Short-run Effects of Feebate Schemes on Car Markets ad CO$_2$ emissions

A simulation analysis of the Swedish feebate scheme

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Acknowledgements

Abstract

In a CO_2-differentiated feebate scheme on new car purchases, the purchaser either pays a fee or receives a rebate depending on the emission performance of the car. In an effort to reduce CO_2 emissions from transportation, several developed countries have implemented such policy measures. In Sweden, a feebate scheme entered in force on the 1st of July 2018. I simulate the short-run effects of the Swedish feebate scheme on new cars market shares and total CO_2 emissions. Results show moderate response in car market shares, particularly in favour of electric cars and low-emission plug-in hybrids. For one vehicle cohort, the CO_2 are reduced by 1.33 % in the short run. Considering the estimated tax revenue of 613 million SEK per vehicle cohort, the emission reductions could be achieved considerably more efficiently with alternative instruments such as a tax on fossil fuels.

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1. Introduction

Transport is the only major sector in the EU where greenhouse gas emissions have increased over the recent decades. Currently, passenger car traffic accounts for around 12% of total CO_2 emissions in the EU, emissions having grown 14.5% over the period 1990–2015. For Sweden, the share of total emissions is substantially higher at 20%. (EEA, 2017) Curbing the emissions from passenger car traffic is therefore an important component in meeting overall CO_2 emission reduction targets.

With the aim of renewing the car fleet towards better environmental performance, the Swedish Goverment implemented a feebate scheme, also known as *bonus malus*, in July 2018 (Swedish Goverment, 2018). In short, in the Swedish scheme, a purchaser of a new car receives a rebate up to 60,000 SEK for vehicles with emissions below 60 g CO_2/km. For vehicles emitting over 95 g CO_2/km a fee is incurred as an increased circulation tax for the first three years after purchase.

Existing research on feebate schemes has mostly examined changes in car fleet composition, and only a handful of studies have estimated emission reductions and cost-effectiveness. However, emission reductions and cost-effectiveness are the key questions that policy makers should consider in the design and implementation of a new policies.

In this study, I simulate the effects of the Swedish feebate scheme, analysing short-run effects on car fleet composition, total mileage, and total CO_2 emissions. The results provide insight into the expected effects of the Swedish feebate scheme and thus contributes to the policy discussion on measures for reducing emissions from road transportation. This study uses detailed micro-level data with car odometer readings and owner attributes, enabling improved methods for simulating counterfactual policy scenarios.

The results of the analysis suggest moderate market responses to the feebate. Electric vehicles and plug-in hybrids gain a considerable increase in their shares relative to no policy scenario, with 37.33 % and 17.81 % increases relative to own share before policy respectively. Low-emitting petrol and diesel cars also gain market share, although only moderately in the

neighbourhood of 2 %. High-emitting diesel cars are estimated to lose 4.79 % in market share relative to own share, and high-emitting petrol cars lose slightly less at a 3.86 % decrease.

The effects on the average emission performance of the fleet are moderate. Average emissions of newly purchased cars are estimated to decrease by 1.74 % from 122.5 g CO_2/km in 2017 to 119.9 g CO_2/km. When taking into account increased car use due to improved fuel economy, the estimated short-run emission reduction becomes 1.33 % for one vehicle cohort. Considering the time span it takes for this effect to penetrate every vehicle cohort the car fleet, the implication is that the effects of the feebate scheme on emissions from car use are projected to be small.

The rest of this paper is organized as follows. Section 2 reviews existing theoretical and empirical literature on feebate schemes. Section 3 introduces the modelling and estimation approaches. Section 4 describes data sources. Section 5 presents estimation and policy simulation results and discusses them. Section 6 concludes.

2. Literature review

2.1   Theoretical framework

A first-best policy option for reducing CO_2 emissions from transport would be to introduce an efficient fuel tax that internalizes the cost of CO_2 emissions. However, car market imperfections, such as consumers' optimization failure, as well as political feasibility constrain the use of an optimal fuel tax. (Aldy et al., 2010; Greene et al., 2005; Konishi and Zhao, 2017) As a second-best policy tool, a feebate on car purchase can improve consumers' optimization, since consumers appear to respond more rationally to car purchase prices than to fuel prices. Moreover, a feebate can be designed as revenue neutral for the government, improving political feasibility. (Greene et al., 2005)

In the simplest form of a feebate scheme, the amount of fee paid or rebate received is a function of two parameters: pivot point and rate. The pivot point is a level of emission performance (measured in grams of CO_2 per km) above which a vehicle is charged a fee and below which a vehicle receives a rebate. The rate determines how the fee or rebate increases (decreases) when distance to the pivot point increases (decreases).

Let us denote E_0 for pivot point, E_j for emission performance of car model j, and R for rate. Then, the net feebate F for car j can be expressed as:

$$F_j = R(E_0 - E_j) \tag{2.1}$$

Two theoretical properties deserve attention. First, with a constant rate R, the scheme gives a constant positive value for saved emissions for the consumer. Therefore, with respect to decisions on vehicle purchase (but not use) a feebate scheme as described above is equivalent to a CO_2-differentiated fuel tax. Second, consider a feebate scheme where E_0 and R are chosen such that the scheme is revenue neutral for the government. A revenue-neutral scheme is equivalent to an emission standard with tradeable credits. (Greene et al., 2005)

Due to these properties, we should expect a response from both the consumers and car manufactures such that consumers choose to buy cars with better emissions performance and that manufacturers increasingly supply them. However, two caveats should be noted. First, car manufacturers have limited ability to adjust vehicle emission performance in the short run. Second, consumers might respond asymmetrically to a fee and a rebate. Rivers and Schaufele (2017) observe that consumers are more sensitive to rebates than to fees. D'Haultfoeuille et al. (2014) observe that in France the consumers shifted their purchases to cars benefitting only marginally from a rebate. A possible explanation is that individuals seek to capture the 'silver lining' the rebate offers (Thaler, 1985). A 'halo effect' from purchasing subsidized, fuel efficient vehicles is possible. Also, car dealers are likely to emphasize subsidies in marketing while lumping fees together with other peripheral costs such as freight. (Rivers and Schaufele, 2017)

A central aim of this study is to quantify how changes in the car fleet composition result in changes in total CO_2 emissions. The most immediate effects arise from changes in the emission performance of new cars (*composition effect*) and changes in total mileage due to increased fuel efficiency and lower costs per kilometer (*rebound effect*). This study delimits the analysis to these two effects in the short run.

D'Haultfoeuille et al. (2014) describe other possible effects. These include changes in emissions from increasing the total number of cars and thus increasing total mileage (*fleet size effect*) and from increased the manufacturing of new cars (*manufacturing scale effect*). As d'Haultfoeuille et al. (2014) demonstrate, the sum of all partial effects is potentially ambiguous in sign and magnitude. The total effect is sensitive to the specific design of the feebate scheme. The effect also differs between the short run and the long run. Importantly, the composition effect is much larger over the long run, reflecting the fact that the entire fleet is eventually replaced. Additionally, in the short run, new cars replace high emitters, while in the long run this effect is smaller.

2.2   Ex post evaluations

Prior to Sweden implementing a feebate scheme in July 2018, feebate schemes have been implemented in France, Switzerland, and Canada, established in 2008, 2005, and 2010 respectively. Policies similar to a feebate include the green car rebate in Sweden and the tax credit and subsidy program in Japan, implemented in 2007 and 2009 respectively. Several studies have evaluated these schemes ex post. A common finding is that the policies have the ability to shift car fleet composition towards the desired direction (Alberini and Bareit, 2017;

Ciccone, 2014; d'Haultfoeuille et al., 2014; Huse and Lucinda, 2014; Klier and Linn, 2015; Konishi and Zhao, 2017; Rivers and Schaufele, 2017).

However, studies on the effect of a feebate on total CO_2 emissions are few. D'Haultfoeuille et al. (2014) have estimated the emission reductions resulting from the French feebate scheme. The authors attribute changes in car fleet composition to the scheme. However, according to the authors, this effect did not translate into decreased CO_2 emissions in either the short or the long run. Increased car sales resulted in increased total mileage as well as increased emissions from car manufacturing, offsetting any emission savings from increased fuel economy. The authors argue that these results happened due to the high pivot point and generous rebates in the French scheme. The authors demonstrate how an alternative feebate scheme – resembling policy modifications implemented in 2010 and 2011 – could have been more effective.

Rivers and Schaufele (2017) evaluate a feebate scheme on Ontario, Canada. They find that the policy reduced vehicle lifetime CO_2 emissions by 0.6 Mt per vehicle cohort. This calculation only considers emissions from car use. The authors estimate that an optimal revenue neutral formulation would have reduced CO_2 emissions by 1.3 Mt relative to the no feebate scenario. All estimated scenarios with a feebate were welfare-enhancing.

Finally, Huse and Lucinda (2014) evaluate the effects of the Swedish green car rebate, likewise limiting the analysis to emissions from car use. The authors find considerable CO_2 emission reductions. However, the reductions come at an estimated cost of \$109–132 per ton of CO_2 saved, which was over five times higher than the price of an EU ETS emission permit at the time of adoption of the rebate.

2.3   Ex ante simulations

Simulations of feebate schemes have explored the impacts of alternative feebate schemes on various outcomes including market shares, CO_2 emission performance of new cars, firm profits, and consumer welfare (Adamou et al., 2012, 2014; Greene et al., 2005; Habibi et al., 2016). A general finding in these studies is that a well-designed feebate scheme can effectively improve the average fuel economy of the car fleet. However, none of these studies extensively model policy effects on total CO_2 emissions.

Of particular relevance to this study is the simulation from Habibi et al. (2016) who model the effects of proposed policy alternatives, including a feebate, in Sweden. The authors find that none of the proposed policy alternatives is likely to lead to the desired level of average emissions of new cars by 2020. However, since the proposed policy alternatives include

also other changes than introducing a feebate scheme, the analysis does not identify the effect of feebate alone. Most importantly, the examined alternatives also abolish the CO_2 differentiation from circulation tax. This change did not take place, however, in the scheme that was implemented in Sweden.

3. Empirical approach

The general strategy is as follows. First, using aggregate-level car market data, I estimate demand parameters in the new cars market using a random coefficients logit model as developed in Berry et al. (1995). With estimates for own- and cross-price elasticities, I employ a Bertrand-Nash equilibrium model to estimate marginal costs for all products. Having estimates for demand and supply parameters, I predict counterfactual market shares following the introduction of a feebate scheme. After obtaining counterfactual market shares, I simulate the changes in total mileage and total CO2 emissions. For this purpose, I estimate car usage parameters using Swedish car registry data.

In what follows, I outline the consumer utility model and the resulting equations to be estimated. In Section 3.4, I give a more detailed account of the choices and assumptions I make in the estimation procedure.

3.1 Consumer utility model

3.1.1 Joint utility and choice of car usage

I employ a structural form random utility maximization framework to model the discrete choice of car purchase decision and the continuous choice of car usage. The functional form follows d'Haultfoeuille et al. (2014), which in turn is based on literature following Dubin and McFadden (1984), De Jong (1990), and Goldberg (1998).

Assume that the indirect utility function of choosing car model j and car usage N takes the form

$$U_{jN} = \alpha p_j^e + x_j \beta + \xi_j + \kappa N^{\frac{\gamma}{\gamma-1}} - \lambda c_j N, \quad \kappa < 0, \ \gamma \in (0,1), \ \lambda > 0 \qquad (3.1)$$

where p_j^e is the effective (tax-inclusive) price of car j, x_j is a vector of observable characteristics of car j, and ξ_j denotes product characteristics that are unobserved for the researcher

but observed for the consumer. The utility from car use is decomposed into two terms: the utility obtained from travelling N kilometres and the disutility from the cost of driving N kilometres. The term c_j denotes cost per kilometer of using car j.

Greek letters denote taste paramteres. The coefficient α is the (negative) marginal utility of income, and β is a vector of taste coefficients corresponding to car characteristics. Assuming $\kappa < 0$ and $\gamma \in (0,1)$ ensures that utility is a concave function of N, and further assuming $\lambda > 0$ ensures that for a given choice of car there exists a unique utility-maximizing N. The parameter γ is of special interest in this study and it is given an interpretation below.

Proceeding from (3.1), the utility-maximizing mileage given the choice of car model j becomes

$$N^* = \left(\frac{\lambda(\gamma-1)}{\kappa\gamma} \right)^{\gamma-1} c_j^{\gamma-1} \tag{3.2}$$

This optimality condition exhibits the rebound effect: Since $(\gamma-1) < 0$, when cost per kilometre decreases, optimal mileage increases. Based on (3.2), we can write the utility-maximizing choice of mileage for individual i as

$$ln\, N_i^* = a + (\gamma-1)ln\, c_{ij} + \eta_i \tag{3.3}$$

where $a = ln \left(\frac{\lambda(\gamma-1)}{\kappa\gamma} \right)^{\gamma-1}$ and η_i is the error term. Now, the coefficient $(\gamma-1)$ can be interpreted directly as the elasticity of mileage with respect to cost per kilometer.

Note that the joint model implicitly considers *anticipated* mileage at the choice occasion of car purchase. The pattern of the differences between anticipated and realized mileage is an empirical question outside the scope of this study.

3.1.2 Choice of car model

Inserting (3.2) into (3.1), we can write the utility for individual i from choosing car model j in market t as

$$U_{ijt|N^*} = \alpha_i p_{jt}^e + x_{jt}\beta_i + \delta_i c_{jt}^{\hat{\gamma}} + \xi_{jt} + \varepsilon_{ijt} \tag{3.4}$$

where $\delta = \frac{\kappa}{\gamma-1} \left(\frac{\lambda(\gamma-1)}{\kappa\gamma} \right)^{\gamma}$ and the error term ε_{ijt} can be interpreted as a product-specific shock for individual i. Note that I have fixed $\gamma = \hat{\gamma}$ in order to allow for a linear estimation problem later in the estimation algorithm.

Importantly, at this point I have introduced consumer heterogeneity into the model via individual-specific taste parameters. Following Nevo (2000), let us collect the parameters to

a vector $\theta_i = [\alpha_i, \beta_i, \delta_i]^T$ and model the individual-specific parameters as

$$\theta_i = \bar{\theta} + \Pi D_i + \Sigma v_i, \ \ D_i \sim \hat{P}_D(D), \ v_i \sim P_v(v) \tag{3.5}$$

where $\bar{\theta}$ is a vector of mean levels of the parameters, D_i is a vector of demographic variables, and v_i captures additional characteristics. The distinction between D_i and v_i is that the distribution of the former is known but the distribution of the latter is unknown and assumed as some parametric distribution. In specific, I assume v to be distributed normal with mean zero, leaving its standard deviation to be estimated. Parameter matrices Π and Σ measure how the taste parameters vary with D_i and v_i respectively. The main benefit of introducing unobserved consumer heterogeneity into the model in a random manner is in how it produces more realistic demand elasticities than simple multinomial logit or nested logit models (see Nevo, 2000, for details).

Now, let $P_{ijt \mid D_i, v_i}$ denote the probability of individual i choosing product j in market t conditional on demographic and additional characteristics of the individual as we have defined them above. The unconditional probability of interest becomes

$$P_{ijt} = \int_v \int_D P_{ijt \mid D_i, v_i} \, d\hat{P}_D(D) \, dP_v(v) \tag{3.6}$$

Noting that $P_{ijt \mid D_i, v_i} = P(U_{ijt} > U_{ikt} \ \forall \ j \neq k \mid D_i, v_i)$ and assuming a Type I extreme value distribution for ε_{ijt} yields

$$P_{ijt} = \int_v \int_D \frac{e^{V_{ijt}}}{\sum_j e^{V_{ijt}}} \, d\hat{P}_D(D) \, dP_v(v) \tag{3.7}$$

where $V_{ijt} = \alpha_i p_{jt}^e + x_{jt}\beta_i + \delta_i c_{jt}^{\hat{\gamma}} + \xi_{jt}$ as per equation (3.4). From (3.7), I estimate the mean levels of taste parameters, $\bar{\theta}$, using the estimation algorithm developed in Berry et al. (1995).

Since the absolute level of utility is irrelevant when comparing choices, the utilities must be normalized against some alternative. A common approach, which I follow, is to define an outside good $j = 0$ s.t. $U_{i0t} = 0 + \varepsilon_{i0t}$ (Nevo, 2000). The outside good can, for example, represent the option of not buying a new car. I return to this issue in Section 4. The scale of utility is also irrelevant. However, assuming a Type I extreme value distribution for the error term implicitly normalizes the utilities for scale and therefore no other normalization is necessary. (Train, 2009, Ch. 3.2)

3.2   Supply model

I construct the supply model following Nevo (2001), Knittel and Metaxoglou (2014), and Konishi and Zhao (2017). There are F firms in all markets and each firm produces a subset of the products, $J_f \subseteq J$. The profits of firm f are

$$\Pi_f = \sum_{j \in J_f} \left[(p_j - mc_j) M s_j(p^e) - FC_j \right] \tag{3.8}$$

where s_j is the market share of car model j as given in (3.7). The market share is a function of p^e, the vector containing the effective (tax-inclusive) prices of all car models defined as $p_j^e = (1 + \tau_j)p_j$. The term mc_j denotes the marginal cost of car model j, M is the market size of the new car market, and FC_j is the fixed cost of production.

Assume that the firms compete à la Bertrand and a unique pure-strategy Bertrand-Nash equilibrium exists. Then, the price of each car model j produced by the firm satisfies the following first-order condition:

$$s_j(p^e) + (1 + \tau_j) \sum_{k \in J_f} \left[(p_k - mc_k) \frac{\partial s_k}{\partial p_j} \right] = 0 \tag{3.9}$$

From (3.9), marginal costs for all firms can be solved as

$$mc = p - \Omega^{-1} s^e(p^e) \tag{3.10}$$

where mc, p, and s^e are $J \times 1$ vectors of marginal costs, prices and market shares respectively. The vector s^e is adjusted for tax rates, the jth element given by $s_j^e = s_j/(1 + \tau_j)$. Ω is a $J \times J$ matrix of share derivatives for each product where a typical element is

$$\omega_{jk} = \begin{cases} -\frac{\partial s_k}{\partial p_j} & \text{if both } j \text{ and } k \text{ are produced by the sam firm} \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

Estimating demand parameters provides also the estimates $\widehat{\Omega}$ and $\hat{s}(p)$. Then, marginal costs and markups can be estimated from equation (3.10). Having estimated demand and supply parameters allows obtaining equilibrium prices after a policy change. The feebate enters the equations through tax rate τ_j.

Solving for equilibrium prices after the policy change would amount to re-solving the system of non-linear equations in (3.10) for a new $p = p^*$. This is not trivial since the

existence and uniqueness of a price equilibrium rests only on an assumption. Knittel and Metaxoglou (2014) point out that with Bertrand competition, multi-product firms, and a random-coefficient demand model there is no result that shows the existence or uniqueness of a pure-strategy equilibrium. Instead, studies that utilise this framework routinely only assume existence and uniqueness. To sidestep this problem, I follow Knittel and Metaxoglou (2014) and approximate the post-policy equilibrium prices as

$$p^{post} = \widehat{mc} + \widehat{\Omega}^{-1}(p^{e,\ post})\hat{s}(p^{e,\ post}) \tag{3.12}$$

where $p^{e,\ post}$ is the vector of tax-inclusive prices after policy.

A limitation of the supply model is that it does not account for how the manufacturers may alter car model specifications as a response to the feebate scheme. This effect is likely negligible in the short run (Klier and Linn, 2015). In the long run, however, it is reasonable to assume that the manufacturers alter their products such that they benefit from the feebate scheme. In this study, however, I delimit the analysis to short-term effects only.

3.3   Simulation of effects on mileage and CO_2 emissions

In this section, I present a parsimonious method to estimate short-run policy-induced changes in total mileage and total CO_2 emissions. The method allows accounting for both composition and rebound effects in policy analysis.

In previous literature, the methods in analysing changes in car usage and emissions have varied considerably. Rivers and Schaufele (2017) assume fixed values for a vehicle's lifetime and annual mileage and calculate emission savings as resulting directly from the changes in market shares. Huse and Lucinda (2014) assume a fixed lifetime but estimate the average yearly usage for each car model. D'Haultfoeuille et al. (2014) base their analysis on estimates of the average mileage in a consumer group.

My approach is different in that for simulating the counterfactuals of interest, I directly apply the car usage model together with micro-level data. The required inputs are parameter estimates from the car usage regression and simulated pre- and post-policy market shares from the demand and supply side models.

For one individual, denote the mileage in a given time period by N_i. Let N_i be a function of individual characteristics A_i, car j that the individual chose to buy, and parameters δ that

specify how individual characteristics and car characteristics affect mileage:

$$N_i = f(A_i, \; j, \; \delta) \tag{3.13}$$

The counterfactual of interest is the mileage after the introduction of the feebate scheme, N_i^{post}. I do not observe the choice of car after the policy, j^{post}. However, the predicted market shares after policy, $\hat{s}(p^{e, \; post})$, provide a prediction of the probability distribution for j^{post}. Denoting the density of this distribution as $\widehat{P}_j^{post}$, the expected mileage after the policy change becomes

$$\widehat{E}(N_i^{post}) = \int f(A_i, \; j, \; \hat{\delta}) \, \widehat{P}_j^{post} \, dj \tag{3.14}$$

where $\hat{\delta}$ denotes parameter estimates obtained from the car usage regression. Simulating this integral with simple random draws from $\widehat{P}_j^{post}$ provides an estimate

$$\widehat{E}(N_i^{post}) = \frac{1}{R} \sum_{r=1}^{R} f(A_i, \; j^{(r)}, \; \hat{\delta}) \tag{3.15}$$

where $j^{(r)}$ is a random draw from $\widehat{P}_j^{post}$ and R is the total number of draws. Comparing the post-policy estimate to the pre-policy quantity gives the expected change in mileage:

$$\widehat{E}(\Delta N_i) = \widehat{E}(N_i^{post}) - N_i^{pre} \tag{3.16}$$

I estimate changes in CO_2 emissions analogously, comparing expected post-policy emissions to the pre-policy emissions:

$$\widehat{E}(\Delta CO2_i) = \widehat{E}(N_i^{post} C_j^{post}) - N_i^{pre} C_j^{pre} \tag{3.17}$$

where C_j is the emissions per kilometer of car j that individual i chose to buy.

Implemented in this manner, the simulation gives the total effect of the policy on CO_2 emissions resulting from both the composition and rebound effects. The composition effect is obtained by setting fuel cost elasticity ($\frac{\partial ln(mileage)}{ln(fuel \; cost/km)}$) to zero and then calculating expected changes in CO_2 emissions.

An apparent missing element in this design is that the probability of choosing a certain car model differs between individuals. As an example, for individuals with a low income, the probability of buying a luxury car is considerably lower than what the market share implies. This introduces bias since individual characteristics also systematically affect

mileage. To account for this problem, the density function for car model distribution should be conditioned on individual characteristics, $\widehat{P}^{post}_{j \mid A_i}$. However, since the estimation is based on market-level, it cannot provide any information on this conditional distribution.

3.4 Estimation

3.4.1 Continuous choice model

From equation (3.3), we need to identify the coefficient $(\gamma - 1)$ in order to account for the rebound effect both in estimating demand parameters and in simulating total mileage. The choice of mileage is dependent on the cost of driving, c_j, which in turn depends on the choice of car model j.

However, it is easy to imagine how some unobserved individual characteristic can affect both choices simultaneously. For example, a person who is generally adverse to driving may prefer to drive less and also invest less in a car than a person who finds driving inherently enjoyable. In presence of such unobserved characteristics, the choice of car model is endogenous in equation (3.3) for car usage. The resulting bias would pull the coefficient estimate towards zero.

The problem is readily dealt with variation in fuel prices which is arguably exogenous to individual preferences. Let $c_j = p_f \cdot F_j$, where p_f is fuel price and F_j is the fuel consumption of the car.[1] F_j is the potentially endogenous part of c_j. Thus, a simple solution is to estimate (3.3) using two-stage least squares instrumenting $ln\ c_j$ with $ln\ p_f$. The resulting estimate $\hat{\gamma}$ is then used the discrete choice model.

3.4.2 Discrete choice model

There is a concern that the unobserved attributes of a car, captured in the term ξ_{jt} in equation (3.7), are correlated with the price of the car. Consumers place value on attributes such as comfort, design, and prestige. These attributes are largely determined subjectively, and measuring them objectively can prove to be difficult. At the same time, implementing these attributes to a product can be costly to manufacturers, affecting marginal costs. Since the unobserved attributes can affect both supply and demand side of the market, we should expect them to be correlated with the price of the product. (Berry et al., 1995; Nevo, 2000; Train, 2009)

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[1] Ideally, we should understand "cost" in a broad sense, reflecting not only monetary costs but also time loss, discomfort, *et cetera*. However, in estimation, only monetary costs are included.

A fundamental advantage of the estimation method developed in Berry et al. (1995) is in how it allows to deal with the correlation between ξ_{jt} and prices within the non-linear estimation procedure for equation (3.7). For given parameters of the non-linear problem, the algorithm equates observed and predicted market shares and then constructs a Generalized Method of Moments (GMM) objective function where ξ_{jt} becomes the error term. I develop this below following Berry et al. (1995) and Nevo (2000).

Assume that z is a vector of exogenous instruments such that

$$E[z'\xi(\theta^*)] = 0 \tag{3.18}$$

where ξ is the structural error term and θ^* denotes the true values of the parameters in the model. The GMM estimate is chosen such that it sets the sample analogue of $E[z'\xi(\theta^*)]$ to zero. The estimate becomes

$$\hat{\theta} = \operatorname*{argmin}_{\theta} \xi(\theta)'zW^{-1}z'\xi(\theta) \tag{3.19}$$

where W is a consistent estimate of $E[z'\xi\xi'z] = 0$.

Then, the question of valid instruments arises. I closely follow Berry et al. (1995) who use the location of observed product attributes in the characteristics space, sums of the characteristics of other products from the same firm, and the sums of the characteristics of the products from other firms (*BLP instruments*). Formally, let z_{jk} denote the kth exogenous characteristic of choice alternative j. For z_{jk}, the set of BLP instruments is

$$z_{jk}, \sum_{r \neq j,\ r \in J_f} z_{rk}, \sum_{r \neq j,\ r \notin J_f} z_{rk} \tag{3.20}$$

For the purposes of this study, I construct the above set of instruments from variables power (in HP), consumption (l/km), and displacement (cm^3).

The material argument for the correlation between prices and characteristics of other products arises both from the assumed demand specification and competitive structure of the market. As for demand, it is visible in equation (3.7) that the market share of a product is a function of the characteristics of all products in the market. (Byrne et al., 2015) As for supply side, looking at equation (3.10), the markups, $p - mc$, of each product depend on the distance to the nearest neighbour in the characteristics space. (Bresnahan et al., 1996; Nevo, 2001)

The exogeneity assumption, i.e. the orthogonality of observed z_j and unobserved ξ_j, is not entirely unproblematic. As Konishi and Zhao (2017) point out, in the market for low-emission cars, some observed attributes, such as vehicle weight, fuel type, and consumption, may be causally connected with unobserved brand images that consumers have about these cars. Accordingly, instead of a one-way relationship where product characteristics determine prices, it is plausible that firms strategically choose some characteristics jointly with prices. (Byrne et al., 2015)

A possible alternative would be to use instruments that rely on exogenous cost shocks for product j across markets. (Hausman, 1996; Nevo, 2001) Identification would essentially rely on panel structure of the data and in practise on regional differentiation. However, the structure of the data used in this study does not permit identification with these instruments. Firstly, I do not observe spatially but only temporally defined markets. Second, the number of markets is low and I observe one product typically only in 2-3 different markets. Thus, given the data, BLP instruments remain the best available option.

To alleviate any endogeneity concerns with the instruments in (3.20), I include fixed effects for fuel type and manufacturer in the demand specification. This amounts to explicitly accounting for some of the correlation between prices and the mean level of unobserved characteristics. Product-level fixed effects or even manufacturer-fuel interactions could be preferable. (See Nevo, 2000, for discussion on product-level fixed effects.) However, due to the high number of choice alternatives, estimation with product-level fixed effects turned out infeasible.

4. Data

4.1   Data sources and estimation sample

In this section, I describe the data sources and certain choices in data preparation. Table 4.1 below summarizes the data used in this study.

Table 4.1 Data sources

Data	Description	Source
Car market data	Car attributes, prices, and quantities. Observation = car model.	Bilvision AB
Car registry data	Car attributes and odometer readings. Owner's age, gender, and postal code. Observation = individual car.	Swedish Transport Agency
Fuel price data	Monthly average retail prices for different fuels.	Swedish Petroleum and Biofuels Institute
Demographics	Income by age, gender, and municipality. Population density by municipality.	Statistics Sweden

Car market data.   The car market data is available for car model years 2006–2018. However, in an effort to limit the computational burden in estimation, I have limited the analysis to model years 2010–2017. I define one market as the market for one model year. This definition is an approximation, as in reality several model years are available at the same time. For the remainder of this study, a "market year" refers to a car model year unless otherwise noted.

An important choice in data preparation is the definition of a choice alternative. At the outset, I define one car model j as a unique combination of manufacturer, model, generation,

fuel, and displacement. Displacement is rounded to the nearest 250 cubic centimeters. This definition will include several similar but differing car models within one choice alternative. Since one choice alternative may have only one unique set of characteristics per market, for one alternative I assign the characteristics of the most common model within the models included in that alternative.

Also, I drop the highest and lowest price percentiles as well as rare alternatives for which less than five individual cars are observed. This is crucial for the performance of the estimation algorithm. For car models with a very small market share, the differences between observed and predicted market shares become unreasonable. Also, price elasticities become unreasonable, causing problems in policy simulations. As a result of these choices, I obtain between 550–640 choice alternatives per market. All in all, the car models removed this way represent less than 3% of the total quantity of cars sold per year.

However, the removal of choice alternatives causes the composition of my estimation sample to slightly deviate from the full observed sample. Additionally, some observations have been dropped due to missing values, and natural gas vehicles had to be dropped entirely due to fuel price data being unavailable. The last two columns in Table 4.2 below compare the observed market shares with the shares in the estimation sample.

Another important modelling choice is to define the market size relative to the outside option $j = 0$. I define the outside option as *buying a second-hand car not older than four years*. From the car registry data it is simple to verify that the quantities of people buying new cars and people buying second-hand cars not older than four years are roughly equal, thus yielding a market share of 50% for the outside option.

The main motivation behind this choice is that allowing a broader outside option comes at the expense of introducing more heterogeneity within the outside option. Since I delimit simulating changes in CO_2 emissions to composition and rebound effects only, introducing further heterogeneity into the outside option becomes unnecessary and should be avoided.

Car registry data.   I use the car registry data to identify the coefficient for fuel cost, $(\gamma - 1)$, in equation (3.3). The registry data contains an observation for every vehicle registered in Sweden. Odometer readings exist only for cars that have been inspected, and in Sweden the first inspection takes place three years after purchase. Moreover, data only contains demographic information on the current owner of a car and only for private car owners. Accordingly, I choose a subset of cars (i) of which the owner is a private individual, (ii) that has had the same owner for the first three years, and (iii) for which an odometer reading is observed. The first cohort available with complete odometer readings is for model year 2014

and I use this cohort for both the car usage regression and for simulating policy effects on total car use and emissions.

Leasing cars and company-owned cars are dropped from the estimation sample. According to the registry data, in 2017, companies accounted for 43.5 % of new car purchases. Moreover, company-owned cars and leasing cars drive 53.7 % more on average than private consumers. Importantly, the drivers of these cars may respond differently to variation in fuel costs as compared to private individuals. The direction of the resulting bias is hard to ascertain. As an example, for some companies the costs of car use may be a significant expense, possibly leading to a higher cost sensitivity. At the same time, due to tax deductions, companies face a substantially different fuel cost than private individuals, possibly leading to a lower cost sensitivity. The exclusion of company-owned cars from the sample is a limitation to this study, but in the present implementation of the simulation analysis, this exclusion only affects the results via the estimate for fuel cost elasticity.

Fuel prices.   In the discrete choice model, I use average fuel prices of the corresponding year. In the car usage model, I use average fuel prices over the three years of ownership between the purchase and the first inspection of the car. While being more realistic, this choice amounts to a deviation from the utility model in equation (3.1), since the model considers the car usage an individual anticipates at the time of purchase.

4.2   Data description

Car markets   Table 4.2 displays observed market shares for the Swedish new cars market for 2010–2017. This time frame captures the emergence of hybrid and electric car technologies in the Swedish market. Also, the previously very popular ethanol cars commanded only a 0.25 % market share in 2017 as compared to a 11.69 % market share in 2010. This shift has come mostly to the benefit of diesel cars.

Considering the sales for market year 2017, only 3.92 % of the sold cars had emissions below 60 g CO_2/km and thus would have been eligible to receive a rebate under the new scheme. 6.45 % of the sold cars would have received no rebate or fee. 65.91 % of the cars fall to the range between 95 and 140 g CO_2/km and would have received an increased fee. 23.72 % of the cars had emissions above 140 g CO_2/km and would have received an increased fee.

Car registry data   Table 4.3 displays selected statistics from the mileage regression estimation sample and compared to the observations of car models years 2010–2013 and 2015–2017.

Table 4.2 Swedish new cars market shares by fuel and model year

	2010	2011	2012	2013	2014	2015	2016	2017	Observed 2010–17	Estimation sample 2010–17
Petrol	37.18 %	32.38 %	30.15 %	31.53 %	36.17 %	38.15 %	38.52 %	38.42 %	35.84 %	35.56 %
Diesel	46.45 %	59.79 %	64.08 %	64.39 %	58.21 %	55.69 %	53.73 %	51.62 %	55.01 %	58.15 %
Ethanol	11.69 %	5.97 %	2.71 %	1.00 %	1.10 %	0.49 %	0.24 %	0.25 %	4.08 %	2.34 %
Gas	2.86 %	0.83 %	1.69 %	1.11 %	1.15 %	1.53 %	1.14 %	0.69 %	1.34 %	–
Hybird	1.82 %	0.96 %	1.00 %	1.67 %	2.04 %	2.82 %	3.66 %	4.68 %	2.35 %	2.62 %
Plug-in hybrid	0.00 %	0.00 %	0.25 %	0.27 %	0.89 %	0.61 %	1.89 %	3.22 %	0.95 %	1.02 %
Electric	0.00 %	0.07 %	0.12 %	0.03 %	0.45 %	0.71 %	0.80 %	1.10 %	0.43 %	0.32 %

Source: Car market data from Bilvision AB

Two aspects merit attention: First, the individuals selected into the estimation sample are older on average. Second, the lower average income with respect to the 2010–2013 full sample is surprising since the full sample includes owners of second-hand cars but the estimation sample includes only individuals who have bought a new car.

Table 4.3 Descriptive statistics: Swedish car registry data

Variable	Estimation sample 2014		All private individuals 2010–2013		All private individuals 2014–2017	
	Mean	SD	Mean	SD	Mean	SD
Owner						
Age	60.25	13.89	54.47	14.76	55.54	14.67
Income[1]	302.64	81.38	338.35	93.66	339.18	94.15
Population density[2]	559.54	1240.02	540.82	1225.16	569.84	1256.08
Female	35.91 %		35.47 %		33.77 %	
Car						
Km / year[3]	14908.52	8483.56	15182.56	7645.46	15522.42	9311.11
Power	96.96	32.01	101.30	33.73	104.48	35.94
Weight	1457.98	271.31	1511.24	265.64	1524.27	275.81
Consumption	54.43	10.32	57.39	13.01	53.59	11.00
CO2 emissions	13.32	2.58	14.30	3.04	13.38	2.80
N	59 855		739 349		836 519	

Source: Swedish car registry data

Estimation sample: Private individuals who have bought a model year 2014 car as new, who have owned the car for 3 years after purchase, and an odometer reading is observed.

All private individuals: All observations of passenger car model years 2010–2013 and 2014–2017 of which the owner is a private individual.

[1] Median income imputed for every observation by age, gender, and municipality.

[2] Inhabitants per square kilometer in the registered home municipality of the owner.

[3] Data available only for 2010–2014. In the estimation sample, car usage can be attributed to the current owner. In the full sample such attribution is not possible.

5. Results

5.1 Car usage regression

Table 5.1 shows parameter estimates from the car usage regression. The point estimate for $Ln(fuelcost/km)$ is -0.233 and it is statistically highly significant. This estimated fuel cost elasticity is in line with the comprehensive literature survey from Graham and Glaister (2002) who find that short-run elasticities are typically found to be in the region of -0.3. Recalling the utility function in equation (3.1), the estimated value also fits together with the assumptions of the model. As the utility model suggests, I use this estimate in the discrete

choice model to determine the exponent for the cost per kilometer variable. Also, I use the estimate in policy simulations to measure the rebound effect.

Table 5.1 Car usage regression

	(1) OLS	(2) 2SLS
Ln(fuel cost/km)	-0.00918	-0.233***
	(0.0182)	(0.0562)
Female	-0.143***	-0.142***
	(0.00617)	(0.00619)
Age	0.0431***	0.0431***
	(0.00153)	(0.00153)
Age^2	-0.000484***	-0.000483***
	(0.0000142)	(0.0000142)
Income	-0.000675***	-0.000683***
	(0.0000538)	(0.0000539)
Population density	-0.0000374***	-0.0000378***
	(0.00000260)	(0.00000258)
Power	-0.00115***	-0.000812***
	(0.000152)	(0.000175)
Weight	0.000480***	0.000590***
	(0.0000234)	(0.0000348)
Constant	2.398***	2.174***
	(0.0440)	(0.0689)
Fuel FEs	x	x
N	59855	59855
R^2	0.223	0.220

Dependent variable: Ln(km / day).

Standard errors in parentheses. Standard errors clustered at municipality level.

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

5.2   Demand estimation

Table 5.2 shows parameter estimates for the discrete choice model. The first column displays results from a simple OLS regression where the dependent variable is $ln(s_{jt}) - ln(s_{0t})$. The second column displays estimates from 2SLS estimation of the same model where prices are instrumented with BLP instruments as given in (3.20). The Cragg-Donald Wald F-statistic for the first-stage regression is 196.58, suggesting that the instruments are not weak.

In models (3) and (4) I have introduced a random coefficient for price. In column (3), only a parametric distribution is used, i.e. the term ΠD_i in eq. (3.5) is omitted. I assume that v is distributed normally with mean zero, and its estimated standard error σ_v is reported in the table. In column (4), I include the term ΠD_i to the model using an empirical distribution. I use an income distribution obtained from the car registry data. Importantly, the income distribution is observed for each market and with variation between markets, allowing identification of Π. (Nevo, 2000) The estimate for the coefficient Π_{income} is reported in the table.

Parameter estimates   Starting from the coefficient for price, the table shows a pattern similar to Huse and Lucinda (2014) and also Nevo (2001). The absolute value of the coefficient increases first with the use of instruments and then again once a random coefficient is introduced. As for other coefficients, the estimates are in line with expectations. Consumers are averse to fuel costs and show preference to a bigger engine, four-wheel-drive and an automatic gearbox. As for brand preferences, not reported in the table, the findings are similar to Huse and Lucinda (2014). The highest fixed effects are for the domestic brands Volvo and Saab, and German brands also receive generally high estimates. Of non-European brands, Kia receives the highest estimate.

Turning to the random coefficient parameters, in the first BLP model, the estimated standard deviation of v is 3.945 and statistically significant. In the second BLP model in column (4), the demographic coefficient also shows high economic and statistical significance. However, in column (4) the point estimate for σ_v is economically and statistically very insignificant. This may suggest that the included demographic distribution explains most of the heterogeneity in the price coefficient (Nevo, 2000). In both models, however, the significance of the random coefficient parameters can be interpreted such that the data does not reject consumer heterogeneity with respect to the taste parameter for price.

The economic significance of the random coefficient parameters is best displayed by the resulting distributions for the price coefficient. Figure 5.1 shows the distributions

Table 5.2 Demand estimation

	(1) OLS	(2) IV	(3) BLP 1	(4) BLP 2
Price	-3.332***	-5.643***	-8.304***	-8.953***
	(0.408)	(0.737)	(1.261)	(1.351)
Fuel cost	-4.269***	-3.939***	-3.719***	-3.825***
	(0.372)	(0.319)	(0.334)	(0.326)
Displacement	0.243**	0.438***	0.356***	0.330***
	(0.0499)	(0.0902)	(0.0868)	(0.0872)
FWD	0.868***	0.937***	0.952***	0.954***
	(0.104)	(0.0697)	(0.0707)	(0.0703)
Automatic	0.0966	0.143*	0.187**	0.183**
	(0.0634)	(0.0558)	(0.0586)	(0.0576)
Constant	-3.949***	-4.494***	-3.321***	-3.530***
	(0.380)	(0.647)	(0.711)	(0.678)
Random coefficient parameters				
σ_v			3.945***	1.05e-12
			(0.604)	(0.826)
Π_{income}				-38.90***
				(6.664)
Fixed effects				
Make	x	x	x	x
Fuel	x	x	x	x
Emissions class	x	x	x	x
No of doors	x	x	x	x
Market	x	x	x	x
N	4958	4958	4958	4958
$R^2_{adjusted}$	0.321	0.317		

Standard errors in parentheses. In (1) and (2), standard errors clustered at market level. In (2), (3), and (4) prices are instrumented with BLP instruments as provided in eq. (3.20). In (3) and (4), random coefficient is introduced for price and 1000 draws from parametric and demographic distributions are used.

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

resulting from the estimates in Table 5.2, columns (3) and (4). First, note that the estimated distributions provide roughly the same range for the coefficient. The differences result directly from the differences between the empirical income distribution and the assumed parametric distribution. The parametric distribution is more centered at its mean, and the empirical distribution is not symmetrical but skewed.

The skewness leads to a problem with using the empirical distribution. Recall that in eq. (3.5) the terms $\Pi D_i + \Sigma v_i$ can be interpreted as an individual deviation from the population mean level of the coefficient. As for the relationship between income and the price coefficient, we would expect price sensitivity to decrease when income increases, i.e. we would expect $\Pi_{income} > 0$. However, in Table 5.2, column (4), the estimate for Π_{income} is negative in sign. That is to say, contrary to expectation, the model predicts a higher price sensitivity for the higher end of income distribution.

This anomaly is a result of how the estimation algorithm is agnostic about the actual relationship between income and taste for price. Experimenting with different types of scaling and normalisation of the income distribution as well as number of draws, the sign of Π behaved in a very unpredictable manner. Konishi and Zhao (2017) report similar problems when using a non-symmetric parametric distribution. Due to these issues, in policy simulation I use the model and estimates as displayed in Table 5.2, column (3).

Using the specification displayed in Table 5.2, column (3), the median own-price elasticity becomes -2.47 and the median markup becomes 39.01 %. These figures are much in line with the findings of Konishi and Zhao (2017) on Japanese car markets. However, these elasticities are somewhat lower – and, respectively, markups are higher – than what Berry et al. (1995) find in US markets. Also, Goldberg and Verboven (2001) find higher elasticities for European car markets, and Huse and Lucinda (2014) find elasticities in the range of -5.3 to -2.5 for the Swedish car market.

Lastly, recent literature on the properties of the BLP algorithm has stressed the importance of checking sensitivity of results for different choices in implementation. (Brunner et al., 2017; Knittel and Metaxoglou, 2014) Experimenting with different set-ups, the results presented here were not sensitive to gradually increasing the inner and outer loop tolerance levels. Also, the results did not exhibit sensitivity to starting values or the number of random draws for simulation as long as this number was over 400. 1000 Halton draws were used throughout the analysis.

Fig. 5.1 Price coefficient distribution with a paramatric and an empirical distribution
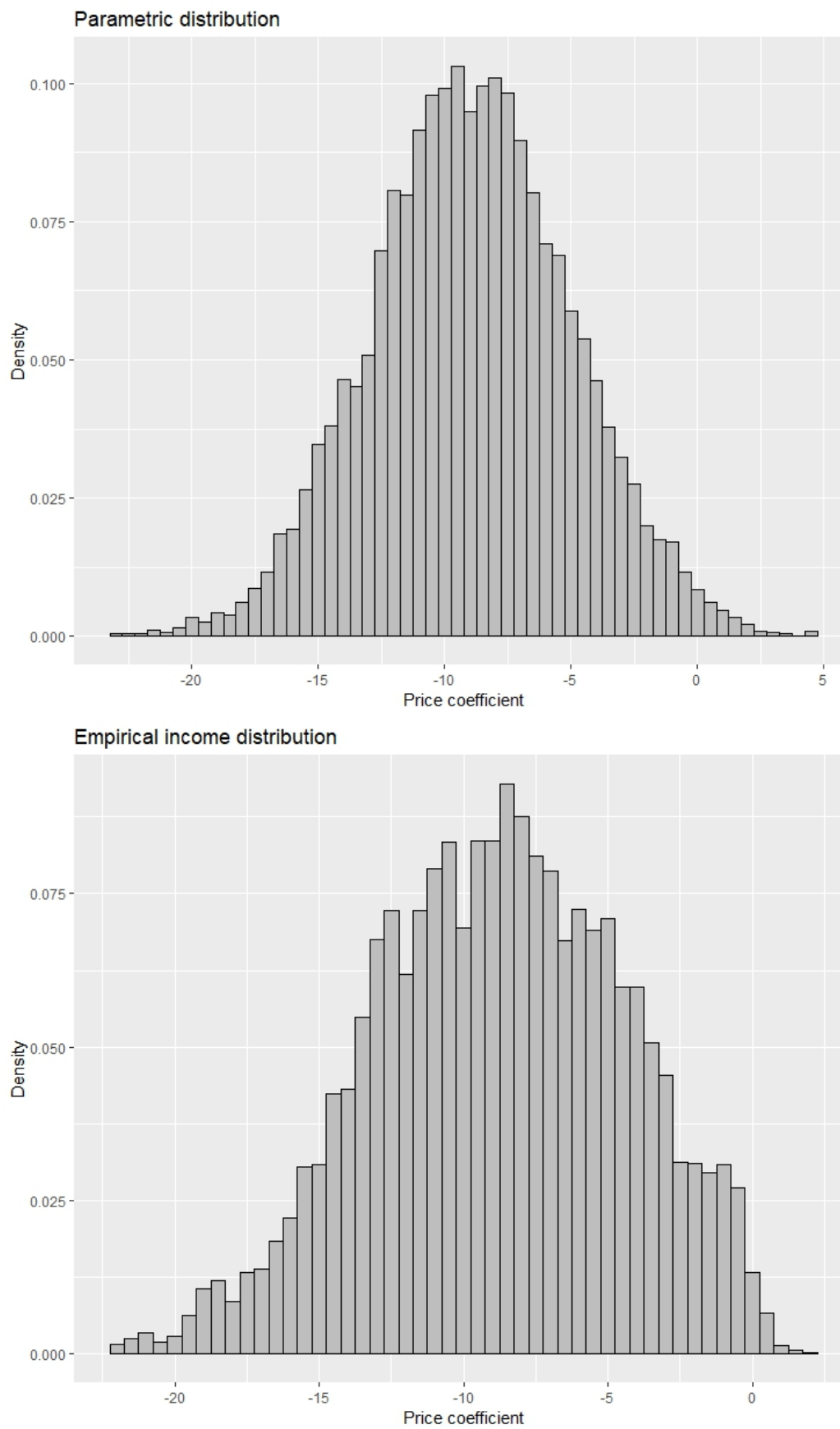
5.3   Policy simulations

In this section, I present results from simulating the Swedish feebate scheme. First, I present and discuss the results from Bertrand-Nash equilibrium analysis. Second, I present and discuss the results from simulating changes in mileage and CO_2 emissions.

The exact details of the feebate schedule I simulate are as follows. Purchasers of zero-emission cars receive a rebate of 60,000 SEK. The rebate decreases linearly by 833 SEK for every additional gram the car emits, to the minimum rebate of 10,000 SEK at 60 g CO_2/km. The fee is incurred as an increased circulation tax for the first three years after purchase. Cars that have emissions above 95 g CO_2/km receive an annual fee of 82 SEK for each additional gram the car emits, and cars emitting over 140 g CO_2/km receive an additional 25 SEK per gram.

In the policy simulations, I simplify the analysis in assuming that a consumer lumps the yearly fees together. Thus, I model an upper bound for consumer valuation as compared to implementing discounting to present value. The more worrisome lack of realism, however, stems from issues discussed earlier in section 2.1. Empirical evidence suggests that consumers are more sensitive to a rebate than to a fee. In the case at hand, differential valuation is likely since the fee is not immediate and may vary depending on how many years the buyers plans to own the car. In light of these considerations, the modelling likely overestimates the effect that the fee has on consumer behaviour.

Car fleet composition.   Table 4.2 displays counterfactual changes in market shares by fuel and by emissions class. The emissions classes correspond to the Swedish feebate scheme, i.e. cars with emissions up to 60 g CO_2/km receive a rebate, cars with emissions above 60 and up to 95 g CO_2/km receive no fee or rebate, and the two highest emission classes receive a linearly increasing fee. The first column of market shares reports the observed inside shares of the estimation subsample.

To ascertain the simulated market shares, I sample 1500 draws from the asymptotic distribution of the demand parameters as reported in Table 5.2, column (3), and calculate the counterfactual quantities for every draw. The figures reported in the table correspond to the mean values from these 1500 draws. The 95% confidence intervals are calculated using the standard deviation of the simulation draws as an approximation of standard error.

In terms of percentage points, the estimated changes in market shares are modest throughout the emission classes. Diesel cars emitting over 140 g CO_2/km see the largest change with a loss of 0.786 percentage points, corresponding to a -4.79 % reduction relative to own

Table 5.3 Policy simulation: Market shares

Fuel	Emissions class	Observed market shares	Simulated market share after policy		Simulated relative difference to own share before policy	
	g CO2 / km	% points	% points	95% CI	% relative	95% CI
Petrol	>60, ≤ 95	0.360 %	0.368 %	0.360 % – 0.375 %	2.152 %	0.093 % – 4.210 %
	>95, ≤ 140	30.206 %	30.237 %	29.643 % – 30.830 %	0.100 %	-1.863 % – 2.064 %
	>140	7.298 %	7.016 %	6.191 % – 7.841 %	-3.863 %	-15.172 % – 7.446 %
Diesel	>60, ≤ 95	2.276 %	2.327 %	2.277 % – 2.376 %	2.244 %	0.062 % – 4.425 %
	>95, ≤ 140	34.285 %	34.179 %	32.418 % – 33.946 %	-0.310 %	-2.606 % – 1.986 %
	>140	16.419 %	15.633 %	14.981 % – 16.094 %	-4.790 %	-8.200 % – -1.380 %
Electric	0	0.913 %	1.239 %	1.096 % – 1.381 %	35.730 %	20.081 % – 51.380 %
Hybird	>60, ≤ 95	3.692 %	3.773 %	3.690 % – 3.856 %	2.204 %	-0.048 % – 4.455 %
	>95, ≤ 140	1.156 %	1.155 %	1.120 % – 1.190 %	-0.078 %	-3.128 % – 2.971 %
	>140	0.003 %	0.003 %	0.002 % – 0.003 %	-3.289 %	-12.927 % – 6.348 %
Plug-in hybrid	≤ 60	3.008 %	3.544 %	3.301 % – 3.787 %	17.808 %	9.724 % – 25.892 %
	>60, ≤ 95	0.126 %	0.130 %	0.111 % – 0.149 %	3.209 %	-11.968 % – 18.385 %
Ethanol	>95, ≤ 140	0.259 %	0.259 %	0.254 % – 0.265 %	-0.014 %	-2.047 % – 2.019 %

Policy simulation of the Swedish feebate scheme. Observed market shares are inside shares of the estimation subsample.
95% confidence intervals calculated by sampling 1500 draws from the asymptotic distribution of the estimated demand parameters.

pre-policy market share. In relative terms, however, the changes are more stark. Electric vehicles and low-emitting plug-in hybrids gain 35.730 % and 17.808 % relative to own pre-policy market shares respectively.

While these gains may seem strong, note that looking at the trends of the market shares reported in Table 4.2, electric cars, hybrids and plug-in hybrids have seen much larger annual gains since 2015. Secondly, Huse and Lucinda (2014) estimate that flexi-fuel vehicles gained 13.8 % relative to own market share under a 10,000 SEK rebate which is small compared to the 60,000 SEK now awarded to all electric vehicles in Sweden. In general, taking into account the differences in policies under examination, the estimated effects on market shares appear more modest both in gains and losses than what Huse and Lucinda (2014) estimate. An obvious explanation is that the estimated price elasticities are lower in this study. Another explanation is that Huse and Lucinda (2014) describe changes over a longer time period than what the implied time period is between the market equilibriums constructed in this study.

Note that the large increase in the market share of plug-in hybrids results from how their emission classifications in the data are based on outdated New European Driving Cycle (NEDC) tests. It is well known that the NEDC tests underestimate the fuel consumption and emission performance of plug-in hybrids. (Mock et al., 2012, 2014) With the new Worldwide harmonized Light vehicle Test Procedure (WLTP), required for all new cars sold in the EU as of September 2018, fewer plug-in hybrids will benefit from the rebate.

Car use and emissions. Table 5.4 displays simulation results for changes in mileage and CO_2 emissions. Note that I simplify the simulation by I allowing car use to vary only with fuel costs and not with other characteristics of the car. Other characteristics, such as car weight, likely have a causal effect on an individual's car usage. However, in the model presented in Table 5.1 I give a causal interpretation only for the fuel cost coefficient. Also, considering the small magnitude of the characteristic coefficients other than fuel cost, the simulation results would be essentially identical in magnitude.

I present results of the simulation with two values for the elasticity of car use. First, setting the elasticity to zero allows measuring the composition effect, i.e. the effect on emissions arising from the changes in car fleet composition only. The estimated composition effect is small at a -1.743 % relative change to emissions before policy.

Second, I present the simulation result using the elasticity value of -0.233 which corresponds to the estimate from the car use regression. For this elasticity, the table shows the relative increase in mileage that results from the lower fuel costs in the post-policy car fleet. This estimated rebound effect is modest at 0.496 % increase in total car usage. However, as

Table 5.4 Policy simulation: Mileage and CO_2 emissions

Elasticity	Mileage	CO_2 emissions
$\frac{\partial ln(Kilometers\ driven)}{\partial ln(Fuel\ cost\ per\ km)}$	*% difference to before policy*	*% difference to before policy*
0	-	-1.743 %
	-	$(0.116$ %$)$[1]
-0.233	0.496 %	-1.334 %
	$(0.131$ %$)$[2]	$(0.095$ %$)$[2]

Simulated effects of counterfactual post-policy Bertrand-Nash equilibrium on total kilometers driven and total CO_2 emissions of new cars.

Elasticity of -0.233 corresponds to the estimate in Table 5.1, column (2).

Standard errors in parentheses.

[1] Standard error approximated as the standard deviation of the result for 1500 draws from the asymptotic distribution of the demand parameters.

[2] Standard errors approximated as the standard deviation of the result for 1000 draws from the asymptotic distribution of the elasticity parameter.

is visible in the table, the increase in car use diminishes the already small emission savings to -1.334 % relative change. This value is my preferred estimate for the sum of short-run rebound and composition effects.

In interpreting the results, one must consider the estimation sample in the car usage regression. As discussed in Section 5.1, the estimation sample of the mileage regression is limited to private individuals. There is uncertainty about the external validity of the estimate for elasticity, and this uncertainty carries on to the estimated CO_2 reductions. However, regardless of fuel cost elasticity, the composition effect is an optimistic upper bound for the emission reductions. Therefore, the conclusion is that the expected emission reductions for one vehicle cohort are small at best.

This result is comparable to the those of d'Haultfoeuille et al. (2014) who find a short run effect of -0.527 % relative to emissions before policy resulting from composition and rebound effects. Note that the French feebate schedule that d'Haultfoeuille et al. (2014) assessed awarded rebates to higher emission classes than the Swedish schedule and also the fee for high-emitters was less severe. Also, the authors estimate a higher fuel cost elasticity than I do, amplifying the rebound effect. Thus, given the setting and elasticity

estimate, the results in this paper are in the expected direction when compared to the results of d'Haultfoeuille et al. (2014).

5.4   Discussion of results

The preferred estimate in this study is a -1.334 % relative change in emissions of new cars due to composition and rebound effects. This is a short-run effect for one vehicle cohort in a counterfactual post-policy market equilibrium. Comparing the magnitude of the simulated changes in market shares to previous trends, it is reasonable to assume that the shift to a post-policy equilibrium may occur in a relatively short time, i.e. within 1–2 years. It is important to note that the modelling choices taken along the way likely result in an overestimation of the overall effects of the feebate scheme.

The immediate question that arises is how does the feebate scheme fare in comparison to an alternative policy such as an increase in fuel taxes. To answer this question, Table 5.5 displays predicted changes in mileage and CO_2 emissions due to increases in fuel prices for fossil fuels. The figures I present are extrapolations of the results of this study to the entire car fleet. The percentage differences are a straightforward consequence of the assumed fuel cost elasticity. In calculating government revenue from the increased fuel tax, car usage of each cohort is adjusted according to yearly means of odometer readings as observed in the registry data. This correction accounts for how newer cars see more use than older cars.

The short run effect of the Swedish feebate scheme is now reported as a change with respect to the usage and CO_2 emissions of the entire car fleet. The last three rows report changes in total emissions assuming a simple extrapolation of the short-run effect over 25 years, each row corresponding to a different assumed car fleet replacement rate. The estimated government revenue for the feebate scheme is a mean value obtained from running the market simulation analysis with 1500 draws from the asymptotic distribution of the estimated demand parameters.

The calculations in Table 5.5 are simple extrapolations of the static analysis and do not consider dynamic effects such as supply side response to the feebate or long-term elasticities of the consumers. Nevertheless, the message is clear. Considering the time span it takes for the effects of a feebate to penetrate the entire car fleet, the emission reductions from the feebate scheme dwarf in comparison to the effects from increasing fuel tax. The table shows that a fuel tax increase in the range 8–9 % would raise the same annual government revenue as I estimate from the Swedish feebate scheme. Such 8–9 % fuel tax increase would lead to a $7.8 - 9.7$ % reduction in CO_2 emissions. Similarly, for an equivalent emission reduction,

Table 5.5 Comparison of results to a fuel tax increase

Policy		Mileage (entire fleet)	CO_1 emissions (entire fleet)	Government revenue
Fuel tax increase[1]		*% difference*	*% difference*	*Million SEK, annual*
	1 %	-0.231 %	-0.231 %	1.781
	2 %	-0.688 %	-0.690 %	10.733
	3 %	-1.366 %	-1.370 %	32.462
	4 %	-2.259 %	-2.265 %	73.005
	5 %	-3.359 %	-3.368 %	139.064
	6 %	-4.656 %	-4.669 %	238.265
	7 %	-6.140 %	-6.157 %	379.475
	8 %	-7.800 %	-7.822 %	573.166
	9 %	-9.625 %	-9.651 %	831.877
	10 %	-11.600 %	-11.632 %	1170.773
Swedish feebate scheme[2]				*Million SEK, per cohort*
	Short run	0.031 %	-0.088 %	613.530
Extrapolation over 25 years[3]				
Fleet replaced in 15 years		0.358 %	-0.961 %	
Fleet replaced in 20 years		0.305 %	-0.819 %	
Fleet replaced in 25 years		0.244 %	-0.678 %	

[1] Predicted effects of fuel tax increase for fossil fuels on CO_2 emissions. Calculations assume fuel cost elasticity of -0.233 as reported in Table 5.1, column (2).

[2] Short-run effects as reported in Table 5.4 now calculated as a share of total mileage and emissions of all passenger cars.

[3] Extrapolation of short-run effects over 25 cohorts with different assumptions for car fleet replacement rate.

the cost of a fuel tax increase is a fraction of the cost of the feebate. Much in contrast to the lagging effects of the feebate, the fuel tax would affect the entire car fleet at once.

Considering the rebate separately and especially for electric cars, a more pronounced comparable policy is found in Norway where electric cars are, among other benefits, exempted from the 25 % value added tax on new cars. The policy has not been received with enthusiasm in literature, criticism including how it effectively subsidizes high-income families to buy a second car. The costs of the policy are considerable but not justified by the expected emission reductions. (Holtsmark and Skonhoft, 2014) The analysis in this paper only reiterates the same message.

The total emission reductions from the feebate would vary were we to consider emissions from car manufacturing. In their analysis, d'Haultfoeuille et al. (2014) find that emissions from manufacturing increased due to the feebate. However, this was a result of how the French feebate scheme initially was a net subsidy for car purchases. In the Swedish feebate scheme, this is clearly not the case. The fee would have applied to 89.63 % of the cars sold in market year 2017, and I estimate expected government revenue at 613 million SEK per vehicle cohort. This aspect of the Swedish feebate could be examined in more detail. The expected short-term effect should be diminishing new cars sales, but the end result will depend on the suppliers' ability to adjust their products in order to escape the fee and capture the rebate.

Accordingly, compared to a pure subsidy, the feebate such as implemented in Sweden is likely the better option. Considering the nature of the Swedish feebate scheme as a net tax, indirect effects such as changes in car manufacturing scale and total fleet size may bring some arguments in favour of the implemented schedule.

6. Summary

In this study, I recovered estimates for demand and supply side parameters in the Swedish car market as well as car usage parameters. Using the parameter estimates, I simulated the effects of the feebate scheme introduced in Sweden in July 2018. The simulations cover effects on market shares and short-run effects on car use and CO_2 emissions.

The results show expected responses in market shares, namely that low-emitting cars gain market share and high-emitting cars lose market share. The magnitude of changes is small in terms of percentage points. In relative terms, however, some observed changes are more noticeable. Electric cars and plug-in hybrids increase their market share by 35.73 % and 17.81 % respectively relative to own share before policy.

As for effects on car use and CO_2 emissions, the simulation analysis shows that the composition effect – the effect arising solely from the changes in market shares towards lower-emitting cars – reduces CO_2 emissions by -1.743 % relative to before policy for one vehicle cohort. As for rebound effect, I estimate that the lowered fuel consumption of new cars leads to a 0.496 % increase in total mileage for buyers of new cars. Considering the rebound and composition effects together, the total short-term emission reduction for one vehicle cohort becomes -1.334 % relative to before policy.

This emission reduction is underwhelming given the net tax revenue which I estimate at 613 million SEK per vehicle cohort. I demonstrate that given an equivalent increase in total government revenue, an additional fuel tax would result in emission reductions in the range of 7.82 % – 9.65 %. Moreover, given certain modelling choices that abstract away from details such as consumers' differing sensitivity towards a fee and a rebate, the simulation in this study is likely overestimate the effects of the feebate.

Given these results, policy makers should not have overly high expectations about the environmental benefits of a feebate scheme such as implemented in Sweden. Effects on CO_2 emissions per vehicle cohort are negligible compared to the cost of the policy. However, the nature of the Swedish feebate scheme as a net tax warrants further inquiry into its indirect effects such as emissions from manufacturing.

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