Road Pricing with Green Vehicle Exemptions: Theory and Evidence*

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December 23, 2024

Abstract

We provide a framework for recovering second-best optimal tolls when policymakers exempt clean vehicles from congestion prices. Our framework includes congestion and emissions externalities, plus policy responses like changes in vehicle ownership, leakage, and residential sorting. Using Swedish administrative microdata, we identify these responses by exploiting vehicle- and location-based exemptions from Stockholm's congestion charge. Commuters respond by adopting exempted alternative fuel vehicles, shifting trips away from conventional and toward alternative fuel vehicles, and changing where they live and work. We combine these estimates with our optimal tax framework to recover an optimal congestion charge of €9.46 per trip in Stockholm.

*We want to thank Nicolas Astier, Luigi Butera, David Byrne, Richard Carson, Lucas Davis, Jonathan de Quidt, Teevrat Garg, Jinwon Kim, Ashley Langer, Leslie Martin, Frikk Nesje, Robert Östling, Torsten Persson, and James Sallee for providing helpful comments and suggestions as well as audiences at the University of Melbourne, University of Sydney, UC Berkeley ARE, the School of Global Policy and Strategy at UC San Diego, the North American Meeting of the Urban Economics Association, Institute for International Economics Studies, University of Arizona, and Copenhagen Business School. Vaibhav Rathi, Ben Chamberlain, and Leiv Storesletten provided outstanding research assistance.

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I. Introduction

In the simplest model of Pigouvian taxation, it is irrelevant how consumers respond to taxes. The optimal Pigouvian tax reflects marginal damages irrespective of whether the demand response comes from substitution to a related good, decreased consumption, or adoption of a new technology. In practice, however, responses to Pigouvian taxes often cause other social costs or benefits, complicating the calculation of optimal prices. Such is the case for road pricing. When cities price roads to address congestion and environmental externalities, commuters can respond in many ways. In the short run, they may reduce their vehicle trips, switch to traveling on non-tolled roads, or take public transit. In the long run, they may change where they live, or adopt clean vehicles that face lower toll rates or are toll-exempt. Some of these responses, like taking public transit, are not associated with any externalities. Other responses, like those regarding moving or vehicle purchase decisions, may alleviate or exacerbate congestion and environmental externalities outside the congestion zone.

Although it is well known that these considerations impact optimal prices, there are several shortcomings in the existing literature on this topic. First, models of second-best pricing tend to focus on a single dimension of response (Wilson, 1983; Verhoef et al., 1996). Second, data constraints make studying long-run responses to congestion pricing difficult. As a result, most existing empirical work on second-best road pricing tends to focus on problems of leakage rather than residential sorting or vehicle choice. Lastly, recent work on congestion pricing using spatial general equilibrium models can incorporate multiple dimensions of responses, but the completeness of these approaches comes at the cost of tractability.

In light of these shortcomings, this paper makes two high-level contributions to the literature on congestion pricing. First, we provide a tractable framework for recovering congestion charges that address emission and congestion externalities while accounting for the multiple dimensions of policy response. This framework decomposes optimal prices into marginal congestion and emissions damages, plus additional terms corresponding to the social costs or benefits of drivers' different types of responses to road pricing. Second, we use Swedish administrative data together with variation in exposure to Stockholm's congestion price to estimate each component required to recover optimal prices. The set of empirical results not only allows us to recover optimal congestion prices, but also describes medium and long-run responses to road prices that are new to the literature.

Our framework for recovering congestion charges builds on the vehicle decision model of Anderson and Sallee (2016) in Section II. In our model, a representative consumer chooses the size of two vehicle fleets – "brown" and "green" vehicles. The consumer also chooses how many congestion and non-congestion zone trips to take in each car and how far to live from work. The social planner chooses a congestion charge on brown vehicles (while exempting green vehicles) with the goal of maximizing social welfare subject to this constraint. The social planner takes into account local congestion and emission externalities as well as how responses to the policy — namely changes in the size of the vehicle fleet, substitution to non-tolled roads, and residential sorting — may alleviate or exacerbate these externalities at the city level. In our main specification, we take as given the constraint that green vehicles are exempted; this modeling choice reflects the trend among planners of exempting clean vehicles in an effort to combine transportation and environmental goals.[1]

Solving the planner's problem yields a formula for the optimal second-best congestion charge that consists of three terms: a fleet size term, a driving behavior term, and a commuting distance term. The first term reflects the impact of congestion pricing on emission and congestion externalities through changes in the composition and size of the vehicle fleet. The second term represents the change in the number of brown and green vehicle trips inside and outside the congestion zone. The third term represents changes in drivers' average trip length, as treated commuters may either move into the congestion zone or relocate to workplaces outside the congestion zone to avoid the congestion charge.

In Section III, we describe our strategy for estimating each of the policy responses required to calculate second-best tolls. Our setting is Stockholm, which imposed a congestion charge starting in August 2007. The policy initially included an exemption for alternative-fuel vehicles (this exemption was phased out between 2009 and 2012, as we detail below). To study how commuters responded to this policy, we use several Swedish administrative data sets. Together, these datasets allow us to track Stockholm resident's vehicle ownership, vehicle kilometers traveled, and work and home location over time.

Our empirical design exploits the fact that two congested motorways (*Essinge bypass* and *Lidingö route*) were exempted from 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, taking fewer trips into the congestion zone, and changing where they work and live. 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

[1] Green vehicle exemptions are common in congestion pricing systems: Milan exempts electric, hybrid, and biofuel vehicles, and London introduced an electric vehicle exemption in 2021. In California, electric vehicles receive free or discounted use of many tolled and HOV highway lanes.

less likely to own a fossil fuel vehicle relative to the non-exposed commuters. Although the congestion charge led to a shift from fossil fuel vehicles to alternative fuel vehicles, the overall size of the vehicle fleet remained unchanged. On the intensive margin, treated commuters increased their use of alternative fuel vehicles by 103 kilometers annually and decreased their use of fossil fuel vehicles by 206 kilometers annually. Based on travel survey data for the Stockholm area, we infer that most of these changes in vehicle kilometers traveled correspond to changes in downtown trips, implying that the resulting substitution to non-cordon trips was relatively minor. Finally, we test for sorting, as moving or changing workplaces could allow residents to avoid crossing the cordon zone boundary where tolls are levied. We show 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 a new company. This sorting causes a modest but meaningful reduction in overall driving commute distances for treated commuters.

Although we focus on a model of a representative commuter when calculating optimal charges, an advantage of our administrative data is that it allows for heterogeneity analyses that speak directly to debates about congestion prices that vary by observable characteristics. For example, we find that 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, suggesting that they may be more reliant on existing commuting patterns or are financially constrained. Finally, we show that the decrease in commuting distances resulting from post-policy sorting is driven by individuals without children. This is consistent with heterogeneity in the costs associated with moving.

In Section V, we use our empirical results together with our optimal tax framework to estimate the optimal congestion fee for Stockholm's congestion zone, given the constraint that green vehicles are exempted. In our baseline specification, the congestion fee for brown vehicles is €9.46 per crossing. 67 percent of the optimal charge reflects changes in trip-taking, 22 percent reflects net changes in the vehicle fleet, and 11 percent reflects changes in commuting distances. Across these components, the social benefits associated with changes in congestion are larger than the social benefits associated with changes in emissions: congestion-related terms account for €8.38 of the charge, while emissions-related terms account for just €1.07.

While the focus of this paper is to estimate optimal congestion charges with green vehicle exemptions, our results allow us to conduct a simple cost-benefit analysis of achieving green vehicle adoption via congestion pricing exemptions. Inducing the adoption of one exempted green vehicle incurs an annual cost of €245 in congestion externalities or €1,225 over the five-year period during which alternative fuel vehicles were exempt in Stockholm. We estimate that the emissions benefits from exempting green cars from congestion charges are equal to €608 per year, which is above the congestion-related cost of exempting these vehicles. Importantly, this cost-benefit ratio depends on the size of the existing green vehicle fleet. Conditional on the amount of adoption induced by an exemption, the larger the size of the existing green vehicle fleet, the higher the cost of green vehicle exemptions. Therefore, congestion pricing exemptions may be an attractive way of inducing adoption in nascent electric vehicle (EV) markets, but the costs of these exemptions may outweigh the benefits in mature EV markets.

Our theoretical framework connects two strands of literature: optimal tax theory and congestion pricing. While congestion pricing is commonly viewed as a straightforward application of the Pigouvian principle (Vickrey, 1963), several papers have noted that congestion pricing is frequently second-best, requiring empirical estimates of tax elasticities (Mun et al., 2003; Verhoef, 2005).[2] 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 tradeoffs between environmental and congestion externalities.[3] Specifically, our derivation of congestion charges that factor in responses to the policy enables us to highlight tradeoffs between road pricing policies and environmental objectives. A key contribution of our theoretical work is that it delivers formulas for congestion charges as a function of policy elasticities that can be estimated in various empirical settings.[4]

In addition to contributing to second-best tax theory, our empirical results provide new evidence about the margins of response to congestion pricing. A robust body of work documents that congestion pricing reduced downtown 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). Our linked microdata allow us to directly document residential and workplace sorting and vehicle switching[5], along with how these responses vary along demographic lines. We estimate these responses in service of our second-best tax calculations, but also view them as contributions in their own right.

[2] See also Small (1982), Arnott et al. (1993), Hall (2018, 2021), Kreindler (2023), and Tarduno (2022) for discussion of first versus second-best congestion pricing.

[3] More broadly, our research is related to work that incorporates policy or behavioral imperfections into the calculation of optimal taxes. 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).

[4] For the remainder of the paper, we refer to "policy elasticities" as the change in behavior due to a congestion policy relative to a counterfactual without the policy.

[5] Existing research has studied vehicle choice in the context of electric vehicle access to high occupancy toll lanes (Bento et al., 2014; Shewmake & Jarvis, 2014; Sheldon & DeShazo, 2017); we see the setting of congestion pricing as related but distinct.

II. Deriving the optimal congestion charge

This section presents a stylized model of the urban personal transportation sector. The goal of this model is to describe the externalities and margins of choice that are relevant when setting congestion prices.

A. Model of urban travel

Our model of driver behavior builds on Anderson and Sallee (2016) — their original model was developed to study how policies like fuel economy standards may impact the vehicle market in several ways, including changing the fleet size, the average fuel efficiency, or kilometers driven. We build an analogous model recognizing that commuters may respond to congestion prices in several ways, especially if certain vehicles are exempted. Specifically, in addition to taking fewer trips to the cordon zone, treated commuters might adopt exempted cars, substitute to outside roads, or change their home or work locations. After presenting our model, we take first-order conditions of the consumer's problem, and plug these conditions into the planner's problem to recover the second-best optimal congestion price.

The consumer's problem. We model a representative agent who makes choices over the vehicle fleet size, the number of trips taken, and the distance between work and home. The agent has an exogenous income and faces prices of vehicles, fuel, and moving, as well as a congestion toll for non-exempt trips to the city center (the *cordon* zone).

More specifically, the representative consumer derives utility from trips (t), 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 ("leakage"), we distinguish between trips occurring within congestion zones and those outside.[6] In all expressions, congestion zone-specific details are shown as superscripts, while characteristics specific to the type of vehicle are shown as subscripts. 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. v is not exogenous and reflects where people choose to live and work. The agent can adjust the length of congestion or non-congestion zone trips, but there are costs r associated with either type of adjustment.[7] The cost of each type of vehicle is represented by c_b and c_g. l is the vehicle fuel efficiency of the respective vehicle type, and y is the

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

[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).

representative consumer's exogenous income. p_g and p_b are the fuel costs 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 (n_g, n_b), the optimal number of trips in each vehicle type completing the kind of trip (t_g^c, t_g^o, t_b^c, t_b^o), and the vehicle kilometers traveled for each trip (v^c, v^o) to maximize consumer welfare, B. 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:

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

For each vehicle fuel type, the term $\mu(n)u(t)$ refers to utility derived from the vehicle fleet of that type. This utility is a function of both the number of vehicles (n) and number of trips per vehicle (t), where $\mu'(\cdot), u'(\cdot) > 0$ and $\mu''(\cdot), u''(\cdot) \leq 0$. The remaining terms represent costs. $n_g(p^c + p_g l_g)v^c t_g^c$, for example, are the total private cost of driving green vehicles inside of the cordon zone, which includes the per-kilometer fuel cost ($p_g l_g$) as well as other per-kilometer costs of driving like time costs (p^c). Multiplying these per-kilometer costs by the average trip length and the number of vehicles yields a total cost associated with vehicle trips of each type. The costs of driving green vehicles outside of the cordon, driving brown vehicles inside the cordon, and driving brown vehicles outside of the cordon are represented analogously. The fixed costs of the green and brown fleets are $n_g c_g$ and $n_b c_b$. Finally, The costs of moving — and thereby adjusting commute lengths — are $r(v^c)$ and $r(v^o)$.

The planner's problem. The social planner's problem is to maximize consumer welfare, $B^{-\tau}$, by setting the congestion charge, τ, which is levied only on brown vehicles. As the revenue from the congestion charges is a transfer from the social planner's perspective, the congestion charges do not directly enter the planner's objective function (indicated as superscript $-\tau$). The planner's problem is identical to that of the consumer, except the planner takes into account emissions (ϕ) and congestion externalities (γ).[8] Emission externalities

[8]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 injuries are minor in Stockholm.

differ by vehicle type (ϕ_g versus ϕ_b) and congestion externalities differ based on whether a trip uses the downtown cordon or outside roads (γ^c versus γ^o).

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

Emission externalities for brown and green vehicles scale by the total vehicle kilometers traveled in the respective vehicle types. We do not differentiate local emissions damages for trips inside versus outside the congestion zone because the wind can transport local pollutants across the zone boundary, implying similar emission damages inside and outside the congestion zone. Congestion externalities scale by vehicle kilometers traveled inside and outside the congestion zone, irrespective of the type of vehicle. In our main calculations, we assume no pre-existing taxes or subsidies on vehicles. In our alternative specifications, we relax this assumption and provide figures that account for overlapping environmental fuel taxes and green vehicle subsidies.

Because congestion externalities are non-constant in the level of driving, our derivation of the second-best congestion charge is valid at the optimum. We do not explicitly endogenize congestion externalities because of the lack of traffic density data in Stockholm and the general complexity of endogenizing congestion costs at the city level (Tsekeris & Geroliminis, 2013). Note, however, that we do not expect the congestion costs that we use in this paper to differ markedly from the costs that would exist under our proposed tax. This is because the congestion cost estimates that we use reflect traffic levels with Stockholm's congestion price in place rather than in an unpriced equilibrium.

A related note is that we recover a second-best time-invariant toll; we do not estimate tolls that differ within commuting hours. Although an optimal time-invariant toll will trivially generate lower welfare gains than an optimal toll that can vary by the time of day, many cities choose to employ flat tolls. London and Milan, for example, charge a constant congestion price for commuting and shoulder periods. For a discussion of how intertemporal substitution and optimal peak-hour congestion pricing, see Yang et al. (2020), Kreindler (2023), and Tarduno (2022).

B. Expression for the optimal congestion charge

Taking first-order conditions of the consumer's problem and plugging these conditions into the planner's problem yields the following proposition. See Appendix A.1 for the derivation.

Proposition 1. *Under the constraint that green vehicles are exempt from congestion pricing, the second-best congestion charge per trip on non-exempt vehicles is:*

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

In equation (3), the optimal charge on non-exempt vehicles reflects both direct externalities from driving these vehicles as well as the social costs or benefits associated with other policy responses, i.e., reducing vehicle purchases, switching to exempted vehicles, or moving. We can also rearrange equation (3) as equation (4). This phrasing is similar to the canonical results in Green and Sheshinski (1976) on indirect taxation. In their setting, there are two externality-generating goods and only one can be taxed. The optimal tax in this setting can be expressed as the direct externality associated with the taxable good plus a term governed by the substitution between goods and the externality associated with the untaxable good. Analogously, our optimal tax expression can be written as the externality generated by the taxable "good" — cordon trips in conventional vehicles — plus a term that represents other policy responses and the externalities associated with those activities:

$$
\begin{aligned}
\tau \ &= v^c(l_g\phi_g+\gamma^c)+\frac{1}{(\frac{\partial n_b}{\partial \tau}t_b^c+\frac{\partial t_b^c}{\partial \tau}n_b)}\Bigg(\frac{\partial n_g}{\partial \tau}\Big((v^ct_g^c+v^ot_g^o)l_g\phi_g+v^ct_g^c\gamma^c+v^ot_g^o\gamma^o\Big)\\
&+\frac{\partial n_b}{\partial \tau}\Big((v^ot_b^o)l_b\phi_b+v^ot_b^o\gamma^o\Big)+\frac{\partial t_g^o}{\partial \tau}\Big(n_gv^o(l_g\phi_g+\gamma^o)\Big)\\
&+\ \frac{\partial t_g^c}{\partial \tau}\Big(n_gv^c(l_g\phi_g+\gamma^c)\Big)+\frac{\partial t_b^o}{\partial \tau}\Big(n_bv^o(l_b\phi_b+\gamma^o)\Big)\\
&+\frac{\partial v^c}{\partial \tau}\Big(n_bt_b^cl_b\phi_b+n_gt_g^cl_g\phi_g+(n_bt_b^c+n_gt_g^c)\gamma^c\Big)\\
&+\frac{\partial v^o}{\partial \tau}\Big(n_bt_b^ol_b\phi_b+n_gt_g^ol_g\phi_g+(n_bt_b^o+n_gt_b^o)\gamma^o\Big)\Bigg)
\end{aligned}
\tag{4}
$$

To build intuition for how we will take Proposition 1 to the data, we introduce notation that allows us to express the optimal tax in terms of policy-induced changes in outcomes — numbers of vehicles, numbers of trips, and commuting distance — multiplied by the appropriately scaled externality. By introducing notation for congestion and emissions externalities per vehicle (indicated with tilde), per trip (indicated with an overbar), and per kilometer traveled (indicated with a hat), we can re-write equation (3) as:

$$
\begin{aligned}
\tau \ &= \underbrace{\Delta N_g\cdot(\widetilde{\phi}_g+\widetilde{\gamma}_g)+\Delta N_b\cdot(\widetilde{\phi}_b+\widetilde{\gamma}_b)}_{\triangle Fleet\ composition}\ +\ \underbrace{\Delta T\cdot(\overline{\phi}+\overline{\gamma})}_{\triangle Trips}\\
&+\ \underbrace{\Delta V^c\cdot(\hat{\phi}^c+\hat{\gamma}^c)+\Delta V^o\cdot(\hat{\phi}^o+\hat{\gamma}^o)}_{\triangle Commute\ Distances},
\end{aligned}
\tag{5}
$$

where ΔN_g, ΔN_b, ΔT, ΔV^c, and ΔV^o refer to the policy-induced changes in green or brown vehicle adoption, the number of inside or outside trips by each vehicle type, and the commuting distance inside and outside the cordon zone, each scaled by the discrete version of the denominator from equation (3). The discretized version of the denominator, $\frac{\partial n_b}{\partial \tau}t_b^c+\frac{\partial t_b^c}{\partial \tau}n_b$, is $\Delta N_bt_b^c+\Delta t_b^cn_b$, where ΔN_b and Δt_b^c represent the policy-induced change in the size of the brown vehicle fleet, and the policy-induced change in the number of trips taken by conventional vehicles, respectively. $\widetilde{\phi}_g+\widetilde{\gamma}_g$ and $\widetilde{\phi}_b+\widetilde{\gamma}_b$ are the emission and congestion externalities per green and brown vehicles (expressed in total € damages). $\overline{\phi}+\overline{\gamma}$ are the emission and congestion externalities per trip (expressed in total € damages). $\hat{\phi}^c+\hat{\gamma}^c$ and $\hat{\phi}^o+\hat{\gamma}^o$ are the emission and congestion externalities per kilometer inside and outside the congestion zone (expressed in € damages per kilometer). The details of these conversions are documented in Appendix A.2.

Equation (5) shows that the optimal congestion charge on non-exempt vehicles is the sum of several products, each consisting of a policy response and an appropriately scaled externality. In the empirical section of the paper, we estimate each of the required policy responses and describe the off-the shelf estimates we use for each type of externality.

Prior to presenting our empirical design, however, we (a) discuss several related cases and (b) demonstrate how the same policy responses used to calculate the optimal tax can be used to compare the costs and benefits of inducing green vehicle adoption through congestion pricing exemptions.

Related cases and extensions. Although our focus in this paper is to estimate the optimal congestion charge when green vehicles are exempted, there are two obvious points of comparison: The optimal uniform toll, where all vehicle types are charged the same toll, and the optimal differentiated toll, where green and brown vehicles are both charged, but these rates are allowed to differ.

In Appendix A.4 we derive a formula for the optimal uniform toll. The approach is identical to the approach used to calculate the optimal tax on non-exempt vehicles, except that all vehicles face a toll for downtown trips. We compare estimates of the optimal uniform charge and the optimal charge with green exemptions in Figure 6.

While it is rare in practice for congestion pricing systems to charge different tolls for different types of passenger vehicles, it may be of interest to policymakers to know whether an optimal toll system that charges different tolls for green versus brown vehicles would have a positive or negative price on green vehicles. Proposition 2 describes the optimal type-specific toll (Appendix A.5). Because this two-toll formula requires substantially more empirical information (e.g., cross-price derivatives specific to tolling each type of vehicle), we do not bring this formula to the data. Recovering the two optimal charges specific to each vehicle type would require estimates of how taxes on green vehicle trips impact the adoption and usage of brown vehicles, which our empirical setting does not allow us to determine. Still, Proposition 2 provides insight into when one should expect tolls on green vehicles to be positive. For example, the optimal toll on green vehicles is more likely to be positive when congestion externalities are large relative to emissions externalities or when cross-price elasticities between green and brown vehicle types are low.

The final extension of Proposition 1 describes how our optimal toll calculation would change to reflect pre-existing policies. For simplicity, we assumed in the derivation of Proposition 1 that there are no pre-existing environmental fuel taxes and no subsidies on green vehicles. Our framework, however, can accommodate both. To account for existing environmental fuel taxes, we replace the per-kilometer environmental externalities of fossil fuel vehicles with the *uninternalized* ($\mathring{\phi}_b$) marginal emission externality (i.e., the per-kilometer emissions-related externality less the per-kilometer environmental fuel tax). Accounting for

EV subsidies is less straightforward. Vehicle subsidies do not distort the decision to drive, but instead, the size of the fleet. Accordingly, in the second-best tax equation, a pre-existing green vehicle subsidy s appears within the term that governs how the tax impacts the size of the green vehicle fleet (Proposition A18). Intuitively, green vehicle subsidies are designed to encourage people away from conventional vehicles but have the side effect of causing the resulting green vehicle fleet to be larger than optimal. All else equal, green vehicle subsidies increase the second-best undifferentiated congestion price. We present calculations using pre-existing taxes in Sweden in Figure 6. The calculation in this Figure correspond to Appendix equation (6), which amends equation (3) as described in this paragraph.

C. Cost-benefit analysis of inducing green vehicle adoption via congestion pricing exemptions

Technology-based exemptions can encourage green car adoption, but they do so at the cost of reducing the congestion benefits from the congestion pricing program. Our setting and data allow us to compare the emissions benefits of inducing green vehicle adoption to the cost of foregone congestion reductions.

To set ideas, we take as fixed Stockholm's congestion price and accompanying green vehicle exemption, and imagine a counterfactual where all vehicles faces the same congestion price. This counterfactual existed during the policy's trial period and again after 2012 when the exemptions were discontinued. We can then use reduced-form estimates of responses in vehicle adoption and the number of trips together with externality estimates to compare the costs and benefits of green vehicle adoption. The benefits of induced green vehicle costs outweigh the foregone congestion costs if the following inequality holds:

$$\underbrace{(l_b\phi_b - l_g\phi_g)\ \cdot\ (v^c t_b^c + v^o t_b^o)\frac{\partial n_g}{\partial \tau}}_{\text{benefits of green car adoption}}\ \geq\ \underbrace{(n_g v^c \gamma^c)(|\frac{\partial t_b^c}{\partial \tau}| - |\frac{\partial t_g^c}{\partial \tau}|)}_{\text{foregone congestion benefits}}. \tag{6}$$

We calculate emissions benefits of induced green vehicle adoption by multiplying the change in the size of the green vehicle fleet by the emissions savings that result from using a green rather than brown vehicle. Note that these emissions savings reflect all trips, not just congestion zone trips. To compare the emissions savings to foregone congestion benefits, we estimate how many trips would have been avoided on net if all cordon zone trips had faced a congestion price. We achieve this by separating the price effect from the substitution effect within Stockholm's price-plus-exemption policy. Figure 1 shows the price and substitution responses for each policy type. From this Figure, it is clear that the *net* difference in trips between the exemption and no-exemption policy does not depend on the degree of substitution between green and brown vehicles: The foregone congestion benefits from exempting a green vehicle is the pure price effect times the per-trip damages. Because our main empirical design focuses on a policy that includes an exemption, we back out the pure price effect by subtracting the change in green vehicle trips (a substitution effect) from the change in brown vehicle trips (consisting of a price effect plus a substitution effect).

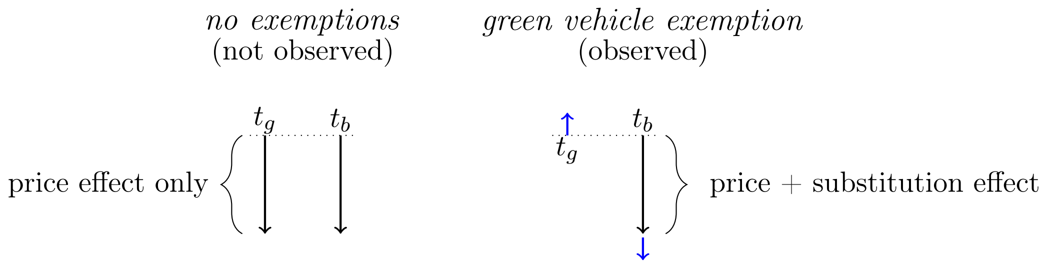

Figure 1: Responses by vehicle type with and without exemptions

Note that these foregone congestion benefits are a lower bound on the total cost of achieving green car adoption through congestion pricing exemptions — we abstract from the marginal reduction in the sorting incentive here for simplicity. We nonetheless see this simple comparison − emissions benefits against foregone congestion benefits − as a straightforward test that can be used as input when policymakers design downtown road pricing schemes.

Specifically, we see two uses for this exercise. First, it provides an estimate of the cost of inducing green car adoption through a congestion pricing threshold. This provides a valuable point of comparison: EV subsidies are ubiquitous but have been scrutinized as poorly targeted at marginal buyers. Although exempting EVs in road pricing systems is not a first-best approach for inducing their adoption, it may outperform the most commonly used policy tool in terms of cost-benefit. Second, note that exempting EVs is costly (in terms of foregone congestion benefits) when the existing EV fleet is large. Inequality (6) allows us to derive the cutoff for when the foregone costs from additional congestion exceed the emission benefits of EV adoption.[9] Above this market share threshold, the congestion costs of the green exemptions outweigh the emission benefits of additional green car adoption.

III. Estimating commuter responses to congestion pricing

A. Setting: Stockholm's congestion charge

We use the introduction of Stockholm's congestion pricing system to estimate each of the responses outlined in the previous section. Here, we provide a brief background on the

[9]This relates to the literature on the optimal trajectory of designing environmental policies (De Groote & Verboven, 2019; Newell et al., 2019; Langer & Lemoine, 2022).

congestion zone and describe aspects of the policy that are key to our empirical approach.

The goal of Stockholm's congestion pricing zone was to reduce traffic entering the central city and to improve the air quality in the city center. The implementation of the congestion charge started with a seven-month trial period from January until the end of July 2006 (The Stockholm Congestion Trials, *Stockholmsförsöket*). In a referendum in September 2006, after the trial had ended, the residents of Stockholm municipality voted to permanently implement congestion pricing. As a result, in October 2006, the Swedish government announced that congestion pricing would be permanently implemented starting in August 2007.

Figure 2 maps the 20 congestion pricing toll stations (in red) in Stockholm's inner city.[10] The charging system is designed as a *cordon zone* around the inner city (dotted line). The congestion tax is levied on non-exempt vehicles that cross the cordon boundary between 6:00 and 18:30 on Monday through Friday. Tolls are automatically collected using license plate scanning technology. Between 2006 and 2015, the charge varied between €1.06 (SEK 10) and €2.12 (SEK 20) per passage in Stockholm,[11] depending on the time of the day (Figure B1). The charge was set with the goal of reducing car traffic across the cordon by 10 to 15 percent (Eliasson et al., 2014). The tax is not charged on weekends or public holidays, on a day preceding a public holiday, or during July.

Stockholm's congestion pricing system originally included two important exemptions that we use to identify responses to congestion pricing.

Exemption 1: Essinge bypass and Lidingö rule. The Essinge bypass is a congested motorway west of Stockholm city center (the green line in Figure 2) that crosses the congestion zone. Vehicles that crossed Stockholm's city center via the Essinge bypass were exempt from the congestion fee.[12] However, vehicles that exit or enter the Essinge bypass within the congestion tax area are levied a fee (toll stations 6 to 10). In addition, all traffic to and from Lidingö, an island north-east of Stockholm, is exempt from the congestion fee if it passes both the Ropsten payment station (toll station 26 in Figure 2) and another payment station within 30 minutes. All vehicles that remained longer in the cordon zone were required to pay the congestion fee. The rationale for the Lidingö rule was that the only connection from Lidingö municipality to the national road network ran through the inner city.

[10] The Swedish Transport Agency (*Transportstyrelsen*) provides a detailed description for each toll station.

[11] We convert Euros to Swedish Kronor using the exchange rate from January 1, 2006 (9.42 $\frac{€}{SEK}$).

[12] The Essinge bypass is the only bridge between the south and north of Stockholm, that allows commuters to avoid driving 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.

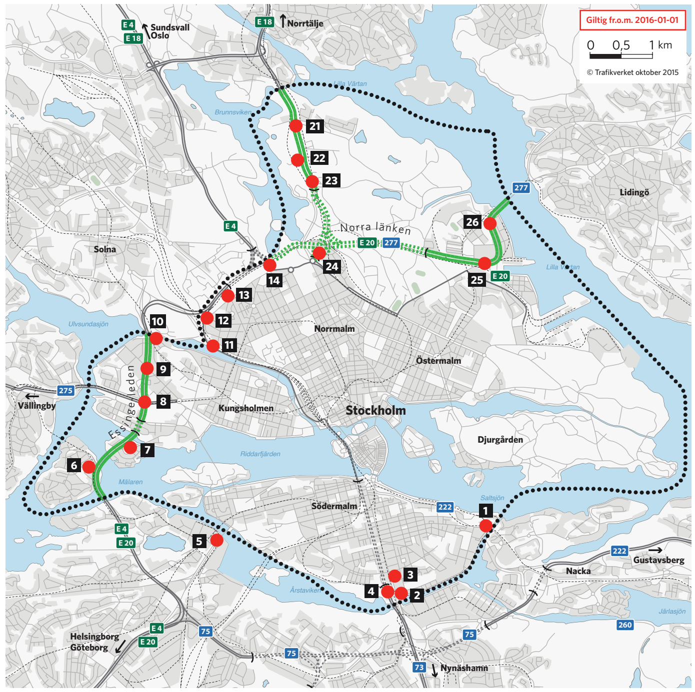

Figure 2: Toll stations in Stockholm

Notes: The map shows toll stations in and around the city center of Stockholm. The red dots indicate where the control points are located.

Exemption 2: Alternative fuel vehicles. In March 2007, the Ministry of Finance decided that alternative fuel vehicles (i.e., ethanol, biogas, hybrid, and EVs) would be exempted from Stockholm's congestion charge (Ministry of Finance, 2007).[13] 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). Following concerns that the green vehicle exemption was limiting the policy's congestion benefits, the tax exemption was phased out in January 2009. Starting in that month, newly-registered green vehicles were no longer exempt from tolls. Legacy exemptions, however, remained in place until August 2012 as long as the vehicle was was not transferred to a new owner.

B. Data sources

To study how vehicle purchases, driving decisions, and sorting respond to congestion pricing, we combine information from several administrative sources provided by Statistics Sweden. These include the Swedish vehicle register (*Fordonsregistret*), the longitudinal integrated

[13]Exemptions to the charge include emergency vehicles, buses, diplomatic vehicles, disabled person vehicles, military vehicles, motorcycles and mopeds, and foreign-registered vehicles. In 2006, taxis were exempt, but the taxi exemption was abolished when the charges were permanently introduced in 2007.

database for health insurance and labor market studies (*LISA*), the Swedish business register (*Företagsregistret*), and the geographic database (*Geografidatabasen*) from 2003 to 2008.

Vehicle characteristics. The Swedish vehicle register contains 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, whether it is in use or not), the vehicle specification (make, model, and trim), and numerous vehicle characteristics (service weight, fuel type, fuel efficiency, particle filter, carbon emissions). Importantly, the register is a panel dataset that contains the annual vehicle kilometers traveled for each vehicle. Finally, each registration also records a vehicle identification number and a social security number equivalent, which uniquely identifies all individuals in Sweden. We restrict our dataset to privately owned vehicles and exclude those registered for commercial purposes.

Demographics. To match individuals to their vehicles, we use individual identification numbers to link the Swedish vehicle registry to the LISA data, which contains socio-demographic information for Swedes over the age of 18 (gender, age, family status, income, gross salary, education, and employment status). We do not directly observe individual-level congestion toll payments during our main study window, but these data are available after 2016. We use this toll payment data to speak to heterogeneity in responses to congestion pricing across demographic groups.

Residence & workplace location. To attribute commuting distances to each individual, we bring in data on employers and home locations via the geographic database. This allows us to infer how far one would have to travel to get to work and whether individuals move offices or employers in response to the congestion charge. The geographic information is reported in $250m$ grid cells in urban and $1000m$ cells in rural areas. Lastly, we complement our data with information from The Swedish National Travel Survey (2007), which contains information on the travel patterns of the Swedish population. These survey data provide valuable population statistics that we use to apportion observed vehicle kilometers traveled into cordon versus non-cordon trips.

C. Empirical design

To identify the causal effects of congestion pricing on individual-level vehicle ownership, driving behavior, and location choices, we exploit variation in individuals' exposure to tolls between home and work.

To do this, we define two groups of individuals, which we refer to as *treated commuters* and *non-treated commuters*. *Treated commuters* are individuals who cross the congestion zone on their way to work.[14] 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 use the Essinge bypass or the Lidingö route on the (time-minimizing) route between home and work. Said differently, the control group we use would have paid Stockholm's congestion price if these route-specific exemptions did not exist. 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 416,245 individual×year observations over six years (2003-2008). Appendix C.1 and C.2 give additional details on the definition of treatment and control groups and sample restrictions.

Prior to the implementation of congestion pricing, the treatment and control groups are demographically similar and have similar observable commuting characteristics. Table B1 contains summary statistics for each group. Treated and control commuters are similar in age, salary, and education, as well as vehicle ownership patterns, distance between home and work, and vehicle kilometers traveled annually.

To provide some intuition for the empirical design, Figure 3 displays a commuting route for an individual who is exempted from the congestion charges on the way to work (grey dotted line) and an individual who pays the charges (red dashed line). Suppose both individuals reside in the southwestern region of Stockholm (*Hägersten*). 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 via the Essinge bypass, eliminating the congestion charge. In contrast, the quickest route for an employee in *Vasastan* involves crossing the congestion zone border and incurring congestion fees. Note that because both our treated and control groups have similar commutes, they are not differentially impacted by any traffic improvements that result from the implementation of congestion pricing — on the margin, reductions in travel time make driving somewhat more attractive for both groups.

After isolating treatment and control commuters who are largely similar except for their exposure to congestion pricing after August 2007, we compare the changes in vehicle ownership, driving behavior, and location choices of these two groups. Our identification strategy compares the two groups' responses before and after the policy in a Difference-in-Differences (DiD) framework; the two dimensions of difference are (i) *pre* vs. *post*, and (ii)

[14] Isaksen and Johansen (2021) use a similar identification strategy based on congestion price exposure between work and home. The distinction is that we exploit variation within cities instead of comparing the adoption of environmentally friendly vehicles between cities.

treated commuters vs. *non-treated commuters*.

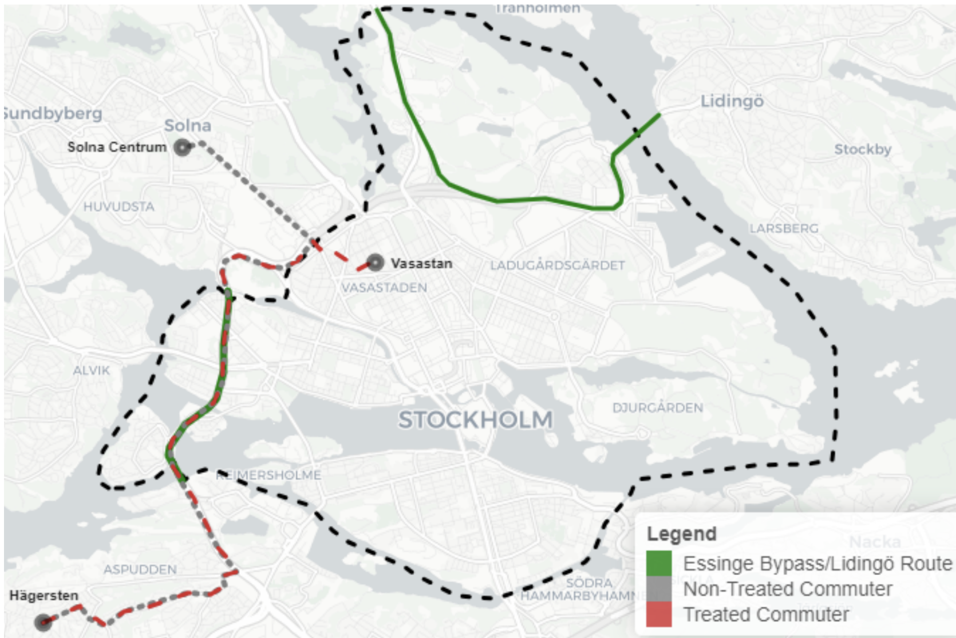

Figure 3: Example of treated versus non-treated commuters

Notes: This figure displays a commuting route for a "non-treated" individual who is exempted from the congestion charge on the way to work (grey dotted line) and a "treated" individual who pays the congestion charge (red dashed line). The black dashed line represents the boundary of Stockholm's cordon zone. The exempted Essinge bypass and Lidingö route are represented by green lines crossing the congestion zone in the west and northeast, respectively. Figure C1 gives an overview of the share of treated commuters in Stockholm per neighborhood in 2006.

Specifically, we estimate the following regression for each outcome of interest:

$$y_{it} \;=\; \beta post_t \cdot T_i \;+\; \theta T_i \;+\; \delta X_{it} \;+\; \lambda_t \;+\; \phi_n \;+\; \varepsilon_{it}, \tag{7}$$

where i indexes the individual and t the year. y_{it} refers to the outcome of interest (e.g., adoption of alternative fuel vehicle, number of trips, commuting distance) in a given year. $post_t$ is a dummy variable that equals 1 after the congestion zone trial (2006) when we measure the effect on fossil fuel vehicles and location choices and equals 1 after the alternative fuel vehicle exemption (2007) when we measure the effect on green vehicles. T_i is a dummy variable equal to 1 if the individual is classified as a *treated commuter*. The coefficient of interest (β) measures the impact of Stockholm's congestion pricing policy on vehicle ownership, number of trips, and commuting distance.

The vector X_{it} represents a rich set of individual demographic variables, work-route-specific controls, and previous vehicle attributes.[15] The year fixed effect λ_t captures time-varying factors such as nationwide vehicle incentives, gas price shocks, or expansion of public transport. ϕ_n is a neighborhood of residence fixed effects that controls for all time-invariant neighborhood-specific factors. We define neighborhoods as $250m$ grid cells in urban areas and $500m$ in rural areas. $\varepsilon_{i,t}$ is individual i's error term. Standard errors are clustered at the neighborhood level.

D. Identifying Assumptions and Threats to Identification

Parallel trends. The key identifying assumption underlying our empirical strategy is that treated and non-treated commuters would have experienced parallel trends in vehicle ownership, driving behavior, and location choices in the absence of the congestion charge introduction, conditional on control variables and fixed effects. To assess the validity of the parallel trends assumption, we estimate an event study version of our DiD estimator, which allows treatment effects 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:

$$y_{it} = \sum_{s \epsilon \{T | s \neq 2006]} \beta_t T_i \cdot 1[t = s] + \theta T_i + \delta X_{it} + \lambda_t + \phi_n + \varepsilon_{it}, \tag{8}$$

where year-specific effects are captured by β_t. 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 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 and fossil fuel vehicle ownership and driving behavior for treated and non-treated commuters for the years before the congestion zone implementation suggest that the assumption is plausible (Figure 4). Finally, improvements in public transport in the fall of 2004 (e.g., expanded bus and train services, park-and-ride sites) 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 argue that expanding public transportation had a negligible stand-alone effect on the shift from vehicle use to

[15]The control variables include age, gender, family income, gross salary, employment status, being self-employed, married or cohabitant, an indicator for having at least one child, years of education, and commuting distance.

public transportation.[16]

In addition, our estimation requires no differential anticipatory effects prior to the charge, which implies that the average outcome of treated commuters was not affected by the congestion trial. Two pieces of information suggest that anticipatory effects are likely minor. First, although the congestion charge trial was announced in October 2002, the permanent implementation depended on a 2006 referendum that would determine the ruling government's decision. Due to the significant public resistance and uncertainty surrounding its permanent implementation (Börjesson et al., 2012),[17] we do not expect treated commuters to change their fossil fuel trips and car acquisitions in response to the policy announcement. Second, we measure the effect on alternative fuel vehicle adoption and usage in the post-exemption period after 2007. As the exemption of alternative fuel vehicles was announced in March 2007, there were no anticipatory effects on commuters before the policy announcement at the start of 2007.

The congestion rebound effect and SUTVA. Driving behavior in the post-period reflects both changes in relative prices and lighter traffic in the post-implementation period. This could potentially lead to a violation of the stable unit treatment value assumption (SUTVA). That is, the treatment status of one individual may impact the traffic faced by other individuals, thereby changing their behavior. This concern is related to the concept of "rebound" as well as "induced demand" in transportation planning (Duranton & Turner, 2011). Because treated and non-treated commuters share similar home-work routes, both commuter groups experience a similar change in travel conditions (Appendix C.4). As a result, we do not expect our results to be biased by SUTVA violations.[18]

That said, because the rebound effect should net out between the treatment and control groups, our DiD estimates reflect relative responses and not necessarily total responses inclusive of the rebound effect. The policy-relevant responses, however, should incorporate both the direct congestion charge effect and the congestion rebound effect because the congestion charges depend on the overall traffic changes caused by the policy implementation. In other words, an ideal control group would face similar traffic conditions in the pre- and

[16] Similarly, 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). Even if increased public transit availability differentially impacted treated and non-treated commuters, this evidence suggests that the resulting bias would be minor.

[17] The percentage of trial-related newspaper articles with a positive angle was only 3% in fall 2005 (Winslott-Hiselius et al., 2009).

[18] The effect of the congestion charge on traffic volume was consistent across different toll stations in Stockholm, suggesting that both types of commuters crossing the cordon zone would encounter similar changes in traffic conditions (Eliasson et al., 2009) even if the two groups were not uniformly spatially distributed.

post-period, as opposed to improved traffic conditions during the post-period.

Absent this type of control group, we infer the size of the rebound effect. To do so, we apply the DiD specification (equation 7) to drivers who already owned exactly one green car and no other vehicles prior to the introduction of the congestion zone. These drivers were exempt from any charges, but experienced different aggregate traffic condition changes.

The congestion-zone induced reduction in traffic lead to an (insignificant) increase of 21 vehicle kilometers traveled annually among exempted green car owners (Figure D2). This suggests that the congestion rebound effect is relatively small compared to the direct effect of the policy. For reference, we estimate that annual vehicle kilometers traveled in brown vehicles decreased by roughly 250 for treated commuters. To the best of our knowledge, there are no existing estimates of rebound effects from congestion pricing, but our findings are consistent with existing work on the rebound effect in the context of fuel efficiency, which suggests that the rebound effect in personal vehicle travel tends to be small (Gillingham et al., 2013).[19] Given these findings, we do not explicitly include the rebound effect in our optimal congestion charge calculation, and expect any such inclusion to be second-order.

IV. Empirical results

A. Responses to Stockholm's congestion charge

Table 1 displays results from equation (7), which estimates the impact of exposure to Stockholm's congestion price on our outcomes of interest: vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C). Each panel shows results separately for alternative fuel vehicles, fossil fuel vehicles, and all vehicles (i.e., pooled).

Fleet size. Using equation (7), we find that Stockholm's congestion charge reduced the size of the conventional vehicle fleet and increased the adoption of alternative fuel vehicles. Panel A of Table 1 shows that exposure to Stockholm's congestion charge resulted in a .64 percentage point increase in the probability of owning an alternative fuel vehicle in the post-implementation years (column 1). Relative to the baseline probability (1.4%) of owning an alternative fuel vehicle, treated commuters are 46 percent more likely to own a new alternative fuel vehicle. The point estimate in column 2 suggests that treated commuters were .83 percentage points less likely to own a conventional vehicle. Together, these effects

[19] Gillingham (2018), for example, recommends that the US government use a rebound effect of 8% when analyzing the impacts of fuel economy regulations. In the context of Stockholm's congestion pricing system, the permanent reduction in traffic congestion point implies that the direct congestion charge effect outweighed the effect from lighter traffic conditions (Eliasson et al., 2013).

roughly offset, meaning the overall fleet size remains relatively stable (column 3).[20]

Vehicle Kilometers Traveled. Mirroring responses in the vehicle fleet, Panel B of Table 1 shows that Stockholm's congestion charge resulted in an annual increase of 121 vehicle kilometers traveled by commuters in alternative fuel vehicles (column 1) and a decrease of 253 kilometers in fossil fuel vehicles (column 2), which led to a total reduction of 150 vehicle kilometers traveled (column 3).

As calculating the optimal congestion charge requires estimates of changes in the number of trips by vehicle and trip 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 attribute the observed changes in vehicle kilometers traveled to changes in trips inside versus outside the congestion zone. To do so, we combine the above estimates of changes in kilometers traveled by vehicle type with changes in the number of crossings into the cordon zone and information about average commuting trip lengths in Stockholm. We take advantage of the fact that some changes in the congestion zone price only directly impact brown vehicles (i.e., August 2007) and other changes impact only green vehicles (i.e., the removal of the exemption in 2012). These pieces of empirical information combined with an accounting identity relating changes in vehicle kilometers traveled to a weighted average of trip type changes allows us to identify these four derivatives. The details of this exercise are in Appendix E.

Panel B of Table D1 documents that removing the alternative fuel exemption resulted in a decrease of 103 kilometers traveled in alternative fuel vehicles, and an increase of 206 vehicle kilometers traveled in fossil fuel vehicles. This implies that approximately 85% of trips in alternative fuel vehicles and 81% in fossil fuel vehicles were trip changes crossing the congestion zone.[21] Given this information and The Swedish National Travel Survey (2007) on average trip lengths, we infer that implementing the congestion charge led to an increase of 5.9 congestion and .7 non-congestion zone trips per year in alternative fuel vehicles, and a reduction of 11.8 congestion and 2 non-congestion zone trips per year in fossil fuel vehicles (Panel C of Table 1).

Commuting distances. In addition to changing vehicle ownership or driving behavior, treated commuters may sort across the congestion zone, which has implications for the average commute distance of drivers. In Table D2, we estimate the effect of the congestion zone on the likelihood of moving residences (Panel A) and relocating to workplaces (Panel

[20]The pre-period is slightly different across these specifications to match the fact that green vehicles were not exempt during the congestion pricing trial period. As a result, 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 D4 documents that treatment effects perfectly match when using the same reference year for both fuel types.

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

Table 1: Estimated changes in vehicle ownership, kilometers traveled, and commuting distance

	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. Vehicle Kilometers			
Post x Treated Commuters	121.4***	-253.6***	-150.3**
	(26.8)	(71.0)	(69.5)
Mean Kilometers Traveled (t-1)	242.7	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C). The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is the post-period for fossil fuel vehicles. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

B). For this exercise, we restrict the non-treated commuters to individuals living outside the congestion zone — as this allows for a more straightforward interpretation of how neighbors with differing exposure to congestion pricing adjust their commuting distances.

The empirical findings in Panel A suggest that treated commuters are .2 percentage points more likely to move inside the congestion zone relative to non-treated commuters. In addition to moving residences, we also find evidence of moving companies or offices. 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 switch their workplace to be outside of 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. 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.

We estimate that this residential sorting and workplace relocation together reduce commuting distances: Panel C of Table 1 shows that the average commute distance for treated individuals decreased by approximately .086 kilometers relative to the non-treated group.[22] Using our empirical estimates of the changes in the number of non-congestion trips and kilometers traveled, we infer that the average trip distance for travel outside of the congestion zone decreased by .007 kilometers. Both of these results are inputs in our optimal congestion price calculations.

B. Event-study results

To visually assess the plausibility of the parallel trends assumption, Figure 4 displays annual treatment effects estimated from the DiD specification in equation (8). Treated and non-treated commuters display similar trends in alternative fuel vehicle ownership and usage in the pre-exemption period (2003-2006). Treated and non-treated commuters also have comparable trends in vehicle ownership, and vehicle kilometers traveled of fossil fuel vehicles and all vehicles.

Additionally, Panel A and B suggest that individuals exposed to the Stockholm congestion charge were .63 percentage points more likely to own an alternative fuel vehicle and increased the average distance traveled in alternative fuel vehicles by 123 kilometers by the end of 2008. Consequently, the congestion charge can explain 16 and 17 percent of the rise in alternative fuel adoption and usage (Figure D1).[23] Since the first post-period year

[22]Conditional on residential moving, treated commuters reduce their average commute by .62 kilometers. In contrast, relocating to a new workplace does not lead to a significant reduction in commuting distances.

[23]In Panel A of Figure D1, we observe that the share of toll-paying commuters in Stockholm that owned

(2007) is only partially treated as the exemption of alternative fuel vehicles started in August 2007 with the announcement in March 2007, the treatment effects on vehicle ownership of alternative fuel vehicles and kilometers driven are larger in 2008 than in 2007.

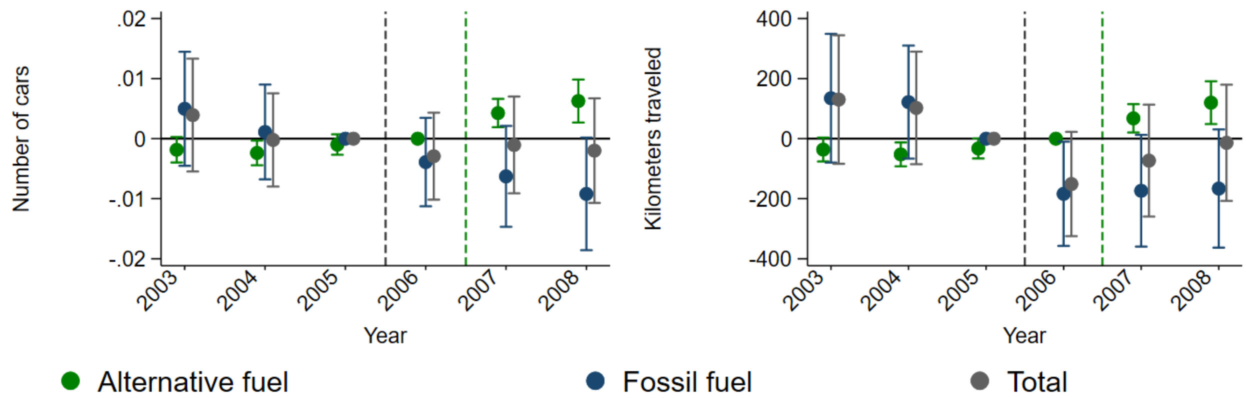

Figure 4: The impact of congestion pricing on alternative fuel vehicles

Notes: These figures plot the annual treatment effect from a dynamic DiD specification (equation 8) on the probability of owning an alternative fuel, fossil fuel, and any vehicle (Panel A) and the kilometers traveled with alternative fuel, fossil fuel, and any vehicle (Panel B). For alternative fuel vehicles, β_{2006} is normalized to zero and 2007-2008 is the post-period. For fossil and any vehicle, β_{2005} is normalized to zero, and 2006-2008 is the post-period. The black and green vertical dashed line denote the imposition of the Stockholm Congestion Trial (2006) and the year of the alternative fuel vehicle exemption (2007). Standard errors are clustered at the neighborhood level.

C. Heterogeneity in responses to congestion pricing

In this subsection, we investigate the heterogeneity in responses to Stockholm's congestion pricing policy. This serves two purposes: it allows us to contribute to discussions regarding the incidence of congestion pricing policies, and it provides the inputs to calculate group-specific optimal congestion prices. The latter may be relevant for policy discussions in cities like San Francisco and New York, which have considered income-based toll systems.

Figure 5 illustrates heterogeneous treatment effects of vehicle ownership and driving behavior of alternative fuel (indicated in green), fossil fuel (indicated in blue), and the total number of vehicles (indicated in gray) for four different income groups. We find an income gradient in both alternative fuel adoption and driving behavior. While individuals with an annual income of more than SEK 600k are more likely to adopt an alternative fuel vehicle and increase vehicle kilometers traveled in alternative fuel vehicles, there is no such effect for individuals with an income of less than SEK 400k. Low-income individuals are

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).

significantly more likely to adopt and drive fossil fuel vehicles. The lack of response on the intensive margin may suggest that low-income individuals cannot switch to cycling or public transportation. One possible explanation for the increased adoption of fossil fuel vehicles is that these vehicles may have traded at a discount on the used market following the regional shift towards alternative fuel vehicles.

Using these differences in responsiveness as well as differences in average trip length, we derive optimal group-specific congestion prices in Section V.

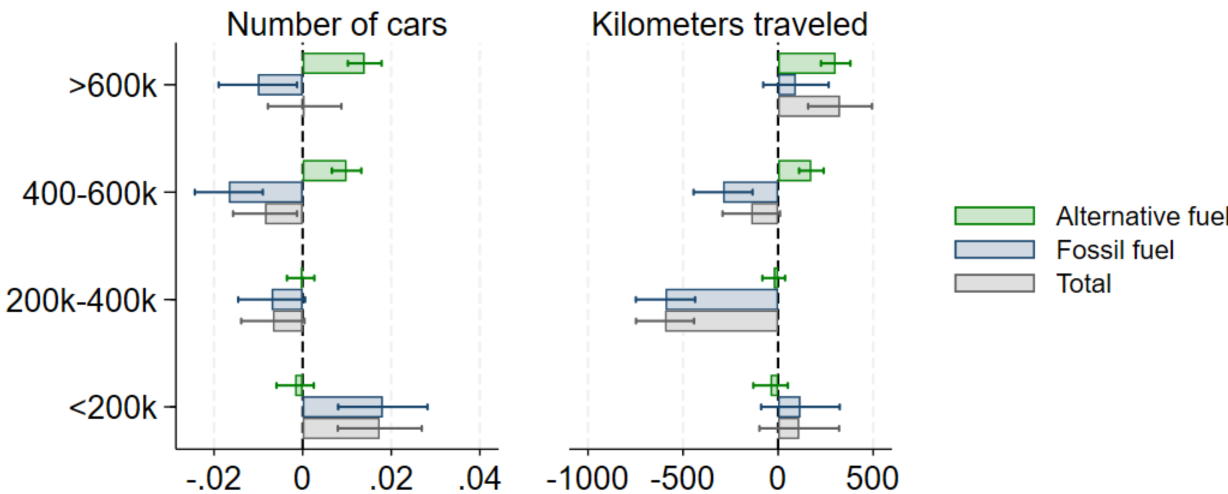

Figure 5: The impact of congestion pricing on income groups

Notes: This figure plots the estimates of the effect of Stockholm's congestion charge on vehicle ownership and driving behavior for alternative (green), fossil fuel (blue), and any vehicle (gray) for four different income groups: Individuals with an annual income of less than 200k SEK, between 200k to 400k SEK, between 400k to 600k SEK, and more than 600k SEK. Green indicates alternative fuel vehicles, blue indicates fossil fuel vehicles, and gray indicates all vehicles. 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. Income groups are based on 2006 demographics. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors clustered by neighborhoods.

In addition to describing heterogeneous responses by income, we present a series of results that describe how different economic and demographic groups responded to Stockholm's congestion pricing system, even though we do not derive optimal congestion prices based on these groups. Figure D3 documents heterogeneous treatment effects along four additional socio-economic dimensions: family size, education, age, and commuting distance. Panel A of Figure D3 suggests 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. Panel B of Table D3 shows that individuals without children are the only group exhibiting a statistically significant reduction in commuting distances;

couples with children increase the distance between their residence and workplace.

Panel B of Figure D3 shows that the response in green vehicle adoption increases with education. This pattern could reflect preferences for new technologies and a higher awareness of the environmental and climate benefits of driving alternative fuel vehicles among highly educated individuals, or may simply reflect the correlation between income and education.

We also show a gradient in the relationship between alternative fuel vehicle adoption and age. Point estimates in Panel C of Figure D3 suggest individuals below 45 are the most responsive group to the policy. In contrast, people close to retirement reduce their driving due to the congestion charge rather than adopting a new vehicle. Panel D of Table D3 also shows that the mean decrease in commuting differences arises from heterogeneous responses by age group. Only individuals aged between 35 and 45 reduce their commuting distance, and those above 60 move farther away from work, on average.

Finally, Panels D and E of Table D3 describe heterogeneity in policy responses broken down by commuting distance. Individuals residing within a 10-kilometer radius of the congestion zone reduce their commuting distance in the post-period (Panel E). The effects of the policy on alternative fuel vehicle adoption and driving, however, are similar across individuals with different commute lengths (Panel D).

D. Robustness

We examine the sensitivity of our main results to alternative sample restrictions and treatment and control group definitions.

In the regressions above, we allow individuals to enter or leave the sample. Restricting the sample to individuals observed in all years (2003-2008) does not meaningfully change our estimates of the impact on vehicle kilometers traveled or alternative fuel vehicle adoption (Table D5). We also show that our results on alternative fuel vehicle adoption and driving behavior are robust to different treatment and control 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 D6). Symmetrically, if we restrict the treatment group to commuters living inside the congestion zone, our estimates become larger (Table D7). This suggests that treated commuters inside the congestion zone are generally less responsive to the policy along each dimension.

If we include commuters who work and reside within the congestion zone (and therefore face no congestion toll on the way to work) into the group of non-treated commuters, we estimate slightly larger effects on green vehicle use and adoption, and smaller effects on fossil fuel vehicle use (Table D8). The high-level takeaways, however, are unchanged.

Finally, our main identification strategy uses variation in whether an individual's workplace is located within or outside of Stockholm's congestion zone. One might worry that the workplaces far outside of the city center are different than those within the congestion zone, and these differences in the workplace could be related to other unobservables that determine responses to congestion pricing. To address this concern, we re-run our main specification, but exclude workplaces far from the cordon boundary. We find that excluding workplaces more than three kilometers from the congestion zone does not affect the coefficients (Table D9). Similarly, we show that including workplace-location fixed effects has virtually no effect on our main results (Table D10).

To summarize our regression results, we find that commuters in Stockholm responded to the city's congestion policy and accompanying green vehicle exemption by reducing trips in conventional vehicles, buying and driving exempt alternative fuel vehicles, and moving their residence or workplace. We now turn to using our estimates of responses to Stockholm's congestion price together with the theoretical model outlined in Section II to recover second-best optimal prices on the non-exempt fleet.

V. Calculating optimal congestion charges

A. Mapping empirical results to theory

To estimate the optimal congestion charge on non-exempt vehicles described in equation (3), we combine estimates of commuter responses to congestion pricing from Section IV with existing estimates of congestion and emission externalities from the literature.

Table 2 summarizes key population statistics (Panel A), policy elasticities (Panel B), and estimates on congestion and emission costs (Panel C) that we use to make these calculations. Appendix E.4 and E.5 provide additional details. We convert externalities into real 2021 € using the Consumer Price Index from Statistics Sweden.

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. The main local air pollutants are ammonia (NH_3), particulate matter (PM), and sulfur dioxide (SO_2), and the global pollutant is carbon dioxide (CO_2). To quantify the emission externalities, we combine the vehicle emission factors – the amount of a particular pollutant that a vehicle emits – with the social costs of each pollutant, as per the European Environment Agency (2014, 2021a).[24] Table E1 summarizes the vehicle

[24]Relative to the average petrol price of 11.4 SEK in Sweden in 2006 (using historical data on fuel prices from *bensinstation.nu*), the emission externalities of €.397 (≈ 3.7 SEK) per liter fuel for brown vehicles correspond to around 32.8 percent of the average petrol price.

emission estimates and costs of pollutants. Emission externalities equal €.04 per kilometer in brown vehicles, and €0 for green vehicles.[25]

Table 2: Parameter estimates used to calculate optimal congestion charges

Coefficient	Description	Type of Car		Source
		Green	Brown	
Panel A: Registry Data				
n_g, n_b	Number of cars per person	.014	1.138	Table 1, Panel A
t_g^c, t_b^c	Congestion trips per person	6.4	399.1	Table 1, Panel B
t_g^o, t_b^o	Non-congestion trips per person	6.9	432.1	Table 1, Panel B
v^c	Commuting distance of congestion trips	17.5		Table 1, Panel C
v^o	Commuting distance of non-congestion trips	19		Swedish National Travel Survey (2007)
Panel B: Policy elasticities				
$\frac{\partial n_g}{\partial \tau}$, $\frac{\partial n_b}{\partial \tau}$	Car ownership	.0064	$-.0083$	Table 1, Panel A
$\frac{\partial t_g^c}{\partial \tau}$, $\frac{\partial t_b^c}{\partial \tau}$	Congestion zone trips	5.9	-11.8	Table D1, Panel B
$\frac{\partial t_g^o}{\partial \tau}$, $\frac{\partial t_b^c}{\partial \tau}$	Non congestion zone trips	.7	-2	Table D1, Panel B
$\frac{\partial v^c}{\partial \tau}$	Length of congestion zone trips	$-.086$		Table 1, Panel C
$\frac{\partial v^o}{\partial \tau}$	Length of non congestion zone trips	$-.007$		Equation (E14)
Panel C: Emission and congestion externalities $[\frac{€}{km}]$				
$\phi_b \cdot l_b$, $\phi_g \cdot l_g$	Emission externalities	.04	0	Table E1
γ^c	Congestion trip externality	.38		External Costs of Transport (2011), Table 38
γ^o	Non-congestion trip externality	.13		

We rely on existing estimates of congestion externalities to assign social costs to congestion zone and periphery trips. Congestion externalities reflect estimates from the External Costs of Transport study (2011), which provides congestion cost estimates for European cities based on traffic speed-flow relationships, vehicle capacity, the value of travel time, and vehicle occupancy. These congestion costs are €.38 per kilometer for trips inside the congestion zone and €.13 per kilometer for trips outside the congestion zone in Stockholm.

Below, we reprint equation (5), which shows how we use policy responses as analogs for the derivatives in our optimal tax formula, equation (3):

[25] Sweden's electricity predominantly comes from renewable sources, meaning that marginal emissions rates are very low (Morfeldt et al., 2021). The European Environmental Agency, for example, estimates that Sweden's electricity production has the lowest carbon intensity out of all of the EU member states (European Environment Agency, 2021b). In other settings, like the United States, where marginal emissions factors for electricity consumption are higher, it may be necessary to include nonzero per-mile emissions externalities for green vehicles.

$$\tau \;=\; \underbrace{\Delta N_g(\widetilde{\phi}_g+\widetilde{\gamma}_g)}_{\triangle Green\ Cars} + \underbrace{\Delta N_b(\widetilde{\phi}_b+\widetilde{\gamma}_b)}_{\triangle Brown\ Cars} + \underbrace{\Delta T\cdot(\overline{\phi}+\overline{\gamma})}_{\triangle Trips} + \underbrace{\Delta V^c(\hat{\phi}^c+\hat{\gamma}^c)}_{\triangle Inside\ Driving} + \underbrace{\Delta V^o(\hat{\phi}^o+\hat{\gamma}^o)}_{\triangle Outside\ Driving}$$

$$\tau \;=-\text{€}.02 \;+\; \text{€}2.15 \;+\text{€}6.32 \;+\; \text{€}.97 \;+\; \text{€}.04 \;\approx\; \text{€}9.46 \tag{9}$$

Our baseline estimate of the optimal congestion charge for non-exempt vehicles is €9.46 per trip. Using an average congestion zone trip length of 17.5 kilometers, this corresponds to €.54 per kilometer. Congestion-related terms – whether direct congestion externalities or changes in congestion related to responses in fleet size or trip length – account for around 89 percent (€8.39) of the total charge. Emissions-related terms account for the remaining 11 percent (€1.07).

We can contextualize our estimate in two ways. First, we can compare it to the actual charge levied by Stockholm. Second, we can compare our estimated optimal charge to the naive Pigouvian benchmark, where the toll price reflects the average emissions and congestion externalities associated with trips that use the cordon zone, but does not account for spillovers, moving decisions, or vehicle purchases. Our optimal toll estimate is above both Stockholm's congestion price (€4.78) as well as the naive Pigouvian benchmark (€7.35).

Table 3: Congestion charge decomposition

		Externality (€)	
	Per crossing (€)	Congestion	Emission
Fleet Size	**2.13**		
Number of green vehicles $\Delta N_g(\widetilde{\phi}_g+\widetilde{\gamma}_g)$	$-.02$	-0.02	0
Number of brown vehicles $\Delta N_b(\widetilde{\phi}_b+\widetilde{\gamma}_b)$	2.15	1.85	.3
Number of Trips	**6.32**		
Green trips outside $\Delta T^o_g(\overline{\phi^o_g}+\overline{\gamma^o_g})$	0	0	0
Green trips inside $\Delta T^c_g(\overline{\phi^c_g}+\overline{\gamma^c_g})$	$-.03$	$-.03$	0
Brown trips inside $\Delta T^c_b(\overline{\phi^c_b}+\overline{\gamma^c_b})$	5.9	5.34	.56
Brown trips outside $\Delta T^o_b(\overline{\phi^o_b}+\overline{\gamma^o_b})$	.45	.34	.11
Commuting Distance	**1.01**		
Inside commute length $\Delta V^c(\hat{\phi}^c+\hat{\gamma}^c)$	.97	.88	.09
Outside commute length $\Delta V^o(\hat{\phi}^o+\hat{\gamma}^o)$	.04	.03	.01
Congestion charge (€)	**9.46**	**8.39**	**1.07**

Notes: This table reports the congestion charge per crossing from equation (9) separated by each component (column 1). We split the congestion charge by congestion (column 2) and emission externalities (column 3). All charges and externalities are expressed in real 2021 €.

To better understand how the different responses to congestion pricing contribute to the optimal charge, Table 3 decomposes the optimal charge into the three components: fleet size, number of trips, and commuting distance. First, the "fleet size" component accounts for €2.13 (23%) of the total optimal charge. This reflects the induced decrease in the brown vehicle fleet and its associated externalities (€2.15) and the increase in the size of the green vehicle fleet and its associated externalities (€ − .02). Second, the "number of trips" component accounts for €6.32 (62%) of the total congestion charge. This term largely reflects the impact of the zone on total brown trips inside and outside of the zone; increases in driving in green vehicles decreases this term by just €.03. As the brown fleet is substantially larger than the green fleet, a change in the number of brown trips has a much greater impact on externalities compared to an equivalent change in green trips. Third, €1.01 (11%) of the congestion charge reflects responses in commuting distances. This term comes from a shorter commuting distance between the neighborhood and the workplace (€.97). As a result of relocating, the charge also reduces the distance of non-congestion zone trips (€.04).

B. Extensions

We calculate several variations of equation (5) with the goal of providing intuition for how our baseline estimate changes under alternative policy designs. Figure 6 reports these extensions alongside our initial results ("Baseline").

First, we calculate the optimal uniform congestion charge assuming no exemptions. This is the empirical analog of equation (A19). We find that the optimal uniform charge equals €10.3, primarily due to its stronger impact on reducing brown vehicle trips compared to a charge with exemptions. The fact that the uniform congestion charge exceeds the charge with exemptions suggests that the larger reduction in brown vehicle trips also outweighs the emission benefits from green car exemptions.

To accommodate pre-existing policies in our framework, we implement the optimal congestion charge formula that accounts for pre-existing environmental fuel taxes and green vehicle subsidies (Proposition A18). We calculate the *uninternalized* marginal emission externalities for brown vehicles by subtracting the carbon tax on fuel (€.023 per kilometer) from the total emission externalities.[26] Given an average vehicle lifetime of 16.3 years in Sweden (Morfeldt & Johansson, 2022), the 10,000 SEK vehicle rebate provided during the exemption period (converts to €1,212 in 2021) corresponds to an annualized subsidy of €74 over the driving lifecycle of the vehicle. On net, we find that the effects of pre-existing en-

[26]Using data on fuel tax components retrieved from the Budget Bill of the Swedish Swedish Ministry of Finance (2010), the carbon tax, which is included in the Swedish retail fuel price, was 2.13 SEK per liter in 2006.

vironmental fuel taxes slightly dominate the green vehicle subsidies in our setting (€8.89). Elsewhere, this may not be the case. In the United States, for example, environmental fuel taxes tend to be low or nonexistent, and EV subsidies are substantial. As a result, the second-best optimal congestion prices that account for these existing policies may be meaningfully higher than one would estimate if they ignored overlapping policies.

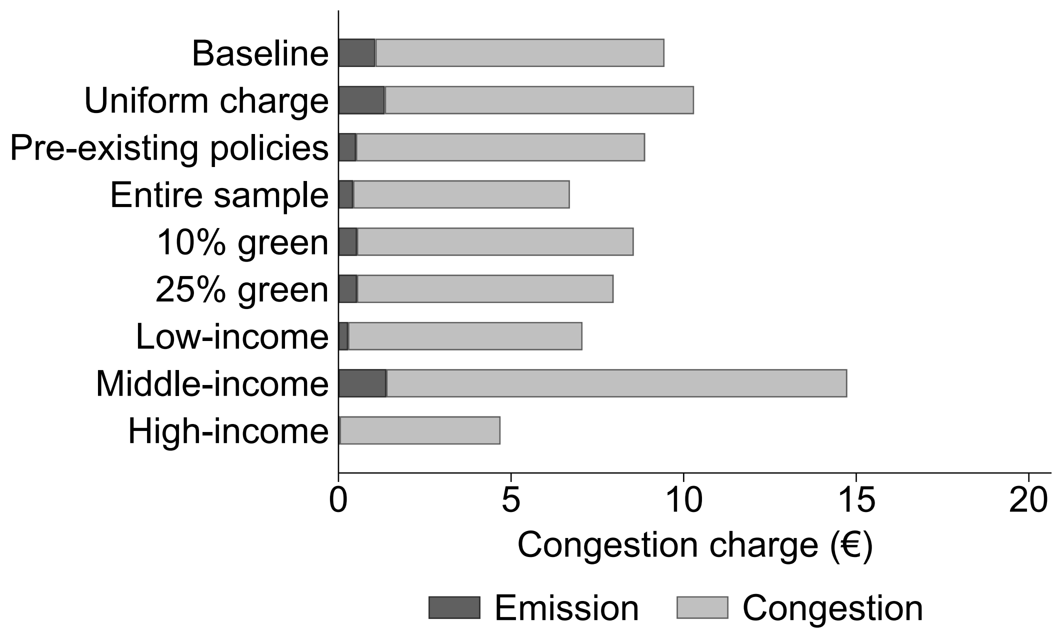

Figure 6: Congestion charges under alternative assumptions

Notes: This figure reports the optimal brown vehicle congestion charge across a range of assumptions. The first bar reports our baseline calculations using equation (5), separated by emission-related (black) and congestion-related externalities (grey). The second bar shows the optimal uniform charge for all vehicle crossings according to equation (A19). The third bar reports the charge accounting for existing Swedish policies. The fourth bar reports the congestion charge for all commuters with vehicles. The fifth and sixth bars report the congestion charge, assuming that 10% and 25% of vehicles and trips are made with green vehicles. The seventh, eighth, and ninth bars report the congestion charge using the responses of low-, medium-, and high-income individuals.

In our baseline specification, we use the average commuting distance among treated and non-treated commuters in Stockholm, which excludes nearby commuters ($< 3\ km$). In contrast, if we include all individuals who commute to work and own at least one vehicle, the average commuting distance shrinks to 11.9 km and the optimal charge falls to €7.1. Intuitively, longer per-trip commuting distances increase the optimal congestion charge.

The fifth and sixth bars illustrate the impact of a rising share of green vehicles on second-best congestion charges. Before the introduction of the charge, approximately 1% of vehicles were green, and 1.5% of vehicle kilometers were traveled in green vehicles. If we instead assume that the fleet is 10% or 25% green vehicles, the corresponding optimal charge on non-exempt vehicles would be €9.1 and €8.5. All else equal, a larger green vehicle fleet allows for more between-vehicle switching, which drives down the optimal second-best price.

The following three bars report the congestion charge using the responses of low-, medium-, and high-income individuals from Section C. 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 optimal congestion charge for this group is €7.4. In contrast, middle-income individuals respond by reducing their vehicle trips, thereby mitigating emissions and congestion-related externalities. As a result, the optimal congestion charge for this group is €16.2. High-income individuals tend to respond by shifting their travel towards exempted vehicles; their propensity to do so mutes the optimal congestion charge for their group (€4.7).

The systematic differences in how individuals adjust to the congestion fee relates to a common objection that the benefits and costs are distributed unevenly across socioeconomic groups. In addition to the substitution pattern to other transportation modes, three additional dimensions influence the regressive effect of the policy. First, congestion fees constitute a non-negligible portion of income and fall disproportionately on low-income individuals. Figure D4 documents that the congestion charge accounts for approximately .68 percent of the annual income for the lowest income decile and .16 percent for the highest income decile in 2016. 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). Because the benefits of exempting alternative fuel vehicles in Stockholm are centered among high-income groups, the exemption makes the congestion charge's distributional profile even more regressive.[27]

C. Cost-benefit analysis of green vehicle exemptions

Comparing the costs and benefits of induced green vehicle adoption. Exempting green vehicles in congestion pricing schemes trades off reductions in one externality (pollution) for another (congestion). In Section II we show how we can compare the total benefits of induced green vehicle adoption to the total foregone congestion benefits. As the share of green vehicles increases, it becomes less attractive to exempt green vehicles from congestion

[27]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). This reinforces the regressivity, as most company vehicle drivers belong to the highest income bracket.

pricing. At the extreme, there are no emissions benefits from exempting green vehicles if the fleet is 100 percent clean, but substantial costs in foregone reductions in congestion. Our estimated responses in trips taken and vehicle adoption allow us to quantify this tradeoff and calculate the break-even point in the share of green vehicles.

Using the estimates from Section IV and solving equation (6) for the number of green cars per capita n_g^*, we can estimate this cutoff:

$$n_g^* \;=\; \frac{.04\frac{€}{km} \cdot 15,202km \cdot .0064}{17.5km \cdot .38\frac{€}{km} \cdot (11.8 - 5.9)} \;= .099 \tag{10}$$

The numerator is the annual marginal emission benefits of replacing a brown car with a green car (€608) multiplied by the green car adoption in induced by the congestion charging exemptions. The denominator is the annual change in green congestion zone trips per vehicle induced by the exemption. The resulting cutoff is $n_g^* = .099$, assuming that the observed responses to the policy would be similar for modestly different levels of green vehicle adoption. Above this cutoff, the costs of exempting green vehicles outweigh the associated emissions benefits. The size of the green fleet in Stockholm was below this cutoff in the exemption period ($n_g = .04$). When solely accounting for *uninternalized* emission externalities, however, this cutoff is roughly $n_g = .04$, suggesting that the costs and benefits of inducing green vehicles via exemptions were roughly offset during Stockholm's exemption phase.

Calculating the implied cost per vehicle. In addition to understanding whether green vehicle exemptions pass cost-benefit, policymakers may also be interested in the per-vehicle cost of inducing adoption via congestion charge exemptions. This figure allows for comparisons between different available policy levers for encouraging green vehicle adoption. We compute this cost using a simple ratio of policy responses and externalities. The annual marginal costs of inducing .0064 alternative fuel vehicles through the exemption is 5.9 non-avoided congestion zone trips, multiplied by the per-trip congestion costs ($v^c\gamma^c$)

$$MC^{congestion}(.04) = \frac{(11.8 - 5.9)}{.0064}(.04 \cdot 17.5km \cdot .38\frac{€}{km}) = 245.22 \tag{11}$$

The marginal congestion costs per additional green car are €245 annually and €1,225 for the five-year exemption period of alternative fuel cars (August 2007 - August 2012). To put this number in context, during the same period, the Swedish government offered a 10,000 SEK vehicle rebate (converts to €1,212 in 2021). Assuming that 52% of adopters were inframarginal (i.e., who would have purchased a green car without incentives) (Fournel, 2023), the vehicle rebate cost the Swedish government €2,331 per additional green car, which is around €1,106 more than through the congestion charge exemptions.

VI. Conclusion

Many planned or existing road pricing policies fold together environmental and transportation goals. 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 reflect emission and congestion externalities and include three responses to these policies — 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 additional responses to road pricing, recovering optimal prices requires only policy elasticities. 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 demonstrating 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 take more trips with exempted alternative fuel vehicles or switch 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 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 commuting distances outweigh the damages from substituting to other roads and 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 Green Vehicle Exemptions:
Theory and Evidence

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A. Derivations

In this Appendix, we derive optimal congestion charges for (a) policies that exempt green vehicles, (b) policies that charge all vehicles, and (c) policies that charge different tolls for green vehicles versus brown vehicles. We also cover several related extensions, like adjusting optimal tolls to account for pre-existing policies that influence the marginal cost of driving.

A.1. Optimal congestion charges with green exemptions

We begin by taking first-order conditions of the consumer's problem (see equation 1):

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

The derivative of W, social welfare, with respect to congestion charge τ is:

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

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

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

Solving this equation for the optimal congestion charge τ results in Proposition 1.

A.2. Writing the optimal congestion charge in terms of policy responses

Here, we rephrase the optimal congestion tax for policies that exempt green vehicles in terms of observable statistics and policy responses.

Externalities. First, we define the annual emission and congestion externalities per vehicle ($\widetilde{\phi}$ and $\widetilde{\gamma}$) as the product of the emission and congestion damages per kilometer traveled and the kilometers traveled by each vehicle. We calculate this figure separately for green and brown vehicles. The total emission and congestion externalities (expressed in €) per vehicle per year are:

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

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

Second, we define emission and congestion externalities per fleet-trip ($\overline{\phi}$ and $\overline{\gamma}$) as the product of the per-kilometer externality, the number of vehicles, and the average trip distance. We calculate these parameters separately by trip type (inside versus outside) and vehicle type (green or brown), leaving us with eight total parameters:

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

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

Third, we define emission and congestion externalities per fleet kilometer traveled ($\hat{\phi}$ and $\overline{\gamma}$) as the product of the per-kilometer externalities, the number of vehicles, and the number of trips taken. We calculate this parameter separately by trip type (inside versus outside) and vehicle type (green versus brown), leaving us with four parameters:

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

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

Policy responses. We discretize the derivatives of the fleet composition, the number of trips, and commuting distances with respect to the congestion charge and scale them by the common denominator in equation (3) ($\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b$) as follows:

$$\Delta N_g = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial n_g}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta n_g}{\Delta \tau} = \frac{\Delta n_g}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A7}$$

$$\Delta N_b = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial n_b}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta n_b}{\Delta \tau} = \frac{\Delta n_b}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A8}$$

$$\Delta T_g^o = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial t_g^o}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta t_g^o}{\Delta \tau} = \frac{\Delta t_g^o}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A9}$$

$$\Delta T_g^c = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial t_g^o}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta t_g^c}{\Delta \tau} = \frac{\Delta t_g^c}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A10}$$

$$\Delta T_b^o = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial t_b^o}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta t_b^o}{\Delta \tau} = \frac{\Delta t_b^o}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A11}$$

$$\Delta T_b^c = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial t_b^c}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta t_b^c}{\Delta \tau} = \frac{\Delta t_b^c}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A12}$$

$$\Delta V^c = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial v^c}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta v^c}{\Delta \tau} = \frac{\Delta v^c}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A13}$$

$$\Delta V^o = \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \frac{\partial v^o}{\partial \tau} = \frac{1}{(\frac{\Delta n_b}{\Delta \tau} t_b^c + \frac{\Delta t_b^c}{\Delta \tau} n_b)} \frac{\Delta v^o}{\Delta \tau} = \frac{\Delta v^o}{(\Delta n_b t_b^c + \Delta t_b^c n_b)} \tag{A14}$$

As the derivatives in the numerator and the denominator of each response include the change in the congestion charge ($\Delta\tau$), this term cancels out in all equations. Therefore, the congestion charge formula depends only on the responsiveness to taxes, not the magnitude of the tax change used to estimate these empirical objects. Plugging in the converted externalities and discretized responses to the congestion charges allows us to rearrange equation (3) as equation (5).

A.3. Special cases

The optimal congestion charge on non-exempt vehicles described in equation (3) has several special cases that provide insight into how optimal congestion tolls reflect the consumer's different margins of response. We highlight four special cases of particular interest.

No congestion externalities ($\gamma^c = \gamma^o = 0$):

$$\tau^{emission} \;=\; \Delta N_g \cdot (\widetilde{\phi_g}) + \Delta N_b \cdot \widetilde{\phi_b} \;+\; \Delta T \cdot \overline{\phi} \;+\; \Delta V^c \cdot \hat{\phi}^c + \Delta V^o \cdot \hat{\phi}^o + \overline{\phi_b^c} \tag{A15}$$

No emission externalities ($\phi_g = \phi_b = 0$):

$$\tau^{congestion} \;=\; \Delta N_g \cdot (\widetilde{\gamma_g}) + \Delta N_b \cdot \widetilde{\gamma_b} \;+\; \Delta T \cdot \overline{\gamma} \;+\; \Delta V^c \cdot \hat{\gamma}^c + \Delta V^o \cdot \hat{\gamma}^o + \overline{\gamma_I^c} \tag{A16}$$

No trip leakage ($\frac{\partial t^o}{\partial \tau} = 0$):

$$\begin{aligned}
\tau^{no\ leakage} \;=\; & \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \Bigg(\frac{\partial n_g}{\partial \tau} \Big((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o \Big) \\
& + \frac{\partial n_b}{\partial \tau} \Big((v^c t_b^c + v^o t_b^o) l_b \phi_b + v^c t_b^c \gamma^c + v^o t_b^o \gamma^o \Big) \\
& + \frac{\partial t_g^c}{\partial \tau} \Big(n_g v^c (l_g \phi_g + \gamma^c) \Big) + \frac{\partial t_b^c}{\partial \tau} \Big(n_b v^c (l_b \phi_b + \gamma^c) \Big) \\
& + \frac{\partial v^c}{\partial \tau} \Big(n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c) \gamma^c \Big) \\
& + \frac{\partial v^o}{\partial \tau} \Big(n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_g^o) \gamma^o \Big) \Bigg)
\end{aligned} \tag{A17}$$

Pre-existing policies: Here, there are two pre-existing policies that interact with congestion pricing. First, in some settings, existing environmental regulations already partially internalize the per-mile pollution externalities associated with driving brown vehicles. We, therefore, replace the brown vehicle emissions externalities, ϕ_b,with the uninternalized externality, $\mathring{\phi}_b$. Second, depending on the setting, green vehicles may be subsidized. To account for existing subsidies, we include a term, s, that acts to reduce the cost of purchasing a green vehicle. Tracing these changes through the derivation of Proposition 1 yields the following optimal tax formula, which also accounts for these two types of pre-existing regulation:

$$\begin{aligned}
\tau^{policies} = & \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b)} \Bigg(\frac{\partial n_g}{\partial \tau} \Big((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o + s \Big) \\
& + \frac{\partial n_b}{\partial \tau} \Big((v^c t_b^c + v^o t_b^o) l_b \mathring{\phi}_b + v^c t_b^c \gamma^c + v^o t_b^o \gamma^o \Big) \\
& + \frac{\partial t_g^o}{\partial \tau} \Big(n_g v^o (l_g \phi_g + \gamma^o) \Big) + \frac{\partial t_g^c}{\partial \tau} \Big(n_g v^c (l_g \phi_g + \gamma^c) \Big) \\
& + \frac{\partial t_b^o}{\partial \tau} \Big(n_b v^o (l_b \mathring{\phi}_b + \gamma^o) \Big) + \frac{\partial t_b^c}{\partial \tau} \Big(n_b v^c (l_b \mathring{\phi}_b + \gamma^c) \Big) \\
& + \frac{\partial v^c}{\partial \tau} \Big(n_b t_b^c l_b \mathring{\phi}_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c) \gamma^c \Big) \\
& + \frac{\partial v^o}{\partial \tau} \Big(n_b t_b^o l_b \mathring{\phi}_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_b^o) \gamma^o \Big) \Bigg)
\end{aligned} \tag{A18}$$

A.4. Optimal congestion charges without exemptions

This section shows the steps in deriving the optimal "uniform" congestion tax. That is, the optimal charge, τ^u, levied on all vehicles entering the congestion zone without any exemptions. We begin by taking first-order conditions of the consumer's problem (see equation 1). This process is the same as the process for deriving the optimal tax with exemptions, but the congestion tax now enters the representative consumer's utility whenever either type of vehicle, green or brown, takes a cordon zone trip.

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

The derivative of W, social welfare, with respect to the uniform congestion charge τ^u is:

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

The social planner chooses the congestion charge, taking into account how the representative agent will respond (see equation 1). Plugging in the first-order conditions of the representative agent, we have:

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

Solving this equation for the optimal uniform congestion charge τ^u yields:

$$
\begin{aligned}
\tau^u \;=\; & \frac{1}{(\frac{\partial n_b}{\partial \tau} t_b^c + \frac{\partial t_b^c}{\partial \tau} n_b + \frac{\partial n_g}{\partial \tau} t_g^c + \frac{\partial t_g^c}{\partial \tau} n_g)}\Bigg(\frac{\partial n_g}{\partial \tau}\Bigg((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o\Bigg) \\
&+ \frac{\partial n_b}{\partial \tau}\Bigg((v^c t_b^c + v^o t_b^o) l_b \phi_b + v^c t_b^c \gamma^c + v^o t_b^o \gamma^o\Bigg) \\
&+ \frac{\partial t_g^o}{\partial \tau}\Bigg(n_g v^o (l_g \phi_g + \gamma^o)\Bigg) + \frac{\partial t_g^c}{\partial \tau}\Bigg(n_g v^c (l_g \phi_g + \gamma^c)\Bigg) \\
&+ \frac{\partial t_b^o}{\partial \tau}\Bigg(n_b v^o (l_b \phi_b + \gamma^o)\Bigg) + \frac{\partial t_b^c}{\partial \tau}\Bigg(n_b v^c (l_b \phi_b + \gamma^c)\Bigg) \\
&+ \frac{\partial v^c}{\partial \tau}\Bigg(n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_g + (n_b t_b^c + n_g t_g^c)\gamma^c\Bigg) \\
&+ \frac{\partial v^o}{\partial \tau}\Bigg(n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_b^o)\gamma^o\Bigg)\Bigg)
\end{aligned} \tag{A19}
$$

A.5. The optimal differentiated congestion charge

This section shows the steps in deriving the optimal differentiated congestion charge, which sets different tolls for green (τ_g) and brown vehicles (τ_b) entering the congestion zone. 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 give the congestion charge for green (τ_g) and brown vehicles (τ_b). The representative agent's problem is:

$$\begin{aligned}\max_{n_g,n_b,t_g^c,t_g^o,t_b^c,t_b^o,v^c,v^o} B \;=\; & \underbrace{\mu_g(n_g)[u_g^c(t_g^c)+u_g^o(t_g^o)]}_{\text{utility from green trips}} - \underbrace{n_g((p^c+p_el_e)v^c+\tau_g)t_g^c - n_g(p^o+p_el_e)v^ot_g^o}_{\text{utility cost of green trips}} \\ & + \underbrace{\mu_b(n_b)[u_b^c(t_b^c)+u_b^o(t_b^o)]}_{\text{utility from brown trips}} - \underbrace{n_b((p^c+p_bl_b)v^c+\tau_b)t_b^c - n_b(p^o+p_bl_b)v^ot_b^o}_{\text{utility cost of brown trips}} \\ & - \underbrace{n_bc_b - n_gc_g}_{\text{cost of vehicles}} - \underbrace{r^c(v^c)-r^o(v^o)}_{\text{cost of location choice}} + y. \qquad \text{(A20)}\end{aligned}$$

The consumer's first-order conditions are:

$$\begin{aligned}\frac{\partial B}{\partial n_g} &= 0 = \mu_g'[u_g^c(t_g^c)+u_g^o(t_g^o)] - ((p^c+p_gl_g)v^c+\tau_g)t_g^c - (p^o+p_gl_g)t_g^ov^o - c_g \\ \frac{\partial B}{\partial n_b} &= 0 = \mu_b'[u_b^c(t_b^c)+u_b^o(t_b^o)] - ((p^c+p_bl_b)v^c+\tau_b)t_b^c - (p^o+p_bl_b)t_b^ov^o - c_b \\ \frac{\partial B}{\partial t_b^c} &= 0 = \mu_b(n_b)[u'^c_b(t_b^c)] - n_b((p^c+p_bl_b)v^c+\tau_b) \\ \frac{\partial B}{\partial t_g^c} &= 0 = \mu_g(n_g)[u'^c_g(t_g^c)] - n_g(p^c+p_gl_g)v^c+\tau_g) \\ \frac{\partial B}{\partial t_b^o} &= 0 = \mu_b(n_b)[u'^o_b(t_b^o)] - n_b(p^o+p_bl_b)v^o \\ \frac{\partial B}{\partial t_g^o} &= 0 = \mu_g(n_g)[u'^o_g(t_g^o)] - n_g(p^o+p_gl_g)v^o \\ \frac{\partial B}{\partial v^o} &= 0 = -n_g(p^c+p_gl_g)t_g^o - n_b(p^o+p_bl_b)t_b^o - r'(v^c) \\ \frac{\partial B}{\partial v^c} &= 0 = -n_g(p^c+p_gl_g)t_g^c - n_b(p^c+p_bl_b)t_b^c - r'(v^c).\end{aligned}$$

The social planner's problem is to maximize consumer welfare $B^{-\tau}$ from equation (A20) by setting congestion charge for green (τ_g) and brown vehicles (τ_b) entering the congestion zone:

$$\begin{aligned} \underset{\tau_g,\tau_b}{max}\ W = B^{-\tau} \ -\ & \underbrace{n_b(v^c t_b^c + v^o t_b^o) l_b \phi_b}_{\text{emission from brown trips}} - \underbrace{n_g(v^c t_g^c + v^o t_g^o) l_g \phi_g}_{\text{emission from green trips}} \\ -\ & \underbrace{(n_b v^c t_b^c + n_g v^c t_g^c)\gamma^c}_{\text{congestion from inside trips}} - \underbrace{(n_b v^o t_b^o + n_g v^o t_g^o)\gamma^o}_{\text{congestion from outside trips}}. \end{aligned} \tag{A21}$$

The derivative of W with respect to congestion charge on brown vehicles τ_b is:

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

The derivative of W with respect to congestion charge on green vehicles τ_g is:

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

The social planner chooses the congestion charge for green and brown vehicles, taking into account how the representative agent will respond. Plugging in the first-order conditions of the representative agent, we have:

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

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

Solving this system of two equations and unknowns gives the optimal congestion charges for brown and green vehicles.

Proposition 2. *The second-best congestion charge on brown* τ_b *and green vehicles* τ_g *per crossing that address congestion and emission externalities through changes in the fleet composition, the number of trips, and the commuting distance are given by*

$$\tau_b^* = \frac{(c+da)}{(1-db)} \tag{A22}$$

$$\tau_g^* = a + b\frac{(c+da)}{(1-db)}, \tag{A23}$$

where a, b, c, and d are functions of derivatives of the congestion charges and the externalities. The expressions for a, b, c, and d are:

$$\begin{aligned} a =& \frac{1}{\frac{\partial n_g}{\partial \tau_g}t_g^c + \frac{\partial t_g^c}{\partial \tau_g}n_g}\Bigg(\frac{\partial n_g}{\partial \tau_g}\Big((v^c t_g^c + v^o t_g^o)l_g\phi_g + v^c t_g^c\gamma^c + v^o t_g^o\gamma^o\Big) \\ &+ \frac{\partial n_b}{\partial \tau_g}\Big((v^c t_b^c + v^o t_b^o)l_b\phi_b + v^c t_b^c\gamma^c + v^o t_b^o\gamma^o\Big) \\ &+ \frac{\partial t_g^o}{\partial \tau_g}\Big(n_g v^o l_g\phi_g + n_g v^o\gamma^o\Big) + \frac{\partial t_g^c}{\partial \tau_g}\Big(n_g v^c l_g\phi_g + n_g v^c\gamma^c\Big) \\ &+ \frac{\partial t_g^o}{\partial \tau_g}\Big(n_g v^o l_g\phi_g + n_g v^o\gamma^o\Big) + \frac{\partial t_g^c}{\partial \tau_g}\Big(n_g v^c l_g\phi_g + n_g v^c\gamma^c\Big) \\ &+ \frac{\partial v^c}{\partial \tau_g}\Big(n_b t_b^c l_b\phi_b + n_g t_g^c l_g\phi_b + (n_b t_b^c + n_g t_g^c)\gamma^c\Big) \\ &+ \frac{\partial v^o}{\partial \tau_g}\Big(n_b t_b^o l_b\phi_b + n_g t_g^o l_g\phi_g + (n_b t_b^o + n_g t_g^o)\gamma^o\Big)\Bigg) \end{aligned} \qquad b = -\frac{\frac{\partial n_b}{\partial \tau_g}t_b^c + \frac{\partial t_b^c}{\partial \tau_g}n_b}{\frac{\partial n_g}{\partial \tau_g}t_g^c + \frac{\partial t_g^c}{\partial \tau_g}n_g}$$

$$\begin{aligned} c =& \frac{1}{\frac{\partial n_b}{\partial \tau_b}t_b^c + \frac{\partial t_b^c}{\partial \tau_b}n_b}\Bigg(\frac{\partial n_g}{\partial \tau_b}\Big((v^c t_g^c + v^o t_g^o)l_g\phi_g + v^c t_g^c\gamma^c + v^o t_g^o\gamma^o\Big) \\ &+ \frac{\partial n_b}{\partial \tau_b}\Big((v^c t_b^c + v^o t_b^o)l_b\phi_b + v^c t_b^c\gamma^c + v^o t_b^o\gamma^o\Big) \\ &+ \frac{\partial t_g^o}{\partial \tau_b}\Big(n_g v^o l_g\phi_g + n_g v^o\gamma^o\Big) + \frac{\partial t_g^c}{\partial \tau_b}\Big(n_g v^c l_g\phi_g + n_g v^c\gamma^c\Big) \\ &+ \frac{\partial t_b^o}{\partial \tau_b}\Big(n_b v^o l_b\phi_b + n_b v^o\gamma^o\Big) + \frac{\partial t_b^c}{\partial \tau_b}\Big(n_b v^c l_b\phi_b + n_b v^c\gamma^c\Big) \\ &+ + \frac{\partial v^c}{\partial \tau_b}\Big(n_b t_b^c l_b\phi_b + n_g t_g^c l_g\phi_b + (n_b t_b^c + n_g t_g^c)\gamma^c\Big) \\ &+ \frac{\partial v^o}{\partial \tau_b}\Big(n_b t_b^o l_b\phi_b + n_g t_g^o l_g\phi_g + (n_b t_b^o + n_g t_g^o)\gamma^o\Big)\Bigg) \end{aligned} \qquad d = -\frac{\frac{\partial t_g^c}{\partial \tau_b}n_g + \frac{\partial n_g}{\partial \tau_b}t_g^c}{\frac{\partial n_b}{\partial \tau_b}t_b^c + \frac{\partial t_b^c}{\partial \tau_b}n_b}$$

This system of optimal taxes can inform decisions regarding congestion prices that vary by vehicle type. Specifically, a first-order question is whether EVs would be taxed at a positive level under a second-best tax that distinguishes only between conventional and EVs.

Proposition 2 holds two insights that speak to this question: First, if demand for brown vehicle ownerships and trips does not depend on the congestion charge levied on green vehicles, then green vehicles are taxed at a positive level under the second-best optimal tax scheme. Second, the optimal tax on green vehicles is decreasing in the pollution level of brown vehicles so long as sorting responses to congestion pricing are sufficiently small. We briefly explain each claim below.

First, if the cross-price elasticity between green taxes and both brown trip and brown vehicle purchases are zero and leakage is incomplete, then the optimal differentiated green tax from equation (A23) is greater than zero:

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

This allows us to rewrite the green tax as:

$$
\begin{aligned}
\tau_g = & \frac{1}{\frac{\partial n_g}{\partial \tau_g} t_g^c + \frac{\partial t_g^c}{\partial \tau_g} n_g} \left(\frac{\partial n_g}{\partial \tau_g} \left((v^c t_g^c + v^o t_g^o) l_g \phi_g + v^c t_g^c \gamma^c + v^o t_g^o \gamma^o \right) \right. \\
& + \frac{\partial t_g^o}{\partial \tau_g} \left(n_g v^o l_g \phi_g + n_g v^o \gamma^o \right) \\
& + \frac{\partial t_g^c}{\partial \tau_g} \left(n_g v^c l_g \phi_g + n_g v^c \gamma^c \right) \\
& + \frac{\partial v^c}{\partial \tau_g} \left(n_b t_b^c l_b \phi_b + n_g t_g^c l_g \phi_b + (n_b t_b^c + n_g t_g^c) \gamma^c \right) \\
& \left. + \frac{\partial v^o}{\partial \tau_g} \left(n_b t_b^o l_b \phi_b + n_g t_g^o l_g \phi_g + (n_b t_b^o + n_g t_g^o) \gamma^o \right) \right).
\end{aligned}
$$

It is sufficient but not necessary for trip leakage to be incomplete (i.e., the total damages induced by taking trips outside of the congestion zone are less than the externalities from reduced downtown trips, $|\frac{\partial t_g^o}{\partial \tau_g}\left(n_g v^o l_g \phi_g + n_g v^o \gamma^o\right)| < |\frac{\partial t_g^c}{\partial \tau_g}\left(n_g v^c l_g \phi_g + n_g v^c \gamma^c\right)|$) for the above expression of τ_g to be positive.

Intuitively, if these goods are neither substitutes nor complements, the system of equations collapses into two separate second-best tax problems for each vehicle type. As driving in green cars still causes congestion, the optimal tax on this type of vehicle is not zero. This zero cross-price elasticity scenario is not meant to be taken as a description; instead, it serves to show that the rationale for exempting green vehicles is weaker when they are weak substitutes for conventional fossil fuel vehicles.

Second, the cleaner the brown vehicle fleet, the more likely the optimal differentiated charge on green vehicles will be positive. Consider the scenario where both brown and green vehicle emissions approach zero. In this case, the only rationale for a negative tax on either vehicle type would be if leakage induced by the congestion pricing policy generated social damages greater than the social benefits from fewer downtown trips. In terms of the equations presented above, if leakage is incomplete (i.e., the increase in non-cordon externalities is smaller than the decrease in cordon-zone externalities) and own-price derivatives are negative, then (a) terms a and c will be unambiguously positive, (b) $0 < bd < 1$, and (c) both b and d are positive. This means that the taxes on both vehicle types will be positive.

B. Additional background on Stockholm's congestion pricing

In this section, we provide additional details on Stockholm's congestion pricing scheme as a complement to the context provided in Section III.

B.1. Congestion tolls by time of day in Stockholm

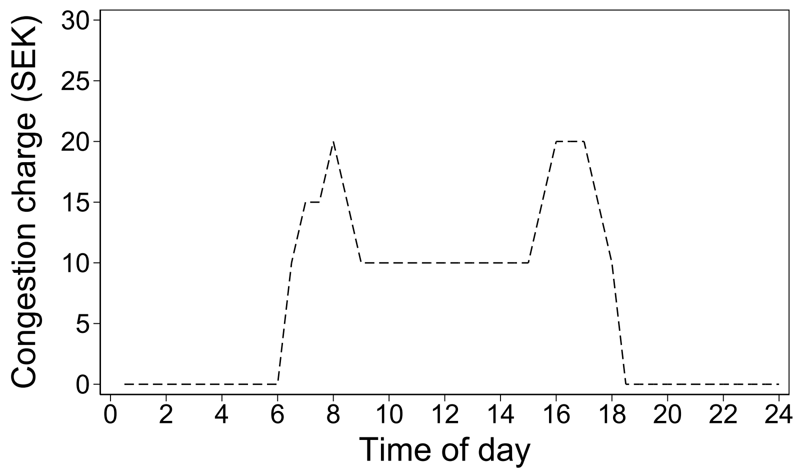


Figure B1: Congestion charges by time of the day in Stockholm, 2006-2015

B.2. Vehicle market

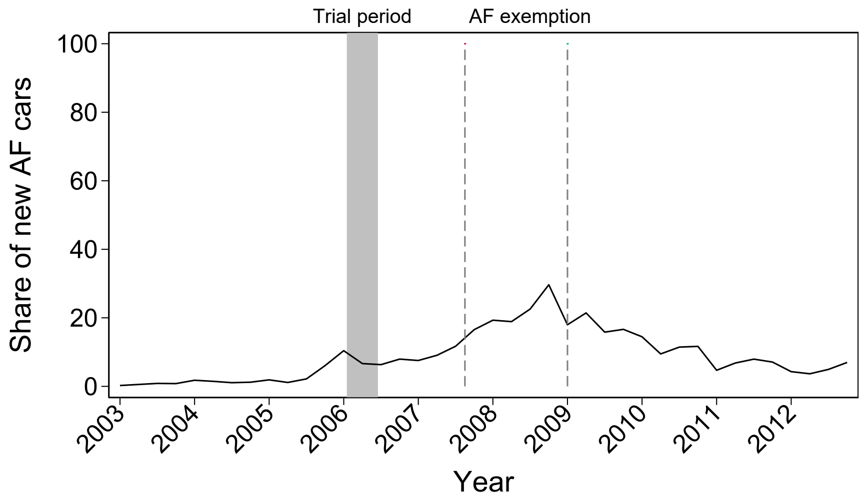


Figure B2: Share of new alternative fuel vehicles in Stockholm

Notes: This figure displays the share of alternative fuel vehicles among private vehicle registrations in Stockholm by quarter from 2003 to 2012. The gray bar indicates the trial period between January 2006 and July 2006. The shaded region represents the congestion pricing trial period. New alternative vehicles were exempt from the charge between August 2007 and December 2008 (grey dashed lines).

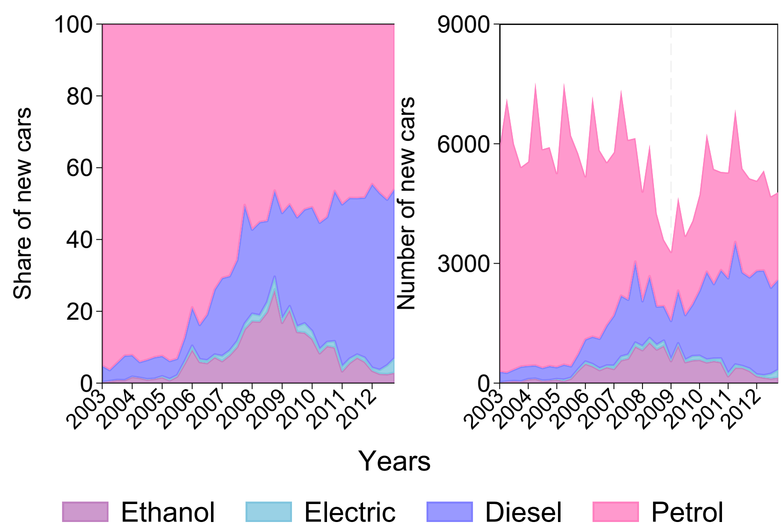


Figure B3: Newly registered cars in Stockholm

Notes: These figures display the share (Panel A) and the total number (Panel B) of new cars registered privately in Sweden between 2003 and 2012 by vehicle type and quarter of year.

B.3. Descriptive statistics for commuters in Stockholm

Table B1: 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: The table shows summary statistics for socio-demographic characteristics (Panel A), and outcome variables (Panel B) for treated commuters, non-treated commuters, and all people in Stockholm, before the implementation of the congestion charge in 2005. Treated commuters are defined as individuals who cross the congestion to or from Stockholm on their way to work. Non-treated commuters are defined as 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.

C. Sample selection and treatment definitions

C.1. Definition of control and treatment group

The potential pool of *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, plus 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.

The potential pool of *non-treated commuters* are 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 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 2005. This control and treatment group classification results in 335,723 treated and 80,522 non-treated commuters. 41,121 treated commuters reside inside and work outside, while 294,602 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 administrative data sources provided by Statistics Sweden contain information at the individual-level for all individuals 18 years or older. We further restrict our sample in the following ways:

1. Individuals must have existed in the dataset in 2006.

2. Individuals must be employed.

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

    - We remove people who both work and live inside of Stockholm's congestion zone
    - We 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 was implemented.

6. Individuals must own at least one but 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 vehicles 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, individuals need to fall within the definitions of our treatment and be observed after the implementation of the congestion charge.[28] 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 97,298 unique individuals over six years, resulting in 416,245 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 D5).

Finally, to estimate the effect on commuting distance, we restrict the sample to consider only individuals outside the congestion zone (column 8).

[28]As we cannot identify the work-trip exposure of company cars, we exclude those cars throughout the entire empirical analysis.

Table C2: Observations by year and sample selection criteria

	Sample selection criteria					Main sample	Balanced Sample	Outside zone
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years								
2003	1,217,085	845,890	298,372	280,328	125,872	53,176	38,762	48,267
2004	1,236,578	859,827	301,486	283,134	139,182	59,138	38,762	53,597
2005	1,260,738	870,769	306,109	287,582	157,940	66,671	38,762	60,250
2006	1,293,780	903,686	315,005	295,839	192,485	77,653	38,762	69,590
2007	1,329,834	972,133	336,640	315,534	192,485	79,259	38,762	79,259
2008	1,366,838	993,526	345,715	324,067	192,485	80,348	38,762	80,348
Individuals	1,525,337	1,247,558	605,322	570,621	192,4845	97,298	38,762	95,644
Total	7,704,853	5,445,831	1,903,327	1,786,484	1,000,449	416,245	232,572	391,311

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 who were not observed between 2006 and 2008; (6) removing individuals without vehicles or more than three vehicles. Column (6) is our main sample. Column (7) corresponds to the balanced sample. Column (8) removes individuals that reside within the congestion zone.

C.3. Mapping treated and non-treated commuters

Figure C1 displays neighborhoods within 50 kilometers of Stockholm by the share of treated commuters. We exclude the congestion zone from this map as 100 percent of the sample who live in the congestion zone are "treated" (recall that we drop individuals who both live and work inside the congestion zone). Neighborhoods with access to the Essinge bypass (the Southwest of Stockholm) and neighborhoods close to the island of Lidingö (east of Stockholm) have fewer treated commuters.

C.4. The congestion rebound effect

The DiD estimator that we use in our main specifications can be written as follows, where an individual's driving choices depend on treatment status, T_i, as well as the treatment status of others, T_{-i}:

$$\hat{\beta} \;=\; [\bar{y}^{post}(T_i = 1|T_{-i}) - \bar{y}^{pre}(T_i = 1)] \;-\; [\bar{y}^{post}(T_i = 0|T_{-i}) - \bar{y}^{pre}(T_i = 0)].$$

To separate the change in traffic conditions from the direct price effect of the policy, we can decompose the outcome for both treated and non-treated commuters:

$$
\begin{aligned}
\hat{\beta} \;&= [\underbrace{\bar{y}^{post}(T_i = 1|T_{-i} = 0)}_{\text{price effect treated}} + \underbrace{\Delta\bar{y}^{post}_{traffic}(T_i = 1|T_{-i} = 1)}_{\text{traffic effect treated}} - \bar{y}^{pre}(T_i = 1)] \\
&\quad - [\underbrace{\bar{y}^{post}(T_i = 0|T_{-i} = 0)}_{\text{price effect non-treated}} + \underbrace{\Delta y_{tr\bar{a}ffic}{}^{post}(T_i = 0|T_{-i} = 1)}_{\text{traffic effect non-treated}} - \bar{y}^{pre}(T_i = 0)].
\end{aligned}
$$

As treated and non-treated commuters share the same home-work route when entering the congestion zone, both commuter groups experience a similar change in travel conditions:

$$
\hat{\beta} \;=\; [\bar{y}^{post}(T_i = 1|T_{-i} = 0) - \bar{y}^{pre}(T_i = 1)] \;-\; [\bar{y}^{post}(T_i = 0|T_{-i} = 0) - \bar{y}^{pre}(T_i = 0)]. \quad \text{(C1)}
$$

Hence, our estimated coefficients reflect responses to Stockholm's congestion charge but not the "rebound" effect from lighter traffic.

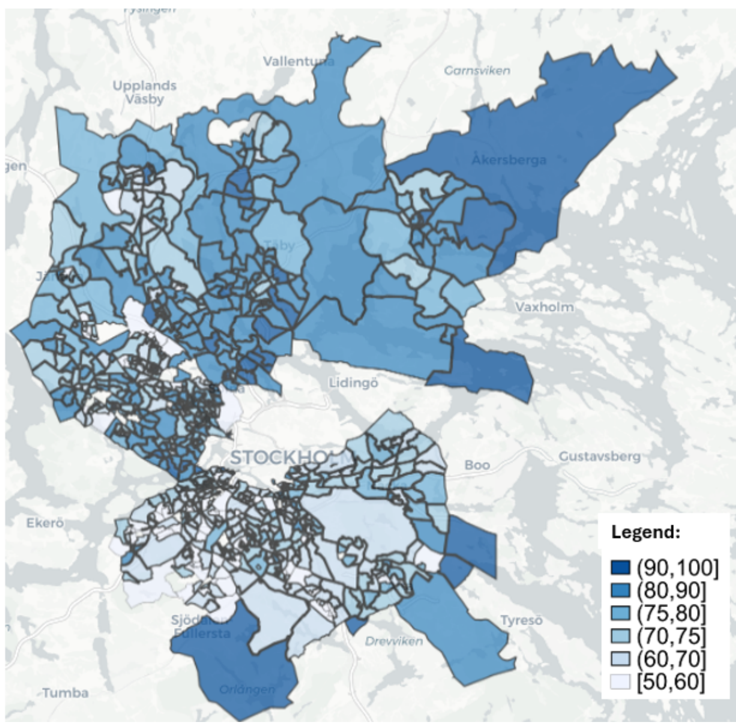


Figure C1: Share of treated commuters

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

D. Supporting results and robustness checks

D.1. Additional tables

Table D1: The impact of congestion pricing on vehicle kilometers traveled: imposition versus removal

	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: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle kilometers traveled. Each column uses a different dependent variable. The dependent variable in column 1 is the annual kilometers traveled in alternative fuel vehicles. Columns 2 and 3 have analogous dependent variables for fossil fuel vehicles and all vehicles, respectively. We estimate responses in kilometers traveled for two policy changes. Panel A shows estimates from the DiD using the introduction of the congestion pricing policy, which included exemptions for alternative fuel vehicles. Panel B shows estimates from the DiD using the removal of the alternative fuel exemption in 2012. For panel A, the sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is the post-period for fossil fuel vehicles. The vehicle kilometers traveled for each type of car are reported below the coefficients. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D2: The impact of congestion pricing on home and workplace locations

	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: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on where individuals live and work. The first column displays estimates on any move; the second column uses a dependent variable that equals one if an individual moves to a location outside the cordon zone; the third column uses a dependent variable that equals one if an individual moves into the cordon zone. Panel A displays results where the dependent variable is an individual's home location; panel B displays results where the dependent variable is an individual's workplace location, and further subsets results into workplace moves where the individual changed firms (the penultimate row) versus workplace moves where the individual stayed at the same firm (the final row). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2006-2008 is the post-period. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

Table D3: The heterogeneous effects of congestion pricing on commuting distances

	Socio-economic Groups			
	(1) Group 1	(2) Group 2	(3) Group 3	(4) Group 4
Panel A. Income				
Post x Paying Commuters	-.0050	.0025	-.0426	-.0396
	(.0430)	(.0323)	(.0316)	(.0311)
Panel B. Family Status				
Post x Paying Commuters	-.0868**	-.0614	-.0238	.0776*
	(.0419)	(.0420)	(.0302)	(.0426)
Panel C. Education				
Post x Paying Commuters	-.0347	-.0582*	-.0118	.0207
	(.0333)	(.0308)	(.0307)	(.0513)
Panel D. Age				
Post x Paying Commuters	.0032	-.0701**	-.0318	.0787**
	(.0505)	(.0318)	(.0285)	(.0354)
Panel E. Commute Distance				
Post x Paying Commuters	-.1632***	.0271	.0206	-.0309
	(.0464)	(.0329)	(.0324)	(.0362)

Notes: This table displays the results from the DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on commuting distances. We break down these estimates by five socio-economic characteristics: Income (Panel A), family status (Panel B), education (Panel C), age (Panel D), and commuting distance (Panel E). Columns refer to individuals with an annual income of (1) less than 200k SEK, (2) between 200k and 400k SEK, (3) between 400k and 600k SEK, and (4) more than 600k SEK in Panel (A); (1) singles without children, (2) singles with children, (3) couples without children, and (4) couples with children in Panel (B); individuals with an educational level of (1) pre-high school, (2) high school, (3) bachelor's degree, and (4) master's degree in Panel (C); individuals aged (1) below 35, (2) between 35 and 45, (3) between 45 and 60, and (4) above 60 in Panel (D); and individuals with a commuting distance of (1) less than 10 kilometers, (2) between 10 and 15 kilometers, (3) between 15 and 25 kilometers, and (4) more than 25 kilometers in Panel (E). The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D4: 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. Vehicle Kilometers			
Post x Treated Commuters	103.2***	-253.6***	-150.3**
	(22.7)	(71.0)	(69.5)
Mean Kilometers Traveled (t-1)	242.7	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), using the same post period specification for both alternative fuel and fossil fuel vehicles. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D5: Estimates using a balanced panel

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A. Vehicle Ownership			
Post x Treated Commuters	.0049***	-.0059	-.0017
	(.0019)	(.0048)	(.0046)
Mean Car Ownership (t-1)	.015	1.164	1.171
B. Vehicle Kilometers			
Post x Treated Commuters	82.4**	-269.8***	-195.8**
	(38.1)	(90.8)	(87.9)
Mean Kilometers Traveled (t-1)	249.1	15695.6	15798.5
C. Commuting Distance			
Post x Treated Commuters			-.029
			(.034)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), using the balanced sample from column (8) in Table C2. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D6: Treatment effects for individuals living outside of the congestion zone

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A. Vehicle Ownership			
Post x Treated Commuters	.0037***	-.0037	-.0025
	(.0013)	(.0035)	(.0034)
Mean Car Ownership (t-1)	.014	1.145	1.152
B. Vehicle Kilometers			
Post x Treated Commuters	70.3***	-208.7***	-181.0**
	(26.0)	(72.1)	(70.7)
Mean Kilometers Traveled (t-1)	242.7	15324.1	15413.4
C. Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), restricting the sample of treated commuters to individuals who live outside of the congestion zone. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D7: Treatment effects for individuals living inside the congestion zone

	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. Vehicle Kilometers			
Post x Treated Commuters	321.7***	-583.1***	61.7
	(33.5)	(102.4)	(97.1)
Mean Kilometers Traveled (t-1)	242.7	15497.7	15607.1
C. Commuting Distance			
Post x Treated Commuters			-.186***
			(.048)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), restricting the sample of treated commuters to individuals who live inside the congestion zone. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D8: Effects including inside-inside commuters

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A. Vehicle Ownership			
Post x Treated Commuters	.0081***	-.0114***	-.0044
	(.0014)	(.0035)	(.0033)
Mean Car Ownership (t-1)	.015	1.132	1.139
B. Vehicle Kilometers			
Post x Treated Commuters	154.5***	-280.9***	-144.7**
	(27.4)	(70.2)	(68.6)
Mean Kilometers Traveled (t-1)	257.1	14990.8	15089.4
C. Commuting Distance			
Post x Treated Commuters			-.064**
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), extending the sample of treated commuters to individuals who both live and work inside the congestion zone. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D9: Estimates with workplaces near congestion zone

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A. Vehicle Ownership			
Post x Treated Commuters	.0044***	-.0111**	-.0079*
	(.0016)	(.0045)	(.0043)
Mean Car Ownership (t-1)		1.139	1.146
B. Vehicle Kilometers			
Post x Treated Commuters	80.4**	-290.0***	-222.2**
	(32.3)	(90.3)	(88.6)
Mean Kilometers Traveled (t-1)	225.8	15117.9	15210.7
C.Commuting Distance			
Post x Treated Commuters			-.148***
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), restricting the sample of treated commuters to individuals with workplaces that are within three kilometers of the congestion zone. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D10: Estimates with workplace-location fixed effects

	Type of Car		
	(1) Alternative	(2) Fossil	(3) Total
A. Vehicle Ownership			
Post x Treated Commuters	.0073***	-.0062*	-.0004
	(.0014)	(.0035)	(.0034)
Mean Car Ownership (t-1)	.014	1.138	1.145
B. Vehicle Kilometers			
Post x Treated Commuters	134.1***	-227.7***	-115.8
	(27.4)	(72.6)	(71.3)
Mean Kilometers Traveled (t-1)	242.7	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters			-.086***
			(.030)
Mean Commute Distance (t-1)			17.5

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), including workplace-location fixed effects. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D11: 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. Vehicle Kilometers			
Post x Treated Commuters	-51.5	-239.2***	-252.4***
	(34.6)	(88.6)	(88.1)
Mean Kilometers Traveled (t-1)	96.5	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters	-.070*	-.070*	-.070*
	(.036)	(.036)	(.036)
Mean Commute Distance (t-1)	17.7	17.7	17.7

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), for individuals with an annual income of less than 350k SEK. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D12: 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. Vehicle Kilometers			
Post x Treated Commuters	105.8***	-413.6***	-320.1***
	(29.0)	(74.4)	(72.6)
Mean Kilometers Traveled (t-1)	242.7	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters	-.000	-.000	-.000
	(.018)	(.018)	(.018)
Mean Commute Distance (t-1)	17.7	17.7	17.7

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), for individuals with an annual income of between 350k to 500k SEK. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is 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 D13: 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. Vehicle Kilometers			
Post x Treated Commuters	299.5***	87.7	315.4***
	(39.4)	(87.7)	(85.6)
Mean Kilometers Traveled (t-1)	242.7	15202.4	15299
C. Commuting Distance			
Post x Treated Commuters	-.110***	-.110***	-.110***
	(.032)	(.032)	(.032)
Mean Commute Distance (t-1)	16.9	16.9	16.9

Notes: This table displays the coefficients from a DiD specification (equation 7) that estimates the impact of Stockholm's congestion pricing policy on vehicle ownership (Panel A), vehicle kilometers traveled (Panel B), and commuting distance (Panel C), for individuals with an annual income of over 500k SEK. The dependent variables in Panel A are indicators for whether an individual owns an alternative fuel vehicle (column 1), a fossil fuel vehicle (column 2), or any vehicle (column 3). The dependent variables in Panel B are vehicle kilometers traveled in alternative fuel vehicles (column 1), fossil fuel vehicles (column 2), and all vehicles (column 3). The dependent variable in Panel C is the home-to-work commuting distance (column 3). The mean dependent variables of the previous year are reported below the coefficients. The sample is restricted to 2003-2008, where 2007-2008 is the post-period for alternative fuel vehicles, and 2006-2008 is the post-period for fossil fuel vehicles. Standard errors are clustered at the neighborhood level. *, **, ***: statistically significant with 90%, 95%, and 99% confidence, respectively.

D.2. Additional figures

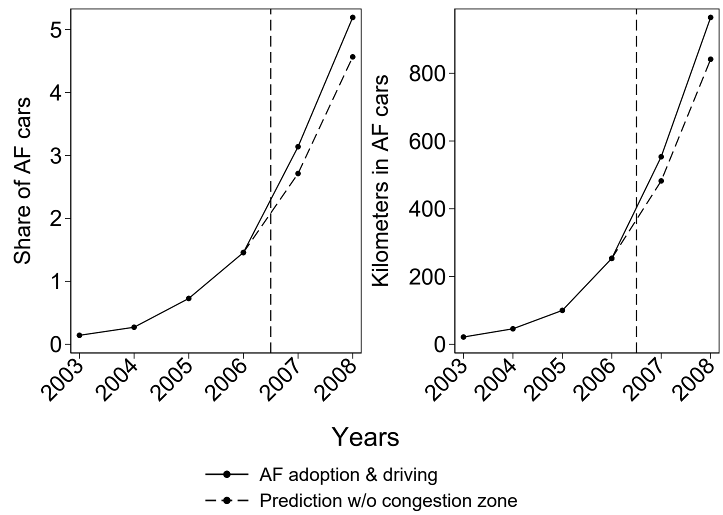


Figure D1: Predicted vehicle ownership and driving behavior

Notes: The solid lines in Panel A and Panel B show the share of individuals among treated commuters in Stockholm who owned an alternative fuel vehicle and the kilometers traveled in alternative fuel vehicles from 2003-2008. The dashed lines in Panel A and B show the predicted share of individuals among treated commuters in Stockholm that would have owned an alternative fuel vehicle and the predicted alternative fuel vehicle kilometers traveled in the absence of the congestion charge, based on the treatment estimates reported in Figure 4. The vertical dashed line denotes the implementation of the exemption policy (2007).

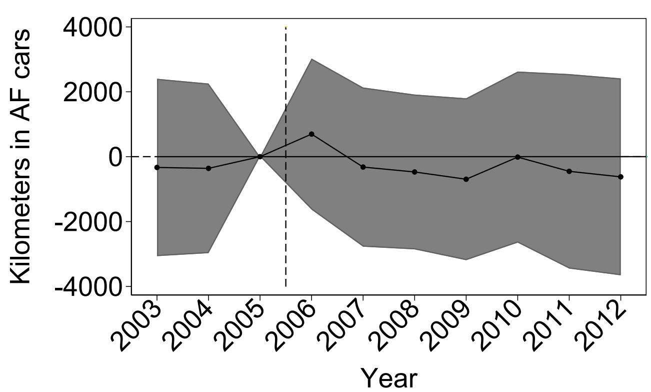
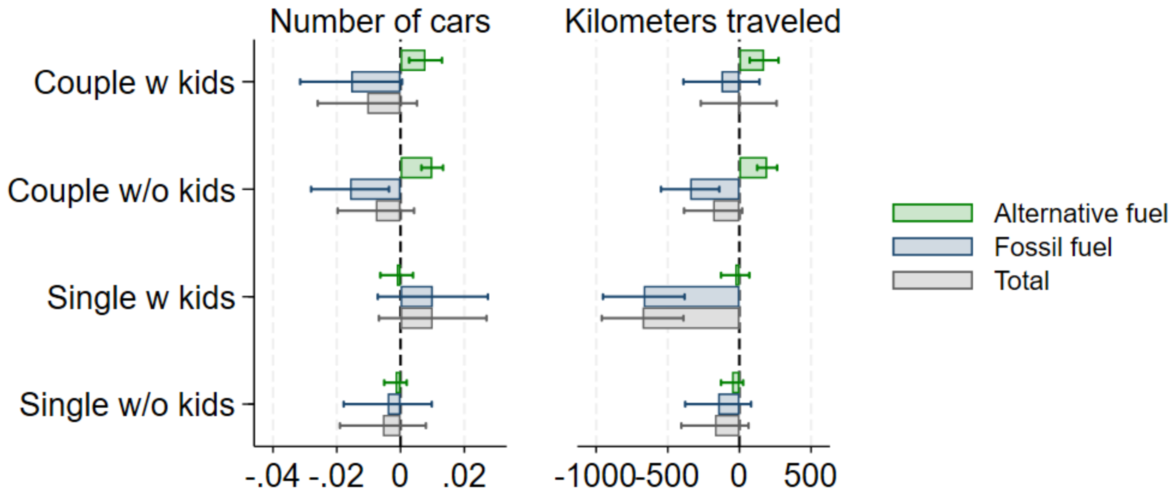
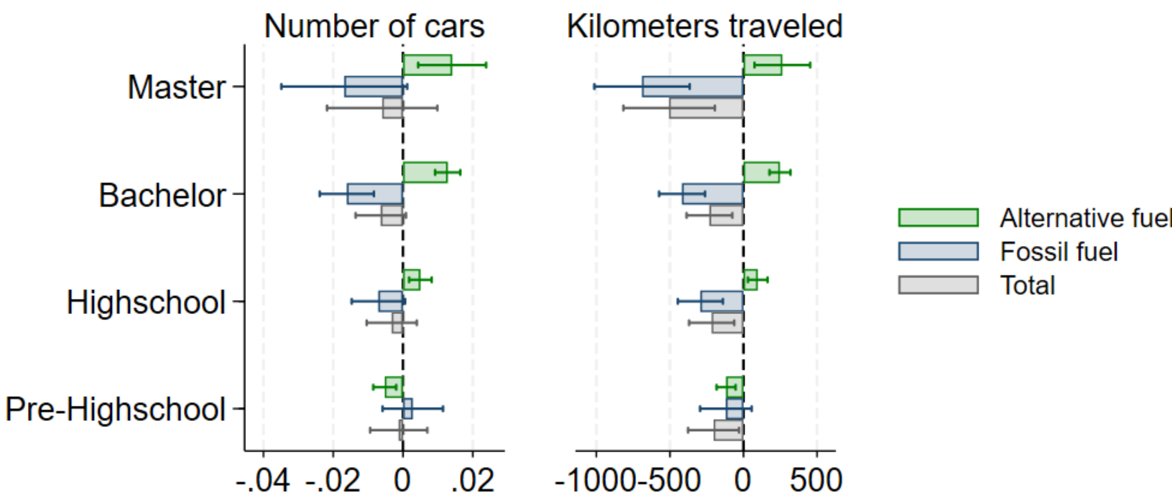


Figure D2: The impact of reduced congestion on alternative fuel driving

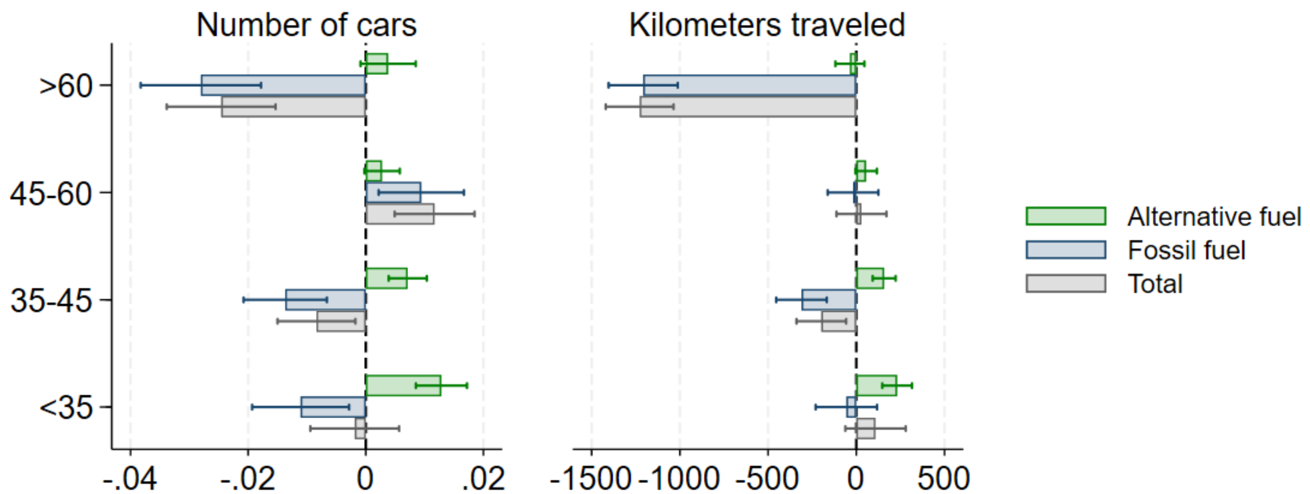
Notes: This figure plots the annual treatment effect on vehicle kilometers traveled in alternative fuel cars from the cordon-zone-induced reduction in congestion using the dynamic DiD specification (equation 8), where β_{2005} is normalized to zero. Treated and non-treated commuters are those who cross the congestion zone between their home and workplace (i.e., reduced congestion) and those who live and work outside the congestion zone (i.e., no congestion changes), conditional on owning a green car prior to the zone's implementation. Standard errors are clustered at the neighborhood level.



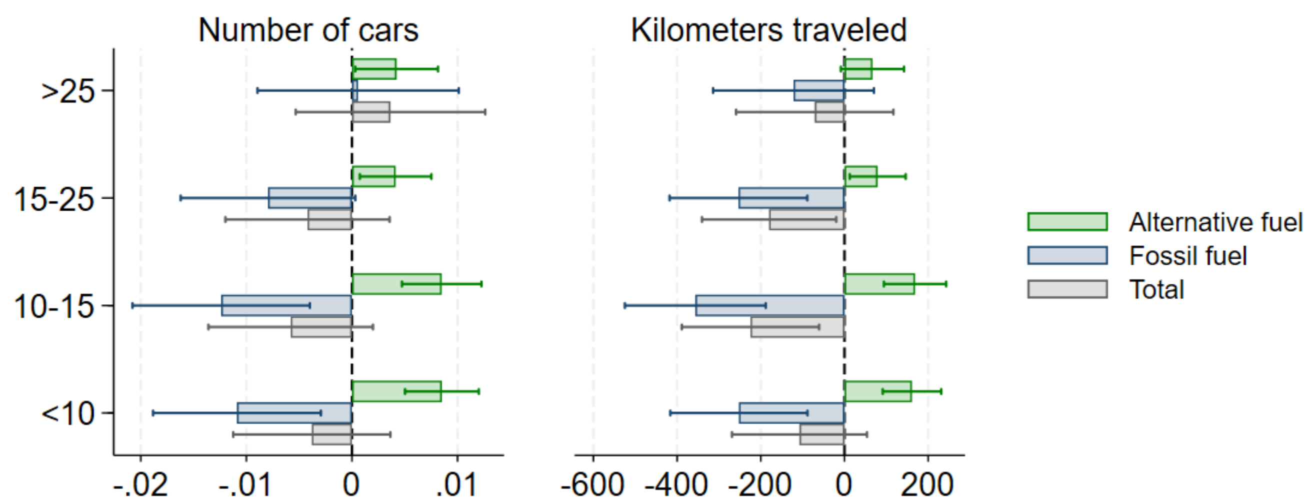
(a) Family status



(b) Years of education



(c) Age



(d) Commuting distance

Figure D3: The impact of congestion pricing on different socio-economic groups

Notes: These figures plot the coefficients β_k on vehicle ownership and driving behavior for alternative (green), fossil fuel (blue), and any vehicle (gray) for four socio-economic characteristics: family status (Panel A), education (Panel B), age (Panel C), and commuting distance (Panel D). Green indicates alternative fuel vehicles, blue indicates fossil fuel vehicles, and gray indicates all vehicles. 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. 95%-confidence intervals are indicated through whiskers and reflect robust standard errors clustered by neighborhoods.

D.3. Distributional burden of Stockholm's congestion pricing

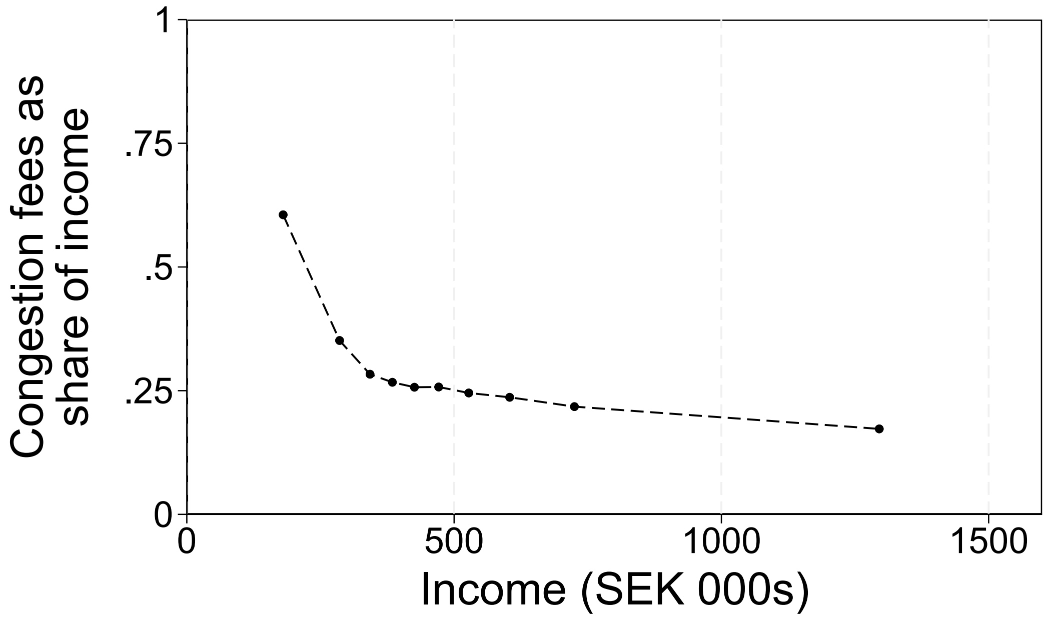


Figure D4: Congestion charges by share of salary

Notes: This figure plots Stockholm's congestion charges as a share of income for each income decile in 2016. We use data from the vehicle registry provided by Statistics Sweden, which includes records of annual congestion charges (*trängselskatt*) per individual.

E. Details of calculating the optimal congestion charge

We combine our empirical results with equation (3) to recover estimates of the optimal congestion charge in the presence of green vehicle exemptions.

E.1. Converting changes in vehicle kilometers traveled to changes in trips

We observe individual-level data on vehicle kilometers traveled, but not on cordon zone trips. As such, we convert changes in vehicle kilometers traveled to changes in trips using survey data from Stockholm. To begin, we write the total kilometers traveled for each vehicle type as the sum of kilometers traveled on cordon trips and the sum of kilometers traveled on outside trips:

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

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

We observe the individual-level vehicle kilometers traveled for both fuel types (Panel A of Table D1) 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 of 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 then calculate the total number of trips in the congestion zone for green and brown vehicles as follows:

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

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

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

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

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

E.2. Estimating changes in the number of trip by vehicle type

The congestion charge formula from equation (9) requires two sets of empirical objects that we do not estimate directly: (1) changes in the number of congestion zone crossings and outside trips, by vehicle type ($\frac{\partial t_g^c}{\partial \tau}$, $\frac{\partial t_b^c}{\partial \tau}$, $\frac{\partial t_g^o}{\partial \tau}$, $\frac{\partial t_b^o}{\partial \tau}$), and (2) changes in outside vehicle kilometers traveled ($\frac{\partial v^o}{\partial \tau}$) per trip. 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.

Changes in number of congestion trips by vehicle type. To convert the estimates of changes in vehicle kilometers traveled for green and brown vehicles into changes in the number of congestion trips by vehicle type, we use the fact that the exemption of alternative fuel vehicles of 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 vehicle kilometers traveled in green and brown vehicles after 2012 mirrors the effect of the initial implementation of the congestion charge:

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

To calculate the change in congestion zone trips taken in green vehicles, we combine the information on (a) the effect of removing the alternative fuel vehicle exemption on vehicle kilometers traveled (Table D1) and (b) what we inferred above about the average length of a cordon zone trip v^c:

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

Then, we estimate the change in the number of non-congestion zone trips in green vehicles by taking the difference between the change in all green congestion zone trips (Table 1, Panel B) less the change in green trips from equation (E8):

$$\frac{\partial t_g^o}{\partial \tau} = \frac{\partial t_g}{\partial \tau} - \frac{\partial t_g^c}{\partial \tau} = 6.6 - 5.9 = .7 \tag{E9}$$

Similarly, to calculate the change in congestion zone trips made using brown vehicles, we combine the information on (a) the effect of removing the alternative fuel vehicle exemption on vehicle kilometers traveled (Table D1) and (b) what we inferred above about the length on non cordon trips, v^c:

$$\frac{\partial t_b^c}{\partial \tau} = -\frac{\partial KM_b}{\partial \tau_{-g}} \cdot \frac{1}{v^c} = -\frac{206.3km}{17.5km} = -11.8 \tag{E10}$$

Finally, we estimate the change in the number of non-congestion zone trips in brown vehicles by taking the difference between the change in all brown congestion zone trips (Table 1, Panel B) less the change in brown trips from equation (E10):

$$\frac{\partial t_g^o}{\partial \tau} = \frac{\partial t_g}{\partial \tau} - \frac{\partial t_g^c}{\partial \tau} = -13.8 + 11.8 - = -2 \tag{E11}$$

E.3. Changes in trip length for trips outside of the congestion zone

The total outside vehicle kilometers traveled per vehicle is equal to the product of the number of trips and the average trip length outside the congestion zone. Using data on per-vehicle total vehicle kilometers traveled (Table 1) and the average outside commuting distance v^o from the Swedish National Travel Survey (2007), we calculate the number of outside trips:

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

We then estimate the change in vehicle kilometers traveled per trip for trips outside the congestion zone. This is equal to the change in total vehicle kilometers traveled (Panel A, Table D1) less the change in kilometers traveled inside the congestion zone (Panel B, Table D1):

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

Finally, we estimate the change in the length of outside-zone trips ($\frac{\partial v^o}{\partial \tau}$) by taking the derivative of the total vehicle kilometers traveled outside the congestion zone with respect to the congestion charge:

$$\begin{aligned}\frac{\partial KM^o}{\partial \tau} &= \frac{\partial v^o}{\partial \tau}\cdot t^o + \frac{\partial t^o}{\partial \tau}\cdot v^o\\ \frac{\partial v^o}{\partial \tau} &= \frac{\frac{\partial KM^o}{\partial \tau} - \frac{\partial t^o}{\partial \tau}\cdot v^o}{t^o}\\ \frac{\partial v^o}{\partial \tau} &= \frac{-47 + 2.3\cdot 19km}{434.8} \approx -.007km\end{aligned} \tag{E14}$$

In calculating the change in outside trip distances, we use 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 D1).

E.4. Emission externalities

To quantify the emission externalities, we combine the vehicle emission factors – the amount of a particular pollutant that a vehicle emits – with the social costs of each pollutant. Table E1 summarizes the vehicle emission factors and social costs of each pollutant.

We rely on a recent report by the European Environment Agency (2021) that provides vehicle emission factors for the main local (i.e., NH_3, PM, SO_2) and global pollutants (i.e., CO_2) for petrol and diesel vehicles in Sweden. These pollution externalities have been shown to make up most of kilometer-weighted average emissions factors (Tarduno, 2022). Although these emissions factors are based on a large number of assumptions concerning vehicle technology mix (e.g., the share of passenger cars), driving conditions (e.g., traveling speeds), and climatic conditions (e.g., temperature) (Zachariadis et al., 2001), we assume a constant emission factor for inside and outside the congestion zone. We use the fleet composition of Swedish petrol and diesel vehicles in 2006 to quantify the average local emissions rates per kilometer traveled.

As EVs produce no local emissions from tailpipes, we set the vehicle emission factors from Ammonia (NH_3) and Sulfur dioxide (ΔSO_2) for green vehicles to zero. Following a recent report by the OECD (2020), we assume that non-exhaust particulate matter emissions for fossil fuel cars are approximately equivalent to those of EVs. In addition, EVs charge from the electrical grid, which may generate emissions depending on the marginal fuel source (Holland et al., 2016). Based on the Swedish average electricity generation technology mix, the average carbon intensity for electricity used for charging equals 29 $\frac{g\ CO2}{kWh}$ (348 $\frac{g\ CO2}{kg\ fuel}$ assuming an energy content of 12 $\frac{kWh}{kg}$) in 2020 (Morfeldt et al., 2021). We convert externalities into real 2021€ using the Consumer Price Index from Statistics Sweden.

We convert these emissions rates into damages 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.[29] The report's methodology quantifies the damage costs for the local pollutants following the European Commission's DG Research (Holland et al., 1999; Bickel et al., 2005), which uses dispersion modeling in combination with estimates of pollution-mortality gradients to back out estimates of the damages from emitting a specific pollutant in a given location. 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. We convert kilogram into liter by assuming that one kilogram of petrol is equal to .72 liter. Finally, we express the costs per kilometer based on the average fuel efficiency of fossil fuel vehicles ($8.37\frac{l}{100km}$).

Table E1: Social costs of pollutants

Pollutant	Emission factors $[\frac{g}{kg\ fuel}]$	Social cost of pollutant $[\frac{€}{kg}]$	Costs per liter $[\frac{€}{l}]$	Costs per km $[\frac{€}{km}]$
A.Brown Vehicle				
Emission externalities				
Fine particulate matter ($PM_{2.5}$)	.31	23.2	.005	.0004
Particulate matter (PM_{10})	.31	15.01	.003	.0003
Ammonia (NH_3)	11.14	12.15	.097	.0082
Sulfur dioxide (SO_2)	8.19	15.44	.091	.0076
Carbon dioxide (CO_2)	3,870	.105	.293	.0245
			.489	.041
B.Green Vehicle				
Fine particulate matter ($PM_{2.5}$)	.31	23.2	.005	.0004
Particulate matter (PM_{10})	.31	15.01	.003	.0003
Carbon dioxide (CO_2)	348	.105	.026	.0022
			.034	.0029

Notes: This table reports the vehicle emission factors and social costs of each pollutant for brown (Panel A) and green vehicles (Panel B). All externalities are expressed in real 2021€.

[29] The European Environment Agency reports a "high" and "low" value for each pollutant. We take the mean of these two values.

E.5. Congestion externalities

To assign congestion 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, 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 rural areas for the congestion externalities outside the congestion zone. The congestion costs in small and medium urban areas arrive ($< 2,000,000$ citizens) at a value for passenger vehicles of around €.38 per kilometer and €.13 per kilometer in rural areas.[30] 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.

[30]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.

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