Road Pricing with Multiple Policy Goals: The Effect on Vehicle Ownership, Driving, and Commuting*

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Abstract

Many road pricing systems exempt or discount clean vehicles to achieve environmental objectives with transportation policies. Setting optimal road prices is not straightforward because the responses to the policy, such as vehicle acquisitions, driving on suburban roads, and residential sorting, interact nontrivially with the multiple policy goals. We provide a framework for setting optimal congestion charges that reflects emission and congestion externalities and accounts for these responses. Using Swedish administrative microdata, we identify these responses by exploiting a temporary exemption for alternative fuel vehicles and variation in individuals' exposure to congestion charges based on whether an individual crossed one of Stockholm's two exempted highways to travel to work. We find that exempting alternative fuel vehicles induced tolled commuters to reduce the adoption of fossil fuel vehicles and increase the adoption of alternative fuel vehicles, leaving the overall fleet size unchanged. However, increased driving in alternative fuel vehicles did not fully offset the reduction in trips from fossil fuel vehicles. Treated commuters were also more likely to move into the congestion zone, leading to shorter commuting distances. Finally, we combine the estimated responses with the framework to recover an optimal congestion charge of €9.46 per crossing.

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I Introduction

Many cities struggle with the dual challenge of poor local air quality and traffic congestion from road transportation. The transport sector accounts for about a quarter of Europe's greenhouse gas emissions and is a major contributor to local air pollution, which exceeds the health-based guidelines in over 90 percent of cities (WHO, 2016). Automobile use also leads to considerable congestion costs that were estimated at over $\$1,000$ in cost of delays per person, with commuters losing nearly seven full working days in traffic delays (Schrank et al., 2019). One policy tool implemented to address the negative externalities associated with urban driving is to charge drivers through congestion zones - regions in the city center where drivers are charged for entry (Vickrey, 1963; Parry, 2002).

In theory, the policy prescriptions from Pigou (1924) and Vickrey (1963) suggest that optimal congestion charges for road users equal the sum of congestion and emission externalities. However, this disregards how individuals respond to the imposition of a congestion zone and how congestion and emission externalities interact. First, to prevent paying congestion charges, commuters may respond by adopting exempted vehicles, adjusting driving patterns, or relocating, which has implications for congestion and emission externalities. Second, as congestion and emission externalities interact in nontrivial ways, reducing one externality may exacerbate or alleviate the other distortion. Exempting electric vehicles from congestion charges, for instance, may encourage their adoption and improve air quality, but it exacerbates congestion. This paper provides a framework for setting and evaluating congestion charges that explicitly addresses emission and congestion externalities while accounting for multiple response dimensions to the policy.

To shed light on the relevant choice dimensions that govern congestion charges, we build on the vehicle decision model of Anderson and Sallee (2016) in Section II. In this model, a representative consumer chooses the size of two vehicle fleets – "brown" and "green" vehicles. The consumer also chooses how many congestion zone and non-congestion zone trips to take in each car, and how far to live from work. In the accompanying social planner's problem, the planner chooses a congestion charge on brown vehicles that addresses local congestion and emission externalities inside and outside the congestion zone, taking into account how the congestion charge may impact the representative consumer's vehicle choice, how many trips they take, and where they choose to work.

Solving the planner's problem yields a formula for the congestion charge that consists of three components. The first term represents the "fleet-composition": the desire to address emission and congestion externalities from the composition and size of the vehicle fleet. The second term represents the "driving behavior": the change in the number of brown and green vehicle trips inside and outside the congestion zone. The third term represents the "commuting distance": which accounts for changes in the average commuting distance inside and outside congestion zone trips. Treated commuters may either move into the congestion zone or relocate to workplaces outside the congestion zone to avoid the congestion charge. The emission and congestion externalities then depend on the changes in the average commuting distance of drivers. To characterize the charge and evaluate its impact on congestion and emission externalities, we estimate the influence of the congestion zone on vehicle ownership, driving behavior, and residence and workplace location choices.

Our theoretical framework connects two literature strands: optimal tax theory and congestion pricing. While congestion pricing is commonly viewed as a straightforward application of the Pigouvian principle, several papers have noted that congestion pricing is frequently second-best, requiring empirical estimates of tax elasticities (Mun et al., 2003; Verhoef, 2005).[1] We extend the characterization of second-best congestion prices to account for the effect of the congestion charge on the composition and usage of the fleet, commuting distances, and the dual challenge of emission and congestion externalities.[2] Specifically, our derivation of congestion charges that factor in key responses to the policy enables us to highlight trade-offs between road pricing policies and environmental objectives.

An essential contribution of our theoretical work is that it delivers formulas for congestion charges as a function of sufficient statistics that can be estimated in various empirical applications. In Section III, we describe our strategy for empirically estimating the responses stipulated by our model. In August 2007, Stockholm imposed a congestion charge on vehicles entering or exiting the city center. Notably, alternative fuel vehicles were exempt from this charge for the first 18 months of the policy. We merge several Swedish administrative data sets that combine socioeconomic information with all vehicle ownership records. We supplement this data with information about the location of the residence and workplace, the road network, and the location of toll gates. This allows us to identify the toll payments faced by each individual when traveling between home and work and to study how these tolls and exemptions impacted commuters' decisions.

Our empirical design exploits the fact that two heavily congested motorways (*Essinge bypass* and *Lidingö route*) were exempted from the congestion charges. As a result, the policy reduced the costs of owning and driving alternative fuel vehicles relative to fossil fuel

[1] We build on an extensive theoretical literature analyzing second-best road pricing (Vickrey, 1963; Small, 1982; Arnott et al., 1993; Hall, 2018, 2021; Kreindler, 2023).

[2] This relates to a significant body of research on the optimal design of policies that encompass various consumer responses. Prominent examples include social reputation (Benabou & Tirole, 2011), salience (Chetty et al., 2009), inattention (Farhi & Gabaix, 2020), social norms (Allcott, 2011), and non-standard decision making (Bernheim & Taubinsky, 2018).

vehicles for treated commuters. At the same time, the policy may induce treated commuters to move into the congestion zone or relocate to workplaces outside the congestion zone to avoid the congestion charges. To identify the causal effects of the policy, we construct a differences-in-differences design that compares the vehicle ownership, driving behavior, and location choices by individuals exposed to tolls on the road between home and work (*treated commuters*) to exempted commuters (*non-treated commuters*).

In Section IV, we show that individuals respond to the congestion charge by adopting alternative fuel vehicles and taking fewer trips into the congestion zone. Individuals exposed to the congestion charge on their commute are .64 percentage points more likely to own an alternative fuel vehicle and .83 percentage points less likely to own a fossil fuel vehicle. Although the congestion charge led to a substantial shift from fossil fuel vehicles to alternative fuel vehicles, the size of the vehicle fleet remained stable. The congestion charge resulted in an annual increase of 5.9 congestion zone trips by commuters in alternative fuel vehicles and a decrease of 11.8 congestion zone trips in fossil fuel vehicles, which correspond to an increase of 103 kilometers in alternative fuel vehicles and a decrease of 206 kilometers in fossil fuel vehicles. At the same time, the congestion charge led to an annual increase of .7 non-congestion zone trips in alternative fuel vehicles, and a reduction of 2 non-congestion zone trips in fossil fuel vehicles. In addition, we document that treated commuters are .2 percentage points more likely to move into the congestion zone and 1.6 percentage points more likely to relocate to workplaces outside the congestion zone, either to a new office or company, to avoid paying the congestion charges. This decreased the average commuting distance inside and outside congestion zone trips for treated commuters by approximately .086 and .007 kilometers, respectively.

Our estimated treatment effects can explain approximately 20 percent of the adoption and usage of alternative fuel vehicles between 2007 and 2008.[3] We further observe substantial differences in how individuals respond to the congestion charge along multiple socioeconomic dimensions. High-income individuals adopt alternative fuel vehicles in response to the policy, whereas middle-income individuals primarily reduce their vehicle kilometers traveled and switch to other modes of transportation. Individuals with low incomes continue to drive fossil fuel cars, indicating that they may be more reliant on existing commuting patterns or financially constraint. We also find that treatment effects are larger for young, university-

[3] We establish road pricing policies as an essential policy tool in promoting the adoption of environmentally friendly vehicles and contributes to the existing literature on the adoption of such vehicles, which focuses primarily on the effects of vehicle subsidies (Muehlegger & Rapson, 2018; Clinton & Steinberg, 2019), charging infrastructure (Li et al., 2017; Springel, 2021), and low emission zones (Wolff, 2014). As opposed to a set of papers that measures vehicle ownership on the zip code, metropolitan, or state level, we quantify individual-level responses to the congestion zone on vehicle ownership.

educated couples with shorter commutes.

In Section V, we implement the congestion charge formula using our empirical findings on vehicle ownership, number of trips, and commuting distance. In our baseline specification, the congestion fee equals €9.46 per congestion zone crossing. Congestion externalities account for €8.39 of the total charge, while emission externalities correspond to €1.07. The social benefits of exempting green vehicles from the congestion charge are relatively small compared to the benefits of reduced congestion by changing to other modes of transport. The fleet size component accounts for 22 percent of the charge, which comes through an increase in congestion from green vehicles, but a reduction of congestion and emission through fewer brown vehicles. 67 percent of the congestion charge are attributable to changes in the driving behavior component, with fewer congestion zone trips in fossil fuel vehicles constituting most of the charge. Finally, the change in commuting distance explains around 11 percent of the congestion charge, which implies that relocating is an important additional margin that decreases congestion and emission externalities.

We calculate the congestion charge under alternative assumptions and show that a higher share of green vehicles and lower commuting distances decrease the congestion charge. Conversely, leakage towards unpriced roads increases the optimal charge. Medium-income groups incur the highest charges due to their significant reduction in vehicle trips. Low- and high-income groups face considerably lower charges due to a limited policy responsiveness and a strong substitution towards alternative fuel vehicles, respectively. Finally, we document strong regressive patterns in congestion charges, which are exacerbated by the revenue recycling of the policy, the exemption of alternative fuel cars, and differential substitution patterns to public transport.[4]

In addition to contributing to optimal tax theory, our work connects to the empirical literature on the responses to second-best road pricing policies. These studies find that congestion charges have significantly reduced the traffic in Singapore (Phang & Toh, 1997; Olszewski & Xie, 2005), London (Santos et al., 2004; Santos & Shaffer, 2004), Stockholm (Eliasson, 2009; Börjesson et al., 2012), Gothenburg (Börjesson & Kristoffersson, 2015), and Milan (Gibson & Carnovale, 2015; Beria, 2016) and commuters shift driving to non-rush hours in response to time-varying tolls (Foreman, 2016; Small & Gómez-Ibáñez, 1997).[5]

[4]This relates to a literature on the distributional impacts of environmental policies that have examined gasoline taxes (Poterba, 1991; Bento et al., 2009), carbon taxes (Cronin et al., 2019), fuel economy standards (Davis & Knittel, 2019), building codes (Bruegge et al., 2019), utility rates (Borenstein, 2012; Borenstein et al., 2021), solar panel subsidies (Borenstein, 2017; Feger et al., 2022), and heat pump adoption (Davis, 2023).

[5]Our paper relates to the empirical literature on the effects of road pricing policies on air pollution. Previous studies have shown that low emission zones, road tolls, and congestion charges can help improve urban air quality (Wolff, 2014; Gibson & Carnovale, 2015; Fu & Gu, 2017; Gehrsitz, 2017; Pestel & Wozny,

Whereas previous papers measure the impact of congestion charges on total traffic volume measured at toll stations, our exceptionally rich data set on driving behavior paired with an identification strategy that exploits individual-level variation in exposure to the congestion charges on people's way to work allows us to establish four ways in which individuals adapt to the congestion charge: (i.) adopt exempted alternative fuel vehicles, (ii.) reduce annual vehicle kilometers traveled in fossil fuel vehicles or change mode of transportation, (iii.) move into the congestion zone, and (iv.) relocate to workplaces outside the congestion zone. This paper is the first to examine the impact of congestion charges on individual-level driving behavior, moving decisions, and workplace relocation.

II Deriving the congestion charge

This section presents a stylized model of the urban personal transportation sector. It is useful for describing the key distortions and margins of choice that are relevant when setting congestion charges.

II.A Model of urban travel

Our model of driver behavior builds on Anderson and Sallee (2016), and aims to capture how congestion charges impact consumer's vehicle purchase, driving and commuting decisions. We first solve a model of consumer behavior and then use the first-order conditions from the consumers' problem to write the congestion charge in terms of policy responses.

1. *The consumer's problem.* A representative consumer derives utility from trips, which can be completed with brown (subscript b) or green vehicles (subscript g). n_g and n_b are the number of green and brown vehicles, respectively. There are two kinds of trips: cordon (superscript c) and outside-cordon (superscript o) trips. Because drivers may substitute their trips to unpriced roads (i.e., "leakage"), we distinguish between trips occurring within congestion zones and those outside them to allocate congestion externalities to the appropriate locations.[6] In all notations, congestion zone specific details are shown as superscripts, while characteristics specific to the type of vehicle are shown as subscripts. t refers to the number of trips; t_c^b, for example, is the number of cordon trips by brown vehicles. v^c are the vehicle kilometers traveled on congestion zone trips, and v^o are the vehicle kilometers traveled on non-congestion zone trips. The individual-level vehicle kilometers traveled in green and

2019), reduce asthma rates in children (Simeonova et al., 2021), and lower infant mortality (Currie & Walker, 2011).

[6] Tarduno (2022) documents that drivers substitute to non-tolled roads as a response to the bridge tolls in San Fransisco.

brown vehicles are equal to the sum of the number and length of congestion crossings and non-congestion zone crossings:

v is not exogenous and reflects where people choose to live and work. People can have shorter congestion or non-congestion zone trips, but there are costs r associated with this adjustment.[7] The cost of each type of vehicle are c_b and c_g, respectively. l is the vehicle fuel efficiency of the respective vehicle type measured as liter per 100 kilometers, and y is the representative consumer's exogenous income. p_g and p_b are the fuel cost of green and brown vehicles. The per-kilometer costs of driving (time cost) for each kind of trip are p^c and p^o, respectively.

The representative consumer's optimization problem is to pick the optimal fleet size for each vehicle type (i.e., n_g, n_b), the optimal number of trips in each vehicle type completing the kind of trip (i.e., t_g^c, t_g^o, t_b^c, t_b^o), and the vehicle kilometers traveled for each trip (i.e., v^c, v^o) to maximize consumer welfare B.[8] We assume that the representative consumer has a quasi-linear utility in transportation services and other goods such that welfare is given by the following equation:[9]

$$\begin{aligned} \underset{n_g,n_b,t_g^c,t_g^o,t_b^c,t_b^o,v^c,v^o}{max} B \; = \; & \underbrace{\mu_g(n_g)[u_g^c(t_g^c)+u_g^o(t_g^o)]}_{\text{utility from green trips}} - \underbrace{n_g(p^c+p_e l_e)v^c t_g^c - n_g(p^o+p_e l_e)v^o t_g^o}_{\text{utility cost of green trips}} \\ & + \underbrace{\mu_b(n_b)[u_b^c(t_b^c)+u_b^o(t_b^o)]}_{\text{utility from brown trips}} - \underbrace{n_b((p^c+p_b l_b)v^c+\tau)t_b^c - n_b(p^o+p_b l_b)v^o t_b^o}_{\text{utility cost of brown trips}} \\ & - \underbrace{n_b c_b - n_g c_g}_{\text{cost of vehicles}} - \underbrace{r^c(v^c)-r^o(v^o)}_{\text{cost of location choice}} + y \end{aligned} \tag{1}$$

Within in vehicle fuel type, the term $\mu(n)u(t)$ refers to utility derived from the number of trips, scaled by a function of the number of vehicles, where $\mu'(\cdot), u'(\cdot) > 0$ and $\mu''(\cdot), u''(\cdot) \leq 0$. The term nc represents the total costs for n vehicles. The term $n_g p_g l_g(v^c t_g^c + t_g^o v^o)$ and $n_b p_b l_b(v^c t_b^c + t_b^o v^o)$ are the total fuel expenditures on green and brown vehicles. The term $n_g(p^c v^c t_g^c + p^o v^o t_g^o)$ and $n_b(p^c v^c t_b^c + p^o t_b^o v^o)$ are private cost of driving green and brown vehicles.

[7]We abstract from a full spatial sorting model for tractability. For an application of congestion pricing with a sorting model, see Barwick et al. (2021).

[8]Consumer choices may deviate from the optimization problem if they misperceive the future congestion costs when choosing their privately optimal vehicle and commuting choices. This is related to the market imperfection of fuel-economy internalities when consumers ignore external costs when choosing their privately optimal level of fuel consumption documented in Allcott et al. (2014) and Allcott and Sunstein (2015). Given the high salience of costs when crossing the congestion zone (Figure B5), we assume that consumers correctly internalize the congestion charges into their optimization problem. Intuitively, if consumers undervalue a dollar of future congestion charges by $\beta < 1$, the optimal congestion scales by the degree of misperception.

[9]The quasi-linear utility specification rules out income effects.

2. *The planner's problem.* The social planner's problem is to maximize consumer welfare $B^{-\tau}$ by setting the congestion charge (τ) on brown vehicles. The planner's problem is identical to that of the consumer, except that the consumer does not internalize the emission (φ) and congestion externalities (γ) from driving.[10] Emission externalities differ by vehicle type (i.e., ϕ_g and ϕ_b) and congestion externalities differ by location (i.e., γ^c and γ^o).[11] Accordingly, we define ϕ_g and ϕ_b as the sum of marginal emission externalities (in € per kilometer) from driving green and brown vehicles.[12]

$$\begin{aligned} \max_{\tau} W = B^{-\tau} \; - \; & \underbrace{n_b(v^c t_b^c + v^o t_b^o) l_b \phi_b}_{\text{emission from brown trips}} - \underbrace{n_g(v^c t_g^c + v^o t_g^o) l_g \phi_g}_{\text{emission from green trips}} \\ - \; & \underbrace{(n_b v^c t_b^c + n_g v^c t_g^c)\gamma^c}_{\text{congestion from inside trips}} - \underbrace{(n_b v^o t_b^o + n_g v^o t_g^o)\gamma^o}_{\text{congestion from outside trips}} \end{aligned} \tag{2}$$

The emission externalities for brown and green vehicles scale by the individual-level vehicle kilometers traveled in the respective vehicles. We do not differentiate local emissions damages for trips inside versus outside of the congestion zone as local pollutants can swiftly spread, implying similar emission damages across the metropolitan area. Congestion externalities scale by the vehicle kilometers traveled inside and outside the congestion zone, irrespective of the type of vehicle.[13] We assume no pre-existing taxes or subsidies on vehicles.

Our model addresses how congestion charges on brown vehicles can target the dual challenge of emission and congestion externalities, taking into account what type of vehicle commuters choose, how many trips they take, and where commuters choose to live and work. Understanding the interplay between these margins of response and the externalities is crucial when evaluating the impact of road pricing policies. Because the first-best policy in our model is differentiated Pigouvian taxes on both types of kilometers traveled, we refer to the welfare maximizing congestion charge on brown vehicles as second-best.

[10]We do not include accident externalities as the social benefits from reduced accidents in congestion zones are small compared to reduced congestion and air pollution (Green et al., 2020). Simeonova et al. (2021) document that the effects of the congestion zone on visits for childhood unintentional injuries was small in Stockholm.

[11]To account for substitution to non-tolled roads, the social planner separates congestion externalities by congestion and non-congestion zone trips.

[12]We assume that marginal damages are linear in vehicle kilometers traveled, which is consistent with the EPA's social cost of carbon calculations and research on local air pollution Muller and Mendelsohn (2009) and Fowlie and Muller (2019).

[13]We assume that the social planner has no redistributive motives. This implies that social marginal welfare weights are constant across high- to low-income consumers. In Section V.B, we discuss how the regressive effects of the policy influences the optimal congestion charge for different income groups.

II.B Expression for the congestion charge

Optimizing the social planner's welfare function gives the following proposition. All derivations are contained in Appendix A.1.

Proposition 1. *The second-best congestion charge subsidy τ on brown vehicles per crossing that addresses congestion and emission externalities through changes in the fleet composition, the number of trips and the commuting distance is given by*

$$\begin{aligned}
\tau \;=\; & \frac{1}{\left(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b\right)} \Bigg(\frac{\partial n_g}{\partial \tau}\Big((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o \Big) \\
& + \frac{\partial n_b}{\partial \tau}\Big((v^c t_b^c + v^o t_b^o) l_b \phi_b + v^c t_b^c \gamma^c + v^o t_b^o \gamma^o \Big) \\
& + \frac{\partial t_g^o}{\partial \tau}\Big(n_g v^o (l_g \phi_g + \gamma^o) \Big) + \frac{\partial t_g^c}{\partial \tau}\Big(n_g v^c (l_g \phi_g + \gamma^c) \Big) \\
& + \frac{\partial t_b^o}{\partial \tau}\Big(n_b v^o (l_b \phi_b + \gamma^o) \Big) + \frac{\partial t_b^c}{\partial \tau}\Big(n_b v^c (l_b \phi_b + \gamma^c) \Big) \\
& + \frac{\partial v^c}{\partial \tau}\Big(n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c) \gamma^c \Big) \\
& + \frac{\partial v^o}{\partial \tau}\Big(n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_b^o) \gamma^o \Big) \Bigg)
\end{aligned} \tag{3}$$

In equation (3), the congestion charge represents the responses to the policy including fleet composition, number of trips, and commuting distance due to the congestion charge multiplied by the respective sum of congestion and emission externalities.

For the purpose of building intuition, we convert the emission and congestion externalities from marginal externalities (in € per kilometer) into externalities per number of vehicles (indicated as tilde), per number of trips (indicated as bars), and per kilometer traveled (indicated as hats) (Appendix A.2). This allows us to rearrange equation (3) as:

$$\begin{aligned}
\tau \;=\; & \underbrace{\Delta N_g \cdot (\widetilde{\phi_g} + \widetilde{\gamma_g}) + \Delta N_b \cdot (\widetilde{\phi_b} + \widetilde{\gamma_b})}_{\triangle Fleet\ composition} + \underbrace{\Delta T \cdot (\overline{\phi} + \overline{\gamma})}_{\triangle Trips} \\
& + \underbrace{\Delta V^c \cdot (\hat{\phi^c} + \hat{\gamma^c}) + \Delta V^o \cdot (\hat{\phi^o} + \hat{\gamma^o})}_{\triangle Commute\ Distances}
\end{aligned} \tag{4}$$

where ΔN_g, ΔN_g, ΔT, ΔV^c,and ΔV^o refer to changes in green and brown vehicle adoption, the number of trips, and the commuting distance inside and outside the cordon zone scaled by the denominator in equation (3). The denominator $(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)$ corresponds to the total trip changes inside the congestion zones in brown vehicles that come through changes in the brown vehicle fleet and the total trip changes. $\widetilde{\phi}_g + \widetilde{\gamma}_g$ and $\widetilde{\phi}_b + \widetilde{\gamma}_b$ indicate the emission and congestion externalities per green and brown vehicles (expressed in total € damages). $\overline{\phi} + \overline{\gamma}$ indicate emission and congestion externalities per trip (expressed in total € damages). $\hat{\phi}^c + \hat{\gamma}^c$ and $\hat{\phi}^o + \hat{\gamma}^o$ indicate the emission and congestion externalities per kilometer inside and outside the congestion zone (expressed in € damages per kilometer).

Equation (4) shows that the congestion charge on brown vehicles is a combination of the three responses to the policy: the fleet composition, the number of trips, and the average commuting distances. The first two terms, $\Delta N_g(\widetilde{\phi}_g + \widetilde{\gamma}_g)$ and $\Delta N_b(\widetilde{\phi}_b + \widetilde{\gamma}_b)$, correspond to the fleet composition changes and corresponding emission and congestion changes through adopting green and brown vehicles as a response to the congestion charge. The congestion effect solely depends on the net effect on total vehicle ownership, as congestion externalities are independent of the vehicle type. The emission effect depends on how much of the green vehicle adoption crowds out the ownership of brown vehicles. The third term, $\Delta T(\overline{\phi} + \overline{\gamma})$, corresponds to the changes in emission and congestion externalities through changes in the number of trips. The congestion part scales solely with the total effect on the number of trips, while emissions depend on how people substitute driving from brown to green vehicles. Finally, the fourth and fifth term, $\Delta V^c(\hat{\phi}^c + \hat{\gamma}^c)$ and $\Delta V^o(\hat{\phi}^o + \hat{\gamma^o})$, correspond to changes in emission and congestion externalities caused by changes in the commuting distance inside and outside of the congestion zone. Treated commuters may either move into the congestion zone or relocate to workplaces outside the congestion zone to avoid the congestion charge. The emission and congestion externalities then depend on the changes in the average commuting distance of drivers. We now estimate the impact of the congestion charge on vehicle ownership, number of trips, and commuting distance to provide an estimate for the congestion charge derived in equation (4).

II.C Interpreting the formula

The congestion charge in equation (3) has a number of special cases that illustrate important insights about the forces governing the congestion charge. We highlight three special cases of particular interest.

1. *No congestion externality ($\gamma^c = \gamma^o = 0$).*

$$\tau^{emission} \;=\; \Delta N_g \cdot \widetilde{\phi}_g + \Delta N_b \cdot \widetilde{\phi}_b \;+\; \Delta T \cdot \overline{\phi} \;+\; \Delta V^c \cdot \hat{\phi}^c + \Delta V^o \cdot \hat{\phi}^o + \overline{\phi^c_b} \tag{5}$$

If the social planner solely cares about emission externalities, equation (5) stresses that the congestion charge equals the changes in emission externalities that are caused by the the three margins of response and the emission damages from brown vehicles. This matches the core principle of Pigouvian taxation (Pigou, 1924).

2. *No emission externality ($\phi_g = \phi_b = 0$).*

$$\tau^{congestion} \;=\; \Delta N_g \cdot \widetilde{\gamma}_g + \Delta N_b \cdot \widetilde{\gamma}_b \;+\; \Delta T \cdot \overline{\gamma} \;+\; \Delta V^c \cdot \hat{\gamma}^c + \Delta V^o \cdot \hat{\gamma}^o + \overline{\gamma_I^c} \tag{6}$$

If the social planner solely cares about congestion, equation (6) stresses that the congestion charge equals the changes in congestion externalities multiplied by the three policy responses and the congestion damages from driving brown vehicles to work. The fleet composition component $\Delta N \cdot \gamma$ clarifies that only the total number of vehicles matter for the congestion externalities.

3. *No leakage ($\frac{\partial t^o}{\partial \tau} = 0$).*

$$\begin{aligned}
\tau^{leakage} \;=\; & \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \Bigg(\frac{\partial n_g}{\partial \tau} \Big((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o \Big) \\
& + \frac{\partial n_b}{\partial \tau} \Big((v^c t_b^c + v^o t_b^o) l_b \phi_b + v^c t_b^c \gamma^c + v^o t_b^o \gamma^o \Big) \\
& + \frac{\partial t_g^c}{\partial \tau} \Big(n_g v^c (l_g \phi_g + \gamma^c) \Big) + \frac{\partial t_b^c}{\partial \tau} \Big(n_b v^c (l_b \phi_b + \gamma^c) \Big) \\
& + \frac{\partial v^c}{\partial \tau} \Big(n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c) \gamma^c \Big) \\
& + \frac{\partial v^o}{\partial \tau} \Big(n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_g^o) \gamma^o \Big) \Bigg)
\end{aligned} \tag{7}$$

As congestion zones leave nearby roads unpriced, our model of urban transport assumes that commuters partly substitute their driving to non-tolled roads allowing for externality leakage. However, when we assume that there is no leakage to other externality-generating driving, we assign all of the trip and commuting distance changes within the congestion zone. Put differently, we assume that there is no effect on outside congestion zone trips. The congestion charge that only accounts for changes within the congestion zone corresponds to equation (7). As all changes occur within the congestion zone, the charge scales with congestion externalities within the congestion zone. Conversely, to get the optimal congestion charge that assumes commuters solely change their driving behavior outside the congestion zone (i.e., full leakage), we can multiply the congestion charge with congestion externalities outside the congestion zone.

III Estimating responses to congestion charges

III.A Design of the congestion charge

The implementation of the congestion charge started with a seven-month trial period, the Stockholm Congestion Trials (*Stockholmsförsöket*). The purpose of the congestion pricing zone was to reduce traffic entering the central city and improve the environmental situation in central Stockholm. The trial period lasted from January, 2006, through the end of July 2006. In September 2006, the residents of Stockholm municipality voted in favor of its permanent implementation in a referendum.[14] As a result in October 2006, the Swedish government declared it would permanently implement the Stockholm congestion charge. The congestion charge came into effect permanently on August 1, 2007. In anticipation of a transition away from driving into Stockholm city, the congestion charging program was accompanied by an expansion of public transportation (Eliasson et al., 2009).[15]

Figure I maps the 20 toll stations surrounding Stockholm's inner city.[16] The charging system is designed as a toll cordon around the inner city (dotted line). The congestion tax is charged for vehicles driven into and out of central Stockholm, Mondays to Fridays, between 6.00 and 18.29. Between 2006 and 2015, the charge ranged between €1.06 (SEK 10) and €2.12 (SEK 20) per passage in Stockholm,[17] depending on the time of the day.[18] The average congestion charge per person for each neighborhood is illustrated in Figure B2. Vehicles are charged when crossing the congestion zone in both directions. The tax is not charged on weekends or public holidays, on a day preceding a public holiday, or during July. The toll is automatically collected using license plate scanning technology as cars cross the perimeter of the congestion zone.

[14] Börjesson et al. (2012) discuss how public and political acceptability has developed over time.

[15] Beginning on August 22, close to 200 new buses, 16 new bus lines, and new park-and-ride spaces were introduced so that longer-distance travelers from the municipalities surrounding Stockholm could enter the city's core more easily. Additional departures and carriages have been added to buses, subways, and train lines to accommodate the increased commuter volume.

[16] The Swedish Transport Agency (*Transportstyrelsen*) provides a detailed description for each toll station here: https://www.transportstyrelsen.se/sv/vagtrafik/Trangselskatt/Trangselskatt-i-stockholm/Betalstationernas-placering1/. The number of checkpoints was increased from 18 to 20, and some of the original checkpoints were moved.

[17] I convert Euro to Swedish kronor using the exchange rate from January 1, 2006 ($9.42\ \frac{€}{SEK}$).

[18] Figure B1 displays the congestion charges in Stockholm and Essinge for different periods.

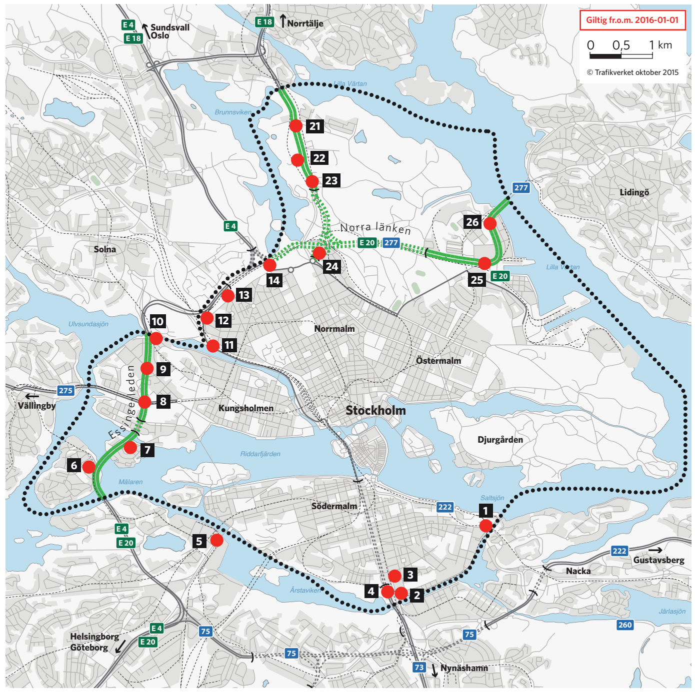


Figure I: Toll stations Stockholm

Notes: The map shows toll gates in and around the city center of Stockholm. The red dots indicate where the control points are located. The average monthly number of passages for each toll gate can be found in Figure B7. The average number of vehicles passing through each toll cordon over the course of a day based on 30 minute intervals can be found in Figure B8.

1. *Essinge bypass and Lidingö rule.* The Essinge bypass is a heavily congested motorway west of Stockholm city center (represented by the green line in Figure I) that crosses the congestion zone. Vehicles that bypassed Stockholm via the Essinge bypass were exempt from the congestion fee.[19] However, vehicles that exit or enter the Essinge bypass within the congestion tax area are levied a fee (toll station 6 to 10). In addition, all traffic to and from Lidingö, an island east of Stockholm, is exempt from the congestion fee if it passes the Ropsten payment station (26) and another payment station within 30 minutes. All vehicles that remained longer in the cordon zone were required to pay the congestion fee. The reason for the Lidingö rule was that the only connection from Lidingö municipality to the national road network runs through the inner city.

2. *Alternative fuel vehicle exemption.* In March 2007, it was decided that alternative fuel vehicles (i.e., ethanol, biogas, hybrid, and electric vehicles) were exempted from the con-

[19]The Essinge bypass is the only bridge between the south and north of Stockholm, except through the inner city. In 2006, the decision-makers believed that maintaining the bypass as the only uncharged route between southern and northern Stockholm was crucial for public acceptance.

gestion charge (Ministry of Finance, 2007).[20] The incentive policy of exempting alternative fuel vehicles from the congestion tax was so successful that policymakers became concerned that the effectiveness of the congestion reduction was being weakened. As a result, the tax exemption was phased out beginning in January 2009 for all new alternative fuel vehicles, less than 18 months after its introduction. However, the policy remained in effect for all existing alternative fuel vehicles already exempt until August 2012. After 2009, the exemption privileges of alternative fuel vehicles could no longer be transferred.[21]

3. *Evolution of alternative fuel vehicles.* Before 2005, the Swedish vehicle fleet mainly consisted of vehicles that run on petrol or diesel. However, since 2005, the registrations of ethanol-powered vehicles have increased rapidly, making them the first alternative fuel type to reach the market.[22] Figure II displays the share of new alternative fuel vehicles by individuals between 2003 and 2012.[23] The share of quarterly new registrations of alternative fuel vehicles in Stockholm increased from close to 0% in 2003 to around 40% in 2009. Most sold were ethanol, accounting for more than 98% of new alternative fuel vehicles, while the remaining 2% mainly run on CNG.[24] In 2006, during the congestion tax trial, only 2% of cordon boundary crossings were made by alternatively fueled vehicles. By the end of 2008, this share had increased to 14% (Börjesson et al., 2012).

[20] Exemptions to the charge include emergency vehicles, buses, diplomatic vehicles, disabled person vehicles, military vehicles, motorcycles and mopeds, and foreign-registered vehicles.

[21] At the time of the trial, "clean vehicles" were defined in Sweden as alternative fuel vehicles, including ethanol, biogas (CNG), hybrid and electric vehicles. Since the congestion charging trial, the definition of clean vehicles has changed and now includes petrol and diesel vehicles emitting less than 120 gram CO_2 per kilometer. Still, when congestion charges were introduced permanently, the old definition of clean vehicles was kept.

[22] Alternative fuel vehicles can partly or fully run on alternative fuels rather than gasoline and diesel. Among the most common are different types of electric vehicles (i.e., hybrid electric, electric, plug-in hybrid) and vehicles that run on ethanol, compressed natural gas (CNG), or LPG.

[23] Figure B6 illustrates the corresponding market shares of all newly registered vehicles.

[24] Table B1 summarizes the average new car characteristics of alternative and fossil fuel vehicles at the vehicle-by-year level in 2007 and 2008. Regarding fuel efficiency, carbon emissions, engine power, and service weight, new alternative fuel, and fossil fuel vehicles are remarkably similar. The average new alternative fuel (fossil fuel) vehicle requires 7.54 (7.27) liter fuel per 100 kilometers, emits 182.9 (179.4) grams CO_2 per kilometer, and travels around 13,205 (10,008) kilometers per year.

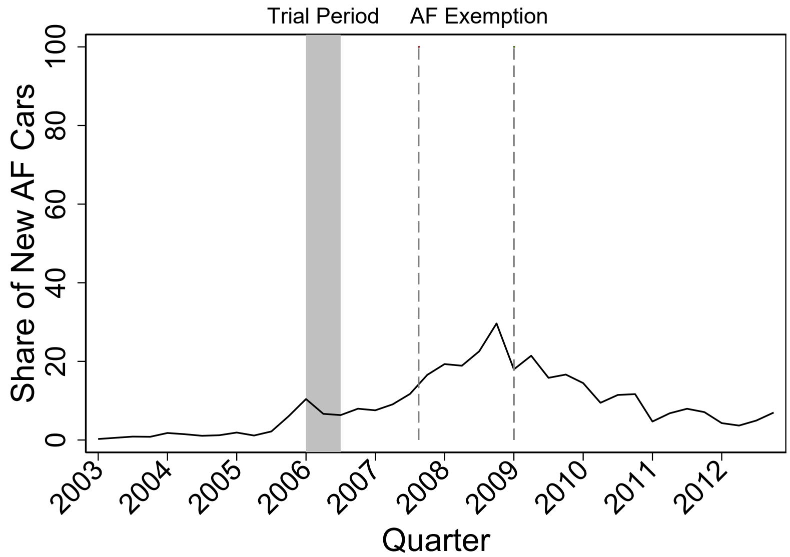


Figure II: Share of new alternative fuel vehicles in Stockholm

Notes: The figure displays the share of quarterly new registrations of alternative fuel vehicles that were registered by private individuals in Stockholm between 2003 and 2012. The trial period is indicated through the gray bar between January 2006, and August 2006. The exemption period of alternative fuel vehicles for the congestion zone is indicated through the two dashed lines between January 2007 and December 2008.

III.B Data sources

To construct a dataset on vehicle ownership, individual demographic characteristics, and congestion charge exposure, the primary data sources are the Swedish vehicle register (*Fordonsregistret*), the longitudinal integrated database for health insurance and labor market studies (*LISA*), the occupational register (*Yrkesregistret*), the Swedish business register (*Företagsregister*), and the geographic database (*Geografidatabasen*) for the period 2003 to 2008 provided by Statistics Sweden.

1. *Car characteristics.* The Swedish vehicle register collects information on all vehicle ownership and purchase records on the whole population of Sweden. The data includes information on the car's general status (registration date, owner type, whether it is leased, when the vehicle became the property of the current owner, in use or not, etc.), the vehicle specification (make, model, and trim), and numerous vehicle characteristics (service weight, fuel type, fuel efficiency, particle filter, carbon emission, etc.), and the annual vehicle kilometers traveled. Each registration also records a vehicle identification number and a social security number equivalent, which uniquely identifies all individuals in Sweden. The vehicle identification number allows us to track the ownership of vehicles over time. We restrict our dataset to privately owned passenger vehicles and vehicles registered for non-commercial

purposes.

2. *Individual attributes.* To match individuals to their vehicles, we link the vehicle registry through the personal identification number to the LISA data, which merges several administrative and tax registers for Swedes aged 18 and above. LISA contains a list of socio-demographic information (such as gender, age, family situation, income, education, and employment status). To add occupational status, we link the data to the Swedish occupational register, which includes information on the gross salary, employment status, workplace industry code, and duration of employment on an annual basis. Similarly for firms, we add information on the universe of Swedish firms using the business register. This includes a rich set of information on the firm (the number of employees, net revenue, personnel cost, and social contribution cost).

3. *Residence & workplace location.* Using the geographic database (*Geografidatabasen*), we supplement the data with the geographic location of the residence and the workplace, which are measured by 250m grid cells in urban and 1000m cells in rural areas. There are more than 14,000 neighborhoods in Sweden, with an average population of around 400 individuals. We also supplement this with individual-level data on annual congestion fees paid between 2016 and 2021. Lastly, we complement our data with information from The Swedish National Travel Survey (2007), which contains information on the daily travel patterns of the Swedish population.

4. *Traffic volume.* To investigate the effects of the congestion charge on traffic volume, we collect sensor-level data on traffic volume from the Swedish transport agency (*Transportstyrelsen*). The sensor level data contains information on all vehicles passing the automated toll road gates between 6 am and 19 pm on weekdays from 2006 to 2023, within a 30-minute resolution.[25] In the main analysis, we focus on the total number of vehicles passing any toll gate in or out of Stockholm in a given period.

III.C Empirical design

Confounding factors typically make it challenging to evaluate traffic policies, as drivers are aware of the policy's implementation date in advance and may alter their commuting behavior accordingly, thereby diminishing the estimated treatment effects. Stockholm, for example, expanded public transportation services while implementing a congestion charge (Eliasson et al., 2009). To identify the causal effects of the congestion charge on individual-level vehicle ownership, driving behavior and location choices, we exploit variation in individuals'

[25] The traffic data does not capture unpaid congestion zone crossings between 19 pm and 6 am.

exposure to toll rates on the road section between home and work. To do this, we define two groups of individuals which we refer to as *treated commuters* and *non-treated commuters* for the remainder of the article. Appendix C.1 and C.2 give additional details on the definition of treatment and control groups and sample restrictions. *Treated commuters* are defined as individuals that cross the congestion zone to or from Stockholm on their way to work in 2006. This includes all individuals who reside within the congestion zone but work outside and those who live outside the congestion zone but work inside. *Non-treated commuters* are individuals who reside and work outside the congestion zone and pass the Essinge bypass or the Lidingö route on the (time-minimizing) route between home and work. We use HERE Technology's Routes API to identify the time-minimizing route and travel time between the home and work address. The sample leaves us with 416,256 individual×year observations over six years (2003-2008).

After the permanent implementation of the congestion charge in August 2007, treated commuters confronted an increase in the cost of driving to work and a greater incentive to adopt alternative fuel vehicles to be exempt from the congestion charge. This increased cost is a proxy for policy exposure.[26] Our identification strategy compares the two groups' vehicle ownership and driving behavior before and after the policy in a Difference-in- Differences (DiD) framework. Our DiD strategy hence aims to exploit variation along two dimensions: (i) *pre* vs. *post*, (ii) *treated commuters* vs. *non-treated commuters*.[27]

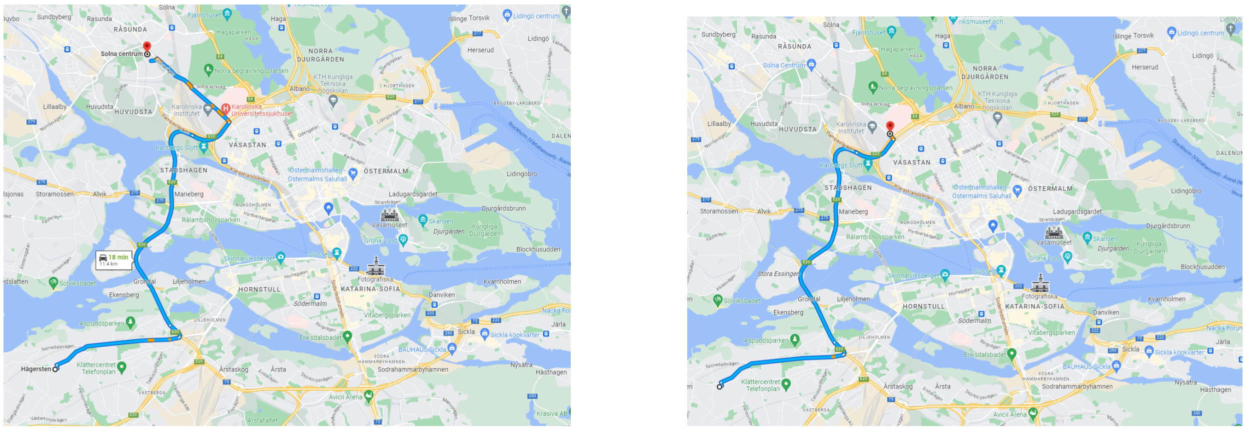
1. *Intuition for identification.* To provide some intuition for the empirical design, Figure III displays a commuting route for an individual who is exempted from the congestion charges on the way to work (Panel a) and an individual that pays the charges (Panel b). Suppose both individuals reside in the southwestern region of Stockholm (*Hägersten*). However, the non-treated commuter's workplace is just outside the congestion zone in the northern area of Stockholm (*Solna centrum*), whereas the treated commuter's workplace is just inside the congestion zone (*Vasastan*).

The time-minimizing way to work for an employee in *Solna centrum* is direct via the Essinge bypass, eliminating the congestion charge. In contrast, the quickest route for an employee in *Vasastan* involves driving through the Stockholm city center and incurring congestion fees. Our empirical approach takes advantage of whether or not the workplace location lies within or outside the congestion charge. The objective of the underlying iden-

[26] Although individuals may be subjected to congestion pricing on non-work trips, we expect that the increasing driving costs on the road segment between home and work significantly impacts how individuals respond to the policy.

[27] In contrast to a recent study by Isaksen and Johansen (2021) that develops a similar identification strategy based on commuting exposure from home to the workplace, we exploit variation within cities instead of comparing the adoption of environmentally friendly vehicles between cities.

tification technique is to compare the subsequent adoption of alternative fuel vehicles and the driving patterns of treated and non-treated commuters. Figure C1 gives an overview of the share of treated commuters in Stockholm per neighborhood in 2006.



(a) Non-treated commuters (b) Treated commuters

Figure III: Commuting example

Notes: The figures display a commuting route for an individual who is exempted from the congestion charges on the way to work (Panel a) and an individual that pays the congestion charges (Panel b).

2. *Estimating equation* To empirically estimate the impact of the congestion charges in Stockholm on driving behavior and adoption of alternative fuel vehicles, the DiD framework in equation (8) can be written as:

$$y_{it} \;=\; \beta post_t \times T_i \;+\; \theta T_i \;+\; \delta X_{it} \;+\; \lambda_t \;+\; \phi_n \;+\; \varepsilon_{it}, \tag{8}$$

where i indexes the individual and t the year. y_{it} refers to the relevant outcome of interest (e.g., adoption of alternative fuel vehicle, kilometers traveled) in a given year. $post_t$ is a dummy variable equal to 1 after the alternative fuel vehicle exemption, and T_i is a dummy variable equal to 1 if the individual is classified as a *treated commuter*. The vector X_{it} represents a rich set of individual demographic variables, work-route specific controls, and previous vehicle attributes.[28] The year fixed effect λ_t captures time-varying factors such as nationwide incentives for vehicles, gas price shocks, or expansion of public transport. ϕ_n indicates neighborhood fixed effects and absorbs any time-invariant variation within Stockholm neighborhoods shared by treated and non-treated commuters. We define individuals living within the same $125m$ radius in urban and $500m$ in rural areas as the neighborhood

[28]The control variables include age, gender, disposable family income, gross salary, employment status, self-employment dummy, married or cohabitant, having at least one child, years of education, and commuting distance.

population. $\varepsilon_{i,q}$ is individual i's error term. The coefficient of interest (β) reflects the DiD estimator and measures how the implementation of the congestion zone influenced the outcome of interest. To calculate the congestion charge, we need to estimate the effect of the congestion zone on vehicle ownership, the number of trips, and commuting distances. In our identification strategy, we use the effect on alternative and fossil fuel vehicle adoption and usage as responses for green and brown vehicle adoption and usage in the congestion charge formula.

The key identifying assumption underlying our empirical strategy is that our definition of treated and non-treated commuters in Stockholm would have experienced parallel trends in vehicle ownership and driving behavior in the absence of the congestion charge introduction - conditional on control variables and fixed effects. To examine the validity of the parallel trends assumption, we estimate a version of our DiD estimator where treatment effects are allowed to vary by year. By defining the year before the alternative fuel vehicle exemption as the reference year (2006), the dynamic DiD estimator can be written as:

$$y_{it} \; = \sum_{s \epsilon \{T | s \neq 2006]} \beta_t T_i \times 1[t = s] \; + \; \theta T_i \; + \; \delta X_{it} \; + \; \lambda_t \; + \; \phi_n \; + \; \varepsilon_{it}, \tag{9}$$

where annual treatment effects are captured by β_t. θ absorbs the 2006 level difference between treated and non-treated commuters in Stockholm. Hence the annual treatment effects β_t are identified from the annual deviations from 2006 levels. To identify the effects on vehicle ownership and driving behavior of fossil fuel vehicles, we define the year before the Stockholm Congestion Trials as the reference year (2005). This is because introducing the Stockholm Congestion Trials differentially influenced treated and non-treated commuters to adopt and drive vehicles, whereas the differential impact for alternative fuel vehicles only occurred during the exemption period.

While the parallel trends assumption is inherently untestable, we document that the trends in alternative fuel vehicle ownership and driving behavior for treated and non-treated commuters for the years before the policy announcement in 2006 ($\hat{\beta}_t \approx 0$) suggest that the assumption is likely to hold.[29] Figures D1 and D2 demonstrate that treated and non-treated commuters have comparable trends in vehicle ownership and vehicle kilometers traveled of fossil fuel vehicles and the total number of vehicles. In addition, we document that the socio-demographic characteristics, vehicle ownership, driving behavior, and commuting patterns

[29] Figure C2 displays the alternative fuel vehicle ownership and driving behavior for treated- (solid line) and non-treated commuters (dashed line). Panel A suggests that the annual share of individuals owning an alternative fuel vehicle increased from 0% in 2003 to approximately 5.1% for treated and 4% for non-treated commuters in 2008. Panel B indicates that the vehicle kilometers traveled with alternative fuel vehicles increased from 15 in 2003 to around 963 for treated and 752 for non-treated commuters in 2008.

among treated and non-treated commuters are similar prior to the congestion charge (Table B2).[30] Finally, the enhancement of public transport in the fall of 2004 (e.g., park-and-ride sites, expanded bus and train services) had no noticeable impact on switching to public transport before the congestion charges. This is consistent with the findings of Kottenhoff and Freij (2009) and Eliasson et al. (2009), who contend that expanding public transportation had a negligible stand-alone effect on the shift from vehicle use to public transportation.[31]

3. *Interpretation of DiD estimates.* The identification strategy compares the vehicle ownership, driving behavior, and commuting distances of a group exposed to the policy on the road segment between home and work (i.e., the treatment group) relative to a group not charged on their commute to work (i.e., the control group). Hence, the empirical estimates should be interpreted as average treatment effect on the treated (ATT) of those individuals that cross the congestion zone on their way to work.[32]

We anticipate that the estimated ATT represents a lower bound relative to the average population for at least three reasons. First, our design excludes individuals who reside and work within the city center, do not own a vehicle, or are unemployed from the control group. Excluding these individuals diminishes our results relative to the average population because they are less inclined to use alternative fuel vehicles and drive less (Table B2). Second, we utilize work-trip exposure to the congestion charge as a proxy for policy exposure, even though the congestion charge may also impact non-work visits. Hence, the empirical strategy might be viewed as a type of treatment intensity, assuming that commuters who must pay a congestion charge on their way to work will be exposed more intensely than others. This

[30]Panel A shows that the average treated (non-treated) commuter is around 45 (45) years, with about 13.3 (12.7) years of education, and earns a gross salary of approximately 515 (474) thousand SEK conditional on being employed. In addition, 77% (75%) of treated (non-treated) commuters are married or live with a cohabitant, 38% (31%) have at least one child, and around 5% (3%) are self-employed. Panel B illustrates that the number of alternative fuel, fossil fuel, and all vehicles is similar for both commuting groups. Treated- and non-treated commuters travel 15,101 kilometers and 16,373 kilometers per year. The distance between work and residence for treated and non-treated commuters is 16.9 and 19.4 kilometers, respectively.

[31]If treated and non-treated were influenced differentially through the expansion of public transport, then part of the effect of the congestion charge should instead be registered as an interaction effect with expanded public transportation. However, onboard surveys from Stockholm's Local Traffic (*Storstockholms Lokaltrafik*) operator indicate that the number of passengers on the new bus lines in the spring of 2006 who had traveled by car in the fall of 2005 was negligible compared to the decrease in the number of passages during the Stockholm Congestion Trials (Report to the City of Stockholm, 2006).

[32]If we expect imperfect compliance of the non-treated commuters (i.e., pay for the congestion charge on their way work), then we would interpret $\hat{\beta}$ as an intention-to-treat effect (ITT). As treated commuters cannot avoid paying the charge when crossing the congestion zone, we can rule out "never-takers" in our empirical design. To derive the ATT, we need to multiply the ITT estimate by the proportion of individuals who adhered to the treatment. However, given that we expect of a low incidence of non-treated commuters paying the congestion charge, we anticipate the ATT to closely approximate the ITT. To the extent that non-compliance in our empirical setting exist, the ITT reflects the appropriate estimate for determining optimal pricing strategies.

implies that *non-treated commuters* are also subject to increasing driving costs, albeit to a smaller degree than those in the treatment group. Third, the first post-period year (2007) is only partially treated as the exemption of alternative fuel vehicles started in August 2007. As our empirical design only exploits differential exposure to the policy for five months in 2007, we anticipate greater treatment effects for treated commuters when the treatment lasts for the entire year.

4. *Rebound effects.* Our estimated responses in adopting and using conventional and alternative-fuel vehicles reflect a change in relative prices and the behavior induced by lighter traffic in the post-implementation period. The latter can be seen as a violation of the stable unit treatment values assumption (SUTVA):[33] The treatment of others can affect how an individual responds to congestion pricing, as it impacts the traffic conditions they experience. This concern is related to the concept of "induced demand" in transportation planning (Duranton & Turner, 2011). The policy-relevant responses should incorporate both "pure" substitution effects and the "rebound" effect because the congestion charges depend on the overall traffic changes caused by the policy implementation. However, our estimated treatment effects may be less pronounced in settings with a smaller traffic reduction among treated commuters. For example, a high share of exempted green vehicles among treated commuters may mute substitution to alternative modes of transport and mitigate the rebound effect on non-treated commuters.

IV Main results

IV.A Effects of the congestion charge

Table I displays the impact of the congestion zone estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commuting distance (Panel C) for alternative fuel, fossil fuel, and all vehicles. We restrict the post-period for alternative fuel vehicles to 2007-2008 and for fossil fuel vehicles to 2006-2008.

1. *Fleet composition.* Panel A of Table I documents that the congestion charge induced a .64 percentage points increase in the probability of owning an alternative fuel vehicle in the post-implementation years (column 1). Relative to the average baseline probability of 1.4% of owning an alternative fuel vehicle, treated commuters are around 46 percent more

[33]This pertains to the literature on DiD, which takes into account spillover effects without imposing the SUTVA assumption. Spillover effects can be essential in various economic scenarios, like when a policy in one region impacts the surrounding areas or when people are linked through a network (Butts, 2021; Huber & Steinmayr, 2021).

likely to own a new alternative fuel vehicle. At the same time, the policy decreased the average number of fossil fuel vehicles by .83 percentage points (column 2), resulting in a slight decrease in the total number of vehicles possessed (column 3).[34] Our findings indicate that the congestion charge led to a substantial shift from fossil to alternative fuel vehicles, while the average number of vehicles owned by individuals is relatively stable. We find that the implementation of the congestion charge led to a .17 percentage points rise in the adoption of new alternative fuel vehicles, which indicates that 26% of the impact on alternative fuel vehicles was due to the acquisition of new vehicles (Table D1). Despite the uptake of exempted alternative vehicles among treated commuters, we document that the congestion charge had no significant impact on fuel efficiency, carbon emission, vehicle service weight, and engine size (Table D2).[35]

2. *Number of trips.* Based on an average commute distance of 18.2 kilometers,[36] Panel B of Table I suggests that treated commuters increased the number of trips with alternative fuel vehicles by about 6.6 in the post-implementation years (column 1). In addition, the policy induced a decrease of -13.8 number in trips traveled in fossil fuel vehicles (column 2), leading to an overall reduction of 8.2 trips in all vehicles (column 3). This implies that the congestion charge resulted in an annual increase of 121 vehicle kilometers traveled by commuters in alternative fuel vehicles, and a decrease of 253 kilometers in fossil fuel vehicles, which led to a total reduction of 150 vehicle kilometers traveled (Table D3). The reduction in vehicle usage indicates a shift away from personal vehicle trips into the congestion zone in the post-implementation years.

As the congestion charge formula requires changes in the number of congestion trips by vehicle type ($\frac{\partial t_g^c}{\partial \tau}$, $\frac{\partial t_b^c}{\partial \tau}$, $\frac{\partial t_g^o}{\partial \tau}$, $\frac{\partial t_b^o}{\partial \tau}$), we need to determine how many trip changes were made inside versus outside the congestion zone by each vehicle fuel type. To do this, we assume that the effect of removing the alternative fuel vehicle exemption on the kilometers traveled after 2012 equals the effect on the kilometers traveled inside the congestion zone after the implementation of the congestion charge. Specifically, we estimate how the removal of the alternative fuel vehicle exemption influenced the vehicle kilometers traveled in alternative and fossil fuel vehicles in the post-period 2013 and 2014. We view this estimate as the impact

[34]As our identification strategy exploits different post-periods, the treatment effects of alternative fuel (column 1) and fossil fuel vehicles (column 2) do not precisely correspond to the total change in vehicle ownership and kilometers traveled (column 3). Table D5 documents that treatment effects perfectly match when using the same reference year for both fuel types.

[35]The main reason for this is that alternative fuel vehicle share similar vehicle characteristics with fossil fuel vehicles (Table B1).

[36]We use the fact that the average work commute is 17.4 kilometers, non-congestion zone trips are approximately 19 kilometers, and 46 percent of kilometer-weighted trips are business-related (The Swedish National Travel Survey, 2007).

on the driving behavior inside the congestion zone. Intuitively, this implies that removing the exemption only affects people's choice of vehicle type when crossing the congestion zone, and not other means of transportation. Appendix E.2 provides additional details on estimating the number of trips by fuel type.

Panel B of Table D3 documents that abolishing the alternative fuel exemption resulted in a decrease in the number of kilometers traveled with alternative fuel vehicles by about 103 kilometers, an increase of 206 vehicle kilometers traveled in fossil fuel vehicles, and a total increase of 103 kilometers. This implies that approximately 85% of trips in alternative fuel vehicles and 81% in fossil fuel vehicles were trip changes crossing the congestion zone.[37] Finally, implementing the congestion charge led to an increase of 5.9 congestion and .7 non-congestion zone trips in alternative fuel vehicles, and a reduction of 11.8 congestion and 2 non-congestion zone trips in fossil fuel vehicles (Panel C of Table I).

[37]This is in line with the trip changes of the London congestion zone that estimated around one-quarter of trips were diverted around the charging zone (Leape, 2006).

Table I: Estimates on vehicle ownership, trips, and commuting

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0064***	-.0083**	-.0030
	(.0014)	(.0035)	(.0033)
Mean Car Ownership (t-1)	.014	1.138	1.145
B.Number of Trips			
Post x Treated Commuters	6.6***	-13.8***	-8.2**
	(1.5)	(3.9)	(3.8)
Inside Congestion Trips	5.9**	-11.8**	-5.9
	(2.9)	(5.0)	(4.7)
Mean Trips Inside (t-1)	6.4	399.1	401.7
Change Trips Outside (t-1)	.70	-2	-2.3
Mean Trips Outside	6.9	432.1	434.8
C.Commuting Distance			
Post x Treated Commuters			-.086***
Mean Commute Distance (t-1)			17.5
Changes in Outside Distance			-.007
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

3. *Commuting distance.* In addition to modifying vehicle ownership or driving behavior, treated commuters may be inclined to either move into the congestion zone or relocate to workplaces outside the congestion zone, which has implications for the average commute distance of drivers. In Table D4, we estimate the effect of the congestion zone on the like-

lihood of moving residences (Panel A) and relocating to workplaces (Panel B). We restrict the non-treated commuters to individuals living outside the congestion zone.

The empirical findings in Panel A suggest that treated commuters are .2 percentage points more likely to move inside the congestion zone. This is consistent with commuters avoiding the congestion charges since the workplace is located inside the congestion zone. In addition, Panel B reveals that treated commuters are .5 percentage points more likely to alter their workplace location and 1.6 percentage points more likely to relocate outside the congestion zone. Compared to a baseline probability of moving of 2.5 percent, treated commuters are nearly 64 percent more likely to relocate to a workplace outside the congestion zone. In addition, around 43 percent of treated commuters (.7 percentage points) transfer to a new company outside the congestion zone, while 57 percent (.8 percentage points) relocate to a new office outside the congestion zone within the same organization. In contrast, the effect on relocating to workplaces inside the congestion zone is negative as this would not prevent paying congestion charges. Although our congestion charge formula abstracts from direct effects on labor market outcomes, we find that treated commuters experience a slight increase in gross salary after the implementation of the congestion charge (Table D12).

As a result of moving into the congestion zone and relocating to workplaces outside the congestion zone, either to a new office or company, Panel C of Table I shows that the average commute distance for treated commuters decreases by approximately .086 kilometers. Using our empirical estimates on the changes in the number of non-congestion trips and kilometers traveled, we derive that the average commuting distance outside the congestion zone reduced by .007 kilometers. This implies that treated commuters reduced the average distance between congestion and non-congestion zone trips.

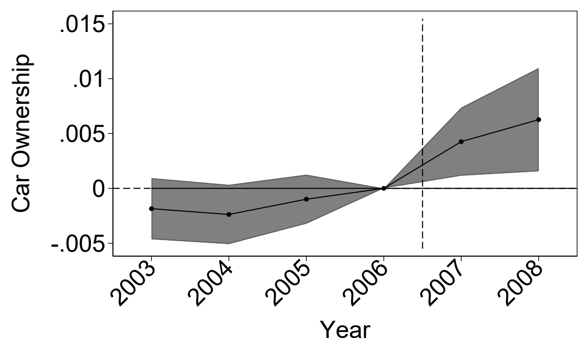
IV.B Dynamics

1. *Dynamic estimates.* Figure IV displays annual treatment effects estimated from the DiD specification in equation (9). Panel (a) indicates that individuals exposed to the Stockholm congestion charge were more than .63 percentage points more likely to own an alternative fuel vehicle by the end of 2008. In addition, Panel (b) demonstrates that by the end of 2008, the average distance traveled by alternative fuel vehicles increased by 123 kilometers. As the exemption of alternative fuel vehicles started in August 2007, so that 2007 is only partially treated, the treatment effects on vehicle ownership of alternative fuel vehicles and kilometers driven are substantially larger in 2008 than in 2007. However, if we multiply the treatment effects in 2007 by the exposure period of five months, the impact on adopting

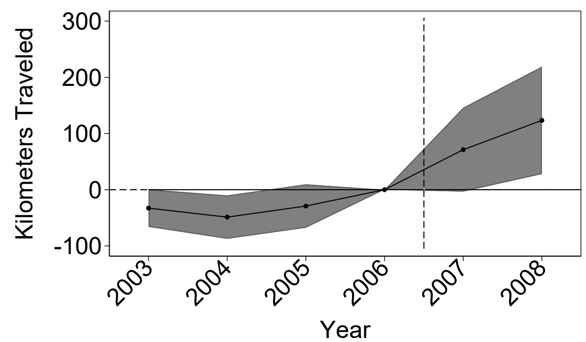
alternative fuel vehicles and driving behavior was greater in 2007.[38]

Figure D1 displays that the negative treatment effects on fossil fuel vehicles are slightly larger than the positive effects on alternative fuel vehicle adoption, suggesting that individuals substituted from fossil fuel to alternative fuel vehicles as opposed to adding an additional vehicle to their fleet. This is supported by the insignificant treatment effects on the total number of vehicles owned in Figure D2.

The estimated coefficients for the pre-intervention period (2003-2005) are close to zero, supporting the validity of the parallel trends assumption. We also document that treated and non-treated commuters in Stockholm are relativity similar across socio-demographic characteristics, commuting patterns, and outcome variables before the imposition of the congestion zone.



(a) Number of alternative fuel vehicles



(b) Kilometers traveled with AF vehicles

Figure IV: Dynamic estimates on alternative fuel vehicles

Notes: The figures plot coefficients β_t estimated from equation (9), where β_{2006} is normalized to zero. Panel (a) shows the annual treatment effect on the probability of owning an alternative fuel vehicle. Panel (b) shows the annual treatment effect on vehicle kilometers traveled with alternative fuel vehicles. Standard errors are clustered at the neighborhood level. The vertical dashed line denotes the year of the alternative fuel vehicle exemption (1st of August 2007).

2. *Predictions.* In Panel (a) of Figure V, we observe that the share of toll-paying commuters in Stockholm that owned an alternative fuel vehicle increased by 3.7 percentage points, from 1.5 percent in 2006 to 5.2 percent in 2008 (solid line). Without the congestion charge, we estimate that the share of alternative fuel vehicles would have been 4.6 percent (dashed line). Consequently, the congestion charge accounts for 16 percent of the increase in the adoption of alternative fuel vehicles in 2008. Equivalently in Panel (b), the congestion charge can explain 17 percent of the rise in vehicle kilometers driven by alternative fuel vehicles.

[38] As the permanent implementation of the congestion tax was announced in October 2006, individuals may also respond to the policy announcement at the start of 2007.

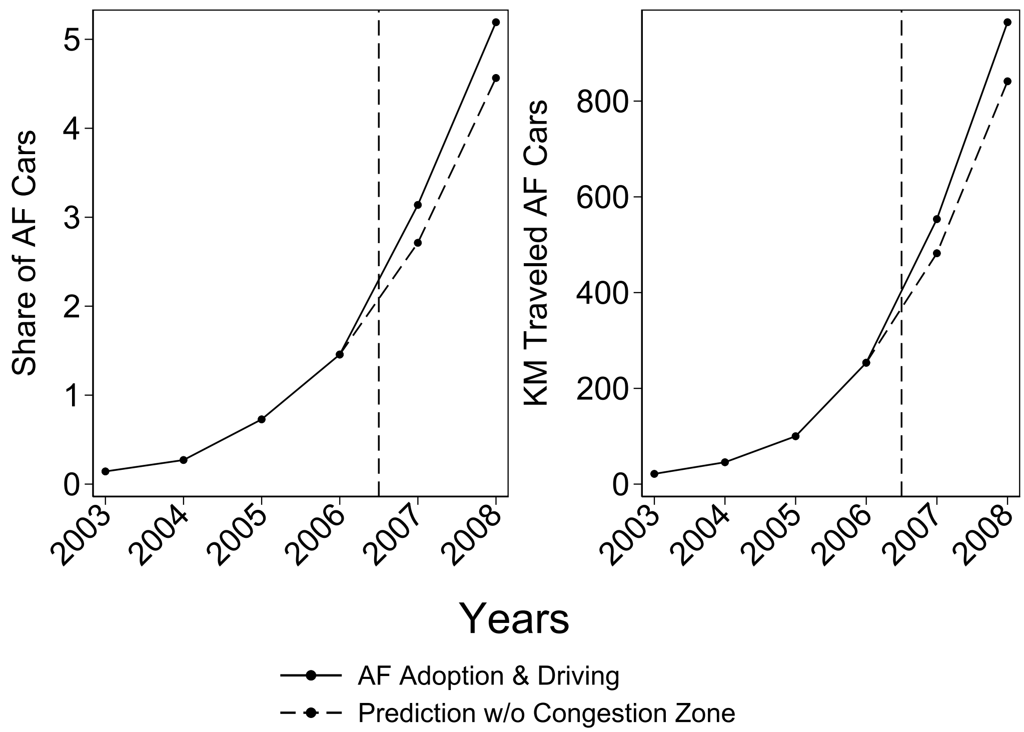


Figure V: Predicted vehicle ownership and driving behavior

Notes: The solid line shows the share of individuals among treated commuters in Stockholm that owned an alternative fuel vehicle in the period 2003-2008. The dashed line shows the predicted share of individuals among treated commuters in Stockholm that would have owned an alternative fuel vehicle in the absence of the congestion charge, based on the treatment estimates reported in Figure IV. The vertical distance between the two lines indicates the annual treatment effects. The vertical dashed line denotes the implementation date (1st of August 2007).

IV.C Heterogeneous effects

Figure VI illustrates significant heterogeneous treatment effects of vehicle ownership and driving behavior of alternative fuel vehicles, fossil fuel vehicles, and the total number of vehicles along five socioeconomic dimensions: income, family size, education, age, and commuting distance.

Panel (a) displays a strong gradient in alternative fuel adoption and driving behavior in response to the congestion charge. While individuals with an annual income of more than SEK 600k are 1.6 percentage points more likely to adopt an alternative fuel vehicle and drive 260 kilometers more with alternative fuel vehicles, there is no effect for individuals with an income of less than SEK 400k. In contrast, low-income individuals are significantly more likely to adopt fossil fuel vehicles and increase their usage. This may suggest that low-income individuals with limited public transportation options are unable to switch to cycling or public transportation. Individuals with a medium-range income adjust their commuting by reducing their fossil fuel vehicles, and kilometers traveled. This suggests that high-income individuals prefer to adopt alternative fuel vehicles in response to the policy, while middle-income individuals prefer to change their mode of transportation (e.g., public transit, cycling). However, the observed heterogeneous patterns in vehicle ownership and driving adjustments could also reflect preferences for new technologies, environmental awareness, or financial constraints.[39]

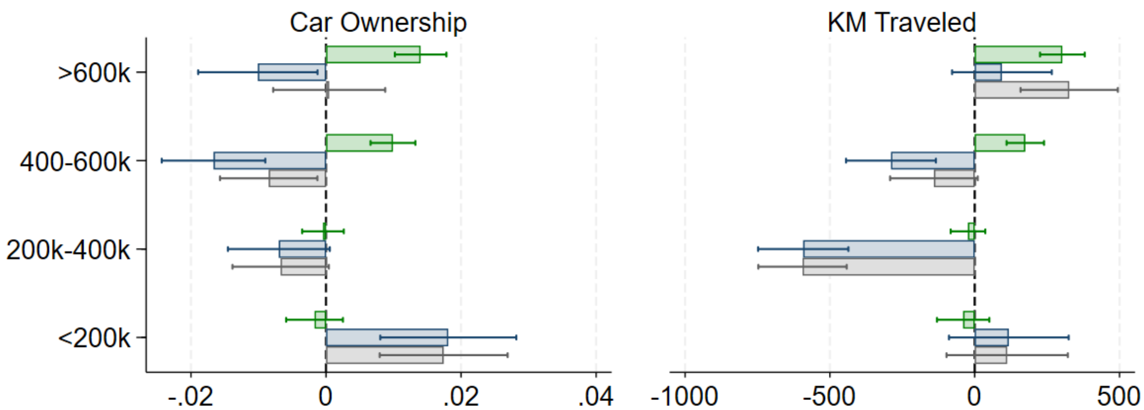
In Panel (b), we document that couples entirely drive the substitution to alternative fuel vehicles in response to the policy. In contrast, single adult households without kids are more likely to adopt fossil fuel vehicles. This may reflect that singles are more flexible in changing their mode of transportation, and economies of scale make it more cost-efficient for couples to invest in at least one alternative fuel vehicle.

Panel (c) indicates that the treatment effect is increasing in educational attainment, with the largest impact on master and bachelor graduates. As the total effect on the number of vehicles for these groups is negative, individuals partly substitute to alternative fuel vehicles and change their mode of transportation. This pattern could reflect preferences for new technologies, and a higher awareness of environmental and climate benefits of driving alternative fuel vehicles among higher educated individuals.[40]

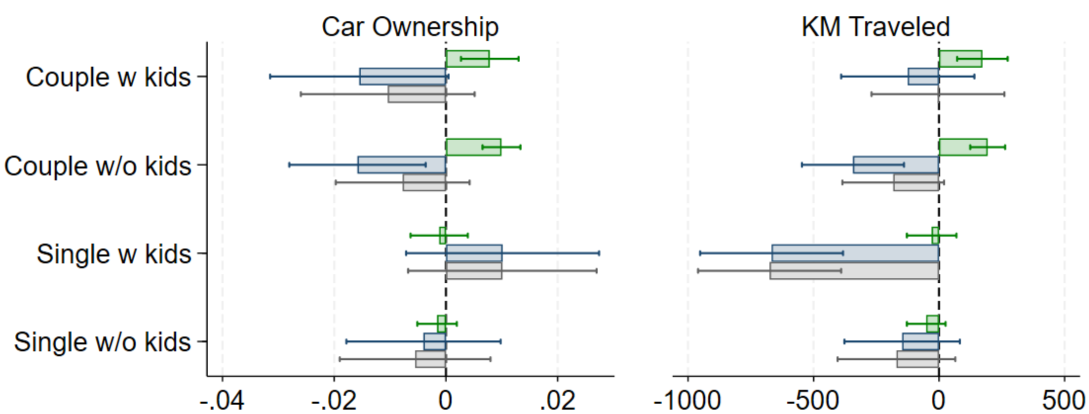
We also show a strong gradient in the relationship between alternative fuel adoption and age in Panel (d), with individuals below 45 as the most responsive group to the policy. In contrast, people close to retirement reduce their driving due to the congestion charge. An individual's adaptation decision may also depend on the quality of transportation substitutes. Finally, we find that the likelihood of adopting an alternative fuel vehicle is essentially the same for individuals with varying work commutes in Panel (e).

[39]First, differences in the margin of adjustment could reflect different preferences for adopting a new technology, differences in the value of time, or differences in utility from cycling or using public transit. Second, the heterogeneous pattern may reflect financial barriers to purchasing an alternative fuel vehicle. Low-income individuals may have a more limited opportunity set than high-income individuals, as fossil fuels were the only used vehicles available during the policy implementation.

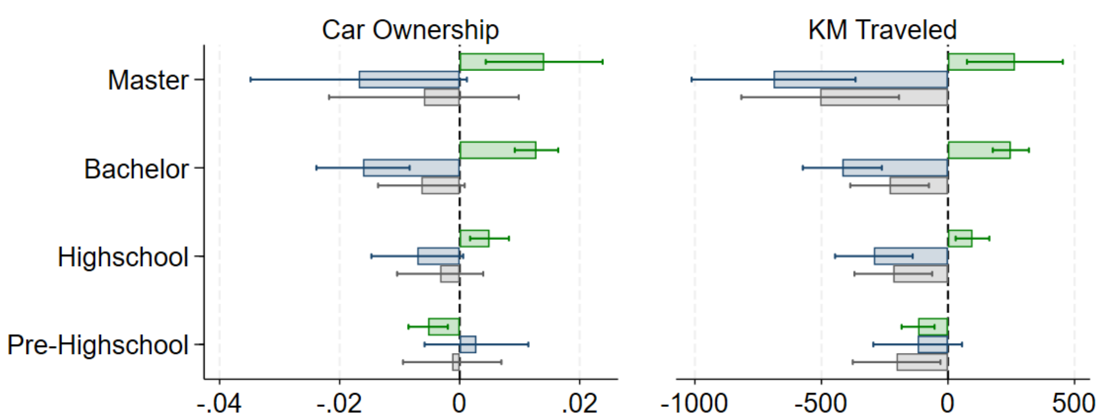
[40]Previous literature also suggest that individuals tend to "undervalue" future fuel savings when purchasing a vehicle (Allcott & Wozny, 2014), and this tendency might weaken with education.



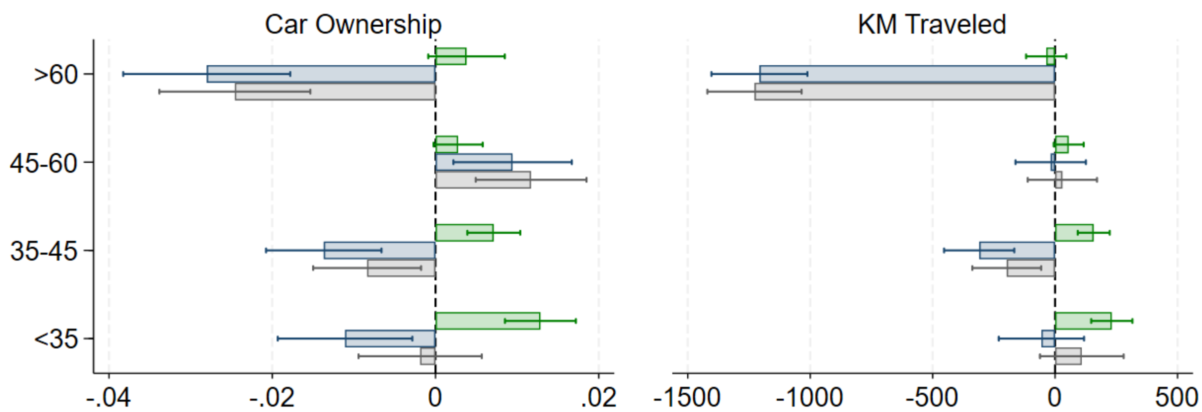
(a) Income



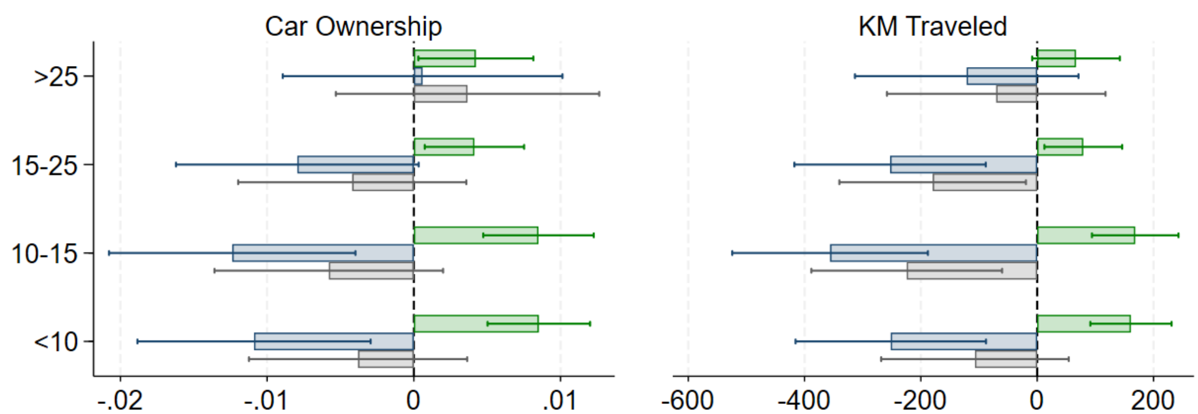
(b) Family Status



(c) Years of Education



(d) Age



(e) Commuting Distance

Figure VI: Heterogeneous Diff-in-diff estimates

Notes: The figures plot the coefficients β_k on vehicle ownership and driving behavior for each vehicle fuel type, where k refers to the group (e.g., income quintile). Green indicates alternative fuel vehicles, blue for fossil fuel vehicles, and gray for all vehicles. Each panel (a-e) plots coefficients estimates from a separate regression. The dependent variable for vehicle ownership is a dummy variable equal to 1 if the individual owns the type of vehicle and 0 otherwise. The dependent variable for driving behavior indicates the vehicle kilometers traveled with the type of vehicle. Groups are based on 2006 demographics. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post period for fossil fuel vehicles. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors, clustered by neighborhoods.

IV.D Robustness checks

Next, we examine the sensitivity of our main results to various specifications of sample restrictions, treatment group definitions, firm-level effects and placebo tests. Restricting the sample to individuals observed in all years (2003-2008), the empirical estimates on alternative fuel adoption and kilometers traveled based on a balanced sample are very similar to our main results (Table D6). We also show that our main results on alternative fuel adoption and driving behavior are robust to different treatment group definitions. When we restrict the sample of treated commuters to individuals residing outside the congestion zone, the effect on alternative fuel adoption and kilometers traveled becomes slightly smaller (Table D7). In contrast, if we define the treatment group as treated commuters inside the congestion zone, our empirical findings become larger (Table D8). This suggests that treated commuters in the city center are less likely to adopt and use alternative fuel vehicles to respond to the congestion charge.

As our identification strategy exploits predetermined variation of whether the workplace is located within or outside the congestion zone, a potential threat may be that vehicle policies of workplaces (e.g., provision of parking spaces) operating within the congestion zone changed from those outside after the policy. To mitigate this concern, we document in Table D9 that including firm-level fixed effects and various firm-specific characteristics has virtually no effect on the coefficient estimates. In addition, we demonstrate in Table D10 that excluding workplaces located more than three kilometers from the congestion zone does not affect the coefficients, reaffirming that workplace differences do not generate our empirical findings.

As a validity test, we check whether the effects for the treated commuters vanish after the exemption of alternative fuel vehicles was abolished. Table D11 verifies that the congestion zone did not impact alternative fuel vehicle adoption and driving behavior after 2009.

V Computing the congestion charge

V.A Mapping empirical results to theory

To provide an estimate of the congestion charge derived in equation (3), we combine the empirical estimates on vehicle ownership, number of trips, and commuting distance from Section IV with estimates from the literature on vehicle emission factors − the amount of a particular pollutant that a vehicle emits while traveling a kilometer − and costs of congestion externalities. We calculate that congestion externalities correspond to €.38 per kilometer inside the congestion and and €.13 per kilometer outside the congestion (External Costs of Transport, 2011).[41] Emission externalities equal €.033 per kilometer in brown vehicles, while we set emission externalities to €0 for green vehicles derived from the European Environment Agency (2014, 2021).[42] All externalities are expressed in real 2021 €. Table E2 summarizes

[41]The estimates refer to marginal damages in congested peak hours and our empirical estimates should be interpreted as peak-hour prices.

[42]Previous studies have shown that low emission zones, road tolls, and congestion charges can help improve urban air quality (Wolff, 2014; Gibson & Carnovale, 2015; Fu & Gu, 2017; Gehrsitz, 2017), with resulting

key population statistics (Panel A), treatment effects on vehicle ownership, number of trips, and commuting distance estimated in Section IV(Panel B), and estimates on the costs of emission (Panel C) and congestion externalities (Panel D). Appendix E provides details on the mapping of our empirical results to the theory, and the computation of the emission and congestion externalities.

Equation (10) shows how these statistics enter the theoretical formula of the congestion charge per crossing from equation (3):

$$\begin{aligned}
\tau \; &= \underbrace{\Delta N_g(\widetilde{\phi}_g + \widetilde{\gamma}_g)}_{\triangle Green\ Cars} + \underbrace{\Delta N_b(\widetilde{\phi}_b + \widetilde{\gamma}_b)}_{\triangle Brown\ Cars} + \underbrace{\Delta T \cdot (\overline{\phi} + \overline{\gamma})}_{\triangle Trips} + \underbrace{\Delta V^c(\hat{\phi}^c + \hat{\gamma}^c)}_{\triangle Inside\ Driving} + \underbrace{\Delta V^o(\hat{\phi}^o + \hat{\gamma}^o)}_{\triangle Outside\ Driving} \\
\tau \; &= -\,.0004 \cdot €59.6 + .0004 \cdot €4329.1 - .354 \cdot €.09 - .043 \cdot €.03 + .7 \cdot €8.36 + .122 \cdot €3.67 \\
&\quad + .0051km \cdot 190.83\frac{€}{km} + .0004km \cdot 83.6\frac{€}{km} \\
\tau \; &= -\,€.02 \; + \; €2.15 \; + €6.32 \; + \; €.97 \; + \; €.04 \; \approx \; €9.46 \qquad (10)
\end{aligned}$$

Our baseline calculation of the congestion charge for fossil fuel vehicles equals €9.46 per congestion zone crossing or €.54 per kilometer traveled using an average congestion trip length of 17.5 kilometers. Congestion externalities account for around 89 percent (€8.39) of the total charge, while reduced emission externalities correspond to 11 percent (€1.07). The benefits of reducing congestion outweigh the small reduction in emissions caused by exempting green vehicles from the congestion charge, raising questions about such exemptions' efficiency. This surpasses a congestion charge (€7.35), which does not consider the adjustments in vehicle ownership, driving behavior, and commuting decisions, by approximately 21 percent.[43] Our estimate exceeds peak-hour congestion pricing in Stockholm of €4.78 ($\approx SEK$ 45), which implies that the current congestion zone does not fully capture the emission and congestion externalities from our average commuter and the responses to the policy. However, our estimate falls within the range of a flat fee congestion charge in London (£15), the congestion charge in Milan (€7.5), and the highway tolling system in San Diego ($8).

Table II gives an overview of the calculated key components of the congestion charge derived in equation (4) separated by emission type. First, the fleet size component corresponds to €2.13 of the congestion charge, which results from a decrease in the brown fleet minus the increase in the green fleet. The first term increases the optimal congestion charge

health benefits such as lower asthma rates in children (Simeonova et al., 2021), lower infant mortality (Currie & Walker, 2011), and fewer hospital admissions related to chronic cardiovascular and respiratory diseases (Pestel & Wozny, 2019).

[43] We derive this static congestion charge through the multiplying the average congestion trip distance ($17.5km$) by the marginal emission (€.04) and congestion externalities (€.38).

by €2.15 through a reduction of congestion and emissions, and the second term decreases the charge by €.02 through an increase in congestion from green vehicles. The reduction in total congestion (€1.85) and the substitution to greener vehicles (€.3) result in a positive fleet size component. 86 percent is attributable to decreased traffic and 14 percent to reduced emissions. Therefore, reduced vehicle ownership had a much greater impact on the congestion charge than emission changes from adopting green vehicles. In contrast, if the congestion charge would result in a perfect substitution from brown to green vehicles, there would be no reduced traffic, and the fleet size would only correspond to the change in emission externalities.

Second, the changes in the number of trips account for €6.32 of the total congestion charge, which is due to fewer congestion (€5.9) and non-congestion zone trips in brown vehicles (€.45) and an increase in congestion zone trips with green vehicles (−€.03). The emission and congestion externalities on tolled congestion zone trips in brown vehicles account for 62 percent of the total charge. In addition, leakage (€.33) explains around three percent of the total congestion charge, whereas the effect of substituting to congestion zone trips with green vehicles is rather small due to the low overall size of green vehicles. However, if the share of green vehicles increases, substituting green vehicle trips becomes increasingly essential and reduces the overall congestion charge. This implies that an increasing stock of green vehicles lowers the congestion charge, which may explain why policymakers gradually phase out exemption for congestion charges (e.g, Stockholm, Oslo). Similarly to the fleet size component, reducing trips and substituting lower-emitting reduces the congestion charge.

Third, €1.01 of the congestion charge reflects responses in commuting distances, which come from reducing the average distance between workplace and residence (€.97) and average outside commutes (€.04). Therefore, moving into the congestion zone and relocating to workplaces outside the congestion zone, either to a new office or company, are additional margins for treated commuters that decrease congestion and emission externalities.

Table II: Congestion charge decomposition

	Per crossing (€)	Externality (€)	
		Congestion	Emission
Fleet Composition	**2.13**		
Effect on green vehicles $\Delta N_g(\widetilde{\phi_g} + \widetilde{\gamma_g})$	$-.02$	-0.02	0
Effect on brown vehicles $\Delta N_b(\widetilde{\phi_b} + \widetilde{\gamma_b})$	2.15	1.85	.3
Number of Trips	**6.32**		
Effect on green trips outside $\Delta T_g^o(\overline{\phi_g^o} + \overline{\gamma_g^o})$	$-.00$	$-.00$	0
Effect on green trips inside $\Delta T_g^c(\overline{\phi_g^c} + \overline{\gamma_g^c})$	$-.03$	$-.03$	0
Effect on brown trips inside $\Delta T_b^c(\overline{\phi_b^c} + \overline{\gamma_b^c})$	5.9	5.34	.56
Effect on brown trips outside $\Delta T_b^o(\overline{\phi_b^o} + \overline{\gamma_b^o})$	.45	.34	.11
Commuting Distance	**1.01**		
Effect on inside commute $\Delta V^c(\hat{\phi}^c + \hat{\gamma}^c)$	.97	.88	.09
Effect on outside commute $\Delta V^o(\hat{\phi}^o + \hat{\gamma}^o)$	.04	.03	.01
Congestion charge (€)	**9.46**	**8.39**	**1.07**

Notes: This table reports the congestion charge per crossing from equation (10) seperated by each component (column 1). We split the congestion charge by congestion (column 2) and emission externalities (coumn 3). All charges and externalities are expressed in real 2021 €.

Table VII reports congestion charge results under several alternative assumptions, separated by emission and congestion externalities. The following three bars explore different assumptions regarding the extent of substitution towards unpriced road trips.[44] Assuming that all changes in brown and green vehicle trips occurred within the congestion zone, the congestion charge equals €8.8. If we use empirical estimates of leakage from the London congestion charge that suggests that around one-quarter of trips were diverted around the charging zone (i.e., a 25% leakage rate) (Leape, 2006), our congestion charge increases to €10.02. Finally, assuming that 50% of the total trips were outside the congestion zone, the congestion charge equals €12.11. This implies that the substitution of trips outside the congestion zone increases the congestion charge because the congestion charge becomes an imprecise instrument to address the two policy goals.

In our baseline specification, we use the average commuting distance among treated and non-treated commuters in Stockholm, which excludes nearby commuters ($< 3km$). In contrast, if we include all individuals who commute to work and own at least one vehicle, the average commuting distance shrinks to $11.9km$ and the optimal charge corresponds to €7.14. Therefore, longer commuting distances increase the size of the optimal congestion charge. As the first-best policy would tax the kilometers traveled, our optimal congestion

[44]In Section D.4, we document the responses of various groups to the policy employed for calculating the congestion charge within the framework of these underlying assumptions.

charge scales with the distance of trips.

The sixth and seventh bars explore what happens to the congestion charge when the share of green vehicle increases. Before the introduction of the congestion charge, approximately 1% of vehicles were green, and 1.5% of vehicle kilometers were traveled in green vehicles. Instead, if we assume that 10%, and 25% of vehicles and trips are made with green vehicles, the congestion charge becomes €9.1 and €8.51. Hence, an increasing share of green vehicles implies a reduced congestion charge.

The following three bars report the congestion charge using the responses of low-, medium-, and high-income individuals. Due to the limited responsiveness of low-income individuals to the policy with respect to the adoption of alternative fuel vehicles and the reduction in trips, the congestion charge amounts to €7.36. In contrast, middle-income individuals mainly respond by reducing their vehicular trips, thereby mitigating emissions and congestion-related externalities, leading to a corresponding congestion charge of €16.21. The adoption of alternative fuel vehicles and the shift towards utilizing these vehicles for trips contribute to a reduced congestion charge of €4.73 within the high-income group.

Finally, in accordance with the first-best Pigouvian policy of taxing vehicle kilometers traveled, we examine congestion charges levied on individuals residing in proximity to the congestion zone ($< 10km$), those at intermediate distances ($10 - 25km$), and those residing farther away ($> 25km$). Consistent with the first-best Pigouvian policy, our congestion charge recommends imposing higher congestion charges on individuals commuting from distant locations, while significantly reducing charges for those residing in close proximity to the congestion zone.

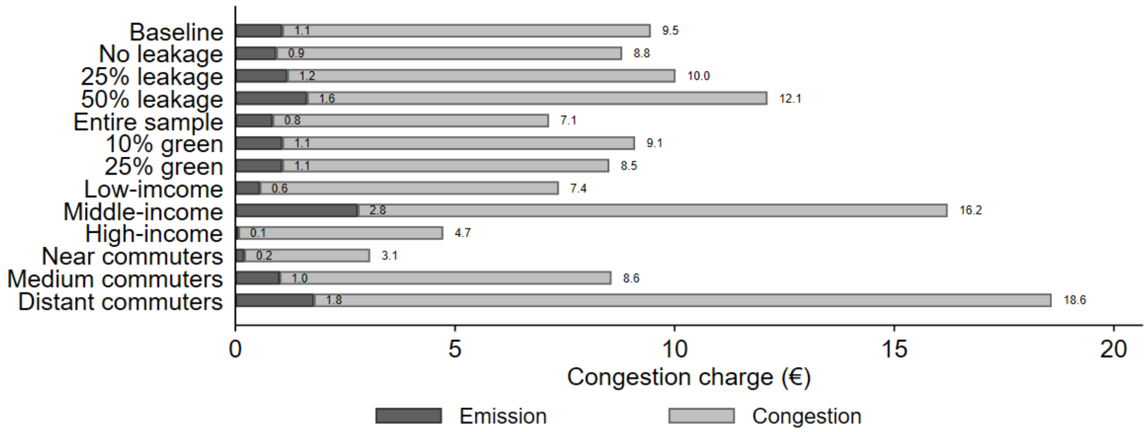


Figure VII: Congestion charge under alternative assumption

Notes: This figure reports the congestion charge across a range of assumptions. The first bar reports our baseline calculations using equation (4), seperated by emission (black), and congestion externalities (grey). The second, third, and fourth bars document the charge under no, 10%, and 25% leakage according to equation (7). The fifth bar reports the congestion charge for all commuters with vehicles. The sixth and seventh bars report the congestion charge, assuming that 10% and 25% of vehicles and trips are made with green vehicles. The eighth, ninth, and tenth bars report the congestion charge using the responses of low-, medium-, and high-income individuals. The eighth, ninth, and tenth bars report the congestion charge using the responses of low-, medium-, and high-income individuals. The The eleventh, twelfth, and thirteenth bars report the congestion charge using the responses of nearby- (<10km), medium- (10-30km), and far commuters (>30km). All charges and externalities are expressed in real 2021 €.

Table III: Congestion charge under alternative assumption

		Externality (€)	
	Per-crossing (€)	Congestion	Emission
Baseline	9.46	8.39	1.07
No leakage	8.8	7.87	.93
25% leakage (Leape, 2006)	10.02	8.84	1.18
50% leakage	12.11	10.48	1.63
Entire sample	7.14	6.29	.85
10% green	9.1	8.03	1.07
25% green	8.51	7.44	1.07
Low-income	7.36	6.81	.56
Medium-income	16.21	13.42	2.79
High-income	4.73	4.66	.07

Notes: This table reports the congestion charge across a range of assumptions. The first row reports our baseline calculations using equation (4). The second and third columns report the congestion charge if the social planner solely cares about either congestion or emission externalities according to equation (6) and (5).The second, third, and fourth rows document the charge under no, 10%, and 25% leakage according to equation (7). The fifth row reports the congestion charge for all commuters with vehicles. The sixth and seventh rows reports the congestion charge, assuming that 10%, and 25% of vehicles and trips are made with green vehicles. The eighth, ninth, and tenth rows report the congestion charge using the responses of low-, medium-, and high-income individuals. All charges and externalities are expressed in real 2021 €.

V.B Distributional concerns

A common objection to congestion charges is that the benefits and costs are distributed unevenly across socioeconomic groups. Figure B3 demonstrates the distributional profile of the congestion charges in 2016, indicating that congestion charges fall disproportionately on low-income individuals.[45] In Stockholm, the congestion charge accounts for approximately .68 percent of the annual salary for the lowest income decile and .16 percent for the highest income decile. Therefore, the congestion fees constitute a non-negligible portion of the income, approximately four times greater for low-income individuals. Similar regressive policy patterns remain even after applying the sample restrictions outlined in Section C.2. Consequently, the congestion charge is regressive for all Stockholm residents, not just those who own a vehicle and are subject to it on their way to work.

Three additional dimensions influence the distributional profile of the policy: substitution to other modes of transport, revenue recycling, and exemption of alternative fuel vehicles. First, we demonstrate systematic differences in how individuals adjust to the con-

[45] The congestion charges amount to around 150 million SEK per month (Figure B4).

gestion fee in Section IV.A. Notably, we find that primarily middle-income individuals switch to other modes of transportation, whereas low-income individuals continue to use fossil fuel vehicles. This suggests that low-income individuals may be more reliant on existing commuting patterns, and substituting to alternative modes of transportation may be more challenging. Second, the net distributional effects of congestion fees depend on how the policy's proceeds are utilized. The congestion charge revenues were designated for a new bypass around Stockholm and road investments (Eliasson et al., 2014). However, as high-income individuals travel more by vehicle, road investments may again benefit higher-income groups disproportionately. Third, a charging system's distribution of costs and benefits depends on exemptions and discounts (Levinson, 2010; Ison & Rye, 2005). The social benefits of exempting alternative fuel vehicles in Stockholm are highly centered among high-income groups. The exemption makes the congestion charge's distributional profile even more regressive since primarily high-income individuals adopt alternative fuel vehicles in response to the policy.[46]

In contrast, low-income individuals tend to reside farther away from the congestion zone, which implies that they should be charged a lower fee in the ideal Pigouvian tax system for kilometers traveled. However, since the congestion fee charges a fixed amount regardless of the distance traveled, it is less regressive compared to the ideal Pigouvian tax system. Hence, the substitution pattern to other transportation modes, revenue recycling, and exemption of alternative fuel vehicles exacerbate the regressive effect of the policy, whereas the commuting distances reduce the regressive effect of the charge.

VI Conclusion

As the expansion of congestion pricing in the policy world coincides with a period of concern about environmental policy, many existing and proposed policies fold together multiple policy goals. In many cities, pollution and congestion externalities motivate policies to price local vehicle travel. These policies often deviate from an ideal Pigouvian policy, either because of practical constraints or policymakers want to achieve multiple policy goals with a single instrument. This paper provides two main contributions to economists' thinking about tradeoffs and optimal prices in this setting.

First, we provide a framework for recovering optimal congestion charges that targets

[46]In addition, the congestion charge is included in the "taxable benefit value" of company vehicles, which are either exempt or can deduce the charge from their gross income (West & Börjesson, 2020). Drivers can deduct charges incurred on commute trips, if driving saves them more than an hour each way relative to transit and they travel five kilometers Börjesson et al. (2012). This reinforces the regressivity, as most company vehicle drivers belong to the highest income bracket.

emission and congestion externalities and includes three responses to the policy — vehicle ownership, number of trips, and location choices — often missing from second-best congestion pricing models. The advantage of our approach is tractability. While our model incorporates these three responses to the congestion zone, recovering optimal prices requires only policy responses. By phrasing optimal prices in terms of responses, this approach highlights key policy tradeoffs in a way that quantitative spatial approaches may not. It also allows researchers to plug in estimates of these responses from other settings when data or natural experiments are unavailable.

Our second contribution is showcasing the use of this framework to recover optimal congestion charges. Several of our empirical estimates from Stockholm's congestion zone are of interest as stand-alone results: We find evidence that the alternative fuel exemption induced individuals to switch vehicle types but left the total amount of vehicles roughly unchanged. We document that commuters substituted to taking more trips with exempted alternative fuel vehicles or switched to alternative transport modes. Finally, the congestion charge induced individuals to sort across the zone to limit their pricing exposure between work and home, ultimately leading to marginally shorter commuting distances. Our findings are a new addition to the literature and can provide valuable insights for researchers or policymakers interested in these specific dimensions.

At the same time, the magnitude of these responses is small, meaning that a naive Pigouvian price applied to conventional fossil fuel vehicles within the congestion zone accounts for roughly 79 percent of the optimal charge. Overall, the second-best prices are above this Pigouvian benchmark because on the margin, the induced reductions in fossil fuel vehicles and reductions in commuting distances outweigh the damages from substitution to other roads of increased usage of exempt vehicles. While these results are inherently setting-specific, the responses provide valuable priors for researchers interested in studying policies with similar attributes elsewhere.

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Appendix

Road Pricing with Multiple Policy Goals:
The Effect on Vehicle Ownership, Driving, and Commuting

Peter Nilsson Matthew Tarduno Sebastian Tebbe

A Deriving the congestion charge

A.1 Deriving first oder conditions

The consumer's first-order conditions are:

$$\frac{\partial B}{\partial n_g} = 0 = \mu_g'[u_g^c(t_g^c) + u_g^o(t_g^o)] - (p^c + p_g l_g)v^c t_g^c - (p^o + p_g l_g)t_g^o v^o - c_g$$
$$\frac{\partial B}{\partial n_b} = 0 = \mu_b'[u_b^c(t_b^c) + u_b^o(t_b^o)] - ((p^c + p_b l_b)v^c + \tau)t_b^c - (p^o + p_b l_b)t_b^o v^o - c_b$$
$$\frac{\partial B}{\partial t_b^c} = 0 = \mu_b(n_b)[u_b'^c(t_b^c)] - n_b((p^c + p_b l_b)v^c + \tau)$$
$$\frac{\partial B}{\partial t_g^c} = 0 = \mu_g(n_g)[u_g'^c(t_g^c)] - n_g(p^c + p_g l_g)v^c$$
$$\frac{\partial B}{\partial t_b^o} = 0 = \mu_b(n_b)[u_b'^o(t_b^o)] - n_b(p^o + p_b l_b)v^o$$
$$\frac{\partial B}{\partial t_g^o} = 0 = \mu_g(n_g)[u_g'^o(t_g^o)] - n_g(p^o + p_g l_g)v^o$$
$$\frac{\partial B}{\partial v^o} = 0 = -n_g(p^c + p_g l_g)t_g^o - n_b(p^o + p_b l_b)t_b^o - r'(v^c)$$
$$\frac{\partial B}{\partial v^c} = 0 = -n_g(p^c + p_g l_g)t_g^c - n_b(p^c + p_b l_b)t_b^c - r'(v^c)$$

The derivative of W with respect to τ is:

$$
\begin{aligned}
\frac{\partial W}{\partial \tau} = 0 = & \frac{\partial n_g}{\partial \tau}\Bigg(\mu_g'[u_g^c(t_g^c) + u_g^o(t_g^o)] - (p^c + p_g l_g)v^c t_g^c - (p^o + p_g l_g)t_g^o v^o \\
& - c_g - (v^c t_g^c + v^o t_g^o)l_g \phi_g - v^c t_g^c \gamma^c - v^o t_g^o \gamma^o\Bigg) \\
& + \frac{\partial n_b}{\partial \tau}\Bigg(\mu_b'[u_b^c(t_b^c) + u_b^o(t_b^o)] - (p^c + p_b l_b)v^c t_b^c - (p^o + p_b l_b)t_b^o v_b \\
& - c_b - (v^c t_b^c + v^o t_b^o)l_b \phi_b - v^c t_b^c \gamma^c - v^o t_b^o \gamma^o\Bigg) \\
& + \frac{\partial t_g^o}{\partial \tau}\Bigg(\mu_g(n_g)[u_g'^o] - n_g(p^o + p_g l_l)v^o - n_g v^o l_g \phi_g - n_g v^o \gamma^o\Bigg) \\
& + \frac{\partial t_g^c}{\partial \tau}\Bigg(\mu_g(n_g)[u_g'^c] - n_g(p^c + p_g l_g)v^c - n_g v^c l_g \phi_g - n_g v^c \gamma^c\Bigg) \\
& + \frac{\partial t_b^o}{\partial \tau}\Bigg(\mu_b(n_b)[u_b'^o] - n_b(p^o + p_b l_b)v^o - n_b v^o l_b \phi_b - n_b v^o \gamma^o\Bigg) \\
& + \frac{\partial t_b^c}{\partial \tau}\Bigg(\mu_b(n_b)[u_b'^c] - n_b(p^c + p_b l_b)v^c - n_b v^c l_b \phi_b - n_b v^c \gamma^c\Bigg) \\
& + \frac{\partial v^c}{\partial \tau}\Bigg(-n_g(p^c + p_g l_g)t_g^c - n_b(p^c + p_b l_b)t_b^c - r'(v^c) \\
& - n_b t_b^c l_b \phi_b - n_g t_g^c l_g \phi_g - (n_b t_b^c + n_g t_g^c)\gamma^c\Bigg) \\
& + \frac{\partial v^o}{\partial \tau}\Bigg(-n_g(p^c + p_g l_g)t_g^o - n_b(p^o + p_b l_b)t_b^o - r'(v^c) \\
& - n_b t_b^o l_b \phi_b - n_g t_g^o l_g \phi_g - (n_b t_b^o + n_g t_g^o)\gamma^o\Bigg)
\end{aligned}
$$

The planner chooses the congestion charge, taking into account how drivers will respond. Plugging in the first order conditions of the representative driver, we have:

$$
\begin{aligned}
0 =& \frac{\partial n_g}{\partial \tau}\left(-(v^c t_g^c + v^o t_g^o) l_g \phi_g - v^c t_g^c \gamma^c - v^o t_g^o \gamma^o\right) \\
&+ \frac{\partial n_b}{\partial \tau}\left(\tau t_b^c - (v^c t_b^c + v^o t_b^o) l_b \phi_b - v^c t_b^c \gamma^c - v^o t_b^o \gamma^o\right) \\
&+ \frac{\partial t_g^o}{\partial \tau}\left(-n_g v^o l_g \phi_g - n_g v^o \gamma^o\right) \\
&+ \frac{\partial t_g^c}{\partial \tau}\left(-n_g v^c l_g \phi_g - n_g v^c \gamma^c\right) \\
&+ \frac{\partial t_b^o}{\partial \tau}\left(-n_b v^o l_b \phi_b - n_b v^o \gamma^o\right) \\
&+ \frac{\partial t_b^c}{\partial \tau}\left(n_b \tau - n_b v^c l_b \phi_b - n_b v^c \gamma^c\right) \\
&+ \frac{\partial v^c}{\partial \tau}\left(-n_b t_b^c l_b \phi_b - n_g t_g^c l_g \phi_b - (n_b t_b^c + n_g t_g^c)\gamma^c\right) \\
&+ \frac{\partial v^o}{\partial \tau}\left(-n_b t_b^o l_b \phi_b - n_g t_g^o l_g \phi_g - (n_b t_b^o + n_g t_g^o)\gamma^o\right)
\end{aligned}
$$

A.2 Externality conversion

First, we define the emission and congestion externalities per brown and green vehicle ($\widetilde{\phi}$ and $\widetilde{\gamma}$) by multiplying the emission and congestion damages per kilometer traveled with the respective commuting distance and number of trips. This can be expressed as total emission and congestion externalities (expressed in €) per brown and green vehicle as follows:

$$\widetilde{\phi}_g = (v^c t_g^c + v^o t_g^o) l_g \phi_g \qquad \widetilde{\phi}_b = (v^c t_b^c + v^o t_b^o) l_b \phi_b \tag{A1}$$

$$\widetilde{\gamma}_g = v^c t_g^c \gamma^c + v^o t_g^o \gamma^o \qquad \widetilde{\gamma}_b = v^c t_b^c \gamma^c + v^o t_b^o \gamma^o \tag{A2}$$

Second, we define emission and congestion externalities per trip ($\overline{\phi}$ and $\overline{\gamma}$) by multiplying the emission and congestion damages by the number of vehicles and the average commuting distance inside or outside the congestion zone. This can be expressed as emission and congestion externalities per trip (expressed in €) for each brown and green vehicle inside and outside the congestion zone as follows:

$$\overline{\phi_g^c} = n_g v^c l_g \phi_g \qquad \overline{\phi_b^c} = n_b v^c l_b \phi_b \qquad \overline{\phi_g^o} = n_g v^o l_g \phi_g \qquad \overline{\phi_b^o} = n_b v^o l_b \phi_b \tag{A3}$$

$$\overline{\gamma_b^c} = n_b v^c \gamma^c \qquad \overline{\gamma_b^c} = n_b v^c \gamma^c \qquad \overline{\gamma_g^o} = n_g v^o \gamma^o \qquad \overline{\gamma_b^o} = n_b v^o \gamma^o \tag{A4}$$

Third, we define emission and congestion externalities per kilometer traveled ($\hat{\phi}$ and $\overline{\gamma}$) by multiplying the emission and congestion damages by the number of vehicles and trips of each vehicle type inside and outside the congestion zone. This can be expressed as emission and congestion externalities per kilometer traveled (measured in € per kilometer) for brown and green vehicles inside and outside the congestion zone as follows:

$$\hat{\phi}^c = n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g \qquad \hat{\phi}^o = n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g \tag{A5}$$

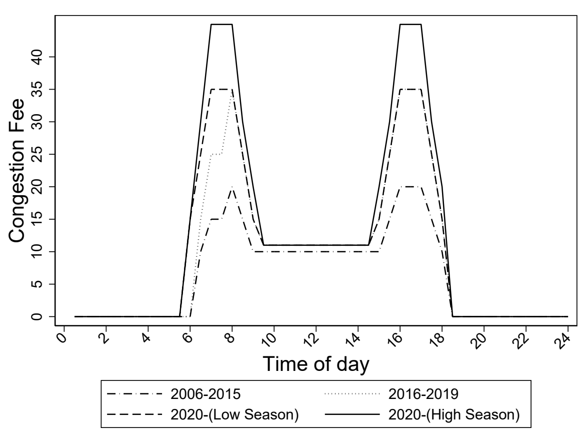
$$\hat{\gamma}^c = (n_b t_b^o + n_g t_g^o) \gamma^o \qquad \hat{\gamma}^o = (n_b t_b^o + n_g t_g^o) \gamma^o \tag{A6}$$

B Background

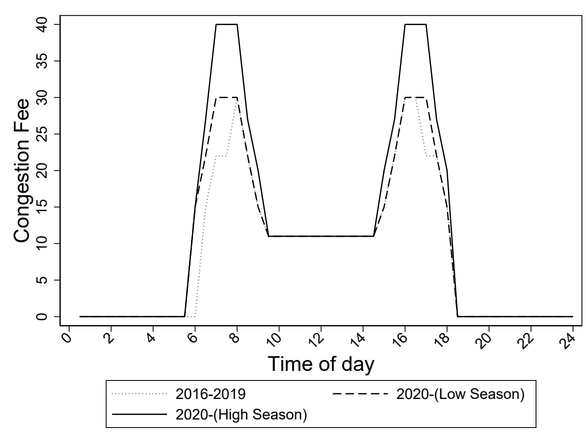
B.1 Congestion charges

In January 2016, the charging levels were increased and ranged from 10 to 35 SEK per passage, which corresponded to an increase of 75% in the peak but only 10% in the off-peak. The maximum charge for one day also increased from 60 to 100 SEK. In addition, the congestion charge was levied on the Essinge bypass.

In January 2020, the congestion tax in Stockholm was adjusted according to the season - a high season and a low season were introduced. This is because traffic flows and congestion in the road network are generally greater during late spring, summer, and autumn than during winter. High season is from March 1 to the day before Midsummer's Eve and August 15 to November 30. Low season is the rest of the time. The congestion charge is still differentiated whether you enter or leave the inner city or use the Essinge bypass. However, the charge on the Essinge bypass is slightly lower than the charge in the inner Stockholm city.



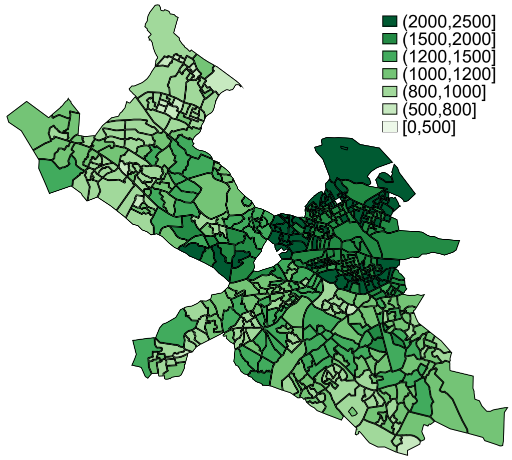
(a) Stockholm



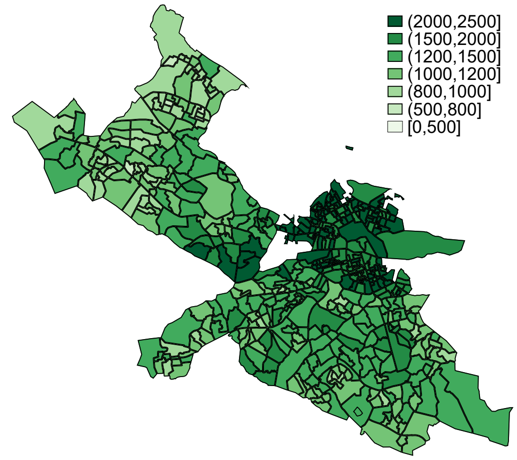
(b) Essinge

Figure B1: Congestion charges in Stockholm

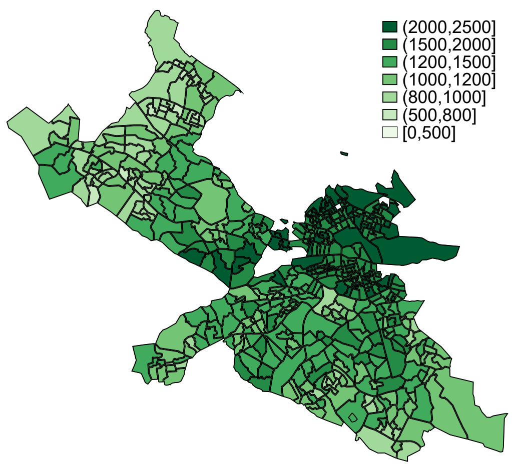
Notes: The figures show toll rates for Stockholm (Panel A) and Essinge (Panel B) for the period 2006 to 2020.



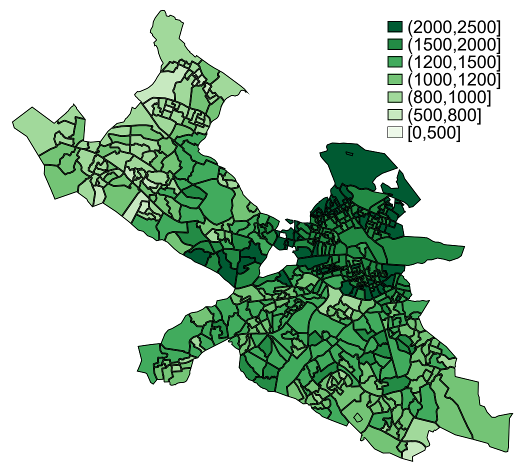
(a) 2016



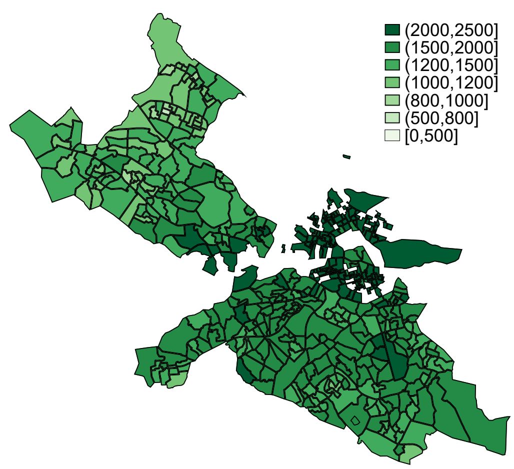
(b) 2017



(c) 2018



(d) 2019



(e) 2020

Figure B2: Annual congestion charges

Notes: The figure illustrates the average annual congestion charges per vehicle owner for each neighborhood in Stockholm between 2016 and 2020.

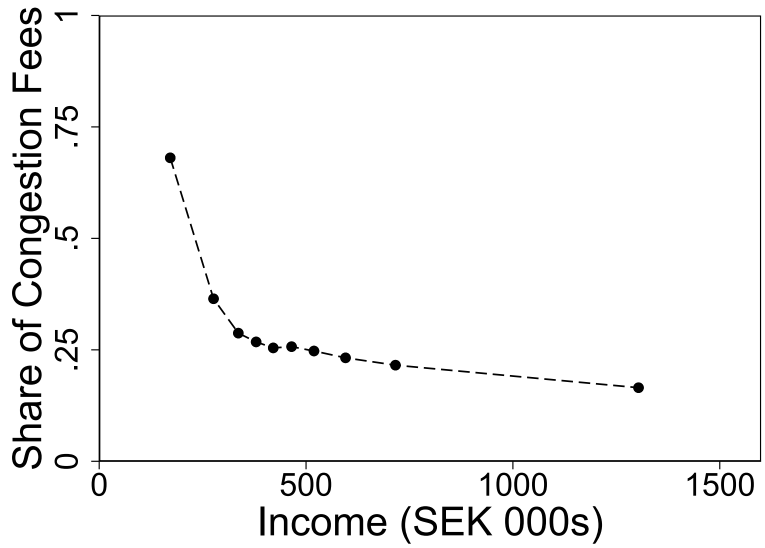


Figure B3: Congestion charges by share of salary

Notes: The figure illustrates the Stockholm congestion charges as a share of income for each income decile in 2016.

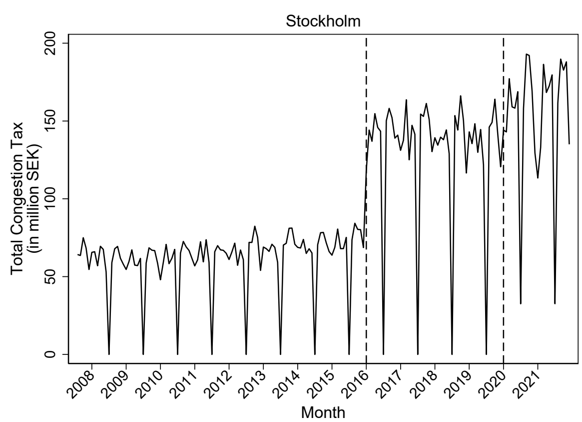


Figure B4: Total congestion fees

Notes: The figure show the total congestion charges in Stockholm between 2007 and 2022.

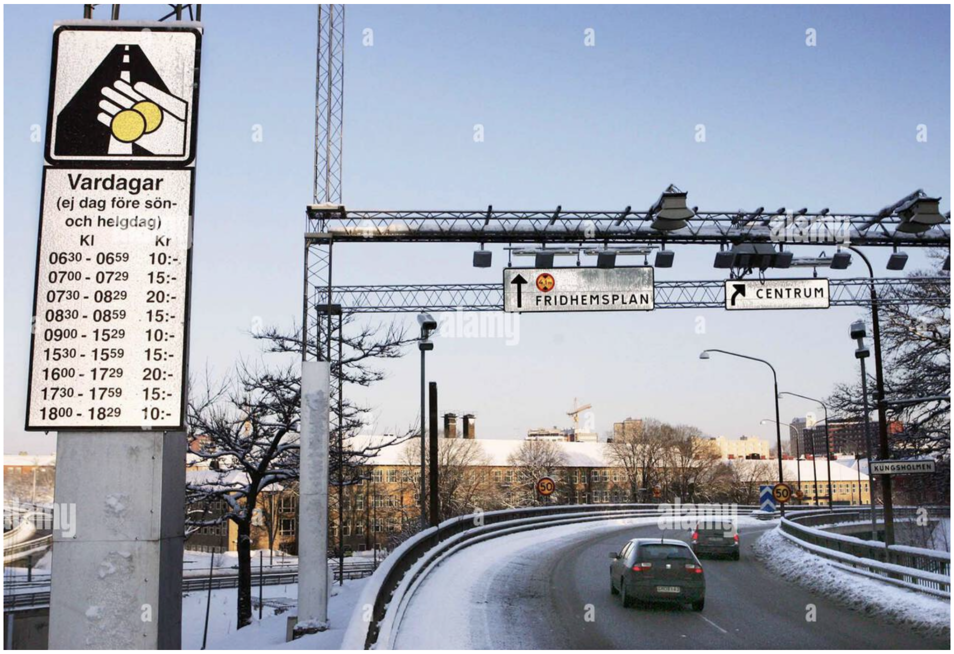


Figure B5: Congestion charges at entry

Notes: The pictures illustrates the Stockholm congestion charges at each entry point.

B.2 Vehicle market

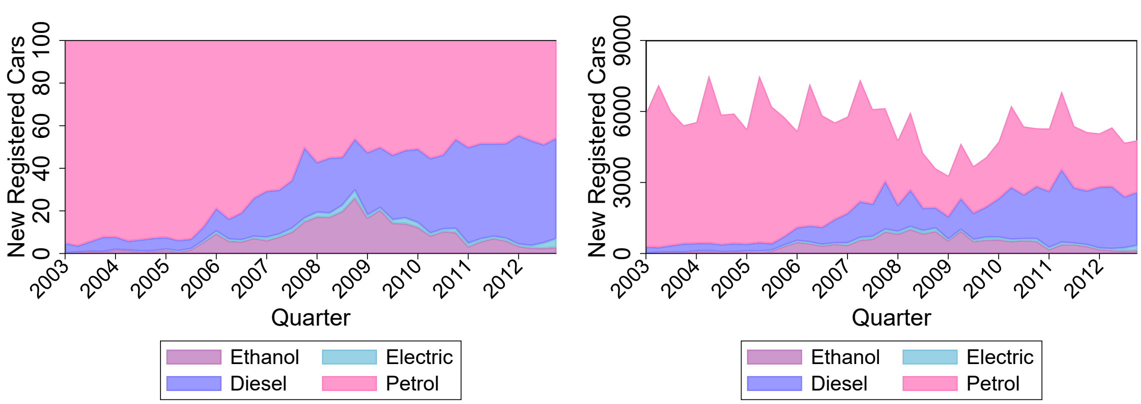


Figure B6: Share of newly registered cars in Stockholm

Notes: The figures display the share (Panel a) and the total number (Panel b) of quarterly new registrations of cars that were registered by private individuals in the Swedish vehicle market between 2003 and 2012.

Table B1: New vehicle characteristics by fuel type

	Alternative fuel		Fossil fuel	
	Mean	Std. Dev.	Mean	Std. Dev.
A.Vehicle attributes				
Fuel efficiency (l/100km)	7.54	1.47	7.27	1.89
Carbon emission (g/km)	182.90	33.16	179.40	45.85
Engine power (horsepower)	96.13	27.41	110.90	51.50
Service weight (kg)	1468.64	210.26	1510.21	360.75
Vehicle Kilometers Traveled	13205.93	12454.03	10008.64	9489.03
N(New Cars)	6,917		37,089	

Notes: The table shows summary statistics of vehicle attributes (Panel A) for newly registered alternative fuel and fossil fuel vehicles in 2007 and 2008.

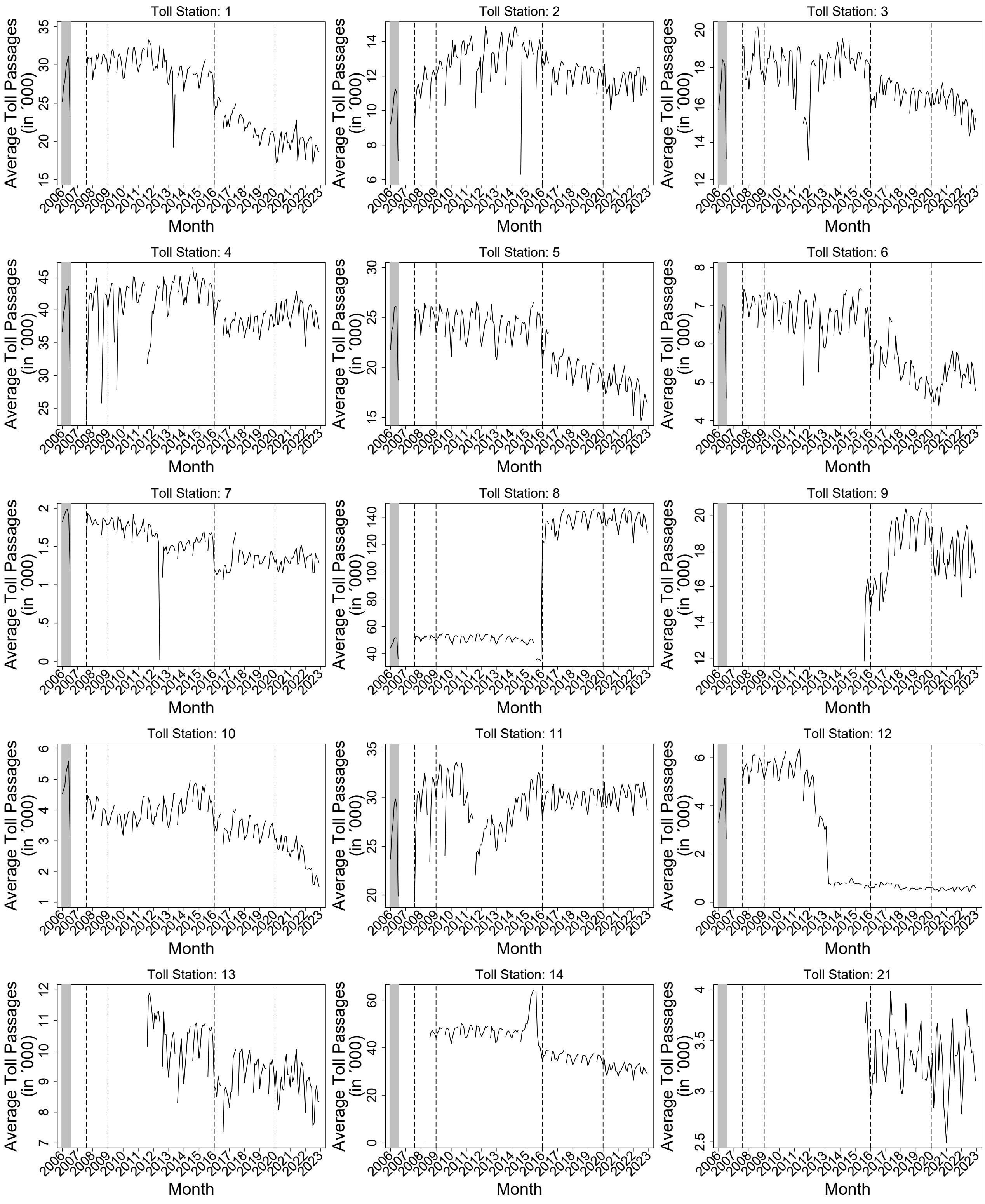
B.3 Descriptive Statistics

Table B2: Summary statistics by commuter group in 2005

	Treated		Non-Treated		Stockholm	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
A.Demographic Variables						
Age	45.27	9.84	44.59	9.71	40.63	13.05
Female	0.37	0.48	0.25	0.43	0.50	0.50
Gross Salary (in tho.)	515.91	501.51	474.28	291.09	303.43	311.61
Disposable Income (in tho.)	258.04	428.28	232.23	151.98	212.60	813.84
Unemployment Days	0.00	0.00	0.00	0.00	0.00	0.00
Self-Employmed	0.05	0.22	0.03	0.18	0.10	0.29
Married or Cohabitant	0.77	0.42	0.75	0.44	0.58	0.49
At Least 1 Child	0.38	0.48	0.31	0.46	0.45	0.50
Years of Education	13.32	2.48	12.74	2.43	12.59	2.47
B.Outcome Variables						
Alternative Fuel Cars	0.01	0.08	0.01	0.08	0.00	0.05
Fossil Fuel Cars	1.14	0.40	1.17	0.43	0.49	0.72
Total Cars	1.15	0.39	1.17	0.43	0.49	0.72
Alternative Fuel Kilometers	96.24	1287.11	79.73	1173.27	30.71	754.09
Fossil Fuel Kilometers	15004.70	8571.05	16293.30	8997.19	6753.97	13611.45
Vehicle Kilometers Traveled	15101.09	8522.75	16373.02	8964.44	6784.77	13631.37
Distance Commute (km)	16.86	9.75	19.43	8.87	24.22	75.94
N(Observation)	46.056		10.430		870.769	

Notes: Table shows summary statistics for socio-demographic (Panel A), and outcome variales (Panel B) for treated, non-treated commuters, and all people in Stockholm before the implementation of the congestion charge in 2005. Treated commuters are defined as individuals that cross the congestion to or from Stockholm on their way to work. Non-treated commuters are individuals who reside and work outside the congestion zone and pass the Essinge bypass or the Lidingö tunnel on the (time-minimizing) route between home and work.

B.4 Traffic volume



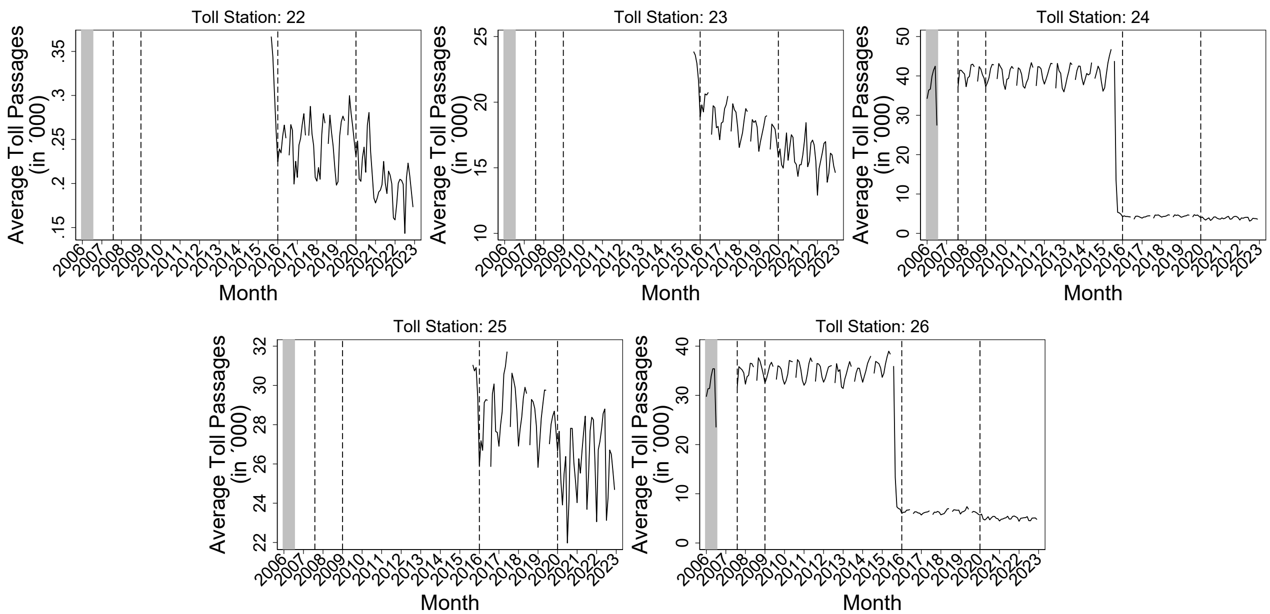
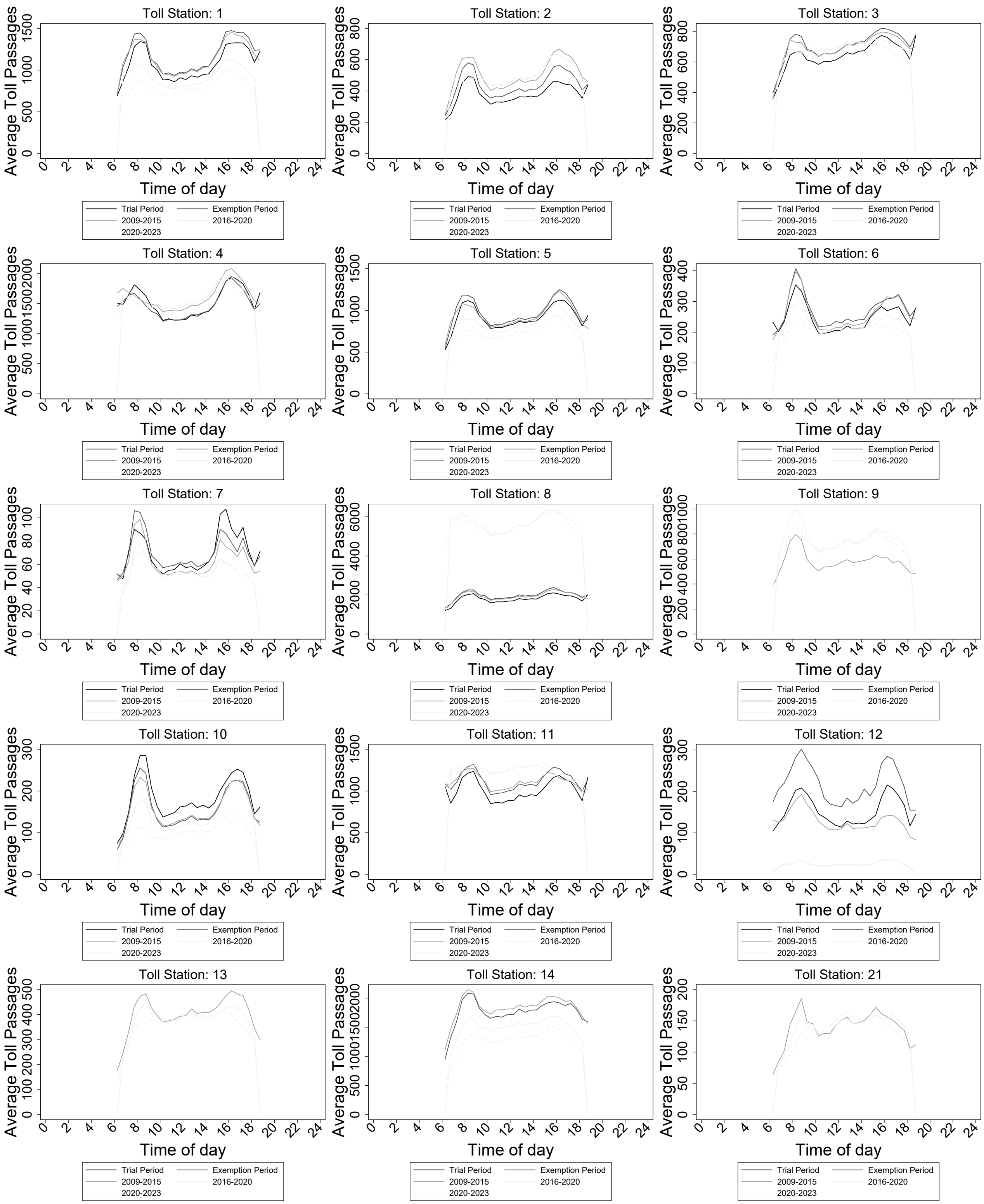


Figure B7: Toll station passages

Notes: The figures show the total number of passages for each toll station between 2003 to 2023. The corresponding toll station number can be found on the map in Figure I.


Toll Station: 1
Toll Station: 2
Toll Station: 3
Toll Station: 4
Toll Station: 5
Toll Station: 6
Toll Station: 7
Toll Station: 8
Toll Station: 9
Toll Station: 10
Toll Station: 11
Toll Station: 12
Toll Station: 13
Toll Station: 14
Toll Station: 21
Average Toll Passages
Time of day
Trial Period
Exemption Period
2009-2015
2016-2020
2020-2023

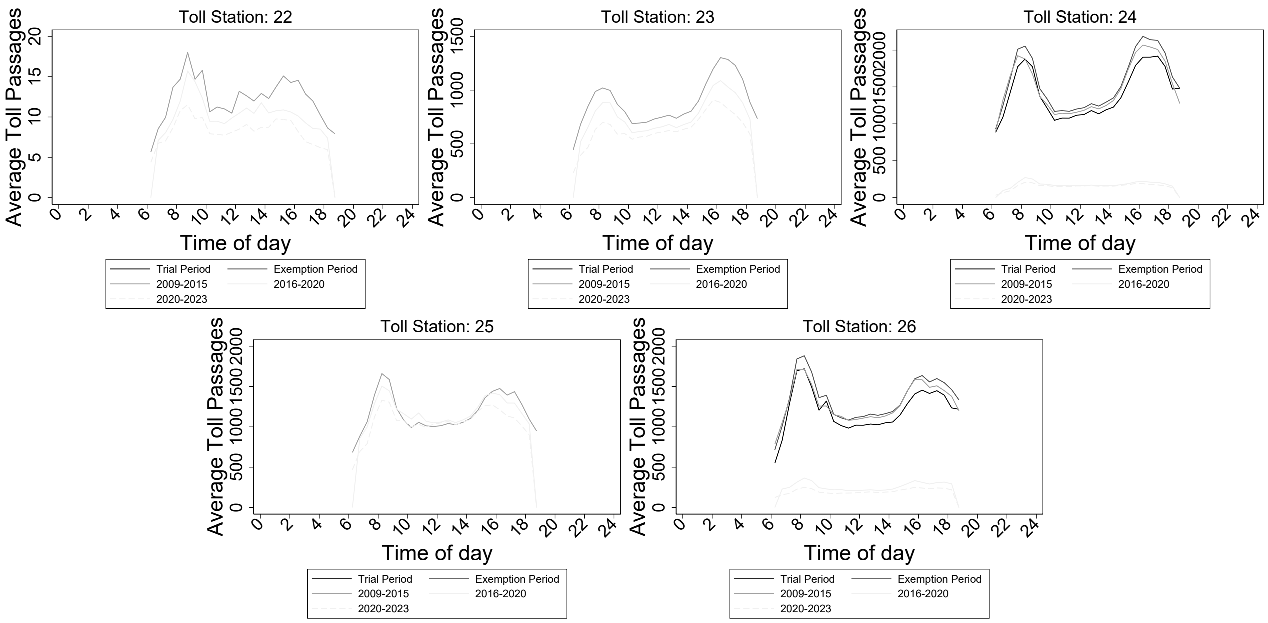


Figure B8: Toll station passages by time of day

Notes: The figure shows the average number of vehicles passing for each toll cordon over the course of a day based on 30 minute intervals. The corresponding toll station number can be found on the map in Figure I.

C Identification

C.1 Definition of control and treatment group

Treated commuters are individuals who crossed the congestion to or from Stockholm on their way to work in 2006. This includes all individuals who reside within the congestion zone and work outside and those who live outside the area and work inside. Table C1 summarizes the classification of treated- and non-treated commuters depending on the neighborhood and workplace location. *Non-treated commuters* are defined as individuals who live and work outside the congestion zone and use the Essinge bypass or the Lidingö tunnel on their (time-minimizing) way to and from work. We exclude individuals who live and work outside of the congestion zone from the non-treated commuters if their (time-minimizing) route went through the city center as these individuals faced an increase in congestion charges. Finally, we exclude individuals living and working within the congestion zone because they are less likely to be affected by the congestion charges.

The allocation of individuals into treated commuters and non-treated commuters is based on toll payments in 2006 − the year before the congestion charge in Stockholm was announced. Therefore, we consider 2003 until 2005 as a pre-period and 2007 until 2008 as a post-period. This control and treatment group classification results in 342,163 treated commuters and 85,704 non-treated commuters. 44,970 treated commuters reside inside and work outside, while 297,193 live outside and commute into the congestion zone.

Table C1: Treatment and control group

		Workplace Location	
		Inside	Outside
Neighborhood Location	Inside	Excluded	*Treated commuters*
	Outside	*Treated commuters*	*Non-treated commuters* via Essinge/Lidingö

C.2 Sample selection

The database contains information at the individual-level restricted to persons above 18. Based on our definition of treated and non-treated commuters in Stockholm, we restrict our sample in the following way:

1. Individuals must have existed in 2006.

2. Individuals must be employed.

3. Individuals must fall within the definitions of *treated commuters* or *non-treated commuters.*

    - Remove people working and living inside Stockholm.

    - Remove individuals working and living outside of Stockholm who do not cross the cordon zone.

4. Individuals must have a commuting distance between 3 and 50 kilometers.

5. Individuals must be observed after the congestion charge.

6. Individuals must own at least one and not more than three vehicles.

As treatment is defined as a time-invariant attribute on the individual-level, the individual must have existed in 2006 to be part of the analysis. Individuals must be employed and own at least one vehicle to ensure that the person likely commutes to a workplace. We exclude individuals with more than three individuals to ensure these are not used for business purposes. We consider work distances below 3 kilometers as walking and cycling distances less likely to be affected by congestion charges. The 50 kilometers cutoff ensures comparable work distances for treated and non-treated commuters. Finally, the individuals need to fall within the definitions of our treatment and be observed after the implementation of the congestion charge. We do not require individuals to be observed during all years to be included in our sample (2003-2008), meaning that the dataset is an unbalanced panel.

Applying the sample restrictions listed above leaves us with a dataset of 97,299 unique individuals over six years, resulting in 416,256 annual observations. Table C2 shows how each sample selection criterion affects the number of observations. Restricting the sample to individuals observed in all years significantly reduces the number of observations (column 7). However, results based on a balanced sample are similar to our main results (Table D6). To estimate the effect on commuting distance, we restrict the sample to individuals residing outside the congestion zone (column 8).

Table C2: Observations by year and sample selection criteria

	Sample Selection Criteria						Balanced Sample	Outside Zone
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years								
2003	1,217,085	845,890	298,371	280,329	125,873	53,178	38,765	48,269
2004	1,236,578	859,827	301,500	283,150	139,185	59,138	38,765	53,597
2005	1,260,738	870,769	306,148	287,517	157,950	66,677	38,765	60,257
2006	1,293,780	903,686	315,007	295,840	192,484	77,654	38,765	69,591
2007	1,329,834	972,133	336,640	315,534	192,484	79,260	38,765	79,260
2008	1,366,838	993,526	345,715	324,067	192,484	80,349	38,765	80,349
Individuals	1,525,337	1,247,558	605,330	570,629	192,484	97,299	38,765	95,645
Total	7,704,853	5,445,831	1,903,381	1,786,437	1,000,460	416,256	232,590	391,323

Notes: This table shows how observations per year are reduced as various sample selection criteria are imposed: (1) all individuals in Stockholm existed in 2006; (2) removing unemployed individuals; (3) removing individuals that do not fall within the definitions of treated or non-treated commuters; (4) removing individuals with a commuting distance of less than 3km and more than 50km; (5) removing individuals that are not observed between 2006 and 2008; (6) removing individuals without vehicles or more than three vehicles. Column (6) is our final sample. Column (7) corresponds to the balanced sample. Column (8) removes individuals that reside within the congestion zone.

C.3 Treated and non-treated commuters by area

The Figure C1 displays neighborhoods within 50 kilometers of Stockholm by the share of treated commuters. Neighborhoods within the congestion zone have a share of treated commuters that equals 100 percent as we only include commuters that cross the congestion zone on their way to work. The percentage of treated commuters is particularly low near the Essinge bypass in the Southwest of Stockholm and close to the island of Lidingö in the west of Stockholm. Note that several neighborhoods close to the city centers are too small to be visible.

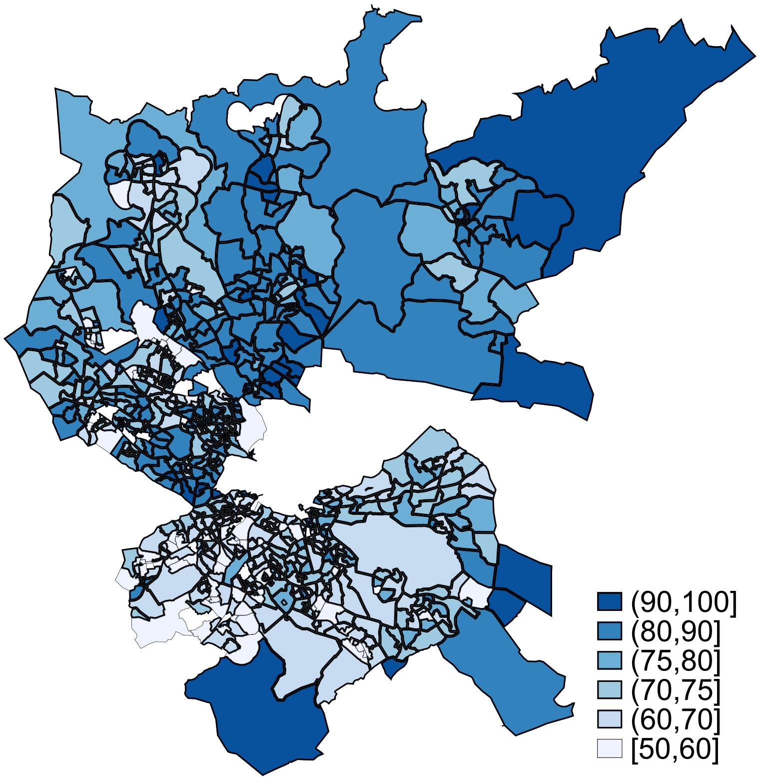


Figure C1: Share of treated commuters

Notes: The map displays the share of treated commuters in Stockholm by DeSO neighborhood in 2006. We exclude DeSO neighborhood inside the congestion zone as the share of treated commuters equals 100 percent.

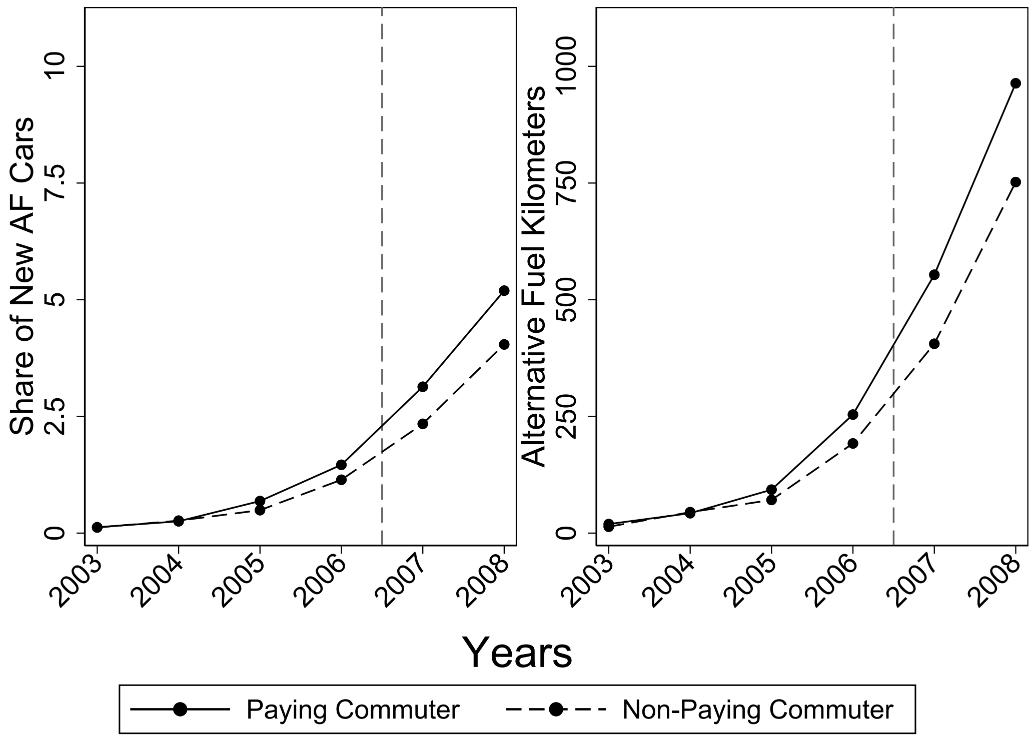


Figure C2: Vehicle ownership and driving

Notes: The figure in Panel a displays the share of alternative fuel vehicles for treated (solid line) and non-treated commuters (dashed line) in Stockholm between 2003 and 2008. The figure in Panel b displays the vehicle kilometers traveled with alternative fuel vehicles for treated (solid line) and non-treated commuters (dashed line) in Stockholm. The vertical dashed line denotes the implementation date (1st of August 2007).

D Supporting results and robustness checks

D.1 Main effects

Table D1: Estimates on new vehicle adoption

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0017***	-.0037**	-.0022
	(.0007)	(.0018)	(.0019)
Mean New Car Adoption (t-1)	.005	.063	.066

Notes: The table plots the coefficient β estimated from equation (8) on new vehicle adoption (Panel A). The dependent variable indicates whether the individual adopted (1) a new alternative fuel vehicle, (2) a new fossil fuel vehicle, and (3) any new vehicle. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D2: Estimates on vehicle attributes

	Vehicle Attribute			
	(1) Fuel	(2) Carbon	(3) Weight	(4) Engine
A.Vehicle Ownership				
Post x Treated Commuters	-.0269	.0385	-.8850	-.0352
	(.0210)	(.3953)	(1.7292)	(.2366)
Mean Dep. Variable (2006)	4.2	200.6	1417.4	99.5
Observations	416256	182236	416256	416256

Notes: The table plots the coefficient β estimated from equation (8) on four vehicle attributes. The outcome of interests is equal to the changes in vehicle characteristics per person: (1) fuel efficiency [liter/100km], (2) carbon emission [gCO2/km], (3) service weight [kilogram], and (4) engine power [kilowatt]. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D3: Estimates on vehicle kilometers traveled

	Vehicle Kilometers Traveled		
	(1) Alternative	(2) Fossil	(3) Total
A.Alternative Fuel Exemption			
Post x Treated Commuters	121.39***	-253.05***	-149.78**
	(26.79)	(70.97)	(69.44)
Mean Vehicle Kilometers (t-1)	242.7	15202.4	15299
B.Removal of Alternative Exemption			
Post x Treated Commuters	-103.50**	206.29**	102.79
	(50.88)	(87.48)	(82.69)
Mean Vehicle Kilometers (t-1)	1885.1	12168.6	14053.7

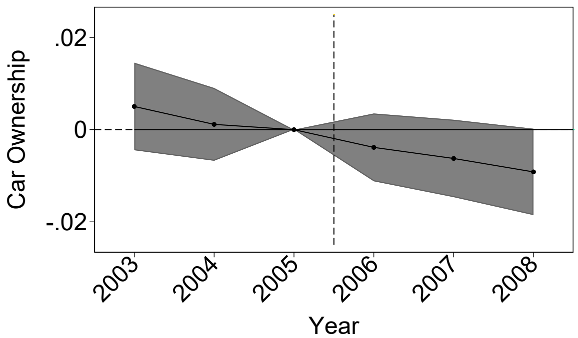
Notes: The table plots the coefficient β estimated from equation (8) on vehicle kilometers traveled (Panel A) in the post alternative fuel exemption period. The dependent variable in Panel A indicates the vehicle kilometers traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. The number of trips for congestion and non-congestion zone trips are reported below the coefficients. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D4: Estimates on residential and plant moving

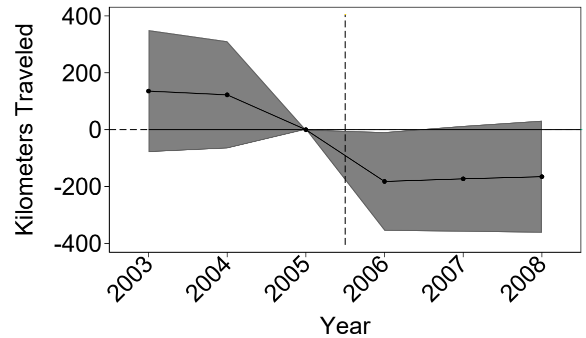
	Probability of Moving		
	(1) Anywhere	(2) Outside	(3) Congestion
A.Residential Move			
Post x Treated Commuters	-.005***	-.006***	.002***
	(.002)	(.002)	(.000)
Mean Dep. Variable	.059	.056	.003
B.Workplace Relocation			
Post x Treated Commuters	.005**	.016***	-.010***
	(.002)	(.001)	(.002)
Mean Dep. Variable	.094	.025	.069
New Employer	-.007***	.007***	-.014***
	(.002)	(.001)	(.001)
Old Employer	.012***	.008***	.004***
	(.001)	(.001)	(.001)

Notes: The table plots the coefficient β estimated from equation (8) on the probabiliy of moving residences (Panel A) and moving plants (Panel B). The dependent variable in Panel A indicates whether the individual moved (1) to a different neighborhood, (2) to a neighborhood outside the congestion zone, and (3) to a neighborhood inside the congestion zone. The dependent variable in Panel B indicates whether the individual moved to (1) a different plant location, (2) a plant outside the congestion zone, and (3) a plant inside the congestion zone. The sample is restricted to 2003-2008, where 2006-2008 denote the post-period. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.2 Dynamic effects



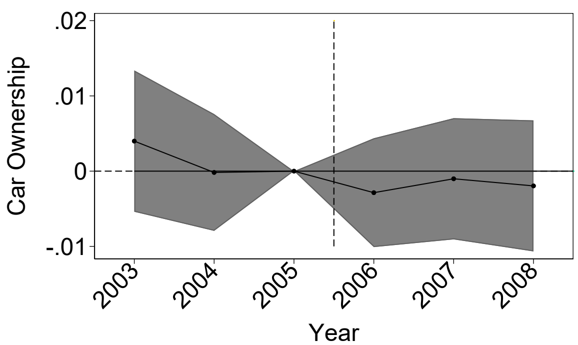
(a) Number of fossil fuel vehicles



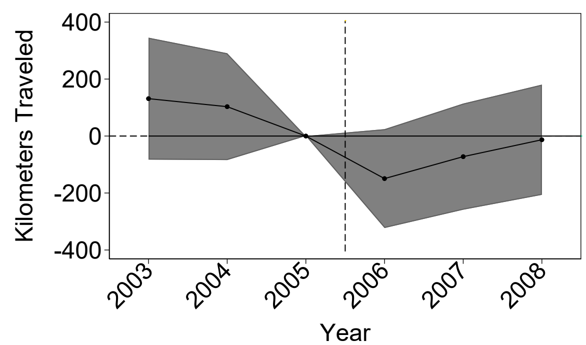
(b) Kilometers traveled with fossil fuel vehicles

Figure D1: Estimates on fossil fuel vehicles

Notes: The figures plot coefficients β_t estimated from equation (9), where β_{2005} is normalized to zero. Panel (a) shows the annual treatment effect on the probability of owning a fossil fuel vehicle. Panel (b) shows the annual treatment effect on vehicle kilometers traveled with a fossil fuel vehicle. The sample is restricted to 2003-2008, where 2006-2008 denote the post period. Standard errors are clustered at the neighborhood level. The vertical dashed line denotes the imposition of the Stockholm Congestion Trial (1st of January 2006).



(a) Number of vehicles



(b) Kilometers traveled

Figure D2: Estimates on all vehicles

Notes: The figures plot coefficients β_t estimated from equation (9), where β_{2005} is normalized to zero. Panel (a) shows the annual treatment effect on the probability of owning any vehicle. Panel (b) shows the annual treatment effect on total vehicle kilometers traveled. The sample is restricted to 2003-2008, where 2006-2008 denote the post period for fossil fuel vehicles. Standard errors are clustered at the neighborhood level. The vertical dashed line denotes the imposition of the Stockholm Congestion Trial (1st of January 2006)

D.3 Robustness checks

Table D5: Same post period estimates

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0052***	-.0083**	-.0030
	(.0011)	(.0035)	(.0033)
Mean Car Ownership (t-1)	.007	1.138	1.145
B.Number of Trips			
Post x Treated Commuters	5.6***	-13.8***	-8.2**
	(1.2)	(3.9)	(3.8)
Inside Congestion Trips	5.9**	-11.8**	-5.9
	(2.9)	(5.0)	(4.7)
Mean Trips Inside (t-1)	2.5	399.1	401.7
Change Trips Outside (t-1)	-.3	-2	-2.3
Mean Trips Outside	2.7	432.1	434.8
C.Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5
Changes in Outside Distance			-.007
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on the vehicle ownership (Panel A) and driving behavior (Panel B). The dependent variable in Panel A indicates whether the individual adopted (1) a new alternative fuel vehicle, (2) the number of alternative fuel vehicles, (3) the number of fossil fuel vehicles, and (4) all vehicles. The dependent variable in Panel B indicates the vehicle kilometers traveled with (2) alternative fuel vehicles, (3) fossil fuel vehicles, and (4) all vehicles. The sample is restricted to 2003-2008, where 2006-2008 denote the post-period for alternative and fossil fuel vehicles. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D6: Balanced sample estimates

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0049***	-.0060	-.0018
	(.0019)	(.0048)	(.0046)
Mean Car Ownership (t-1)	.015	1.164	1.171
B.Number of Trips			
Post x Treated Commuters	4.5**	-14.6***	-10.6**
	(2.1)	(4.9)	(4.8)
Inside Congestion Trips	4.5	-6.5	-2.0
	(3.3)	(6.1)	(5.6)
Mean Trips Inside (t-1)	6.4	404.3	406.9
Change Trips Outside (t-1)	0	-8.1	-8.6
Mean Trips Outside	7.1	446.1	449
C.Commuting Distance			
Post x Treated Commuters			-.028
Mean Commute Distance (t-1)			17.9
Changes in Outside Distance			.007
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C) using the balanced sample from column (8) in Table C2. The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D7: Outside congestion zone effects

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0037***	-.0036	-.0025
	(.0013)	(.0035)	(.0034)
Mean Car Ownership (t-1)	.014	1.145	1.152
B.Number of Trips			
Post x Treated Commuters	3.8***	-11.4***	-9.9**
	(1.4)	(3.9)	(3.9)
Inside Congestion Trips	1.9	-8.8*	-6.9
	(2.9)	(5.0)	(4.8)
Mean Trips Inside (t-1)	6.4	402.3	404.7
Change Trips Outside (t-1)	2	-2.6	-2.9
Mean Trips Outside	6.9	435.5	438.1
C.Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5
Changes in Outside Distance			-.008
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C) restricting the treated commuters to individuals residing outside the congestion zone. The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D8: Inside congestion zone effects

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0174***	-.0422***	-.0078*
	(.0017)	(.0050)	(.0043)
Mean Car Ownership (t-1)	.014	1.13	1.139
B.Number of Trips			
Post x Treated Commuters	17.6***	-31.8***	3.4
	(1.8)	(5.6)	(5.3)
Inside Congestion Trips	33.9***	-33.9***	-.1
	(4.0)	(6.5)	(6.1)
Mean Trips Inside (t-1)	6.4	406.9	409.8
Change Trips Outside (t-1)	-16.3	2.1	3.5
Mean Trips Outside	6.9	440.5	443.6
C.Commuting Distance			
Post x Treated Commuters			-.186***
			(.048)
Mean Commute Distance (t-1)			17.5
Changes in Outside Distance			-.005
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C) restricting the treated commuters to individuals residing inside the congestion zone. The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D9: Estimates with firm-level FE

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0067***	-.0084**	-.0030
	(.0014)	(.0036)	(.0035)
Mean Car Ownership (t-1)	.014	1.138	1.145
B.Number of Trips			
Post x Treated Commuters	6.5***	-15.9***	-10.6***
	(1.5)	(4.0)	(3.9)
Inside Congestion Trips	6.1**	-5.0	1.0
	(2.9)	(5.0)	(4.7)
Mean Trips Inside (t-1)	6.4	399.1	401.7
Change Trips Outside (t-1)	.4	-10.9	-11.6
Mean Trips Outside	6.9	432.1	434.8

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), and number of trips (Panel B) additionally controlling for firm-level fixed effects. The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D10: Estimates with workplaces near congestion zone

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0044***	-.0110**	-.0078*
	(.0016)	(.0045)	(.0043)
Mean Car Ownership (t-1)	.013	1.139	1.146
B.Number of Trips			
Post x Treated Commuters	4.5**	-16.0***	-12.2**
	(1.8)	(5.0)	(4.9)
Inside Congestion Trips	3.7	-15.1**	-11.4*
	(3.8)	(6.4)	(5.9)
Mean Trips Inside (t-1)	6.1	410.2	412.7
Change Trips Outside (t-1)	.7	-.9	-.8
Mean Trips Outside	6.4	429.7	432.3
C.Commuting Distance			
Post x Treated Commuters			-.147***
			(.030)
Mean Commute Distance (t-1)			17
Changes in Outside Distance			-.027
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C) when restricting the sample to plants located within a three kilometers distance to the congestio zone. The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D11: Placebo year estimates

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0032	-.0054	-.0023
	(.0025)	(.0046)	(.0041)
Mean Car Ownership (t-1)	.	.	.
B.Number of Trips			
Post x Treated Commuters	.7	-.6	.1
	(2.7)	(4.7)	(4.6)
C.Commuting Distance			
Post x Treated Commuters			.070***
			(.018)
Mean Commute Distance (t-1)			17.5
Changes in Outside Distance			-.142
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) on the vehicle ownership (Panel A) and driving behavior (Panel B). The dependent variable in Panel A indicates whether the individual adopted (1) a new alternative fuel vehicle, (2) a new fossil fuel vehicle, and (3) any new vehicle. The dependent variable in Panel B indicates the change in vehicle kilometers traveled relative to 2008 with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The pre-period is restricted to 2003-2005, and the post-period is restricted to 2009-2012. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D12: Estimates on labor market effects

	Labor Market Effects	
	(1) Gross Salary	(2) Disposable Income
Post x Treated Commuters	2484.1*	1872.8
	(1475.6)	(1735.0)
Mean Dep. Variable	504373.1	268048.1

Notes: The table plots the coefficient β estimated from equation (8) on annual gross salary (column 1), and annual disposable income (column 2). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2006-2008 denote the post period. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.4 Responses by different groups

Table D13: Estimates for low-income groups

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	-.0020	.0082*	.0076*
	(.0017)	(.0043)	(.0040)
Mean Car Ownership (t-1)	.011	1.112	1.117
B.Number of Trips			
Post x Treated Commuters	-2.8	-13.0***	-13.7***
	(1.9)	(4.8)	(4.8)
Inside Congestion Trips	4.9	-13.7*	-8.8
	(3.9)	(7.1)	(6.7)
Mean Trips Inside (t-1)	5.2	368.1	370.1
Change Trips Outside (t-1)	-7.7	.7	-4.9
Mean Trips Outside	5.7	401.6	403.8
C.Commuting Distance			
Post x Treated Commuters			-.070*
			(.036)
Mean Commute Distance (t-1)			17.7
Changes in Outside Distance			-.008
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for low-income individuals with less than 350k SEK in annual earnings on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D14: Estimates for medium-income groups

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0063***	-.0142***	-.0089**
	(.0015)	(.0037)	(.0035)
Mean Car Ownership (t-1)	.014	1.122	1.13
B.Number of Trips			
Post x Treated Commuters	5.7***	-22.4***	-17.4***
	(1.6)	(4.0)	(3.9)
Inside Congestion Trips	3.5	-3.7	-.2
	(4.2)	(7.4)	(6.9)
Mean Trips Inside (t-1)	6.2	387.9	390.8
Change Trips Outside (t-1)	2.2	-18.7	-17.2
Mean Trips Outside	6.8	424.9	428.1
C.Commuting Distance			
Post x Treated Commuters			-.000
			(.018)
Mean Commute Distance (t-1)			17.7
Changes in Outside Distance			.023
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for medium-income individuals between 350k to 500k SEK in annual earnings on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D15: Estimates for high-income groups

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0138***	-.0098**	.0005
	(.0019)	(.0045)	(.0042)
Mean Car Ownership (t-1)	.017	1.205	1.212
B.Number of Trips			
Post x Treated Commuters	16.6***	4.9	17.5***
	(2.2)	(4.9)	(4.7)
Inside Congestion Trips	11.6**	-46.4***	-34.8***
	(4.9)	(8.9)	(8.3)
Mean Trips Inside (t-1)	8	460.6	462.7
Change Trips Outside (t-1)	5	51.3	52.3
Mean Trips Outside	8.3	480.7	482.9
C.Commuting Distance			
Post x Treated Commuters			-.110***
			(.032)
Mean Commute Distance (t-1)			16.9
Changes in Outside Distance			-.187
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for high-income individuals with more than 500k SEK in annual earnings on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D16: Estimates for near commuters

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0083***	-.0106***	-.0037
	(.0018)	(.0041)	(.0038)
Mean Car Ownership (t-1)	.016	1.1	1.108
B.Number of Trips			
Post x Treated Commuters	11.6***	-18.1***	-7.7
	(2.6)	(6.2)	(6.1)
Inside Congestion Trips	21.5*	-44.5**	-23.0
	(11.5)	(20.1)	(18.7)
Mean Trips Inside (t-1)	18.7	902.5	909.2
Change Trips Outside (t-1)	-9.9	26.4	15.3
Mean Trips Outside	8.2	395.3	398.2
C.Commuting Distance			
Post x Treated Commuters			-.105***
			(.036)
Mean Commute Distance (t-1)			7.1
Changes in Outside Distance			-.582
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for near commuters traveling less than 10 kilometers to work on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D17: Estimates for medium commuters

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0061***	-.0100***	-.0049
	(.0015)	(.0038)	(.0035)
Mean Car Ownership (t-1)	.014	1.142	1.149
B.Number of Trips			
Post x Treated Commuters	6.7***	-16.8***	-11.2***
	(1.7)	(4.3)	(4.2)
Inside Congestion Trips	3.1	-14.0*	-10.9
	(4.4)	(7.9)	(7.5)
Mean Trips Inside (t-1)	6.4	425.3	427.9
Change Trips Outside (t-1)	3.6	-2.9	-.4
Mean Trips Outside	6.5	433.7	436.4
C.Commuting Distance			
Post x Treated Commuters			-.031
Mean Commute Distance (t-1)			16.5
Changes in Outside Distance			-.033
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for medium distant commuters traveling between 10 to 25 kilometers to work on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D18: Estimates for distant commuters

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A.Vehicle Ownership			
Post x Treated Commuters	.0043**	.0004	.0036
	(.0020)	(.0049)	(.0046)
Mean Car Ownership (t-1)	.013	1.174	1.18
B.Number of Trips			
Post x Treated Commuters	2.7*	-5.0	-2.9
	(1.5)	(3.9)	(3.8)
Inside Congestion Trips	2.8	-4.5	-1.7
	(2.7)	(4.8)	(4.5)
Mean Trips Inside (t-1)	3.1	231.8	233.1
Change Trips Outside (t-1)	-.1	-.5	-1.2
Mean Trips Outside	6.2	472.8	475.4
C.Commuting Distance			
Post x Treated Commuters			-.217***
			(.045)
Mean Commute Distance (t-1)			33
Changes in Outside Distance			.011
Mean Outside Distance (t-1)			19

Notes: The table plots the coefficient β estimated from equation (8) for distant commuters traveling more than 25 kilometers to work on vehicle ownership (Panel A), number of trips (Panel B), and commute distance (Panel C). The dependent variable in Panel A indicates whether the number of (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel B indicates the number of trips traveled with (1) alternative fuel vehicles, (2) fossil fuel vehicles, and (3) all vehicles. The dependent variable in Panel C indicates the (3) average commute distance. The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 denote the post-period for alternative fuel vehicles and 2006-2008 denote the post-period for fossil fuel vehicles. Appendix E.2 provides details on the conversion from vehicle kilometers traveled to number of trips by fuel type and the change in commute distances. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

E Computation of congestion charge

In this section, we implement our congestion charge formula from equation (3) using our empirical estimates and supplementing it with costs of emissions and congestion from the literature.

E.1 Registry data

1. *Number of trips.* The individual-level vehicle kilometers traveled of green and brown vehicles are equal to the sum of the number and length of congestion crossings and non-congestion zone crossings:

$$KM_g = v^c \cdot t_g^c + v^o \cdot t_g^o \tag{E1}$$

$$KM_b = v^c \cdot t_b^c + v^o \cdot t_b^o \tag{E2}$$

We observe the individual-level vehicle kilometers traveled for both fuel types (Panel A of Table D3) and assume that the average distance of a congestion zone trip (v^c) equals the driving distance between a person's neighborhood and workplace. To get an estimate on the number of congestion and non-congestion zone trips ($t^c,\ t^o$), we use the fact that 46 percent of kilometer-weighted trips are business-related (The Swedish National Travel Survey, 2007). We calculate the number of trips in the congestion zone for green and brown vehicles as follows:

$$\begin{aligned} .46 \cdot KM_g &= v^c \cdot t_g^c \\ t_g^c &= \frac{.46 \cdot KM_g}{v^c} \\ t_g^c &= \frac{.46 \cdot 242.7km}{17.5km} \approx 6.4 \end{aligned} \tag{E3}$$

$$\begin{aligned} .46 \cdot KM_b &= v^c \cdot t_b^c \\ t_b^c &= \frac{.46 \cdot KM_b}{v^c} \\ t_b^c &= \frac{.46 \cdot 15,202.4km}{17.5km} \approx 399.1 \end{aligned} \tag{E4}$$

We further assume that the average distance traveled by vehicle in The Swedish National Travel Survey (2007) equals the average distance of a non-congestion zone trip (v^o). We obtain the number of non-congestion zone trips for green and brown vehicles as follows:

$$\begin{aligned} .54 \cdot KM_g &= v^o \cdot t_g^o \\ t_g^o &= \frac{.54 \cdot KM_g}{v^o} \\ t_g^o &= \frac{.54 \cdot 242.7km}{19km} \approx 6.9 \end{aligned} \tag{E5}$$

$$\begin{aligned} .54 \cdot KM_b &= v^o \cdot t_b^o \\ t_b^o &= \frac{.54 \cdot KM_b}{v^o} \\ t_b^o &= \frac{.54 \cdot 15,202.4km}{19km} \approx 432.1 \end{aligned} \tag{E6}$$

E.2 Empirical estimates

The congestion charge formula from equation (10) requires changes in the number of congestion zone crossings by vehicle type ($\frac{\partial t_g^c}{\partial \tau}$, $\frac{\partial t_b^c}{\partial \tau}$, $\frac{\partial t_g^o}{\partial \tau}$, $\frac{\partial t_b^o}{\partial \tau}$), and changes in outside vehicle kilometers traveled ($\frac{\partial v^o}{\partial \tau}$). We describe below how we use our empirical estimates of changes in vehicle kilometers traveled to back out the implied changes in congestion zone trips and outside driving by vehicle type that resulted from Stockholm's congestion pricing policy.

1. *Changes in number of congestion trips by vehicle type.* To convert the estimates on vehicle kilometers traveled for green and brown vehicles into changes in the number of congestion trips by vehicle type, we exploit the fact that the exemption of alternative fuel vehicles of the Stockholm's congestion charge was removed in August 2012. Specifically, we assume that the effect of removing the alternative fuel vehicle exemption (τ_{-g}) on the kilometer traveled in green and brown vehicle after 2012 equals the effect on kilometer traveled inside the congestion zone after implementation of the congestion charge:

$$\frac{\partial KM_g}{\partial \tau_{-g}} := -\frac{\partial KM_g^c}{\partial \tau}, \qquad \frac{\partial KM_b}{\partial \tau_{-g}} := -\frac{\partial KM_b^c}{\partial \tau}. \tag{E7}$$

We use the effect of removing the alternative fuel vehicle exemption on the kilometer traveled (Table D3) scaled by the average congestion distance v^c to calculate the change in congestion zone trips with green vehicles as follows:

$$\begin{aligned}\frac{\partial t^c_g}{\partial \tau_g} &= -\frac{\partial KM_g}{\partial \tau_{-g}} \cdot \frac{1}{v^c} \\ \frac{\partial t_g}{\partial \tau_g} &= \frac{103.5km}{17.5km} = 5.9\end{aligned} \tag{E8}$$

We derive the change in the number of non-congestion zone trips in green vehicles as the difference between the change of all green congestion zone trips (Table I, Panel B) less the change in green trips from equation (E8):

$$\begin{aligned}\frac{\partial t^o_g}{\partial \tau} &= \frac{\partial t_g}{\partial \tau} - \frac{\partial t^c_g}{\partial \tau} \\ \frac{\partial t^o_g}{\partial \tau} &= 6.6 - 5.9 = .7\end{aligned} \tag{E9}$$

Similarly, we use the effect of removing the alternative fuel vehicle exemption on the kilometer traveled (Table D3) scaled by the average congestion distance v^c to calculate the change in congestion zone trips with brown vehicles as follows:

$$\begin{aligned}\frac{\partial t^c_b}{\partial \tau} &= -\frac{\partial KM_b}{\partial \tau_{-g}} \cdot \frac{1}{v^c} \\ \frac{\partial t^c_b}{\partial \tau^c} &= -\frac{206.3km}{17.5km} = -11.8\end{aligned} \tag{E10}$$

Finally, we derive the change in the number of non-congestion zone trips in brown vehicles as the difference between the change of all brown congestion zone trips (Table I, Panel B) less the change in brown trips from equation (E10):

$$\begin{aligned}\frac{\partial t^o_g}{\partial \tau} &= \frac{\partial t_g}{\partial \tau} - \frac{\partial t^c_g}{\partial \tau} \\ \frac{\partial t^o_g}{\partial \tau} &= -13.8 + 11.8 - = -2\end{aligned} \tag{E11}$$

2. *Changes in outside commuting distance.* First, the total outside vehicle kilometer traveled are given by multiplying the number of trips and average commuting distance outside the congestion zone. Inserting the the total vehicle kilometers traveled (Table I) and the average outside commuting distance v^o from the Swedish National Travel Survey (2007), we calculate the number of outside trips as:

$$\begin{aligned} KM^o &= v^o \cdot t^o \\ t^o &= \frac{.54 \cdot 15{,}299km}{19km} \approx 434.1 \end{aligned} \tag{E12}$$

Second, we derive the change in vehicle kilometers traveled outside the congestion charge with respect to the congestion charge. This equals equals the change in total vehicle kilometers traveled (Panel A, Table D3) less the change in kilometers traveled inside the congestion zone (Panel B, Table D3):

$$\begin{aligned} \frac{\partial KM}{\partial \tau} &= \frac{\partial KM^c}{\partial \tau} + \frac{\partial KM^o}{\partial \tau} \\ \frac{\partial KM^o}{\partial \tau} &= -149.8km + 102.8km \approx -47km \end{aligned} \tag{E13}$$

Finally, we derive the changes in the outside commuting distance ($\frac{\partial v^o}{\partial \tau}$) by taking the derivative of the total vehicle kilometers traveled outside the congestion zone with respect to the congestion charge:

$$\begin{aligned} \frac{\partial KM^o}{\partial \tau} &= \frac{\partial v^o}{\partial \tau} \cdot t^o + \frac{\partial t^o}{\partial \tau} \cdot v^o \\ \frac{\partial v^o}{\partial \tau} &= \frac{\frac{\partial KM^o}{\partial \tau} - \frac{\partial t^o}{\partial \tau} \cdot v^o}{t^o} \\ \frac{\partial v^o}{\partial \tau} &= \frac{-47 + 2 \cdot 19km}{434.8} \approx -.007km \end{aligned} \tag{E14}$$

We insert the number of outside trips t^o from equation (E12), the change in the vehicle kilometers traveled outside the congestion zone $\frac{\partial KM^o}{\partial \tau}$ from equation (E13) and the change in the number of outside trips $\frac{\partial t^o}{\partial \tau}$ (Table D3).

E.3 Emission externalities

1. *Emission rates for brown vehicles.* Fuel combustion and brake wear in passenger vehicles generate several emission externalities. We assume that the emission externalities consist of "global" pollutants, which contribute to climate change, and "local" pollutants, which negatively impact the health of nearby residents (Anderson, 2020; Currie & Walker, 2011).[47] To quantify the social costs of emission externalities, we combine our empirical

[47] A growing literature has documented various channels through which air pollution has adverse effects on societal outcomes, such as low birth weight (Currie & Walker, 2011), respiratory diseases (Jans et al., 2018), lower productivity in physical and high-skilled work (Zivin & Neidell, 2012; Chang et al., 2016; Ebenstein et al., 2016; Archsmith et al., 2018), criminal activity (Bondy et al., 2020).

estimates with vehicle emission factors - the amount of a particular pollutant that a vehicle emits while traveling a kilometer - and the social costs of the pollutant from the literature. Table E2 summarizes the vehicle emission estimates and costs of pollutants.

First, we rely on a recent report by the European Environment Agency (2021) that provides fuel consumption-specific emission factors for the main pollutants in Sweden.[48] The main air pollutants include ammonia (NH_3), particulate matter (PM) and sulphur oxides (SO_2), and global pollutants include carbon dioxide (CO_2).[49] These pollution externalities have been shown to make up the large majority of kilometer-weighted average emissions factors (Tarduno, 2022). The emission factor production is based on a large number of assumptions concerning vehicle technology mix (e.g., share of passenger cars), driving conditions (e.g., traveling speeds), and climatic conditions (e.g., temperature) (Zachariadis et al., 2001). We use the fleet composition of Swedish vehicles in 2006 to quantify the average emission externality.

Second, we quantify the social costs of pollutants following a recent report by the European Environment Agency (2014) that provides costs of air pollution in Europe between 2008 and 2012 based on a value of a statistical life. The reports methodology quantifies the damage costs for the local pollutants following the European Commission's DG Research (Holland et al., 1999; Bickel et al., 2005). The dispersion modeling tracks pollutants through the atmosphere and follows their chemical reactions, enabling quantification of effects linked to emissions, not simply to the atmospheric concentration of the pollutant in the chemical state in which it was released. The price year used is 2005.

To convert the carbon emission into a monetary equivalent, we use the Swedish carbon tax rate as an approximation for the social cost of carbon, which is currently set to SEK $1,190$ ($\approx$ €105.2) per ton of CO_2. Table E1 summarizes the emission externalities that are derived from the European Environment Agency (2014, 2021). We assume that emission externalities are equal inside and outside the congestion zone. To quantify the monetary equivalent of the emission externalities, we then multiply the average vehicle emission factor by the social cost for each pollutant:[50]

[48] Although vehicle emission factors depend on several variables, including the type of fuel consumed, fuel economy, vehicle age, and vehicle speed, we assume a constant emission factor for each vehicle.

[49] The emission factor corresponds to the exhaust emission, not ultimate CO_2.

[50] We convert kilogram into liter by assuming that that one kilogram of petrol is equal to .72 liter (https://coolconversion.com/density-volume-mass/–1–liter–of–petrol%2C-natural–in–kg).

$$
\begin{aligned}
\phi_b \; &= \Big(\Delta PM \cdot (MC_{PM_{2.5}} + MC_{PM_{10}}) + \Delta CO_2 \cdot MC_{CO_2} + \Delta CNH_3 \cdot MC_{NH_3} \\
&\quad + \Delta SO_2 \cdot MC_{SO_2}\Big) \cdot .72\frac{kg}{l} \\
\phi_b \; &= \Big(.25\frac{g\ PM}{kg\ fuel} \cdot (23.2\frac{€}{kg\ PM} + 15.01\frac{€}{kg\ PM}) + 3162\frac{g\ CO_2}{kg\ fuel} \cdot .105\frac{€}{kg\ CO_2} \\
&\quad + 9.11\frac{g\ NH_3}{kg\ fuel} \cdot 12.15\frac{€}{kg\ NH_3} + 6.69\frac{g\ SO_2}{kg\ fuel} \cdot 15.44\frac{€}{kg\ SO_2}\Big) \cdot .72\frac{kg}{l} \\
\phi_b \; &= (.009 + .33 + .11 + .103)\frac{€}{kg\ fuel} \cdot .72\frac{kg}{l} \; = \; .397\frac{€}{l}
\end{aligned}
\tag{E15}
$$

Equation (E15) states that the marginal emission externality equals €.397 ($\approx$ 3.7 SEK) per liter fuel for brown vehicles. Relative to the average petrol price of 11.4 SEK in Sweden in 2006,[51] the emission externalities corresponds to around 32.8 percent of the average petrol price. We convert the congestion externalities into real 2021 € using the Consumer Price Index from Statistics Sweden. If we multiply this with the average vehicle fuel efficiency for fossil fuel vehicles (l_b) , we obtain the emission externality per kilometer:

$$
\phi_b \cdot l_b \; = \; .397\frac{€}{l} \cdot 8.37\frac{l}{100km} \; \cdot 1.22393 = \; .04\frac{€}{km} \tag{E16}
$$

[51]We use historical data on fuel prices from *bensinstation.nu* (https://www.bensinstation.nu/historiska-br%C3%A4nslepriser/).

Table E1: Emission externalities

Coefficient	Descriptions	Value	Source
ΔPM	Emission of particulate matter $[\frac{g}{kg\ fuel}]$	.25	European Environment Agency (2021), Table A1-0-28
ΔCO_2	Emission from carbon dioxide $[\frac{g}{kg\ fuel}]$	3162	European Environment Agency (2021), Table A1-0-28
ΔNH_3	Emission from ammonia $[\frac{g}{kg\ fuel}]$	9.11	European Environment Agency (2021), Table A1-0-28
ΔSO_2	Emission from sulfur dioxide $[\frac{g}{kg\ fuel}]$	6.69	European Environment Agency (2021), Table A1-0-28
$MC_{PM_{2.5}}$	Costs of fine particulate matter $[\frac{€}{kg}]$	23.2	European Environment Agency (2014)
$MC_{PM_{10}}$	Costs of particulate matter $[\frac{€}{kg}]$	15.01	European Environment Agency (2014)
MC_{CO_2}	Costs of carbon dioxide $[\frac{€}{kg}]$	0.105	
MC_{NH_3}	Costs of ammonia $[\frac{€}{kg}]$	12.15	European Environment Agency (2014)
MC_{SO_2}	Costs of sulfur dioxide $[\frac{€}{kg}]$	15.44	European Environment Agency (2014)

2. *Emissions rates for green vehicles.* Although electric vehicles produce little to no exhaust when in use, they charge from the electrical grid, which may generate emissions depending on the marginal fuel source (Holland et al., 2016). In this Appendix, we describe how we estimate emissions factors for electric vehicles in Sweden.

We use *Revision of emission factors for electricity generation and district heating*, commissioned by the Swedish Environmental Protection Agency for emissions rates for local and global air pollutants. This report uses data from fossil fuel generation in Sweden to suggest emissions factors for use in emissions inventory analyses.
The emissions rates by fuel type are as follows:

Coal: $100g/GJ\ SO_2$; $80g/GJ\ NO_x$; $2g/GJ\ NH_3$; $16.6g/GJ\ PM_{2.5}$
Natural Gas: $50g/GJ\ NO_x$; $.4g/GJ\ PM_{2.5}$[52]

[52]Note that there is no entry for $PM_{2.5}$ emissions for Natural Gas in 2015, we instead use the then forward-looking estimate for a 2020 emissions factor.

Residual Fuel Oil: $60g/GJ\ NO_x$; $8.3g/GJ\ PM_{2.5}$

For emissions damages, we use European Environment Ageny (2014) and convert to 2023 €. We use the following costs for the damages of emitting one ton of each pollutant in Sweden. [53]

$PM_{2.5}$: €21761.94
NO_x: €5540.60
SO_2: €14556.14
NH_3: €11399.15

We multiply the emissions rates by damages and convert units, assuming 3 kWh per kilometer:

$$\underbrace{\frac{[g]}{[GJ]}}_{emissions\ factor} \cdot \frac{[tons]}{[g]} \cdot \frac{[GJ]}{[kWh]} \cdot \underbrace{\frac{[€]}{[ton]}}_{damages} \cdot \frac{[kWh]}{[km]} = \frac{[€]}{[km]}$$

The result is damages per kilometer driven if the marginal kilometer is charged at a time when any of the above fuels are the marginal emissions source.

Coal: .003 $\frac{€}{km}$
Natural Gas: .0004 $\frac{€}{km}$
Residual Fuel Oil: .0007 $\frac{€}{km}$

$$\begin{aligned} \phi_E \cdot e = &\ \Delta Coal + \Delta Gas + \Delta Oil \\ \phi_E \cdot e = &\ (.003 + .0004 + .0007)\frac{€}{km} \ = \ .0041\frac{€}{km} \end{aligned} \tag{E17}$$

E.4 Congestion externalities

Marginal congestion costs denote the costs that road users impose upon one another when competing for scarce road space. Marginal costs of road congestion vary significantly in space and time. The transportation economics literature canonically presents congestion externalities as a function of traffic density, measured in vehicles per lane-mile (Small & Verhoef, 2007).[54] Congestion externalities are negligible when few other vehicles are on the road but increase sharply with the number of vehicles per lane-mile. To assign congestion

[53] The EEA reports a "high" and "low"' value for each pollutant. We take the mean of these two values.
[54] More precisely, Yang et al. (2020) show that the marginal external cost of traffic is convex in traffic density.

externalities to trips, we follow the External Costs of Transport study (2011), which provides external congestion costs in European cities. They assign mean values to typical traffic situations to indicate the magnitude and variability of marginal congestion costs. The main driving factors of marginal congestion costs are speed-flow relationships, road vehicle capacity demand, the value of travel time, and the occupancy of vehicles in terms of passengers and tons of freight (Maibach et al., 2008). To determine congestion externalities, we refer to the estimates (measured in 2008 €) in Table 38 of the External Costs of Transport study (2011). Specifically, we use the estimates for small and medium urban areas for the congestion externalities within the cordon zone, and for rural areas for the congestion externalities outside the congestion zone. We convert the congestion externalities into real 2021 € using the Consumer Price Index from Statistics Sweden.

The congestion costs in small and medium urban areas arrives ($< 2,000,000$ citizens) at a value for passenger vehicles around €.38 per kilometer and €.13 per kilometer in rural areas.[55] Based on an average congestion and non-congestion zone journey length of 17.4km and 19km, respectively, we estimate a congestion externality of approximately €6.57 and €2.47 per trip, which exceeds the peak-hour congestion pricing in Stockholm.

E.5 Compute externalities per vehicle, trip, and kilometer

First, the emission and congestion externalities per brown and green vehicle ($\widetilde{\phi}$ and $\widetilde{\gamma}$) can be computed as:

$$\begin{aligned}
\widetilde{\phi}_g + \widetilde{\gamma}_g &= (v^c t^c_g + v^o t^o_g) l_g \phi_g + v^c t^c_g \gamma^c + v^o t^o_g \gamma^o \\
\widetilde{\phi}_g + \widetilde{\gamma}_g &= 0\frac{€}{km} + 17.5km \cdot 6.4 \cdot .38\frac{€}{km} + 19km \cdot 6.9 \cdot .13\frac{€}{km} \\
\widetilde{\phi}_g + \widetilde{\gamma}_g &\approx 59.6€
\end{aligned} \tag{E18}$$

$$\begin{aligned}
\widetilde{\phi}_b + \widetilde{\gamma}_b &= (v^c t^c_b + v^o t^o_b) l_b \phi_I + v^c t^c_b \gamma^c + v^o t^o_b \gamma^o \\
\widetilde{\phi}_b + \widetilde{\gamma}_b &= (17.5km \cdot 399.1 + 19km \cdot 432.1) \cdot .04\frac{€}{km} + 17.5km \cdot 399.1 \cdot .38\frac{€}{km} + 19km \cdot 432.1 \cdot .13\frac{€}{km} \\
\widetilde{\phi}_b + \widetilde{\gamma}_b &\approx 4329.1€
\end{aligned} \tag{E19}$$

Second, the emission and congestion externalities for brown and green vehicles per trip ($\overline{\phi}$ and $\overline{\gamma}$) inside and outside the congestion zone correspond to:

[55] Marginal congestion costs rise with the size of agglomeration areas because large urban areas attract traffic from surrounding towns, and a shift to outside roads is often impossible.

$$\begin{aligned}\overline{\phi_g^c} + \overline{\gamma_g^c} &= n_g v^c (l_g \phi_g + \gamma^c) \\ \overline{\phi_g^c} + \overline{\gamma_g^c} &= .014 \cdot 17.5km \cdot (0\frac{€}{km} + \cdot .38\frac{€}{km}) \\ \overline{\phi_g^c} + \overline{\gamma_g^c} &\approx .09€ \end{aligned} \tag{E20}$$

$$\begin{aligned}\overline{\phi_g^o} + \overline{\gamma_g^o} &= n_g v^o \cdot (l_g \phi_g + \gamma^o) \\ \overline{\phi_g^o} + \overline{\gamma_g^o} &= .014 \cdot 19km \cdot (0\frac{€}{km} + .13\frac{€}{km}) \\ \overline{\phi_g^o} + \overline{\gamma_g^o} &\approx .03€ \end{aligned} \tag{E21}$$

$$\begin{aligned}\overline{\phi_b^c} + \overline{\gamma_b^c} &= n_b v^c (l_b \phi_b + \gamma^c) \\ \overline{\phi_b^c} + \overline{\gamma_b^c} &= 1.138 \cdot 17.5km \cdot (.04\frac{€}{km} + \cdot .38\frac{€}{km}) \\ \overline{\phi_b^c} + \overline{\gamma_b^c} &\approx 8.36€ \end{aligned} \tag{E22}$$

$$\begin{aligned}\overline{\phi_b^o} + \overline{\gamma_b^o} &= n_b v^o (l_b \phi_b + \gamma^o) \\ \overline{\phi_b^o} + \overline{\gamma_b^o} &= 1.138 \cdot 19km \cdot (.04\frac{€}{km} + .13\frac{€}{km}) \\ \overline{\phi_b^o} + \overline{\gamma_b^o} &\approx 3.68€ \end{aligned} \tag{E23}$$

Third, the emission and congestion externalities inside and outside the congestion zone per kilometer traveled ($\hat{\phi}$ and $\overline{\gamma}$) equal:

$$\begin{aligned}\hat{\phi}^c + \hat{\gamma}^c &= n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c)\gamma^c \\ \hat{\phi}^c + \hat{\gamma}^c &= 1.138 \cdot 399.1 \cdot .04\frac{€}{km} + 0\frac{€}{km} + (1.138 \cdot 399.1 + .014 \cdot 6.4) \cdot .38\frac{€}{km} \\ \hat{\phi}^c + \hat{\gamma}^c &\approx 190.79\frac{€}{km} \end{aligned} \tag{E24}$$

$$\begin{aligned}\hat{\phi}^o + \hat{\gamma}^o &= n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_g^o)\gamma^o \\ \hat{\phi}^o + \hat{\gamma}^o &= 1.138 \cdot 432.1 \cdot .04\frac{€}{km} + 0\frac{€}{km} + (1.138 \cdot 432.1 + .014 \cdot 6.9) \cdot .13\frac{€}{km} \\ \hat{\phi}^o + \hat{\gamma}^o &\approx 83.6\frac{€}{km} \end{aligned} \tag{E25}$$

Table E2: Parameter estimates used for congestion charge

Coefficient	Descriptions	Value	Source
Panel A: Registry Data			
n_g	Number of green vehicles per person	.014	Table I, Panel A
n_b	Number of brown vehicles per person	1.138	Table I, Panel A
t_g^c	Number of congestion-trips with green vehicles	6.4	Table I, Panel B, equation (E3)
t_b^c	Number of congestion-trips with brown vehicles	399.1	Table I, Panel B, equation (E4)
t_g^o	Number of non-congestion-trips with green vehicles	6.9	Table I, Panel B, equation (E5)
t_b^o	Number of non-congestion-trips with brown vehicles	432.1	Table I, Panel B, equation (E6)
v^c	Average kilometers traveled on congestion zone trips	17.5km	Table I, Panel C
v^o	Average kilometers traveled on non-congestion zone trips	19km	Table I, Panel B, Swedish National Travel Survey (2007)
Panel B: Empirical estimates			
$\frac{\partial n_g}{\partial \tau}$	Effect of congestion charge τ on number of green vehicles n_g	.0064	Table I, Panel A
$\frac{\partial n_b}{\partial \tau}$	Effect of congestion charge τ on number of brown vehicles n_b	$-.0083$	Table I, Panel A
$\frac{\partial t_g^o}{\partial \tau}$	Effect of congestion charge τ on number of outside congestion trips in green vehicles t_g^o	.7	Table D3, Panel B, equation (E9)
$\frac{\partial t_g^o}{\partial \tau}$	Effect of congestion charge τ on number of congestion trips in green vehicles t_g^c	5.9	Table D3, Panel B, equation (E8)
$\frac{\partial t_b^o}{\partial \tau}$	Effect of congestion charge τ on number of outside congestion trips in brown vehicles t_b^o	-11.8	Table D3, Panel B, equation (E10)
$\frac{\partial t_b^o}{\partial \tau}$	Effect of congestion charge τ on number of congestion trips in brown vehicles t_b^c	-2	Table D3, Panel B, equation (E11)
$\frac{\partial v^c}{\partial \tau}$	Effect of congestion charge τ on average kilometers on congestion trips v^c	$-.086$	Table D4, Panel C
$\frac{\partial v^o}{\partial \tau}$	Effect of congestion charge τ on average kilometers on non-congestion trips v^o	$-.007$	Table D4, Panel C, equation (E14)
Panel C: Emission externalities [$\frac{€}{km}$]			
$\phi_b \cdot l_b$	Emission externalities for brown vehicles	.04	Equation (E16)
$\phi_g \cdot l_g$	Emission externalities for green vehicles	0	Equation (E17)
Panel D: Congestion externalities [$\frac{€}{km}$]			
γ^c	Congestion externalities for inside cordon driving	.38	External Costs of Transport (2011), Table 38
γ^o	Congestion externalities for outside cordon driving	.13	External Costs of Transport (2011), Table 38

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