness to pay for driving. The drivers that have a larger marginal benefit than the marginal cost will continue driving and the revenue from their tax cost will go towards compensating the third parties, e.g. through building noise walls or investing in more efficient infrastructure (Pigou, 1920).

Road pricing exists for the sole purpose that motorists that use a particular road also have to pay for the congestion that they cause. When analyzing the efficiency of the policy it is appropriate to look at it in two stages i.e. short-run and long-run. In the short-run the congestion pricing should reduce the congestion to the optimal level where marginal benefit

(MB) is equal to marginal damage (MD). When this is a fact the marginal motorist will face a price that is equal to the marginal social cost and damage accounted for, hence overconsumption will diminish (Perman, 2003). At this stage the usage of the roads (that are fixed in the short-run) are optimized and the net savings for the government increase. These net savings in the short-run are used as investment in the long-run to meet the increasing demand in the future (Mohring & Harwitz 1962).

Given the assumption that there are no transaction costs, perverse incentives or smooth demand curves, the road pricing will remove the deadweight loss. This is represented by the triangular area between $Q_1 - Q_{opt}$ and $P_1 - P_{opt}$ in figure 2 and represents the cost to society of this inefficiency. This means that the price paid will equal the social marginal cost and nothing more i.e. no overpricing with the sole purpose of collecting revenue for the government. But these are strong assumptions - in reality the installment and operating cost are often substantial (Button, 1998).

There is also the risk of perverse incentives when imposing road pricing, for example on labor. If the congestion charge would make the net gain from commuting to work too low, the policy would potentially discourage employment and thus lead to social welfare losses. Since an increase in the cost of driving is a marginal increase, people will not stop driving unless the new cost surpasses their gain from the trip or their reservation price. Increased costs might discourage people who live in the inner core of Gothenburg to use their cars and look for alternative transport options such as tram, bicycle etc.

The perfect Pigouvian tax level could also be hard to find in practice, mainly due to imperfect information, e.g. regarding the marginal cost and the demand function (Button, 1998). How effective congestion charges are is largely determined by the responsiveness of the drivers to the cost increase. If the responsiveness is high many drivers will choose to drive less and the congestion will go down substantially. If instead the drivers are insensitive they will decide to pay the charge and continue driving to the same or perhaps slightly lower extent. This depends, among other things, on accessible options, e.g. if there is a well-developed public transport system. This responsiveness is valued by the elasticity measure and while it is an important aspect of the policy performance there are few studies on the subject in connection with congestion charges.

In Evans, R. (2008) Transport for London decided to analyze the elasticity in London from the implementation of their charge in 2003. This report gives a detailed description of how the elasticities are calculated including a discussion of the different types of elasticity and alternatives for valuing cost. They find that the overall elasticity is -0.47, i.e. increasing the price for a daily passage by 1% results in a reduction of approximately 0.5% in traffic. However, the figures differ slightly between regions. They further create projections for the future where they claim that elasticity with most probability will increase over time but also provide some argument for the opposite scenario (Evans, 2008).

In 1963 William Vickrey made a strong statement for road pricing and in particular time-differentiated road pricing which targets peak-hour traffic. He argues that failing to impose such an instrument is highly costly to society. He claims that it is socially inefficient to charge peak and off-peak hours the same price and that rush-hour passengers should be charged higher since they have higher demand and create larger externalities (Vickrey, 1963). Stockholm has similarly to Gothenburg taken this into account as their congestion charges differ depending on the time of day. This has several implications for the methodological approach to finding the elasticity as calculating the relative change in cost becomes more complicated.

Hultkrantz and Liu (2012) approached this aspect in a before-after comparison regarding Stockholm's congestion charges and subtle changes to the tax. The article provides methodology of dealing with measuring cost changes in a time differentiated scheme for the cost of driving before and after the policy is calculated and used. They use cost and charge values for the average commuter instead of dealing separately with each charge period and also provide clear descriptive data on the traffic levels throughout the years. They came to the conclusion that the initial trial period of the congestion charge in 2006 had a significantly larger impact than the subsequent re-opening of the system the following year (Hultkrantz & Liu, 2012).

While *Homo economicus* in the theory of Pigouvian taxation will respond to the cost increase by driving less or changing mode altogether people in reality are often far less rational and predictive. For example, driving a car to work could be a sign of status as opposed to an exchangeable transport option. Another aspect that counteracts the rational individual is habit formation - when we do something without thinking the act itself becomes automatic.

Commuting to work is an example of a habit and influencing the consumption pattern of a habit that might prove more challenging than policy implementers might have predicted. And if policy-makers manage to change the pattern through a stimulus the habit formation process might have an impact on the long term effects. The attitudes of Stockholm drivers did in fact display such a pattern where there were strong protests at first but as time went on people grew accustomed to it (Center for Transport Studies Stockholm, 2014). It does not seem to matter what kind of change we face, we are still going to be reluctant to it in the implementation phase.

If preferences are not stable it complicates finding the optimal charge and contributes with an interesting reflection of the price elasticity in the long term. Since the results of this paper give indications that drivers are less sensitive to price changes in the long run this is a counteracting force to other findings which suggest that we are more elastic in the long term since we have more time to adapt our travel patterns (Center for Transport Studies Stockholm, 2014). Habit formation it makes paying the congestion charge the new norm and people do not longer react to the policy stimuli by decreasing the demand of commuting. In such a scenario the charge would go from internalizing an externality to merely becoming a revenue tool.

3. Data & Methodology

3.1 Data

Our analysis is based on two datasets of the number of car passages in Gothenburg during the periods of interest - one from the Municipality of Gothenburg (MOG) and one from the Swedish Transport Agency (STA). We collected the data through telephone conferences and e-mail with MOG (The Head of Analysis and Models Division) and STA (Business developer). While STA began their data collection after the implementation MOG have observed the data levels in years prior and the implementation year. We were informed that it is not possible to combine the datasets due to measurement differences and thus we approached the two periods separately so as not to produce biased results.

The data set from MOG consists of 3456 observations for the years of 2012 and 2013 (table 1). Due to data availability we had to request a sample of streets and choose Älvsborgsbron, Kungsbackaleden, Alingsåsleden, Marieholmsleden, Oscarsleden, Tingstadstunneln which accounted for 70% of the passages during the period. The data set we received contains daily total amounts for the in- and outflow to Gothenburg, for each hour of the day for a sample of days (except weekends and holidays). The number of observation days of each month differs significantly between the streets – Älvborgsbron and Alingsås were measured for six of the twelve months while the rest of the roads were covered throughout the year.

Table 1: *Descriptive statistics of number of cars 2012 and 2013 (MOG)*[1]

	Obs.	Mean	St.Dev.	Min	Max
2012	1630	12303	4174	3495	18945
2013	1826	11811	3734	3538	18349

The data set from STA has 1518 observations for the years 2014 and 2015 and contains yearly and monthly passages in and out from Gothenburg (table 2). There are 35 streets with measuring points (listed in Appendix A) where all passages are registered from the time 06:00 to 18:29 with different price levels for every hour of the day and the price increase in 2015. All months, except July when there is no congestion charge, were measured. There are no missing values and all streets except one (number 32) have both in- and outflow.

Table 2: *Descriptive statistics of number of cars 2014 and 2015 (STA)*[2]

	Obs.	Mean	St.Dev.	Min	Max
2014	759	66317	98678	1550	458141
2015	759	67618	101457	3541	464303

Thus, in the data set for the period 2012-2013 the observation units are daily whereas 2014-2015 are monthly. However as the analysis is based on relative changes this will not impact the comparability of the results. The most severe congestion levels occur during peak-hours (07:00-08:59 and 15:00-16:59) and the hourly observations were converted into daily or monthly by aggregating the levels from these hours. By not doing this, and using the hourly data, we would have had higher variation in the dependent variable (cost) but have innate endogeneity since the cost levels are decided depending on the transport demand for that hour.

Besides the cars and cost, there are other variables needed in our model, all of which are presented in table 3. *Imp* and *inc* are dummy variables created for MOG and STA respectively for the year in each set where the charge implementation or the charge increase has occurred. The variable *month* represents which month the observations are made. The variable street

[1] Daily observations (MOG)
[2] Monthly observations (STA)

gives a specific number for each street of the datasets, ranging from 1-6 in MOG and 1-35 in STA. All the variables used are listed in table 3.

Table 3: Variables list

Variable	Definition	Values and information
cars	Number of cars, peak-hours	7:00-8.59 and 15:00-16:59
cost	Average daily cost of driving[3]	118.8 SEK plus average charge
imp	Dummy, year of implementation[4]	0=2012, 1=2013
inc	Dummy, year of increase[5]	0=2014, 1=2015
month	Calendar month	1-12 (7 not included in STA)
street	Number for specific street	1-6 (MOG) and 1-35 (STA)
time	Interaction term of months since imp/inc times log(cost)	Months:0 year before imp/inc Months: 1-12 after imp/inc

3.2 Methodology

The aim of our study is to find the causal impact of the congestion charge on driving demand (car passages) in peak-hour traffic. This ex-ante study will investigate the response of the commuters in Gothenburg and by testing the hypotheses (table 4) the results will provide information about the responsiveness of transport demand in Gothenburg and about the impact of time.

Table 4: Hypothesis testing

Research question	Hypotheses
1	H0: The congestion charge does not decrease car passages significantly H1: The congestion charge decreases car passages significantly
2	H0: inelastic peak-hour transport demand H1: elastic peak-hour transport demand
3	H0: non diminishing elasticity over time H1: diminishing elasticity over time

[3] Return trip 36 km in total
[4] Only in MOG
[5] Only in STA

Two sample t- test

In order to see whether the implementation (2013) and the increase in the congestion charge (2015) had significant impact on the number of cars we performed a two sample t-test. This is performed to establish whether the means of the two groups differ significantly. Since our data have different number of observations within a data set we perform an unpaired test. Equation 1 gives the t-test where $\bar{X}_1 - \bar{X}_2$ gives the difference in average means number of differences in cars before and after and *s* is the standard deviation. If the absolute t-value is higher than the critical value, given the degrees of freedom we can reject the null hypothesis and conclude that the congestion charge has an effect (Verbeek, 2012).

Equation (1): t-test

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{x_1 x_2 * \sqrt{\frac{1}{n}}}}$$

Elasticity measure

The price elasticity of demand measures, the responsiveness of demand to price and its value represents the percentage change in quantity demanded from a one percentage price increase. If the absolute elasticity is above one the demand is elastic, if below one it is inelastic and if exactly one it is unit elastic. The elasticity measure is thus a relative measure as it calculates the relative response to a relative change (Verbeek, 2012). The elasticity has an impact on the revenue collection and on who bears the burden of a tax. The determinant for the elasticity value is the willingness to pay (WTP) for the good and the ability to forego consumption. This is determined by the necessity, availability of substitute goods, and percentage of income among other factors.

The elasticity measures the responsiveness in demand to a change in price but in order to calculate this we first need to calculate the baseline cost of driving (pre charge) and the adding of the charge (post charge). To only include the charge as a driving cost would be misleading since this is not the only cost associated with owning and using a car. We use the baseline average cost of commuting in Sweden from Hultkrantz and Liu (2012). It comes to 3.3 SEK/km which includes maintenance, insurance and operating costs.

After the congestion charge was implemented the drivers faced an additional cost in the form of the congestion charge. We only look at the peak-hours but still the charge levels vary and the added expense is calculated as the average according to the level of the charge and the share of the time span (Appendix B). The charge costs are added to the baseline cost to get the total driving cost and the values are presented in table 5.

Table 5: Driving costs 2012-2015

Year(s)	Av. trip (km)	Cost/km	N.o. of trips	Av. charge	Total cost (SEK)	
2012	18	3.3	2	0	**118.8**	(baseline)
2013, 2014	18	3.3	2	31	**148.8**	(+25%)
2015	18	3.3	2	37.75	**155.55**	(+4.5%)

There are different versions of elasticity and the most common type is point elasticity which measures the elasticity at the margin. This is done by differential calculus (equation 2) where the quotient between price (P) and quantity demanded (Q_d) is multiplied by the derivative of quantity to price. In regression format the elasticity is found by specifying a log linear model where both the independent and dependent variables are converted to the logarithmic versions (with the exception of dummy variables) as seen in formula 3 (Verbeek, 2012). In our case the main independent variable is cost of driving and the dependent variable is number of cars.

Equation (2): Elasticity mathematically

$$E_d = \frac{P}{Q_d} x \frac{dQ_d}{dP}$$

Equation (3): Elasticity in a regression

$$log\ y_i = (log x_i)'\gamma + \varepsilon_i$$

While equation 3 gives the generic specification for elasticity measure it is necessary to specify our model with respect to the specific entities in the datasets. Each dataset consists of specific streets (6 in MOG and 35 in STA) and it is important to consider that there could be heterogeneity between the streets. If we fail to take this into account there is a risk of biased results through omitted variables and thus we add a model where the streets are fixed (2). By doing so the model recognizes each street as a specific entity and thus control for the variation between the streets. In a similar approach we also test whether the introducing months as fixed entities gives validation to the model (3) and also perform a model with both months and streets (5). By testing and comparing the different specifications in table 3 we choose one version with economic reasoning and the goodness of fit values.

Table 6: Specifications

	Model	Specification
1	Log linear	$log\ (cars_i) = \beta_0 + \beta_1 * \log(cost_i) + \varepsilon_i$
2	Log linear, fixed streets	$log\ (cars_{i,s}) = \beta_0 + \beta_1 * \log(cost_i) + \gamma_1 s_1 + \cdots + \gamma_k s_k + \varepsilon_i$
3	Log linear, fixed months	$log\ (cars_{i,m}) = \beta_0 + \beta_1 * \log(cost_i) + \gamma_1 m_1 + \cdots + \gamma_{12} m_{12} + \varepsilon_i$
4	Linear	$cars_i = \beta_0 + \beta_1 * cost_i + \varepsilon_i$
5	Log linear, fixed months and fixed streets	$log\ (cars_{i,m,s}) = \beta_0 + \beta_1 * \log(cost_i) + \gamma_1 m_1 + \cdots + \gamma_{12} m_{12} + \gamma_1 s_1 + \cdots + \gamma_k s_k + \varepsilon_i$

Elasticity over time

The elasticity calculations so far have dealt with the annual elasticity of response between two years, either 2012/2013 or 2014/2015. It is also important to go deeper within each year to see the time effect and seasonal implications. We introduce a time variable representing the number of months that have elapsed since the implementation was carried out or the time elapsed since the increase in charge, respectively. Observations before a policy change are given the value of zero. This variable is then multiplied by an independent variable, i.e., the cost variable, and to get the specific elasticity for each month we multiply the coefficient of the time variable by the number of the month minus one and add this to the coefficient for cost. The time variable thus creates a linear variable (equation 4) and assumes a constant trend across the year, an assumption which we investigate by looking at each month's elasticity separately.

Equation (4): Regression with time variable

$$log\ (cars_i) = \beta_0 + \beta_1 * \log(cost_i) + \beta_2 * [\max(t_i - t_0, 0) * \log(cost_t)] + \varepsilon_i$$

An approach would be to code the data as panel but this was hindered by the inconsistency in observation days in the MOG dataset making a supposed panel far too imbalanced. Also, a panel set must have only one observation for each entity at a particular point in time whereas our data set contained several observations per month. Aggregating these to one observation per month would have resulted in a dataset with 130 observations instead of 3,687 and with some of the streets (entities) having several months missing. While we do not combine the two data sets we use the same approach econometrically to make the results comparable.

4. Results

4.1. The implementation

In January 1, 2013 the congestion charge was implemented in Gothenburg with the purpose of decreasing the inflow of cars. In this section we investigate whether this was achieved, by comparing the levels of peak-hour traffic in 2013 to that of the previous year. The measuring unit of cars is per day, aggregated from the two peak hour periods each day.

Significance of implementation

In order to answer the first research question – whether the implementation of the policy has significant effects on the driving demand – we used the two-sample t-test to determine whether the means before and after the implementation differs. One of the samples consists of observation days before the charge (2012) and the other one of days after the charge (2013). The t-test compares the mean number of daily cars during peak-hours for the two groups and determines whether a potential difference is significant.

The t-test concludes that the mean difference between the number of cars per day in 2012 and 2013 is on average 500 (table 7). This difference is statistically significant since the calculated t-value (3.655) is higher than the critical t-value (1.645) and the p-value of 0.0003 means that we can reject the null hypothesis at the 1% level of significance. The mean number of cars in the group from 2012 exceeds the group from 2013 and we can conclude that the congestion charge did have a negative, significant impact on the number of cars when aggregated across the years.

Table 7: t-test of before and after the implementation

Year	n	mean	SD	t-cal	t-crit	df	p	Decision
2012	1,630	12,303	4173.769	3.655	1.645	3454	0.0003	Reject
2013	1,826	11,811	3734.424					

Elasticity from implementation

The size of the effect is established by the elasticity measure but before doing so we test different causal models to find the most appropriate specification (table 8). In all five specifications cars and cost are the dependent and independent variables, respectively. However, in three versions street and month are included as dummy variables and we also test towards a linear specification. The *log* model (1) is a log linear OLS of cost and cars; the *street* model (2) includes a fixed effect for streets thus controlling for omitted variables that impact the roads differently; model (3) does the same but for months, model (4) is a linear version of the first model and model (5) includes fixed effects for both month and street, acknowledging that omitted variables can impact both simultaneously.

The log linear specification (1) gives the elasticity value through the beta-coefficient and when comparing this to the linear version (4) we find that the latter has similar goodness of fit and higher standard error. The log linear model is, however, significant at a 5% level and allows us to see the elasticity. The model which includes months and streets (5) as fixed entities results in reduced standard errors, and has substantially increased the goodness of fit compared to the basic version (1). A reason for the higher R^2 is that the model uses the explanatory power from the fixed entities in explaining the variation.

When switching from fixed streets to months and streets the model explains more of the observations, with smaller standard errors and presents a statistically significant beta-coefficient at -0.126. The remaining beta coefficients of cost (or logged cost) are -0.119 (1) to -0.126 (5) and the higher significance along with the substantially higher goodness of fit. The road conditions vary depending on which months one chooses to study and this leads to a difference between months that is consistent throughout the year. Therefore we choose to focus on the model which includes fixed effects for months and streets (5) as we continue on in our analysis.

Table 8: OLS results with five different specifications

	(1) Log	(2) Fixed streets	(3) Fixed months	(4) Linear	(5) Month & Street
Variables	log(cars)	log(cars)	log(cars)	cars	log(cars)
log(cost)	-0.119**	-0.145***	-0.0525		-0.126***
	(0.0553)	(0.0184)	(0.0528)		(0.0168)
cost				-15.86***	

				(4.339)	
constant	9.914***	10.04***	9.589***	14,187***	9.152***
	(0.271)	(0.0902)	(0.259)	(590.4)	(0.0824)
observations	3,456	3,456	3,456	3,456	3,456
adj-R^2	0.001	0.890	0.115	0.004	0.912

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The second research question regards the elasticity and whether the peak-hour traffic has inelastic- or elastic demand. By looking at the model that we choose from table 8, namely the log-log regression containing fixed effects for months and streets (5) we find that the elasticity is -0.126. This means that when the congestion charge is increased by one percent the number of cars decreases by 0.126 percent. This value is significant at a 1% significance level and is clearly inelastic. Thus we cannot reject the null hypothesis (table 4) that the demand is inelastic. An explanation for this could be the absence of parallel routes and alternative modes of transportation.

Time impact on elasticity

The elasticity of -0.126 is measured from 2012 to 2013 annually, but there are reasons to believe that the effect will differ as time passes, as people get more used to the policy and become less sensitive to the charge. Another pattern could be that commuters have more ability to change their patterns long term and thus become more price sensitive over the year. In order to evaluate the elasticity while taking temporal consideration we include a time variable which represents the number of months passed since the implementation. This is included in the OLS and in table 9 we see that it has a positive and significant coefficient. This implies that as the months go by the elasticity approaches zero, i.e. drivers become influenced by the price change.

Table 9: OLS results with time variable

Months and streets	
Variables	log(cars)
log(cost)	-0.194***
	(0.0322)
time	0.000511**
	(0.000206)

constant	9.486***
	(0.157)
observations	3,456
adj-R^2	0.912

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

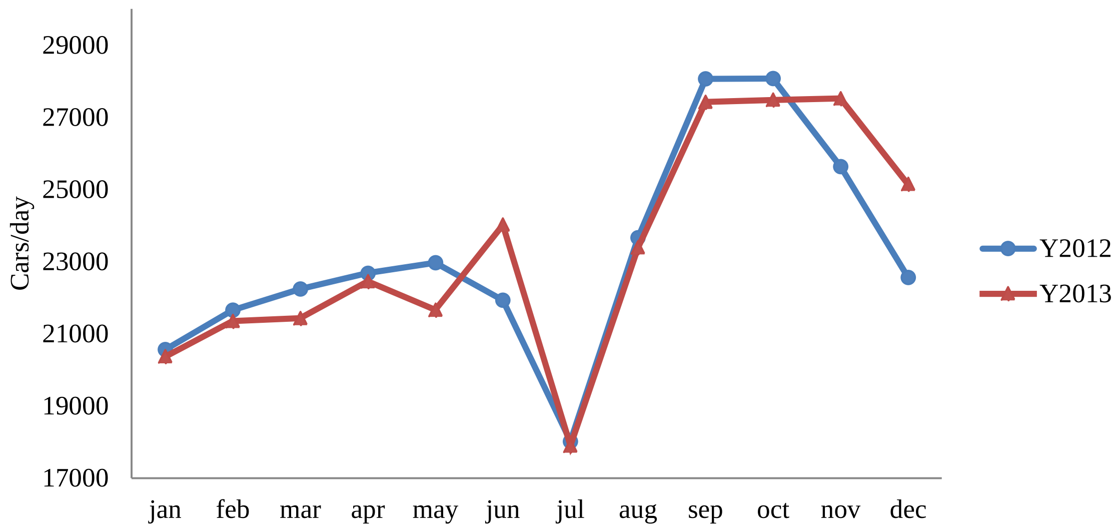
The coefficient for *log(cost)* is now interpreted as the elasticity for January and to get the value for the following months we take the elasticity for January and add the time coefficient times the time value of the month. Table 10 gives each month's elasticity as calculated through the variable of time and the annual average of -0.191. This value implies that the temporal aspect has a significant impact on evaluating the impact and failing to include this would be to underestimate the responsiveness to the congestion charge.

Table 10: Monthly elasticity from time variable

Jan	Feb	Mar	Apr	May	Jun
-0.194	-0.193	-0.193	-0.192	-0.192	-0.191
Aug	Sep	Oct	Nov	Dec	**Annual**
-0.191	-0.190	-0.190	-0.189	-0.188	**-0.191**

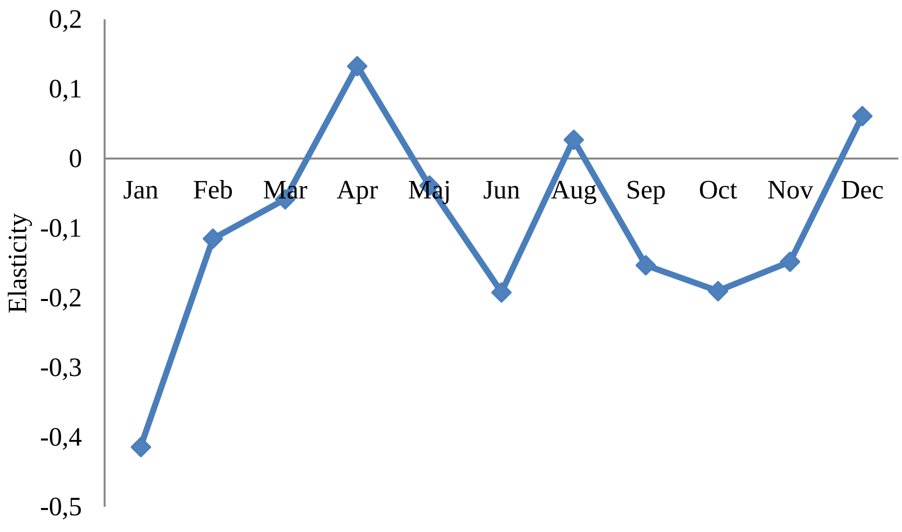
An underlying assumption of model 5 is that the time trend introduced in the model has a linear impact on the elasticity. While it is not unreasonable to assume that the trend overall goes in one direction it is also likely that there are seasonal fluctuations regarding transport demand. Figure 3 shows the number of peak-hour cars over the year between 2012 and 2013 where we see that there is an overall decrease of peak-hour traffic after the implementation (except for the months June, November and December). The lines indicate that there are fluctuations over the months which are fairly consistent from year to year.

Figure 3: Cars each month, 2012-2013



This pattern calls for a closer look at the elasticities each month to see the overall impact. Figure 4 displays the monthly elasticities and shows that drivers are clearly more elastic in January than during the following months but otherwise the patterns are not clear in either direction. For the first four months we see a pattern of the demand growing more inelastic but during the summer months this pattern is broken. During the fall the elasticity is rather stable around -0.16 but then becomes positive in December. All months' elasticities, except May and August, are statistically significant at a 5% level (Appendix C). Looking at the overall pattern we can conclude that the face diminishing elasticity over time ranges from -0.41 at the first month after the implementation to 0.061 a year later.

Figure 4: Monthly elasticities, 2012-2013



Thus, the implementation of the congestion charge had a negative statistical effect on traffic demand (table 9) and the annual traffic demand elasticity is -0.126 (table 8). However, we can conclude from table 10 that overall the effect fades out as time passes.

4.2 The charge increase

On January 1st 2015 the Swedish Transport Agency increased the congestion charge levels from 18 SEK to 22 SEK during peak-hours (4.5% higher costs) and the following section investigates the impact this had on the level of peak-hour traffic between 2014 and 2015. The observation units are in number of cars each month during the peak hours (7:00-8.59 and 15:00-16:59).

Significance of increase

The significance of the increase in price was once again determined by the two-sample t-test where the groups are the observations before the increase (2014) and after the increase (2015). By looking at the difference between the mean numbers of cars we notice that the average numbers of cars passing one of the entities per month after the increase are actually higher than before. Furthermore, the difference is not significant as the calculated t-value (-0.2532) is lower than the critical t-value (1.645) and we can only reject the null hypothesis at a 20% significance level. Thus, our results indicate that the increase in charges did not have a significant impact on peak-hour traffic.

Table 11: *t-test of before and after the increase*

Year	n	mean	SD	t-cal	t-crit	df	p	Decision
2014	759	66317.45	98677.57	-0.2532	1.645	1516	0.8001	Not reject
2015	759	67618.27	101457.3					

Elasticity from implementation

As with the previous period we begin by testing the model to be able to find an appropriate model for the elasticity measure. While the coefficients do not differ between the log linear models (1-3, 5) the standard error and the goodness of fit do differ. The standard errors are substantially lower in the model which includes months and streets as fixed entities and the model explains 96% of the variability in the number of cars. Even though we have more streets in the data sample STA it is very likely that there exists significant heterogeneity between the roads which we need to take into account.

In table 12 the *log(cost)* coefficient of 0.0423 is insignificant and thus we cannot draw any conclusions regarding the elasticity between 2014 and 2015. The fact that the coefficient is positive means that the number of cars has increased between the years, which we cannot connect with the congestion charge increase. The impact of increasing a policy often has proven to have lower impact than the implementation phase due to behavioral aspects. Also, the increasing number of cars might be attributed to other factors and the charge levels have not managed to reduce this time trend sufficiently for the peak-hour traffic.

Table 12: OLS results with four different specifications

	(1) Log	(2) Fixed streets	(3) Fixed months	(4) Linear	(5) Months & Streets
Variables	log(cars)	log(cars)	log(cars)	cars	log(cars)
log(cost)	0.0423	0.0423	0.0423		0.0423
	(1.370)	(0.291)	(1.371)		(0.277)
cost				192.7	
				(761.1)	
constant	10.12	10.12***	10.12	37,449	8.521***
	(6.892)	(1.465)	(6.899)	(116,605)	(1.394)
observations	1,518	1,518	1,518	1,518	1,518
adj-R^2	0.000	0.955	-0.003	0.000	0.960

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Time impact on elasticity

This brings us to the impact of time and introducing the time variable in the model provides significance and noticeably lowers the elasticity. Looking at table 13 the coefficient for *log(cost)* is -0.23 meaning that a one percentage price increase in January would result in a 0.23 percentage decrease in number of car passages. Table 14 gives each month's elasticity -0.23 and the annual average elasticity of -0.23. The results using the time variable shows that there is a higher rate of elasticity than without the time trend, however the value is statistically insignificant.

Table 13: OLS results with time variable

Months & Street	
Variables	log(cars)
log(cost)	-0.230 (0.569)
time	0.000368 (0.000671)
constant	9.890*** (2.859)
observations	1,518
adj-R^2	0.960

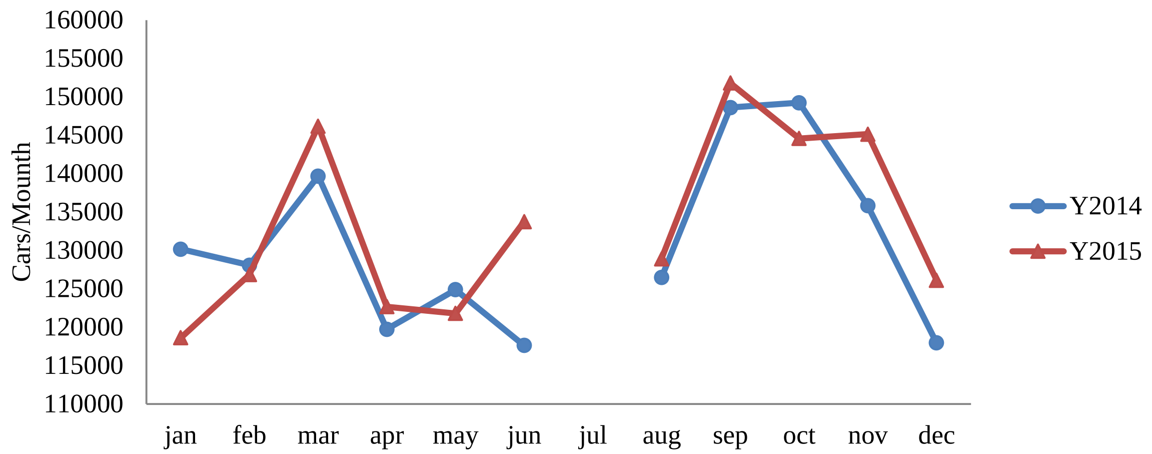
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Monthly elasticity from time variable

Jan	Feb	Mar	Apr	May	Jun
-0.23	-0.23	-0.23	-0.23	-0.23	-0.23
Aug	Sep	Oct	Nov	Dec	**Annual**
-0.23	-0.23	-0.23	-0.23	-0.23	-0.23

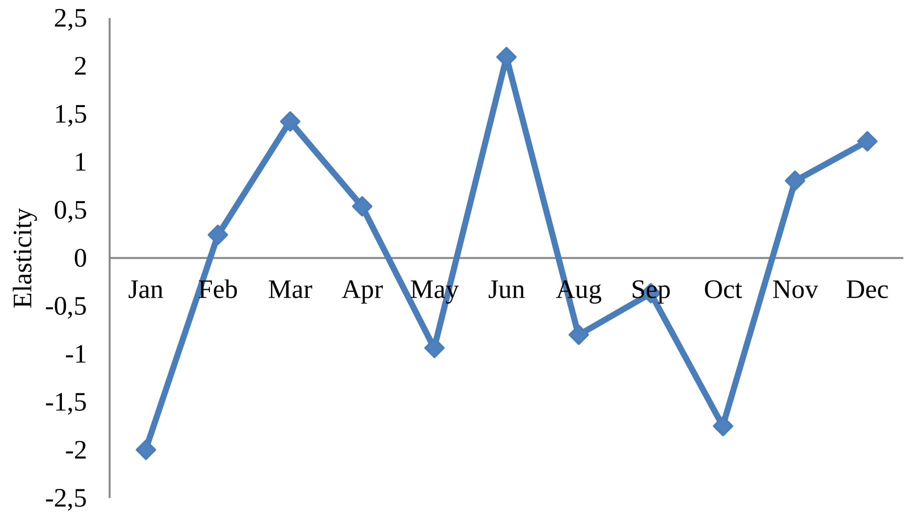
Analyzing monthly levels of cars between 2014 and 2015, we see that in the first quarter of the year between January and March the number of cars is increasing for both years (figure 5). The largest peak is however, in the fall (September/October). The lowest levels are found during winter. So, looking closer at the actual monthly car levels we once again notice a pattern that is more seasonal than linear. Comparing the levels between the years we see a slight increase in 2015.

Figure 5: Cars each month, 2014-2015



Thus, we calculate the elasticities per month and detect clear volatility in the results. While the annual elasticity is weakly positive (table 12) we see that the elasticity per month take on more extreme values. The volatility in the coefficient can be partly explained by the fact that a smaller difference in cost, compared to the period 2014/13, means smaller denominators and thus larger elasticities. The range of values (figure 6) is between -2 (January) and 2,093 (June). Only January and June have statistically significant elasticities at a 10% level (Appendix D). As with the former period, January has the most elastic value and during the first quarter we detect a trend of more inelasticity.

Figure 6: Monthly elasticities, 2014-2015



The price increase in 2015 did not affect the peak-hour demand in a significant manner, the elasticity which was positive revealed a potential positive time-trend. Figure 6 shows that during the first month it did have an impact which quickly disappears as time passes.

5. Sensitivity test

5.1. The implementation

To test the robustness of our results we change some assumptions of our model and compare the size and significance of the elasticity between the specifications. Table 15 column (1) shows results of our original version of the log linear model with fixed month and street effects. In model (2) July is included, a month that is not charged. As observations from two of the streets contain less months than the rest we exclude these in model (3). In model (4) the summer months (June, July and August) are removed since it is likely that people change their driving habits during their vacation. In the last specification (5) the in- and outflows are combined to represent one day as opposed to two directions for each day.

By looking at the size of the coefficient for *log(cost)* we see that all models except model (2) have similar elasticity (between -0.0981 to -0.149). When we add the month July to our original model the elasticity shifts from -0.126 to -0.0091. This could be due to the fact that there is a positive trend between the years. As the cost of driving is the same between the years in July the coefficient now includes 2013 as baseline cost. When we exclude two of the roads we see that the coefficient grows slightly less negative. The model with the two directions combined gives a slightly more elastic demand of -0.149; a reason could be that there is a different valuation and flexibility between trips in the morning versus one in the afternoon.

Table 15: Sensitivity test, 2012-2013

	(1) Original	(2) With July	(3) Less streets	(4) Without summer	(5) In & out
Variables	log(cars)	log(cars)	log(cars)	log(cars)	log(cars)
log(cost)	-0.126***	-0.0091***	-0.0981***	-0.133***	-0.149***
	(0.0168)	(0.0182)	(0.0177)	(0.0159)	(0.0216)
constant	9.152***	9.018***	9.012***	9.184***	9.265***
	(0.0824)	(0.0891)	(0.0868)	(0.0778)	(0.106)
observations	3,456	3,686	2,680	2,992	1,728
adj-R^2	0.9118	0.8971	0.9341	0.9324	0.9346

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2. The increase

A similar robustness test was made for the years 2014 to 2015 with the exception of the previous model of excluding July as the data set STA does not include that month since it is free of charge. As for model (2) fewer streets mean the exclusion of a street where there was only available observation from the inflow towards the city whereas all other streets have both directions. In model (4) we exclude the summer months which in this dataset are June and August. The elasticity values do not differ noticeable between the specifications (1), (2), and (4) but model (3) has a negative (yet still insignificant) coefficient. This means that when we exclude June and August there is a negative elasticity, indicating that the number of people driving in the summer has decreased since the previous year. We think that the reason behind this is that more people are on vacation during this period and joy trips are assumed to be more flexible than commuting. However, since all the values are insignificant we cannot statistically conclude that the coefficients are different from zero.

Table 16: Sensitivity test, 2014-2015

	(1) Original	(2) Less streets	(3) Without summer	(4) In & out
Variables	log(cars)	log(cars)	log(cars)	log(cars)
log(cost)	0.0423	0.0529	-0.0919	0.150
	(0.277)	(0.281)	(0.305)	(0.173)
constant	8.521***	8.469***	9.209***	7.991***
	(1.394)	(1.414)	(1.535)	(0.870)
observations	1,518	1,496	1,242	770
adj-R^2	0.959	0.959	0.960	0.992

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

The results of our analysis differ between the periods of 2012/2013 and 2014/2015 and this highlights the complexity in enforcing an efficient policy. While the implementation in 2013 has had effects in lowering the number of cars significantly, the increase in 2015 has not managed to decrease the number of cars driving during peak-hours. We can thus reject the null hypothesis in the first research question and conclude that the first implementation had an effect. However, we cannot reject the null hypothesis regarding the increase in 2015. Car drivers commuting in and out of central Gothenburg seemed to have reacted more strongly to the beginning of a new policy than the increase in charge and the latter has not stifled the growing driving demand in the way that was the case in 2013.

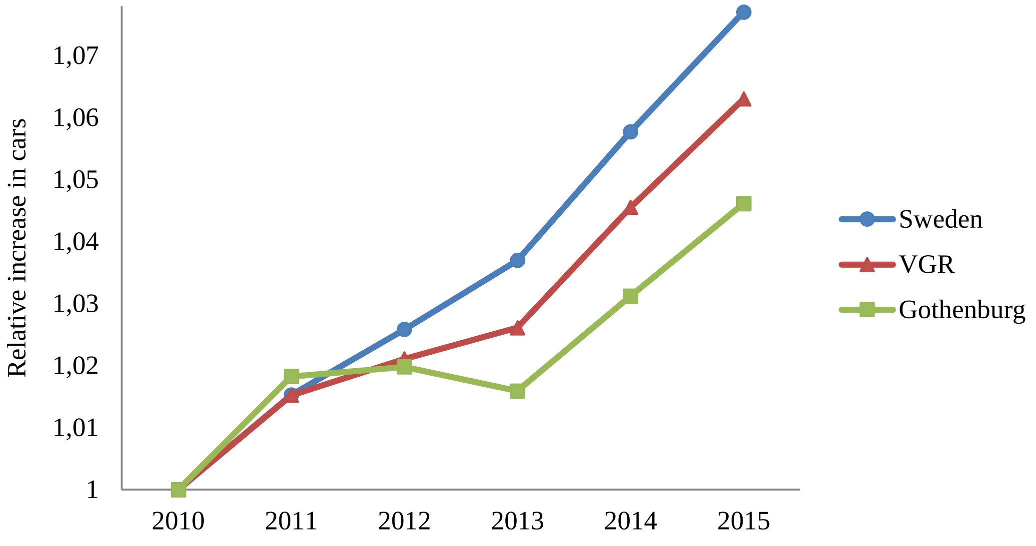
Our second question was whether the peak-hour transport demand price is elastic and once again the results differ between the periods. The elasticity in 2012/2013 is -0.126 while it is 0.0423 in 2014/2015 and the former is significant while the latter is not. We can thus conclude that the elasticity is inelastic in the case of implementation and an increase in cost of one percent leads to a decrease in number of cars by 0.126 percent. Comparing this to the elasticity value from the study in London their value of -0.47 is more elastic than ours, but still inelastic. Driving is a habit that in many ways shapes our schedule and drivers seem to adapt reluctantly to demand policies. Some underlying factors of the inelastic demand could be the absence of parallel routes or lack of transportation alternatives.

The third research question was determining whether time had an impact on the elasticity by introducing a time variable. This variable was significant in both periods and made the overall elasticity clearly more inelastic. We also wanted to investigate more closely how the elasticity changes throughout the year and while it is difficult to detect an overall pattern, January stands out as more elastic for both periods. If we focus solely on the first quarter of the years we can see a trend of the elasticities decreasing in magnitude and thus time having a diminishing effect. But when we look at the entire year(s) we cannot detect a significant trend and thus we fail to reject the null hypothesis for research question three. Still, given the pattern of the beginning of the year, drivers seem to react strongly at first and then grow accustomed to the policy.

The difference in results between the periods is in itself an effect of the passage of time. As Hultkrantz and Liu (2012) detected in Stockholm, the reintroduction of the congestion charge (or in our case a charge increase) does not have the same effect as the first implementation of the policy. While *homo economicus* has a stable elasticity over time, car drivers in Gothenburg seem to quickly grow accustomed to a price increase and become less price sensitive. This complicates the policy makers' assignment in finding the optimal congestion charge (P=MSC) as it is impossible to introduce repeatedly a policy for the first time. Instead they could increase the level of the congestion charge more frequently to counteract the diminishing effect but as our results reveal such a price increase does not hold the same effect. An alternative approach to decreasing passenger demand would be to increase elasticity instead through creating more substitutability, such as lower prices on public transport.

We are looking into the effects of the congestion charge in Gothenburg during the period 2012-2015 but it is also important to discuss time effects that do not originate from the policy. Thus, it is advisable to look at the development in number of cars in areas where there was no such policy in order to discuss a potential time trend. Figure 17 shows the percentage change of the traffic flow of all car drivers (not specific peak-hour) using the year 2010 as index and displays the time trend over five years. In Sweden the traffic has increased from 4.3 million car drivers to 4.6 million between the years 2010 to 2015 which is an increase of approximately 60 000 drivers per year. The same pattern can be seen for Region Västra Götaland (VGR) where it increases by 1.7 percent from 2010 to 2015, acknowledging that Gothenburg is a part of VGR. These upwards sloping trends can be attributed to several factors such as growing population, urbanization and general income increase (Statistics Sweden, 2016).

Figure 17: Traffic development, 2010-2015 (percentages) (Statistics Sweden, 2016)



These time trends highlight the issue of omitted biases of time across years. Since our data are divided we cannot follow the development in peak-hour traffic for more than two years in each sample. Looking at the data we can conclude that in all areas, including Gothenburg, there is a continuous growing demand for driving and thus the impact of the congestion charge might have been larger had it been isolated from the long-term time effect. The data for Gothenburg displays an upwards sloping trend but with the exception of 2013 when the congestion charge was implemented and the traffic actually decreased by -0.5 percent. Thus it is clear that the policy had the effect of reducing effectively the traffic demand. It is fair to assume that the traffic had otherwise continued to increase.

Analyzing the effect of the increase in congestion charge we cannot conclude statistically that it decreased traffic demand. A speculation given the time trend is that without this price increase the demand would have increased even more and that it once again leads to a diminishing decrease compared to what would have been observed otherwise. This would be the case if the demand grows more inelastic, not just within a year but between years. Our study investigates the short-term time impact on demand elasticity and concludes that people become less elastic over time when it comes to congestion charges. Since these types of policies often have long-term goals it would be interesting to investigate the long-term impact of road pricing. An example of future studies would be to casually investigate the congestion charge over several years including other control factors. It would also have been ideal to perform a difference-in-difference study between Gothenburg and a control city (for example Malmö) in order to capture the time effect. The obstacle of doing this lies in the lack of available corresponding data from another city.

Congestion is a problem of over demand and undersupply, but it is difficult if not impossible to manage traffic supply in the short run leaving policy makers to deal with the demand side. The present situation in Gothenburg is an attempt to stifle the growing traffic demand by imposing a cost on the drivers and our results indicate that one has succeeded in slowing down the growth considerably. The elasticity is inelastic and the results indicate the effectiveness of the tool is marginal and with a short time span. In the long run the situation could, however, be very different. The revenue from the charge will go towards infrastructural projects such as *Västlänken* which in the long run (2026) will rebuild the city's infrastructure and improve public transportation. In this scenario there will be less under supply and more substitutes creating a higher elasticity. Conclusively, in short term the dead weight loss will keep growing due to higher traffic demand and fixed traffic supply but given the long run design of the policy our conjecture is that the projections assumed to meet the increased demand in the future will be enough.

Comparing the forecast for 2026 and the planned infrastructural improvements it is still unclear whether the increasing demand of driving that the time trend indicates will be met. Since the capacities of the roads are fixed and the demand is increasing annually for the commuters in Gothenburg, a constant price increase seems unavoidable. Looking at this, with economic vision, the price paid has to be equal to the marginal social cost which includes the external cost created by every driver. If the congestion charge is going to be able to change driving patterns in the short-run, the increase of the charge needs to be higher in comparison to the annual wage increase with inflation taken into account. An example would be if the charge would increase by 5% and the real wage increase is 6% annually, then the cost effect of the charge would only be modest and would not change the driving-pattern.

The congestion charge is perceived as a regressive tax, meaning that it affects low-income earners more than high income earners since the congestion charge is not dependent on income level. However, many low income earners may be without cars and/or chose to use public transportation to a larger extent. Hence, whether the overall impacts of congestion charges are regressive or progressive is debated (Sterner, 2012). As people's wages are higher, their valuation or opportunity cost of time is higher than low-income earners making them benefit more from lower congestion as a result of the policy. If the charge should rise annually (with assumed fixed income levels) driving a car could become an even more positional good since only the high-income earners can afford to drive. Remaining commuters will have to switch to other less improved alternatives until 2026 when the infrastructural improvements are completed.

7. Conclusion

This thesis investigates the effect of the congestion charge on peak-hour traffic and the size of the effect in terms of price sensitivity. The results from the implementation period (2012/2013) do reveal a significant effect and an annual elasticity of -0.126 and thus one managed to reduce the traffic. The 4.5% increase of the charge in January 2015 did not result in a negative and significant elasticity. On the contrary, the result was positive and not significantly different from zero at a 10% level of significance. Obviously this cannot be attributed to the congestion charge but reveals an upward trend that the price increase did not manage to counteract.

When we look closer at the elasticity through the years the monthly results imply that drivers are more sensitive to the charge during the first months after an implementation or an increase have been carried out. Overall, the drivers are clearly inelastic with respect to the congestion charge at these price levels. One approach could be to raise congestion charge on a regular basis to levels where the demand is price sensitive. For the policy to be more than a revenue mechanism the drivers' demand must become more elastic, e.g. through expanding public transportation or making it cheaper. By encouraging demand of other modes of transport in combination with discouraging car traffic the policy would become more efficient in tackling the problems of congestion.

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Appendix A: 35 streets (measuring points), STA

1. Almedalsvägen
2. Backadalen
3. Dag Hammarskjöldsleden
4. Doktor Allards gata
5. E20 Alingsåsleden
6. E45 Marieholmsleden
7. E45 Oskarsleden
8. E6/E20 Kungsbackaleden
9. Ehrenströmsgatan
10. Emigrantvägen
11. Fjällgatan/Jungmansgatan
12. Fridkullagatan
13. Gibraltargatan
14. Hjalmar Brantingsgatan
15. Karlavagnsgatan västra
16. Karlavagnsgatan östra
17. Lindholmsallén
18. Margretebergsgatan
19. Marieholmsgatan
20. Mölndalsvägen
21. Olskroksmotet avfart E20
22. Olskroksmotet påfart E6
23. Partihandelsgatan
24. Polstjärnegatan
25. Redbergsvägen
26. Ringömotet I
27. Salsmästaregatan
28. Sankt Sigfridsgatan
29. Skälltorpsvägen
30. Stigbergsliden
31. Södra Tagenevägen
32. Tingstadsmotet avfart E6
33. Willinsbron
34. Älvsborgsbron
35. Örgrytevägen

Appendix B: Cost calculations

In order to perform calculations regarding the change in cost of driving, we must first calculate the baseline cost, without the charge.

Table A1: Cost of commute

Average daily length of tip (kilometer)	18[6]
Average cost of trip per kilometer	3.3
Number of trips for a commuter	2
Total daily cost	$3.3 * 18 * 2 = 118.8$

After the congestion charge was implemented the drivers now face an additional cost which is added on the baseline cost. We only look at the peak-hour commuter but still the charge levels vary and the added expense is calculated as the average according to the level of the charge and the share of the time span.

Table A2: Charge levels

	2013	2015
7:00-7:59	18	22
8:00-8:29	13	16
8:30-8:59	8	9
15:00-15:29	13	16
15:30-16:59	18	22

To find the average charge level we summarize the weighted charge according to its share for morning traffic respectively afternoon traffic:

$$\sum((time\ share * charge)^{morning} + (time\ share * charge)^{afternoon})$$

Table A3: Cost after implementation/increase

	2013	2015
Morning (7:00-8:59)	14.25	17.25
Afternoon (15:00-16.59)	16.75	20.5
Total	31	37.75

When we add these average congestion charge levels to the baseline cost of 118.8 SEK we arrive at the cost of the average commuter to Gothenburg, which is the independent variable of our study.

[6] Swedish Transport Administration, 2016

Appendix C: Monthly elasticities, 2012/2013

Months	Logcost	Constant	Observations	Adj-R^2
January	-0.414***	10.55***		
	(0.0483)	(0.237)	380	0.935
February	-0.115***	9.138***		
	(0.0320)	(0.156)	410	0.968
March	-0.0583**	8.904***		
	(0.0259)	(0.127)	352	0.983
April	0.133***	7.983***		
	(0.0355)	(0.175)	314	0.973
May	-0.0385	8.846***		
	(0.0489)	(0.239)	302	0.945
June	-0.192***	9.565***		
	(0.0630)	(0.302)	214	0.944
August	0.0274	9.515***		
	(0.124)	(0.608)	250	0.607
September	-0.153***	10.49***		
	(0.0338)	(0.166)	294	0.894
October	-0.190***	10.67***		
	(0.0318)	(0.156)	344	0.889
	-0.148***	10.46***		
November	(0.0310)	(0.152)	330	0.889
	0.0613	1.049***		
December	(0.118)	(0.0494)	266	0.690

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Monthly elasticities, 2014/2015

Months	Logcost	Constant	Observations	Adj-R^2
January	-1.997*	18.85***		
	(1.012)	(5.092)	138	0.952
February	0.241	7.630		
	(0.972)	(4.892)	138	0.955
March	1.424	1.794		
	(0.973)	(4.897)	138	0.955
April	0.538	6.111		
	(0.941)	(4.734)	138	0.957
May	-0.937	13.53***		
	(1.019)	(5.126)	138	0.947
June	2.093**	-1.683		
	(1.019)	(5.128)	138	0.949
August	-0.800	12.63**		
	(1.028)	(5.172)	138	0.950
September	-0.367	10.63**		
	(1.036)	(5.212)	138	0.948
October	-1.750	17.61***		
	(1.064)	(5.357)	138	0.946
November	0.804	4.904		
	(1.112)	(5.599)	138	0.940
December	1.217	2.651		
	(0.924)	(4.649)	138	0.958

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$