Are Prices in Charge of Congestion?

An Empirical Study of Increased Congestion Charge and Traffic in Stockholm

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Abstract

Economic theory often suggests congestion pricing to smooth the demand for traffic from periods of high demand to periods with lower demand. However, the real-world implementation of congestion charges remains limited. This study investigates the relationship between time-varying congestion charges and traffic volumes. By applying a difference-in-difference (DiD) method on hourly level traffic data from Stockholm, we examine the effects of the increased congestion charge in 2016 and 2020 on traffic volumes. The results suggest that increased congestion charge prices have resulted in less traffic during peak hours. However, the increased congestion price has also increased traffic just before and just after the hours covered by the congestion charge. In addition it has also increased traffic for hours with a low congestion charge. Thus, the total effect of the increased prices is twofold since it results in both decreased traffic volumes and substitution to cheaper hours. Using the attained DiD estimates to calculate elasticities, we find modest price elasticities of demand for traffic. Applying a peak-load pricing perspective and the Ramsey model on the results suggests there is room for increased prices where the responsiveness of traffic has been low.

Key words: *Congestion charge, Traffic demand elasticity, Peak-load pricing, Ramsey pricing, Negative externalities*

Contents

1 Introduction

As a larger share of the world's population is moving to urban areas, traffic congestion is becoming an increasingly big problem [Trafikverket, 2020a]. In Stockholm, one of the few cities worldwide to implement congestion charge, the population increases by approximately 40 000 inhabitants per year. Although theory and earlier empirical studies of the implementation of congestion charges imply they decrease traffic, the empirical research on the effects of congestion price increases remains limited. Studying congestion charge increases enables us to investigate the relationship between prices and traffic demand in more depth. Consequently, this study investigates the effects of increased congestion charge in 2016 and 2020 on traffic volumes in Stockholm and connects these results to price elasticities. This study exploits the hourly level data from the City of Stockholm's (Stockholms Stad) measurement stations to apply a difference-in-difference (DiD) method to estimate the causal effects of congestion prices on traffic volumes. On this basis, we can determine whether the pricing schedule with peak-load pricing is an efficient policy measure to smooth traffic over time.

Historically, imposing congestion charges has been a tool to minimise negative externalities, such as congestion and road wear. Although the congestion aspect is still relevant and part of the primary purposes of imposing congestion charges today, the policy's goal has shifted towards also being an environmental instrument. Even if the term congestion charge refers to the congestion externality only, this study will use the term in a broader sense, following the evolution of the policy's purpose. Since transport accounts for approximately one-fifth of the carbon dioxide emissions (CO2e) globally, creating efficient policies towards the transport sector is of high relevance to mitigate a climate crisis [Our World in Data, 2020]. However, results from this study suggest that increased prices may have a moderate impact on total traffic due to substitution effects between hours.

Earlier literature on congestion charges establishes many negative externalities connected to road traffic and congestion, including carbon emissions, time aspects, and road damage [Parry and Small, 2005, Santos, Behrendt, and Teytelboym, 2010, Anas and Lindsey, 2011]. Literature also covers empirical studies of congestion charges in Milan, Beijing, San Francisco, and Stockholm, finding different effects of the congestion charges depending on the city [Percoco, 2014, Foreman, 2016, Yang, Purevjav, and Li, 2020, Anderson, 2014]. Nevertheless, most empirical literature covers the implementation of congestion charges and not the later modifications, which does not enable them to study price elasticities. Also, the Swedish Transport Administration (Trafikverket) makes an evaluating report each time the congestion charge is modified. However, they examine the effect on traffic volumes during a limited number of days, and their prognoses do not consider price elasticities. Our study aims to further the existing literature on how demand for road traffic reacts to different changes and how policymakers can use variations in elasticities throughout the day to create more accurate pricing schedules.

Concerning the extent and scope of this study, we have limited the study's geographical extension and time period. Although similar congestion charges have been implemented in Gothenburg and several other cities internationally, Stockholm will be the main focus of this study. This focus results from the detailed data from the City of Stockholm's office for traffic planning, which undoubtedly facilitated a detailed analysis of the traffic flows in Stockholm specifically. Also, because of existing literature on the topic for the first-time implementation of the policy in Stockholm, this study considers only the increased price for the congestion charges in January 2016 and January 2020, respectively. Despite the various perspectives that can be applied to congestion charges both within and outside the field of economics, this study will only address the traffic volume aspect of the issue. To fulfil the aim of this study, the primary research question for this paper is:

What is the relationship between time-varying congestion charges and traffic volumes in Stockholm?

The study is organised in the following way to answer the research question. Section 2 covers two types of corrective taxes: the Steiner model and Ramsey pricing. Thereafter, Section 3 considers the earlier theoretical and empirical literature on congestion pricing. Further, Section 4 provides an institutional framework of the congestion charge in Stockholm and investigates simultaneous changes that may have affected traffic volumes. In Section 5, the data set and the DiD estimates used to measure the effect of congestion charges are presented. The results will be discussed in Section 6, followed by an analysis of these results in Section 7. Finally, concluding remarks will be presented in Section 8.

2 Theory

In this section, relevant theories that can be applied to congestion charge will be explained. First, externalities and corrective taxes are highlighted, followed by an explanation of peak-load pricing and the Steiner model. Thereafter, a detailed description of Ramsey pricing follows, which connects optimal taxation with customers varying price elasticities of demand.

2.1 Externalities and Congestion Charge

Hindriks and Myles [2006] describe an externality as the external effect that arises when an economic transaction affects the utility of a third party positively or negatively. One example is when traffic results in negative externalities that the individual does not pay for directly. Such negative effects can be congestion, pollution, and fossil fuel consumption. Since the negative externalities of traffic occur outside the price system of the economy, the individuals taking part in the transaction do not take the external effects of their actions into account. The presence of negative externalities implies that the market price of a service or good does not reflect the true cost for society as a whole, which results in a market failure. Cities and governments can impose taxes or subsidies to correct such a market failure and make the private marginal cost equal to the social marginal cost.

One example of how to correct such a market failure is implementing a Pigouvian tax, a corrective tax that internalises the negative effects of an economic decision by increasing the price of that specific good or service [Hindriks and Myles, 2006]. Imposing a congestion charge is one example of how a Pigouvian tax can internalise the social marginal costs of congestion and other traffic externalities. If firms or the public sector want to change a particular behaviour, they can also charge different amounts from diverse customer groups for the same good or service. According to Pigou [1929], setting different prices for different customer groups for identical goods or services, i.e., third degree price discriminating, can be suitable when some customer groups have a higher willingness to pay than others. In the traffic congestion case, third-degree price discrimination can be an efficient way of charging different customer groups at various times since the groups have varying willingness to pay.

2.2 Peak-Load Pricing

In some cases, the fluctuations in demand and non-storability for certain goods and services result in difficulties providing an optimal supply [Crew, Fernando, and Kleindorfer, 1995]. To tackle this issue, firms or the public sector can design a pricing scheme with higher prices when demand for the good or service is high. This type of price differentiation over time is called peak-load pricing. When regulating demand through peak-load pricing, the increased costs of the good or service reduces consumption during high-demand periods. Accordingly, when applied to traffic congestion, peak-load pricing can be a tool to push consumers towards choosing cheaper off-peak periods or choose another mode of transportation [Price, 1977].

Steiner was among the first within applied welfare economics to connect public utility, economic efficiency and marginal costs and developed a peak-load pricing model [Crew et al., 1995]. In the Steiner model, one day is divided into two periods, one part signified by higher demand (x_1) and one part signified by lower demand (x_2). To reach the optimal capacity, Steiner [1957] argues that the optimal prices should be higher in period 1 than in period 2 ($p_1 > p_2$). Compared to uniform pricing, peak-load pricing will decrease the demand in period 1 (x_1) and increase the demand in period 2 (x_2).

In line with this theory, a peak-load pricing framework can be applied to congestion charge schedules since congestion charges are usually only charged at high demand hours (or at least have a higher price than during low demand hours). A decrease in peak-load demand for traffic implies we need less total road capacity and reduces congestion at peak hours. However, one assumption in the Steiner model is that the demands in different periods of the day are independent of each other, implying that a price increase during one hour does not affect the demand in another hour. This independent demand assumption is not a realistic assumption for traffic, which we will further discuss in the analysis section. In conclusion, the Steiner model price discriminates over time periods with different demand levels to minimise demand at peak-load hours.

2.3 Ramsey Pricing

A model that addresses price discrimination over time from another perspective is Ramsey [1927], who presented early work on the topic of optimal taxes. His work examined the issue in designing taxation to maximise the economy's welfare and minimise economic distortions. In order to minimise a welfare loss as a consequence of a certain budget constraint, Ramsey's pricing rule suggests that firms can diversify prices across consumers' different price elasticities. The price elasticity captures the sensitivity of the demand for the good or service to a change in its price [Marshall, 1890]. The social welfare function that lays the foundation for Ramsey's welfare-maximising approach can be formulated in the following way:

$$W = TR + S - TC \tag{1}$$

In equation (1) on the preceding page, W represents the net social benefit, TR the total revenue, S the consumer surplus, and TC the total costs. Ramsey's pricing rule develops the optimal monopoly pricing of public goods to maximise social welfare. While optimal monopoly pricing sets prices equal to or above marginal costs, Ramsey's pricing rule uses the diversified price elasticities of demand to set the optimal price. According to Crew, Fernando, and Kleindorfer [1995], the Ramsey problem can be formulated as in equation (2).

$$Max_{P\geq 0}W(P) = \int_{\theta} \left[V(x(P,\theta),\theta) - \sum\nolimits_{N} P_i x_i(P,\theta) \right] f(\theta) d\theta + \Pi(P) \tag{2}$$

subject to:

$$\Pi(P) = \sum_{j\in N} P_i X_i(P) - C(X) \geq \Pi_0 \tag{3}$$

In equation 2, $\Pi(P)$ represents the profit and Π_0 stands for the desired profit level. Furthermore, the Ramsey solution is attained by taking the first-order condition for the Lagrangian $L(P) = W(P) + v\Pi(P)$, which is obtained from equation (2) and equation (3). Full caluclation can be found in Appendix. Ramsey's solution to the maximization problem has been extended by also including interdependent demands [Crew, Fernando, and Kleindorfer, 1995]. With the interdependent demand assumption, the solution to Ramsey's problem can be formulated as:

$$\sum_{j\in N} \frac{R_j}{R_i} \frac{(P_j - C_j)}{P_j} \eta_{ji} = -\kappa, \qquad i \in N \tag{4}$$

Equation (4) demonstrates the Ramsey number $\kappa = v/(1+v)$, which maximises profits when $\kappa = 1$. This depends on the cross-price elasticity $\eta_{ji} = (\partial X_j/\partial P_i)(P_i/X_j)$ and $R_i = P_i X_i$ represents the revenue. Rewritten and adjusted to two products in a regulated sector we can solve to find:

$$\frac{P_i - C_i}{P_i} = -\frac{\kappa}{\Delta}\Big(\eta_{jj} - \frac{R_j}{R_i}\eta_{ji}\Big) \qquad i \in 1,2, j \neq i \tag{5}$$

When the cross-price elasticity is included in the model, we can reach three different results depending on the goods relationship to each other:

1. **Independent:** $\eta_{ij} = 0$ for all $i \neq j$, makes equation (5) equal to the standard inverse elasticity (equation (6) on the following page).

2. **Substitutes:** $\eta_{ij} \geq 0$ means products 1 and 2 are substitutes which means $P_i \geq C_i$, except at

the unconstrained welfare optimum (i.e., if equation (3) on the previous page is not binding).

3. **Complements:** $\eta_{ij} \leq 0$ means products 1 and 2 are complements which means $P_i < C_i$ is possible at optimum for one of the two products.

In peak-load pricing, the different products are the different times of consumption. Since the products in the peak-load pricing case are identical except for the time of their consumption, we typically assume that the products are substitutes. Consequently, the price will therefore be higher than the marginal cost for every period in optimum, except when the profit constraint is not binding, as described in point 2 listed above. However, the hours could also be complements, in which case the demand for driving in one hour affects the demand for driving out at another. In optimum, the price for product 1 can be lower than its marginal cost since the price for the complementary product 2 can be higher (than its marginal cost) and cover the cost of product 1. For example, if driving at 8:00 and 18:00 are complementary products, the price of driving at 18:00 can be made higher to cover for the lower price at 8:00.

If using the more realistic cross-price elasticity model (such as stated in equation 5), we need to access information regarding marginal costs, own-price elasticities and cross-price elasticities [Allen, 1986]. Nevertheless, finding such estimates requires unattainable detailed information about individual demand curves. Therefore we have assumed independent demand which makes the framework of peak-load pricing applicable to our research question. This independent demand assumption implies that the price at one hour will not affect the demand at another hour. Although this is a considerably strong assumption, it enables us to use the inverse elasticity rule as a tool for our analysis. If solving the Ramsey problem with independent demand, the cross-price elasticities become equal to zero, and the inverse elasticity rule as demonstrated in equation (6) can be applied. Thus, the optimal pricing results in the standard inverse elasticity:

$$\frac{P_i - C_i}{P_i} = -\frac{1}{\epsilon} \tag{6}$$

Equation (6) suggests that the elasticity of demand should determine which goods or services should be further taxed, where inelastic goods or services should be taxed more heavily than elastic ones. If t is the tax rate, the relationship between taxes for two goods should therefore be as follows:

$$\frac{t_i}{t_j} = \frac{\epsilon_j}{\epsilon_i} \tag{7}$$

Equation (7) implies that the own-price elasticities should be inversely proportional to the tax of the goods. Hence, in the congestion charge case, imposing a higher congestion charge during times when the elasticity of demand is low will minimise the economic distortions. More specifically, it will be more efficient to enforce a higher congestion charge when a price increase only has a modest effect on the quantity demanded. Accordingly, the structure of congestion charges can use a diversified price schedule (on both a daily and a yearly basis) to take advantage of Ramsey's idea of primarily collecting taxes during times of inelastic demand.

3 Literature Review

This chapter will highlight previous literature on the external costs of road traffic in Section 3.1, the factors that affect demand for road traffic in Section 3.2, and empirical studies of the real-world application of congestion charges in Section 3.3. The relevant previous research is presented to contextualise our findings on the effects of the congestion charge on traffic.

3.1 External Costs

The economic literature on congestion charges aimed at correcting negative externalities connected to road traffic dates back to Vickrey [1969], who identified the concept of congestion pricing. However, the elements included in the externalities of road traffic have evolved during the last 50 years. For example, when studying gasoline taxes Parry and Small [2005] developed a model to calculate the externalities of road traffic, where they included pollution damages, external congestion costs, and external accident costs. Furthermore, Santos, Behrendt, and Teytelboym [2010] increased the emphasis of carbon emission externalities while including additional external costs, road damage, and the country's oil dependence. Moreover, Anas and Lindsey [2011] shifted the focus of congestion charges as solely a congestion measure by highlighting how cities can use it as a policy directed towards improving air quality and reducing emissions. They also argue that cars emit carbon emissions when driving, but they also emit more when driving very slowly, which occurs more often when there is much congestion. Thus, starting as a matter of time lost in congested traffic, road traffic externalities in the literature have become more comprehensive and complex to reflect the traffic effects better. By investigating the effects of congestion charge prices on traffic volumes, we can understand how congestion charge design can help mitigate the negative externalities of traffic.

3.2 Traffic Supply and Traffic Demand

One solution traditionally used to solve congestion is expanding road networks to make more room for traffic. In contrast to this supply-sided policy of building more roads to solve congestion, Vickrey [1969] suggested congestion charges as a demand-sided solution to move traffic over time and space through peak-load pricing. In addition, Duranton and Turner [2011] used evidence from the United States to show that an increase in road quantity led to higher demand for road traffic since the private cost of driving is lower when congestion is low. Another feature of the demand for road traffic is that it also depends on the substitution effect to public transport. Therefore, Anderson [2014] investigate how much highway traffic increased when transit services ceased to function. The study demonstrated that the net benefits of transit services were more significant than policymakers had estimated. They found that the substitution effect from road traffic to public transport was larger for groups who face high congestion levels. Therefore, congestion charges can have a two-sided effect on substitution to public transport since congestion-sensitive commuters may demand more traffic after congestion charges have decreased the traffic by targeting price-sensitive drivers.

Another element affecting the demand for road traffic are fuel taxes, but according to Parry and Small [2005] and Santos et al. [2010], fuel taxes do not include the full externalities of road traffic. Besides, within cities, parking pricing also decreases the demand for commuting, which Khordagui [2019] and Geroliminis [2015] illustrated. Moreover, they argue that too high parking demand leads to congestion due to increased cruise-to-park behaviour. In summary, the demand for road traffic depends on multiple factors, for example, congestion in itself, public transport, and fuel prices. Although multiple factors affect the demand for road traffic, this study will focus on the effect of congestion charges on traffic volumes specifically.

3.3 Empirical Examples

Only a few cities have implemented congestion charge since Singapore introduced it in 1975. The main additional cities which have applied the policy are Hong Kong (1980), London (2003), Stockholm (2007), Milan (2008) and Gothenburg (2013).

Eliasson [2009] constructed a cost-benefit analysis of the congestion charge in Stockholm. In the study, he argued that the gains from congestion charge implementation in Stockholm were large since many drivers had a high value of time and therefore benefited significantly from less congestion. Moreover, Percoco [2013] conducted an empirical study on the topic to examine how the congestion charge affected the greenhouse gas emissions in Milan. The study only found a temporary effect of the congestion charge on traffic since decreased traffic volumes only lasted a few days after implementing the policy. However, Percoco [2014] argues that this temporary effect results from a poorly designed experiment, which makes it difficult to draw any conclusions from his study. Another conclusion derived from the study is that the congestion charge in Milan resulted in a shifted demand from cars to motorcycles, which were not included in the congestion charge.

Additionally, Yang, Purevjav, and Li [2020] used a natural experiment on congestion charges in Beijing to find an optimal pricing scheme for the congestion charge by focusing on the speed and density of the traffic. In the study, Yang et al. [2020] found that increasing charges within "ring roads" during peak hours combined with decreasing charges outside "ring roads" during off-peak hours. The study argues this would allow the city to benefit fully from peak-load pricing and reduce the cost of negative externalities associated with congestion. Furthermore, Foreman [2016] uses a DiD approach to study the effectiveness of congestion pricing in San Francisco empirically. Foreman [2016] found that peak-load pricing decreases travel time and the total traffic volumes which she uses to calculate price elasticities. However, she argues that these elasticities and calculations cannot be compared to other cities, suggesting that the study may not be fully applicable and generalised across cities. Also, Finkelstein [2009] investigated drivers elasticity to digitising toll stations and found that drivers become less sensitive to road pricing when drivers pay bills electronically.

In conclusion, congestion pricing in the economics literature has been under consideration for a couple pf decades and has coped with concepts such as externalities and peak-load pricing. Nevertheless, during the last couple of years, the purpose of congestion charge has started including new factors such as the usage of fossil fuels and greenhouse gas emissions instead of only focusing on congestion. We further the literature by investigating the effect of the time-varying pricing in Stockholm on total and hourly traffic volumes. The results can help us understand how congestion pricing can be constructed to manage increased congestion and other traffic externalities efficiently.

4 Institutional Framework

The policy design and purposes of implementing the congestion charge will be considered in this section to analyse the effects of the congestion charge on traffic in Stockholm. Therefore, vehicles obliged to pay the congestion charge, exceptions, and regulation modifications are highlighted. Finally, simultaneous changes that may have contributed to the amount of traffic in Stockholm will be discussed.

4.1 Congestion Charges in Stockholm

In August 2007, the Swedish Government implemented congestion charges in Stockholm [Sveriges Riksdag, 2007]. The main objective of the congestion charge is to reduce traffic, improve accessibility and decrease the environmental impact of traffic in Stockholm [Trafikverket, 2020b]. Besides, another purpose of the congestion charge is to increase the tax revenues and facilitate road network infrastructure investments in Stockholm [Sveriges Riksdag, 2007].

4.1.1 Liability and Exceptions

The congestion charge in Stockholm applies to all cars, including private cars, trucks, and buses. Vehicles excluded from paying congestion charges are tractors, trailers, construction vehicles, buses with a total weight above 14 tonnes, motorcycles, emergency vehicles, diplomat registered vehicles, and military vehicles. Another exemption is vehicles with a Swedish parking permit for disabled people [Transportstyrelsen, 2020]. The legal person registered as the owner or user of the vehicle in the Swedish Transport Agency's road traffic register is obligated to pay the congestion charge. However, if the car owner is renting out the car for more than a year and notifies this leasing agreement to the Swedish Transport Agency, the responsibility for paying the congestion charge instead lies on the lessee of the car [Transportstyrelsen, 2014]. This is common when a company owns a car and rents it out to an employee as a "company car" or "benefit car," the company is obliged to pay the congestion charge since the company is the registered owner. Similarly, if the company is the registered user of the car, it must pay the tax if it leases out the car to an employee [Transportstyrelsen, 2013]. Regarding the time covered by the congestion charge, it is debited all weekdays during the year except from the three last weeks of July. Also, public holidays and some weekdays before public holidays are excluded from the congestion charge.

Table 1: Congestion Charge per Passage: Inner city

Time	1 March 2020	1 Jan 2020	1 Jan 2016	1 July 2007
	High Season	*Low Season*		
00:00–05:59	0	0	0	0
06:00–06:29	15	15	0	0
06:30–06:59	30	25	15	10
07:00–07:29	45	35	25	15
07:30–08:29	45	35	35	20
08:30–08:59	30	25	25	15
09:00–09:29	20	15	15	10
09:30–14:59	11	11	11	10
15:00–15:29	20	15	15	10
15:30–15:59	30	25	25	15
16:00–17:29	45	35	35	20
17:30–17:59	30	25	25	15
18:00–18:29	20	15	15	10
18:30–23:59	0	0	0	0

Notes: Congestion price changes since the implementation of congestion charge in 2007. High season is from the 1st of March to the day before midsummer and low season is midsummer to the 14th of August and the 1st of December to the 29th of February. All prices are in SEK.

4.1.2 Policy Design

In 2016, the congestion charge prices were increased for each taxable hour (Table 1) and Essingeleden was included in the tax area (Table 10 on page 50). The inclusion of Essingeleden in the congestion charge in 2016 and how this affects the DiD estimator will be discussed in Section 5.1.2. Additionally, the maximum price ceiling per day per vehicle increased from 60 SEK to 105 SEK in 2016 [Trafikverket, 2016]. Regarding the revenues arising from the congestion charges, they amounted to 1.8 billion SEK in 2015 and 2.6 billion SEK in 2016.

The Swedish Government made some corrections in the congestion charge in January 2020. This modification extended the period of taxation, increased the price for specific hours (see Table 1), and created a differentiation between high and low season. In addition, they lengthened the number of days included in the congestion charge by including the first five days in July and days connected to holidays [Trafikstyrelsen, 2019]. Moreover, the price ceiling per person and day was set at 135 SEK during the high season and 105 SEK for the low season. The high season period extends from the 1st of March to the day before Midsummer and between the 15th of August to the 30th of November. The residual days of the year are included in the low season period. This price differentiation between high and low seasons is also illustrated in Table 1.

The Swedish Transport Administration states that, since the population in Stockholm county increases by approximately 35 000 to 40 000 inhabitants per year, charging higher prices for congestion is one way of dealing with the increased demand for road traffic [Trafikverket, 2020a]. Also, the modification in 2020 was implemented to increase traffic accessibility and finance other infrastructure projects in the Stockholm region. The revenues from the congestion charge amounted to 2.7 billion in 2019 and 2.9 billion in 2020 [Trafikverket, 2020a].

4.1.3 Toll Stations

The toll station measures both passages in and out of the city and makes sure congestion charged hours are billed to the correct driver. These toll stations are mainly situated where there is currently and predicted to be large traffic flows and high congestion in the future. The 26 toll stations that register the congestion charge and the geographical location of each station are demonstrated in Table 2 and Figure 1 on the following page.

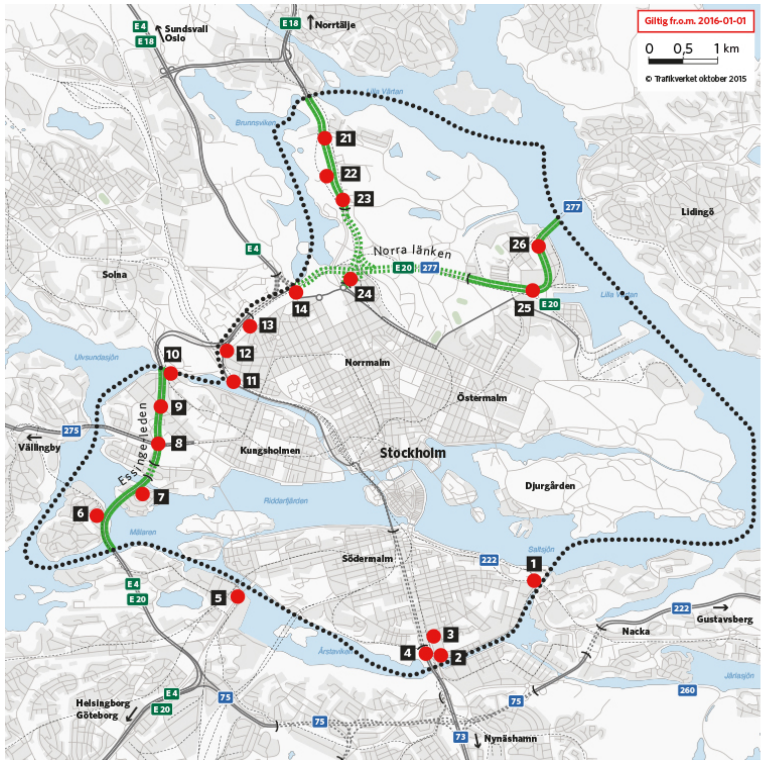


Figure 1: Location of Toll Stations

(Every red dot on the map represents a toll station in Table 2)

1.	Danvikstull	8.	Trafikplats Fredhäll	21.	Trafikplats Ekhagen
2.	Skansbron	9.	Trafikplats Kistineberg	22.	Trafikplats Frescati
3.	Skanstullsbron	10.	Ekelundsbron	23.	Trafikplats Universitetet
4.	Johanneshovsbron	11.	Klarastrandsleden	24.	Trafikplats Roslagstull
5.	Liljeholmsbron	12.	Tomtebodavägen	25.	Värtan
6.	Stora Essingen	13.	Solnabron	26.	Ropsten
7.	Lilla Essingen	14.	Trafikplats Norrtull		

Table 2: Toll Station Plan in Stockholm

4.2 Simultaneous Changes

The demand for road traffic depend on more factors than the price of the congestion charge. Therefore, to get a more complete picture, alternative factors that may have affected the traffic volumes during the period for the modified congestion charge will be examined. These results will be used to control that no other major changes that affect traffic have occurred close to the modifications in the congestion charge.

Firstly, during the period between 2015 and 2020, the total number of cars in Stockholm county increased from 887 057 to 953 391, illustrating an increase of approximately 7 per cent [Statistiska Centralbyrån, 2020b]. However, throughout the same period, the population increased from 2.198 million to 2.344 million, representing a population growth of 6.6 per cent [Statistiska Centralbyrån, 2020a]. Consequently, the total number of cars per inhabitant in Stockholm county only increased by approximately 0.25 per cent [Stockholm Stad, 2020]. The regional nominal Gross Domestic Product (GDP) per capita in Stockholm county has increased from 620 000 SEK in 2015 to 691 000 SEK in 2019 [Statistiska Centralbyrån, 2020c]. Secondly, another aspect that contributes to the demand for traffic is the fuel price, since it is a significant part of the total driving cost. The fuel price depends on value-added tax (VAT), fuel tax, production costs, and gross margins. Nonetheless, there has been a slight increase in the fuel tax between 2016 and 2020 (illustrated in Figure 5 on page 49 in Appendix). The fuel cost has not varied substantially during the period between 2015 and 2020 [Drivkraft Sverige, 2020], and there has been no sudden change in fuel taxation during the time of our study.

Thirdly, the price of parking in and around the city is another factor affecting the cost of driving in Stockholm. The only major changes in parking prices during our period of interest were made in September 2016, when the price of road parking increased in the innermost zone, and the charged hours were extended in the rest of the inner city. Simultaneously, free parking in the inner suburbs was included in the charged parking area (details in Table 9 on page 50 in Appendix). Thus, the changes in parking prices inside the city have been marginal, and no significant price changes interfere with the increased price of the congestion charge.

Lastly, the access to, and cost of public transport, can also affect the demand for driving. In 2015, 32 per cent of the total trips made in Stockholm county were travelled by public transport and the same number was 30 per cent in 2019 [Stockholms Länstrafik, 2020]. Infrastructure investments in public transport during our time period of interest have resulted in the density of commuter train departures increasing by 20 per cent. A one-time ticket that holds for 75 minutes costs 35 SEK, and a monthly card cost 930 SEK in 2020. The prices for monthly cards and temporary tickets are marginally increased every year by Stockholm Public Transport.

In conclusion, there have been changes in the number of cars, size of the population, regional nominal GDP, and the price of fuel, parking and public transport, which could affect the traffic demand. Nevertheless, sudden changes in these factors have not interfered with the date of the modifications of the congestion charge increases in 2016 and 2020, respectively.

5 Methodology

In Section 5.1. we will describe the data, our manipulations to the data, and the data limitations. Thereafter, in Section 5.2, the difference-in-difference estimator and its application to this specific study will be presented.

5.1 Data

For this study, we have received passage measurement data from the City of Stockholm's office for traffic planning [Trafikkontoret, 2021]. The office collects the data from permanent measurement stations, which register vehicle passages continuously throughout the year. The panel data covers the number of vehicles passing every station per hour from the 1st of January 2014 to the 31st of December 2020 from 73 measurement stations located around Stockholm. 24 of the stations started measuring in 2015, one in 2016, and one in 2018. Since three stations stopped measuring in 2016 and 2018, we exclude them from the data. After excluding these stations, approximately 2.9 million observations remain. There are only four variables in the initial data: station ID, the hour of the day, date, and the number of vehicles. Our dependent variable will be the number of vehicles registered, measured per date, per hour, and station.

5.1.1 Data Manipulation

To perform the analysis, we have also created several new variables: day of the week, week of the year, total vehicles per hour and several dummy variables. Since this study is only interested in congestion charged days, we exclude all days that the congestion charge does not include, i.e., all public holidays, July and weekends.

To investigate if and when the amount of vehicles per day changes abruptly during the period of interest, we have performed a structural break test. To examine whether a structural break exists, we perform a test of parameter stability with an unknown break date after running a regression of vehicles on time. We can observe when structural breaks are present in the data by looking for significant changes in the vehicle regression coefficient through this test.

After performing the test, we can reject the hypothesis that the mean is constant over time for both periods since the test finds a structural break on the 21st of December 2019 for the 2020 regression. Also, the test demonstrates a break on the 30th of March 2016 for the 2016 regression. However, both these dates coincide with big holidays, Christmas and Easter. Hence, to avoid an eventual biased estimate, we proceed to exclude all Swedish school holidays: Christmas holiday, winter holiday, Easter holiday, summer holiday, and autumn holiday since commuting trips decrease significantly during these periods. Detailed results of the structural break test can be found in Appendix.

5.1.2 Data Limitations

We have identified limitations of the data regarding the measurement stations, simultaneous changes in traffic, and the data structure. Firstly, since 23 stations were added successively to the data before August 2015, the analysis of the congestion charge will start on the 1st of September 2015. Ideally, the analysis would start with all stations a year before the changes to capture effects during all times of the year. Although September 2015 is relatively close in time to the modification of the congestion charge in January 2016, it still leaves us with observations that date back to four months before the congestion charge was changed. This makes it possible to compare the data to the same period in the following year.

Secondly, when the 2016 modification of the congestion charge was implemented, drivers had to start paying for passages at Essingeleden, which had prior been free. This implies Essingeleden itself is only subject to an implementation of the congestion charge. The primary focus of this study is the effects of the congestion charge modifications and not the effect of implementing the congestion charge on new locations. Consequently, we exclude stations located at Essingeleden from our 2016 regression. However, drivers who preferred to drive on the free Essingeleden before 2016 may now be more indifferent between two roads, even though Essingeleden is still less expensive. This effect could result in biased estimates when looking at the congestion charge increase in 2016 for the other stations. We have performed robustness tests to examine if we underestimate the coefficients due to vehicles shifting from Essingeleden to other roads and find no big differences. In addition, we both include and exclude the Essingeleden stations from the 2016 regressions in the tests, which we present in Appendix.

The Coronavirus outbreak resulted in recommendations from the Public Health Authority [Folkhälsomyndigheten, 2020] for employers to allow their employees to work from home in March 2020. This recommendation makes it difficult to isolate any effects of the congestion charge after this date. Consequently, we exclude any observations from after the 1st of March 2020. Hence, the disturbance caused by the Coronavirus makes it impossible to investigate the long-term effect of the changes made in the congestion charge in 2020. Therefore, due to the Coronavirus outbreak, the analysis of the congestion charge will only cover the low season changes in 2020 from a short-term perspective as well as the changes made in 2016.

Unlike our hourly level data, the congestion charge pricing scheme is divided on a half-an-hour level. This prevents us from studying if there is a shift of cars from just before to just after the congestion charge when it ends in the middle of an hour. For example, we cannot distinguish the effect of an increased congestion charge at 18.00 to 18.30 from the effects on the traffic volumes after the congestion charge ends at 18.30. Altogether, this makes it difficult to identify the size of substitution effects for some hours. Nevertheless, the City of Stockholm's office could only provide us with hourly level data from measurement stations, so we have used this to the extent possible.

Thus, changes in stations included in the congestion charge in 2015 and the coronavirus outbreak limit our analysis to certain stations and periods. Besides, half-an-hourly level data could have facilitated a more detailed analysis. Without these inconsistencies in the data, we could have examined more extended periods and included more stations. Nonetheless, we have considered the data sufficient for answering the research question and obtain the objective of this study.

5.1.3 Summary Statistics

In Table 3 on the next page, summary statistics for each variable is presented with mean value, standard deviation, maximum value and minimum value. Furthermore, in Figure 2, the mean weekly variation in registered vehicles for 2014 to 2020 is illustrated. Figure 2 demonstrates that mean vehicle volume fluctuated significantly over the year and shows the seasonal traffic fluctuations. One reason for excluding some weeks, as discussed in Section 5.1.1., is that there are more prominent traffic disturbances during Swedish public holidays than "normal" commuting weeks. Also, in Figure 3 on page 25 the variation in mean vehicle volume registered per hour of the day is presented. As depicted in Figure 3, the traffic is lowest during the nights and peaks at 15:00.

Table 3: Summary Statistics

	Mean	Sd	Max	Min
N. Vehicles (per station and hour)	399.0	554.0	5139	1
Station	37.71	21.67	73	3
Hour	11.53	6.900	23	0
Sum Vehicles (per hour)	21537.8	13814.8	47687	1
Post20 (=1 if date > 01/01/2020)	0.0584	0.234	1	0
Hour20 (=1 if hour 5-9)	0.209	0.407	1	0
Post20*Hour20	0.0122	0.110	1	0
Post16 (=1 if date > 01/01/2016)	0.763	0.425	1	0
Hour16 (=1 if hour 6-18)	0.587	0.492	1	0
Post16*Hour16	0.448	0.497	1	0
Observations	2862956			

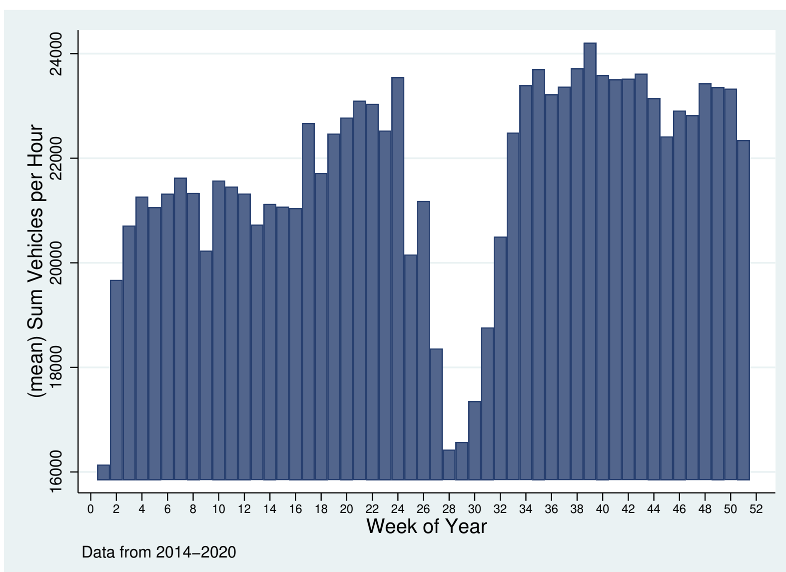


Figure 2: Week of Year Variation

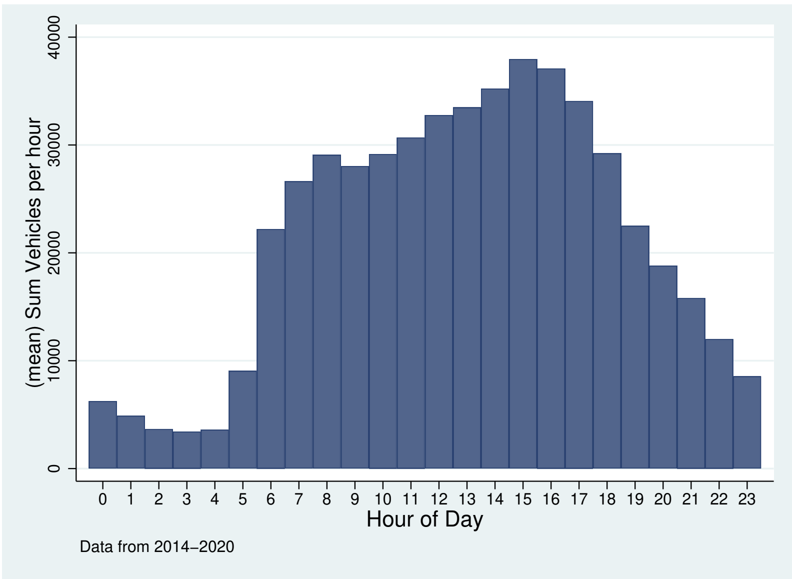


Figure 3: Total Vehicles per Hour of Day Variation

5.2 Difference-in-Difference

We use a DiD approach to examine if increased congestion charges affect traffic volume. The DiD model allows us to compare the difference in traffic volume in the paying hours and non-paying hours after the price change for the congestion charge to the difference in traffic volume in the paying and non-paying hours before the price change. Using these estimates, we can calculate the effect of the treatment on the outcome. We look at the effects for one hour at a time by restricting the regressions to one treatment hour per regression, which allows us to compare the effects during different hours of the day. The DiD model can be specified as in the regression equation (8) on the next page and equation (9) on page 28 [Antonakis, Bendahan, Jacquart, and Lalive, 2010].

5.2.1 Treatment and Control Groups

The treatment group are the hours affected by the congestion charge. We look at one hour at a time when studying time-varying effects. For this study, we need a control group that is neither covered nor affected by the congestion charge. Due to an increased congestion charge, a decreased number of cars driving into the city during the morning could affect the number of vehicles driving out of the city during the afternoon. Accordingly, we can not use hours close to the congestion charged hours as control groups since we conclude that most cars that drive into the city also drive out of the city. We have chosen the hours between 23:00 and 03:00 as the control group since these hours should not be significantly affected by an increased congestion charge. Therefore, we divide our control versus treatment group in the following way:

- Treatment group: One hour per regression between 5:00-19:00
- Control group: All hours between 23:00-03:00

Choosing these hours as our control group comes with some limitations. To start with, our control group captures general effects (weather, general increase in cars, road work, fuel costs). On the contrary, it does not capture heavy-traffic-specific effects since the control hours are defined by that they are not heavily trafficked. Some events primarily affect traffic during peak-load hours. For example, increased peak-load departures in public transport, partial road work (making the traffic slower when traffic is heavy), or specific policies that only affect "benefit cars" or "company cars" that primarily drive at commuting hours. Thus, since peak-load hours are only part of the treatment group, an event exclusively affecting peak hours results in the DiD coefficient capturing this effect. An event with a one-sided effect can result in an under or overestimation of the congestion charge effect.

5.2.2 Assumptions

For the DiD estimator to be valid, we must test that the parallel trend assumption holds. The parallel trend assumption means that, in the absence of treatment, the difference between the control groups and treatment groups should be constant [Angrist and Pischke, 2009]. Thus, without a treatment taking place, the rate of increase or decrease should be the same for both the treatment and control groups. We can test this graphically or with a placebo test. Technically, a placebo test requires us to create a "fake" treatment group, i.e., hours that are not affected by the change, and, after that conducting a DiD estimation on the "fake" treatment group. A significant non-zero impact would imply underlying characteristics, suggesting that the groups might not have had similar trends in the absence of the treatment. Therefore, the DiD estimation should expose zero impact on the "fake" treatment group for the placebo assumption to hold. Exposing such differences casts doubt on that the parallel trend assumption would hold [Gertler, Martinez, Premand, Rawlings, and Vermeersch, 2011]. We present the parallel trend assumption and the result of the placebo test in Section 6.1.

5.2.3 Specification

The DiD model is estimated using equation (8), where $Y_{h,s,t}$ is the traffic volume per hour and station, h stands for the hour, s is per station, and t is representing the time. In equation (9) on the following page, the $Y_{h,t}$ represents the total traffic per hour. Also, $(Hour_h = 1)$ represents the treatment group (hours not affected by the changed price), and $(Hour_h = 0)$ is the control group (hours affected by the changed price). The time variable $PostJan2016_t$ represents a dummy variable taking the value 1 after the price change and 0 before the price change and 1 after the price change. Consequently, the $PostJan2020_t$ also takes the value 1 after the modified congestion charges made in 2020 and 0 before the policy change. The interaction variable $(Hours_h) * (PostJan2016_t)$ demonstrates when $(Hour_h = Post_t = 1)$, which captures the hours with price change after the modifications in 2016. And $(Hour_h) * (PostJan2020_t)$ indicates when $(Hour_h = PostJan(Year)_t = 1)$. Further, we also include the day of the week, week of the year, and station fixed effects as controls represented by α_d, δ_w, and γ_s. The unexplained error term is represented by $\epsilon_{s,h,t}$ for the station level equation (8), and $\epsilon_{h,t}$ for the total equation (9) on the following page. Altogether, this results in the estimated causal effect of the policy reform of increased congestion charge being represented by β_3, which is specified in equation (10) on the next page.

$$y_{h,s,t} = \beta_0 + \beta_1 Hour_h + \beta_2 PostJan(Year)_t + \beta_3 (Hours_h * PostJan(Year)_t) + \alpha_d + \delta_w + \gamma_s + \epsilon_{h,s,t} \quad (8)$$

$$y_{h,t} = \beta_0 + \beta_1 Hour_h + \beta_2 PostJan(Year)_t + \beta_3 (Hours_h * PostJan(Year)_t) + \alpha_d + \delta_w + \epsilon_{h,t} \quad (9)$$

$$\hat{\beta}_3 = \big[(y \,|\, T = 1, X = 1) - (y \,|\, T = 0, X = 1) \big] - \big[(y \,|\, T = 1, X = 0) - (y \,|\, T = 0, X = 0) \big] \quad (10)$$

Thus, we can interpret our DiD estimator (β_3) as the estimated causal effect of the increased congestion charge on the amount of traffic. Accordingly, if β_3 is sufficiently large and statistically significant, it indicates how large the effect of an increased congestion charge is on the amount of traffic.

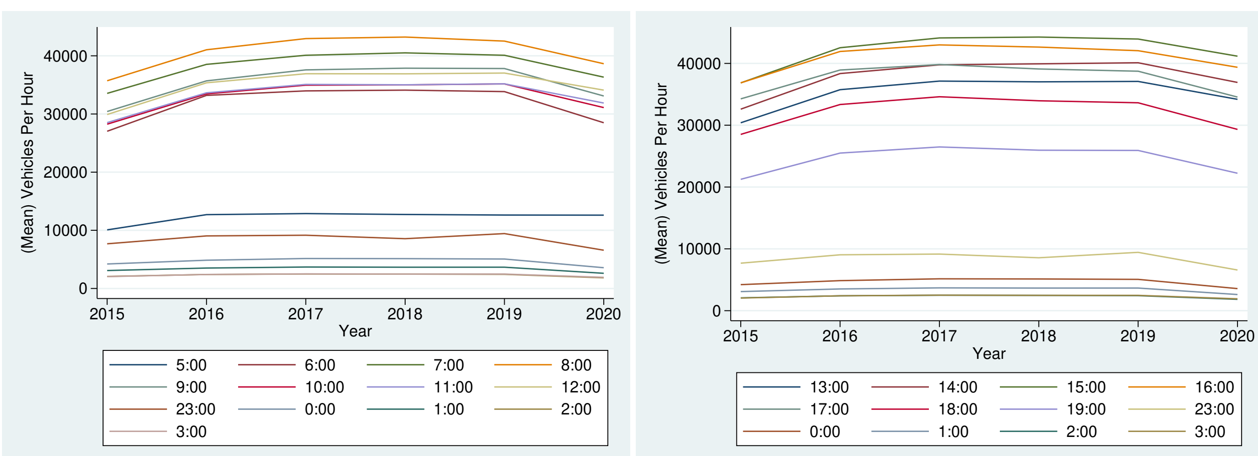
6 Results

In this section, we will first present the results from our parallel trend and placebo tests. Further, Section 6.1.2. and Section 6.1.3 describe the results from our DiD regressions on increased congestion charge in 2016 and 2020. In Section 6.2, we use the attained DiD estimates to calculate own-price elasticities for 2016.

6.1 Difference-in-Difference

6.1.1 Testing Assumptions

We test the parallel trend assumption graphically in Figure 4, which illustrates that the number of passages for different hours undergo a similar trend for each year included in this study. The similar trends motivate why a DiD method has been considered suitable for this study and selected as the methodological framework for this paper. Besides, we have conducted several placebo tests with "fake" treatment groups and "fake" treatment times. The placebo tests demonstrate insignificant or small differences, indicating that this model's control group is appropriate. The results of these placebo tests are presented in the Appendix.



(a) Morning vs. Control

(b) Afternoon vs. Control

Figure 4: Parallel Trend Test, Mean Vehicles by Year

6.1.2 Increased Congestion Charge in 2016

The increased congestion charge in January 2016 applied to all taxable hours, which motivates why we test every hour between 6:00 and 19:00. Table 4 on page 32 illustrates the changes in the number of vehicles per station for different hours as an effect of the price increases in the congestion charge in January 2016. The prices increases on the 1st of January 2016 is demonstrated by the $PostJan2016$ dummy variable. Also, the variable $Hour(Treated)$ is a dummy for hours likely to be affected by the modification in the congestion charge, 6:00-18:00. In each specification, control variables and fixed effects are included for the day of the week, week of year, and station. The regressions includes data from the 1st of September 2015 to the 1st of January 2018, i.e., four months before and two years after the price change. Since Essingeleden was first included in the congestion charge in 2016, the regressions do not include stations on Essingeleden.

Table 4 illustrates a significant decrease in the number of vehicles per station for 7:00, 8:00, 15:00, 16:00 and 17:00. However, for 6:00, 9:00, 10:00, 11:00, 12:00, 13:00, 14:00, 18:00 and 19:00, the coefficients are insignificant and comparably small, varying between approximately -12 and 4.7 vehicles per hour with large standard errors (compared to the size of the coefficients respectively). As illustrated in Table 4, we can observe a significant decrease of approximately 29 vehicles per station at 7:00. Also, at 8:00, a significant negative effect is demonstrated, with a decrease of roughly 21 vehicles per station. A negative effect of approximately 20 vehicles is noticeable at 15:00, and at 16:00 where the number of vehicles has decreased by approximately 27. The greatest significant decrease is evident at 7:00 and 17:00, with a traffic reduction of approximately 28 and 29 vehicles per station. The standard errors for all the significant coefficients vary from approximately 6 to 7. The coefficients for 7:00, 16:00 and 17:00, are significant at a zero-point-one level. For 8:00 and 15:00, the significance is at a one per cent level, which also demonstrates trustworthy coefficients. Additionally, the R-squared for the significant coefficients fluctuates from a low of 0.6 (7:00) to a high of 0.65 (16:00).

The effect of the increased congestion charge on the total amount of vehicles is demonstrated in Table 5 on page 33. All estimates are significant at a zero-point-one per cent level, except for the insignificant coefficients at 13:00 and 18:00. Moreover, the coefficients at 13:00 and 18:00 have large standard errors compared to the size of the coefficients. Therefore, these coefficients may not be trustworthy. Further, the significant estimate at 6:00 illustrates an increase of approximately 232 vehicles. At 7:00, a significant negative effect of the congestion charge increase of roughly -1093 vehicles is evident, followed by a decrease of -446 vehicles at 8:00. In addition, a significant positive increase of 405 and 492 vehicles are present at 9:00 and 10:00, respectively. At 11:00, an increase of

400 vehicles is evident, followed by an increase of 294 vehicles at 12:00. Furthermore, a decrease of -208 vehicles is present at 14:00, followed by a decrease of approximately 663 vehicles at 15:00. In addition, a significant decrease of -1100 vehicles at 16:00 and a significant increase is evident of 764 vehicles at 19:00. Accordingly, the greatest significant effect is found at 17:00, with an estimated decrease of roughly 1351 vehicles. The standard errors for the significant estimates range from 29 to 52. All estimates have an R-squared that varies between 0.948 and 0.983. The R-squared values for the total number of vehicles (Table 5) are higher than those on the station level (Table 4), which can be due to the station level estimates including station fixed effects. The estimates can be compared to the significant average decrease of approximately 160 cars per hour between 6:00 and 19:00 illustrated in Appendix (Table 15 on page 53).

Table 4: Regression of Number of Vehicles per Station on Congestion Tax Increase 2016 (DiD)

Time	**6:00**	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**
PostJan2016	0.630	0.409	0.458	-0.0920	-0.532	-0.476	-0.166
	(1.232)	(1.136)	(1.066)	(0.917)	(0.861)	(0.852)	(0.878)
Hour(Treated)	438.1***	514.5***	571.0***	465.8***	417.0***	415.5***	437.4***
	(7.761)	(6.471)	(6.512)	(5.380)	(4.814)	(4.760)	(5.009)
PostJan2016*Hour	-5.924	-28.85***	-20.52**	-7.486	-1.325	-2.675	-3.942
	(8.510)	(7.077)	(7.165)	(5.904)	(5.295)	(5.230)	(5.497)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147767	148311	147697	147701	147704	147700	147711
R^2	0.493	0.598	0.614	0.636	0.646	0.654	0.655

Time	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**
PostJan2016	0.760	1.059	0.316	-0.866	-0.916	-1.128	-0.962
	(1.141)	(1.244)	(1.136)	(1.033)	(0.953)	(0.855)	(0.721)
Hour(Treated)	481.6***	524.6***	529.8***	551.2***	498.9***	391.0***	258.8***
	(6.950)	(7.937)	(6.513)	(6.687)	(5.947)	(5.020)	(3.745)
PostJan2016*Hour	-7.616	-11.98	-20.27**	-27.63***	-28.33***	-7.630	4.653
	(7.629)	(8.677)	(7.122)	(7.270)	(6.471)	(5.471)	(4.073)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147798	147800	148312	147677	147674	147673	147666
R^2	0.581	0.565	0.643	0.637	0.647	0.647	0.654

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Vehicle data per hour and station for each weekday excluding holidays between September 2016 and January 2018. Controls include day of week and hour of day. Fixed effects include day of week, week of year and station fixed effects. Passages between 23:00-03:59 are used as the control group. Essingeleden is excluded from the regressions.

Table 5: Regressions of Total Number of Vehicles on Congestion Tax Increase 2016 (DiD)

Time	**6:00**	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**
PostJan2016	212.5***	172.5***	183.1***	137.1***	105.2***	94.36***	123.0***
	(17.94)	(14.38)	(14.42)	(13.71)	(13.12)	(13.08)	(13.12)
Hour(Treated)	27837***	35531***	37311***	30848***	28083***	28088***	29720***
	(41.43)	(41.82)	(42.20)	(33.94)	(24.91)	(23.73)	(25.80)
PostJan2016*Hour	232.2***	-1093.1***	-445.9***	405.0***	492.3***	400.9***	293.7***
	(49.98)	(51.91)	(52.47)	(40.23)	(28.82)	(27.52)	(29.81)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148286	147695	147697	147701	147704	147700	147711
R^2	0.948	0.971	0.975	0.976	0.979	0.980	0.981

Time	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**
PostJan2016	123.2***	139.6***	129.1***	79.72***	70.93***	54.38***	52.48***
	(13.22)	(13.36)	(13.71)	(13.87)	(14.00)	(13.79)	(13.71)
Hour(Treated)	30059***	32648***	37109***	36445***	33364***	26409***	17360***
	(29.24)	(23.37)	(26.77)	(36.13)	(40.00)	(39.31)	(34.88)
PostJan2016*Hour	14.84	-208.0***	-662.6***	-1099.6***	-1351.2***	-55.26	763.8***
	(33.74)	(30.12)	(34.47)	(42.41)	(45.79)	(44.04)	(38.66)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147702	147705	147696	147677	147674	147673	147666
R^2	0.980	0.982	0.983	0.982	0.978	0.972	0.953

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Vehicle data per hour for each weekday excluding holidays between September 2016 and January 2018. Controls include day of week and hour of day. Fixed effects include day of week and week of year. Passages between 23:00-03:59 are used as the control group. Essingeleden is excluded from the regressions.

6.1.3 Increased Congestion Charge in 2020

For the 2020 modification of the congestion charge, the price increase only applied to the morning peak hours between 6:00 and 7:30 (see Table 1 on page 16). Therefore, the congestion charge's effect on the number of vehicles for the nearest hours (from 5:00 to 7:00) is presented in Table 6 on the following page. The changes were put in place on the 1st of January 2020, which also constitutes the $PostJan2020$ dummy variable. The variable $Hour(Treated)$ is a dummy for hours potentially affected by the changes in congestion charge, 5:00 to 9:00. At 5:00, there is no congestion charge, but we can see a significant increase of approximately 36 cars per station with a standard error of 7 in Table 6. At 6:00, there is an extension of the congestion charge from 6:30 to 6:00 and a price increase of 10 SEK from 6:30 to 6:59. The 6:00 coefficient represents a decrease of roughly 40 vehicles per station with a standard error of 15, which is significant at the one per cent level.

At 7:00, there has only been an increase of 10 SEK from 7:00 to 7:29, and the price from 7:30 to 7:59 has remained unchanged. Still, we can see no significant effect of the changed congestion charge on vehicles at 7:00. The R-squared for the significant coefficients varies from 0.57 to 0.51. The effect of the congestion charge on the total number of vehicles is illustrated in Table 7 on the next page, where all the coefficients are significant at the zero-point-one per cent level. At 5:00, there has been an increase of roughly 2000 vehicles, with a standard error of approximately 40. In addition, the total number of vehicles has instead decreased with -2540 at 6:00, with a standard error of about 50. There has been an increase with roughly 263 vehicles at 7:00, with a standard error of 42. The R-squared for the coefficients varies between 0.79 and 0.97, which is higher than when estimating the station level effects in Table 6 on the following page. However, when looking at the total number of vehicles, we do not include station level fixed effects, which can affect the size of the R-squared measure. The estimates can be compared to the significant daily average decrease of approximately 600 cars per hour between 6:00 and 19:00 illustrated in Appendix (Table 16 on page 54).

Table 6: Regression of Number of Vehicles per Station on Congestion Tax Increase 2020 (DiD))

Time	**5:00**	**6:00**	**7:00**
PostJan2020	0.720	2.230	0.255
	(1.245)	(2.111)	(2.029)
Hour(Treated)	130.8***	487.0***	602.0***
	(1.152)	(2.983)	(3.045)
PostJan2020*Hour	36.07***	-40.11**	9.060
	(6.630)	(14.53)	(16.73)
Fixed Effects	Yes	Yes	Yes
Observations	263639	263759	263130
R^2	0.573	0.491	0.513

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Vehicle data per hour and station for each weekday excluding holidays between January 2016 and March 2020. Controls include day of week and hour of day. Fixed effects include day of week, week of year and station fixed effects. Passages between 23:00-03:59 are used as the control group.

Table 7: Regression on Total Number of Vehicles on Congestion Tax Increase January 2020 (DiD)

Time	**5:00**	**6:00**	**7:00**
PostJan2020	53.28*	155.5***	48.40**
	(23.61)	(24.10)	(16.99)
Hour(Treated)	7557.0***	28257.1***	34959.6***
	(9.320)	(18.19)	(20.16)
PostJan2020*Hour	2008.3***	-2540.7***	263.0***
	(40.33)	(49.65)	(42.40)
Fixed effects	Yes	Yes	Yes
Observations	263639	263759	263130
R^2	0.781	0.945	0.971

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Total vehicle data per hour for each weekday excluding holidays between January 2016 and March 2020. Controls include day of week and hour of day. Fixed effects include day of week and week of year fixed effects. Passages between 23:00-03:59 are used as the control group.

6.2 Own-Price Elasticities of Demand

Using our results from Section 6.1 and the changes in congestion charge from Table 1 on page 16, we calculate own-price elasticities, i.e., the responsiveness in traffic demand due to changed prices at different hours. By applying the DiD model, we have attempted to isolate the effect of the increased price of the congestion charge on traffic. Using the DiD estimates instead of the changed quantity demanded makes it possible to capture the changed quantity solely caused by the price change and not caused by a general variation in traffic. The own-price elasticity can be calculated by dividing the DiD estimates by the average price change for each hour which is illustrated in Table 8. The hourly level data and data on changed prices make it possible to calculate time-varying elasticities, which have varied throughout the day. Due to insignificant DiD estimates for 7:00-8:00 and a price change from 0-15 SEK 6:00-6:30, it impossible to calculate any price elasticities for the increased congestion charge in 2020. Therefore, only the price elasticities of demand of the modifications made in the congestion charge in 2016 will be considered.

6.2.1 Own-Price Elasticities for 2016

In Table 8 on the next page we can observe the own-price elasticities for different times due to the price changes in the congestion charge occurring in 2016. As observed in Table 8 the own-price elasticities are positive from 9:00 to 12:00 (ranging between 0.019 and 0.147). In this study, we assume that traffic is a normal good. Since the traffic during these hours has increased despite the price increases, we will interpret the positive own-price elasticities between 9:00 to 12:00 as a response to price increases at other hours, i.e., a substitution effect.

The remaining hours (7:00, 8:00, 14:00, 15:00, 16:00, 17:00) with significant DiD coefficients are negative, illustrating that the demanded quantity has decreased due to the increased price (Table 8). Moreover, the lowest elasticity occurs at 8:00, with a 1 per cent decrease in vehicles in response to the average price increase of 71 per cent. Consequently, the own-price elasticity at 8:00 is -0.015, demonstrating an almost insignificant elasticity. The highest price elasticity occurs at 14:00, with a vehicle decrease of 0.53 due to the 10 per cent price increase. In Table 8 on the following page, all elasticities observed range between 0.147 and -0.053, indicating that the traffic demand is relatively inelastic since the change in quantity demanded is lower than the price change.

Overall, these findings are in accordance with the results presented by Foreman [2016], who found price elasticities between 0 to -0.2 for the San Fransisco region. Furthermore, a similar conclusion was reached by Finkelstein [2009], who found elasticities of -0.061 for toll stations in the USA. Thus, the outcomes of the price elasticities of demand presented in Table 8 are similar to but slightly lower than earlier estimates of congestion charge and traffic elasticities.

Table 8: Price Elasticities with DiD Estimates from 2016

Time	Mean Q_{2015}	DiD	$\Delta Q/Q$	Price Change (SEK)	$\Delta P/P$	Elasticity(ϵ)
6:00	33136	232	0.70%	0 SEK, 5 SEK	-	-
7:00	40220	-1146	-2.85%	10 SEK, 15 SEK	71%	-0.040
8:00	42251	-445	-1.05%	10 SEK, 15 SEK	71%	-0.015
9:00	36044	405	1.12%	5 SEK, 1 SEK	58%	0.019
10:00	33530	492	1.47%	1 SEK	10%	0.147
11:00	33785	400	1.18%	1 SEK	10%	0.118
12:00	35668	293	0.82%	1 SEK	10%	0.082
13:00	36252	-	-	1 SEK	10%	-
14:00	39092	-208	-0.53%	1 SEK	10%	-0.053
15:00	43804	-662	-1.51%	5 SEK, 10 SEK	58%	-0.026
16:00	43390	-1099	-2.53%	15 SEK	75%	-0.034
17:00	40560	-1351	-3.33%	15 SEK, 10 SEK	71%	-0.047
18:00	33856	-	-	5 SEK, 0 SEK	-	-
19:00	25060	763	3.04%	0 SEK	-	-

Notes: Approximate price elasticities. $\Delta Q/Q$ has been estimated with the DiD coefficient. In the cases that two different price changes have occurred in the same hour, the changes for each half an hour have been weighted. Insignificant DiD estimates have been left out of the calculation. The mean for Q_{2015} is calculated from September 2015 to December 2015, the same period as the DiD estimates.

7 Analysis

This study demonstrates how increased congestion charges have affected the demand for traffic in Stockholm and how the framework of price elasticities in peak and off-peak hours can enable an analysis of the effects. In this section, we address the results from both Steiner's approach, intending to smooth demand over time, and Ramsey's inverse elasticity model, with the objective to maximise total welfare. Furthermore, we discuss the difficulties of applying these approaches and the effectiveness of the congestion charge from an externality perspective.

When applying the DiD method, a significant negative effect of the increased congestion charge on station level traffic at 7:00, 8:00, 15:00, 16:00 and 17:00 is evident for 2016. In addition, there has been a significant negative effect on the total level at 7:00, 8:00, 14:00, 15:00, 16:00, 17:00. Also, the DiD estimates demonstrate a significant positive effect at 6:00, 9:00, 10:00, 11:00, 12:00 and 19:00. Thus, the general increase in the congestion charge implemented in 2016 has resulted in less traffic for some hours and more traffic in others. The significant positive impact during some hours indicates that commuters have substituted their traffic consumption from slightly more expensive hours to slightly cheaper hours.

From these results, the generally increased congestion charge in 2016 seems to have been an efficient tool to reduce traffic somewhat during certain hours while leaving traffic unchanged or increased at others. The non-negative effect is especially evident during the middle of the day when there is still a high demand but a relatively low congestion charge. According to the Steiner model, these results suggest we can increase prices at, for example, 15:00 to smooth out the demand for traffic and cut off the largest demand peaks of the day. If instead observing the prices from a Ramsey model perspective, we can look at, for example, 12:00 (figure 3 on page 25) where the average demand of traffic is higher than for 8:00, but only experienced a 1 SEK increase in congestion charge compared to a 12.5 SEK increase at 8:00. As a result, the traffic decreased with approximately 450 cars (resulting in a -0.015 elasticity) at 8:00 but increased with almost 300 cars at 12:00 (resulting in a 0.082 elasticity). According to Ramsey's peak-load theory, one should use the elasticities as a tool to target unresponsive hours when pricing congestion, which would suggest a price increase at 12:00 will maximise the economic welfare.

Concretely, we can apply Equation (7) on page 10, which is the standard inverse elasticity rule to calculate the proportions between taxes for different hours. For example, dividing the elasticity at 7:00 by the elasticity at 8:00 ($\epsilon_7/\epsilon_8 = 2.6$) implies the optimal tax rate should be 2.6 times higher at 8:00 than at 7:00. This result implies that by leaving the congestion charge unchanged at 7:00, the congestion charge at 8:00 could be increased from 35 SEK to between 65 SEK and 91 SEK. The same calculations can be applied to the negative elasticities at 14:00, 15:00, 16:00 and 17:00. A few other examples where the Ramsey rule can be applied and tell us where there is a possibility to increase the congestion charge are calculated. For instance, an optimal tax rate at 15:00 would be 22 SEK if keeping 14:00 constant and 45.5 SEK if comparing to 16:00. This would suggest that the average optimal tax rate would be 50.25 SEK at 15:00. Furthermore, the optimal tax rate at 16:00 would be 41.5 SEK if comparing to 17:00. However, these estimates are only an example of how the Ramsey rule can be applied and more complete information is needed to fully compare elasticities and tax rates throughout the day.

Moreover, the increased congestion charge in 2020 illustrates that there has been a significant positive effect on the traffic per station at 5:00. In addition, a significant negative impact on the traffic per station is evident at 6:00. The significant positive effect at 5:00 and the similar size of the coefficient compared to 6:00 suggests that some commuters have substituted driving at 6:00 (covered by the congestion charge) in favour of driving at 5:00 (not covered by the congestion charge). Likewise, this substituting behaviour is also evident for the total traffic. In the 2020 regression of the total number of vehicles, we can observe a significant negative effect on the traffic at 6:00 and a significant positive effect at 5:00. Furthermore, there has been a positive impact of the increased congestion charge on total traffic at 7:00, despite the price increase from 7:00 to 7:30. These results, combined with the size of each coefficient, could imply that people driving at 5:00 and 6:00 are more sensitive to price changes than those driving at 7:00. According to Steiner's theory of peak-load pricing, it is reasonable to price the busier hour at 7:00 even more than the less busy hour at 6:00 (figure 3 on page 25) to further smooth out traffic demand. To target 7:00 with the lower responsiveness to price changes would also be consistent with Ramsey's peak-load theory.

One limitation of our implementation of the Ramsey rule is that the hourly level data and the structure of the congestion charge make it impossible to calculate own-price elasticities for 2020. Consequently, we cannot apply the Ramsey Equation (6) on page 10 to calculate the optimal relationship between prices for different hours. If elasticities were available for 2020, it could have given us a more updated estimate of the traffic response to the congestion charge. Furthermore, it would also have enabled us to investigate the traffic responses when prices are higher in real terms.

Another ambiguity with the results is that traffic has increased for some hours, even when the prices have increased. Nevertheless, this may result from the meagre real congestion price increases during those hours. An example of this is the increase of approximately 300 cars at 12:00 in response to the 10 per cent (1 SEK) increase in congestion charge in 2016. It is more likely that the positive effect is in response to cross-price elasticities making the traffic demand react to price increases at other hours. However, we have not been able to calculate these cross-price elasticities due to the limitations of our hourly level data.

Thus, the increased cost at one hour of the day may also affect the number of vehicles driven at another hour since it is reasonable to assume that many cars that drive into the city centre also drive out. Hence, the estimated effect of the congestion charge at specific hours may be due to price increases at other hours. Both these effects indicate that driving at different hours is interdependent goods. Thus, to capture a more realistic picture of the congestion charge and traffic demand, the assumption of independent demand that lays the foundation for the Ramsey inverse elasticity rule and the Steiner model should be relaxed. Nonetheless, Ramsey pricing and the Steiner model can still be used as methodological tools for understanding congestion charge pricing and its design. As occasionally said about models, "All models are wrong, but some are useful" [Box, 1976]. Although we can never know with certainty exactly how traffic would react to the optimal prices derived from these models, they boil traffic demand down from an intangible - to a tangible issue.

There are also other factors that contribute to the traffic demand. Earlier literature, such as Duranton and Turner [2011] suggests that congestion charges can have a twofold effect. Firstly, it can decrease the traffic demand. Secondly, the decreased traffic caused by the increased congestion charge can, in turn, increase the demand for driving. Hence, increased congestion charge can result in a substitution effect between drivers. More specifically, increased congestion charge may result in price-sensitive travellers opting out, combined with congestion-sensitive drivers driving more. Altogether, this can dampen the total effect of the congestion charge on traffic volumes. If this effect is in play in Stockholm, it would indicate that more aspects than congestion charge determine the traffic demand. Thus, only using price elasticities to determine prices may not be sufficient for creating an optimal congestion charge schedule. However, we have only investigated the responsiveness to the congestion charge, not the response of congestion itself.

Whereas the differences in the own-price elasticity are evident, we want to emphasise that the variation and size of the elasticities are moderate. Moreover, in relationship to the total cost of driving, the congestion charge is relatively small. Depending on the distance and destination of a trip, the cost of driving includes additional fuel and parking costs, usually constituting a more significant part of the total cost than congestion charges. Our price elasticities are smaller than earlier estimates of price elasticities in response to increases in congestion charges or toll prices [Foreman, 2016, Finkelstein, 2009]. Anyhow, other elasticities connected to driving, such as fuel price elasticities, are usually estimated to be significantly higher. This puts the external validity of our estimates into question, especially if this study is to be applied in less or more car-dependent cities or countries. One can also question what the estimates would be if congestion charges are a larger share of the total cost of driving since price elasticities may increase when goods become more expensive. As this study analyses price changes in relatively low real prices, elasticities could increase if the real price of the congestion charge increases. Nevertheless, due to the difficulty of obtaining individual demand curves, this aspect has not been further investigated.

A congestion charge can be an effective or ineffective way of internalising negative traffic externalities. Pricing unresponsive drivers imply that the congestion charge can generate revenues for public transport, road damage, infrastructure, while drivers' pay for the costs. Accordingly, it is effective to charge people with low elasticity if additional congestion charge revenues can solve the negative externalities generated by traffic. Nonetheless, some externalities can only be solved by reduced traffic volumes. These include greenhouse gas emissions, pollution, and in some manner, congestion itself. For example, greenhouse gases and pollution can not solely be solved by tax revenues since a decrease in these variables requires a decrease in total traffic volume. Congestion itself can also partly be solved by substitution effects, which are evident for several hours in our results. Since traffic is relatively even throughout all hours already covered by the congestion charge, substitution effects due to time-varying prices may have little potential to decrease congestion if the population and the number of cars keep growing. This implies that a decrease in total traffic volume may be more desirable to tackle the congestion issue.

In conclusion, the relationship between time-varying prices of congestion and traffic volumes is complex, and the traffic has not uniformly responded to the increased congestion charges in 2016 and 2020. Depending on the objective of the congestion charge, the pricing scheme can be designed in different ways. If solely focusing on decreasing congestion, slightly higher prices during hours with high traffic demand could be combined with lower prices for hours with low traffic demand. This could result in an even higher substitution than is evident from our results. If instead focusing on decreasing the negative externalities on the environment, significantly higher congestion charges may be necessary when elasticities are low to reduce the total traffic volumes.

8 Conclusion

This study has investigated the effect of price changes of increased congestion charge on traffic volumes during different times of the day by using hourly level data on traffic from Stockholm and applying a DiD approach. The study has found both significantly positive and negative effects of the increased congestion charge on traffic volumes. For 2016, morning and evening peak hours, we have observed a total decrease of between 500 and 1300 cars per hour. Meanwhile, hours during the middle of the day, or just before or after the congestion charge, have seen a total traffic increase with roughly 200 and 700 cars per hour. On this basis, we conclude that increased congestion charges have resulted in a slight total average decrease of 275 vehicles per hour. For 2020 there has been an increase of cars at 5:00 and a decrease at 6:00. Notwithstanding, significant substitution effects between different hours of the day are present for 2016 and 2020.

Furthermore, our DiD estimates have been used to calculate price elasticities to deepen the analysis of the responsiveness of increased congestion charge. One interesting result is that the own-price elasticities for traffic have been moderate for the investigated time period. These low elasticities could be a consequence of multiple other factors contributing to the cost of driving, factors that may simultaneously affect the traffic demand. Despite the limitations, our findings can be used to understand the implications of congestion charge as a peak-load pricing schedule. Additionally, according to Ramsey pricing, our findings suggest that less responsive hours should be targeted with higher congestion charge to maximise economic welfare. Furthermore, according to the Steiner model, there is room to increase the congestion charge at hours with high demand and low prices to smooth out demand peaks.

Our results collectively appear consistent with earlier literature, suggesting that tolls and congestion charge both decrease and substitute traffic during the day. Recalling that worldwide, only a small number of cities have implemented congestion charges, and the empirical research of the existing ones remains limited. Therefore, our conclusions can be helpful to design efficient congestion policies in places similar to Stockholm. However, these conclusions may have limited use when designing congestion charges in cities or countries subject to distinct traffic demand curves. Thus, our discussion of the relationship between time-varying congestion pricing and traffic volumes is not completely applicable across time and space. Acknowledging the limited external validity of our study, this analysis of congestion charge still provides useful insights into the varying traffic demand and price elasticities in Stockholm.

8.1 Further Research

Further studies are required to disentangle the full effects of the congestion charge. For instance, the more realistic Ramsey model with the interdependent demand assumption can be investigated. Also, to further deepen the analysis, future research could examine the effects of the increased congestion charge on negative externalities more thoroughly. For example, air quality, greenhouse gases, and travel time can be included in future work to investigate other effects of the increased congestion charge. Focusing more on such environmental aspects would be of considerable interest due to current discussions and suggestions on tackling climate change. Other aspects that may constitute an object for future research are the congestion charge's effects on demand for other modes of transportation. For instance, it would have been interesting to investigate substitution effects to public transport, biking or other substitutes from car traffic due to the congestion charge. Additionally, other costs connected with driving could be included in the elasticity measure to make the elasticity framework more realistic. For example, including fuel cost in the own-price elasticity measure could capture a complete picture of how traffic responds to a price increase in the total cost of driving. Thus, future research could be devoted to combining the price elasticities of the congestion charge with other contributing factors to the demand for driving, since this would result in a more complex analysis of the traffic issue.

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Appendix

A Theory

Lagrangian equations for Ramsey Pricing

$$\frac{\partial L}{\partial P_i} = \int_\theta \left(\sum_{j\in N} \left[-x_i(P,t) + \left(\frac{\partial V(x,t)}{\partial x_j} - P_j \right) \frac{\partial x_j(P,\theta)}{\partial P_i} \right] \right) f(\theta) d(\theta)$$
$$+(1+v)\left(x_i(P) + \sum_{j\in N} \left(P_j - C_j \right) \frac{\partial X_j(P,\theta)}{\partial P_i} \right) f(\theta) d\theta$$

Assuming an interior solution yields:

$$\sum_{j\in N} \frac{(P_j - C_j)}{P_j} \frac{\partial X_j}{\partial P_i} = -\frac{v}{1+v'} \quad i \in N \tag{11}$$

B Institutional Framework

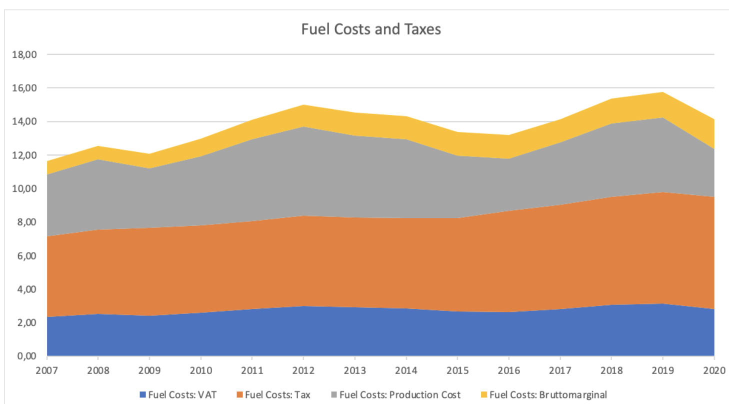


Figure 5: Fuel costs and Fuel Tax

Table 9: Changes in Parking Prices Stockholm

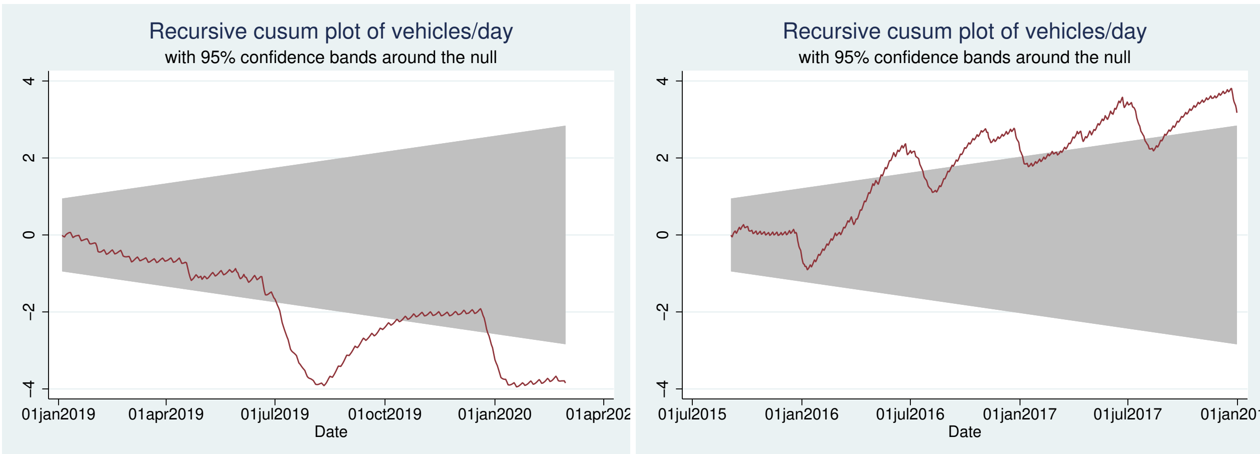
	Autumn 2013	1 September 2016
Zon 1 (inner CBD)	41SEK/h max 1h	50SEK/h
Zon 2 (CBD)	26SEK/h 9-17 15SEK/h	26SEK/h 7-21
Zon 3 (rest of inner city)	15SEK/h 9-17 0SEK	15SEK/h 7–19
Taxa 4 (inner suburbs)	0	10SEK/h 7-19
Taxa 5 (suburbs)	0	5SEK/h 7-19
Resident Parking	Z2,3 900	Z2,3 1100, t4: 50, t5: 30

Table 10: Congestion Charge per Passage: Essingeleden

Time	1 March 2020	1 Jan 2020	1 Jan 2016
	High Season	*Low Season*	
00:00–05:59	0	0	0
06:00–06:29	15	15	0
06:30–06:59	27	22	15
07:00–07:29	40	30	22
07:30–08:29	40	30	30
08:30–08:59	27	22	22
09:00–09:29	20	15	15
09:30–14:59	11	11	11
15:00–15:29	20	15	15
15:30–15:59	27	22	22
16:00–17:29	27	30	30
17:30–17:59	40	22	22
18:00–18:29	20	15	15
18:30–23:59	0	0	0

C Methodology

Structural Break Tests



(a) 2020

(b) 2020

Figure 6: Structural Beak Test

Table 11: Estat Structural Break Test: Unknown Break Date

	2020	2016
Estimated break date:	21dec2019	30mar2016
p-value	0.0000	0.0000

Placebo Tests

Table 12: Placebo Test Fake Treatment Group 2016

	(1) 4:00	(2) 5:00	(3) 20:00	(4) 21:00	(5) 22:00
PostJan2016	2.760***	2.893***	3.148***	3.255***	3.383***
FakeHour(Treated)	-12.70***	105.0***	183.7***	132.9***	70.59***
PostJan2016*FakeHour(Treated)	1.826	0.388	8.696	6.724	0.699
Observations	147279	147583	147662	147636	147521

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Placebo Test Fake Treatment Group 2020

	(1) 4:00	(2) 20:00	(3) 21:00	(4) 22:00
Post20	-7.853***	-6.745***	-6.784***	-6.690***
FakeHour(Treated)	-11.66***	194.3***	143.8***	73.81***
PostJan2020*FakeHour(Treated)	5.387**	-12.71	-5.844	-7.982
Observations	253189	253874	253734	253127

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Placebo Test Fake Treatment Time 2018

	(1) 7:00	(2) 8:00	(3) 9:00	(4) 15:00	(5) 16:00	(6) 17:00	(7) 18:00
FakePostJan18	-0.199	-0.345	-0.292	-0.210	-0.312	-0.335	-0.310
Hour(Treated)	498.7***	551.2***	460.9***	538.2***	523.9***	470.2***	387.0***
FakePostJan18*Hour(Treated)	1.434	-1.455	2.217	0.484	-6.792	-11.25	-8.701
Observations	122553	122552	122558	122556	122558	122558	122557

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Results

Table 15: Regressions of Average Total Number of Vehicles on Increase on Congestion Tax in January 2016 (DiD)

	(1) 6-19	(2) 6-19	(3) 7-18	(4) 7-18	(5) ALL	(6) ALL
PostJan2016	350.7***	350.4***	348.2***	348.0***	527.4***	527.3***
	(19.78)	(19.42)	(15.72)	(15.44)	(25.27)	(24.82)
Hour(Treated)	31905.2***	31907.1***	32458.3***	32460.7***	27091.7***	27094.0***
	(28.07)	(27.57)	(23.31)	(22.90)	(31.75)	(31.19)
PostJan2016*Hour	-159.9***	-161.2***	-275.7***	-277.5***	-384.0***	-385.4***
	(29.88)	(29.35)	(24.66)	(24.22)	(34.96)	(34.35)
Essingeleden	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	475340	492309	424978	440155	600586	622027
R^2	0.898	0.899	0.942	0.942	0.874	0.874

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Regressions of Average Total Number of Vehicles on Increase on Congestion Tax in January 2020 (DiD)

	(1) 6-19	(2) 7-18	(3) ALL
Post20	653.3***	589.9***	419.9***
	(26.09)	(19.85)	(34.20)
Hour	32178.9***	32663.6***	25949.9***
	(11.05)	(9.623)	(12.28)
Post20*Hour	-607.5***	-357.7***	-208.1***
	(41.97)	(33.49)	(56.28)
Constant	1743.0***	1122.6***	647.0***
	(45.31)	(37.15)	(55.87)
Observations	847363	757594	1069933
R^2	0.901	0.944	0.805

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$