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Do tax incentives affect households' adoption of 'green' cars? A panel study of the Stockholm congestion tax

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HIGHLIGHTS

- Uses a database of car owners to analyze impacts of a congestion tax on car fleet.
- Results show that the tax had a significant effect on ethanol car purchases.
- Prior ownership of ethanol car and education correlates with ethanol car purchases.

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ABSTRACT

Policymakers have made several attempts to introduce local and national policies to reduce CO_2 emissions and stimulate the consumer adoption of alternative fuel vehicles (ethanol/E85 cars). The purpose of this paper is to analyze how a local policy measure impacts the composition of the car fleet over time. More specifically, we take advantage of the natural experiment setting caused by the introduction of the Stockholm congestion tax (2006) to analyze how the tax affected purchases of ethanol cars that were exempted from the tax. To estimate effects, we employ a Difference-in-differences methodology. By using a comprehensive database of the car fleet and car owners, sociodemographic and geographic factors are analyzed, which is unique in the existing literature. Our results suggest that the congestion tax had a significant impact on ethanol car purchases although the effect fades away over time. Furthermore, there is a positive relationship between the level of education and ethanol car purchases. Previous adoption of an ethanol car is found to be the strongest predictor of ethanol car purchases. Finally, data indicate that Stockholmers substantially increased purchases of ethanol cars half a year before the introduction of the congestion tax, which we refer to as an anticipation effect.

1. Introduction

In 2010 the transportation sector accounted for 22% of worldwide CO_2 emissions and approximately three quarters of these were due to road traffic (IEA, 2012). Decreasing the emissions of car traffic and making the car fleet less dependent on fossil oil has been the goal of international agencies and national governments for many years, and it has also spurred an interest in finding the most effective policies for shifting the car fleet towards increased environmental sustainability. Based on a unique set of register data, we compare the development in the consumer adoption of alternative fuel vehicles (AFVs; specifically ethanol/E85 cars) in the three largest cities of Sweden following the introduction of the Stockholm congestion tax in 2006. We are able to estimate the effect of the congestion tax on car purchasing behavior since ethanol cars were exempt from the congestion tax between 2006 and 2009. Thus, although the introduction of the congestion tax was not explicitly aimed at people's car choices, it provides a natural experiment for testing the effectiveness of economic incentives on the purchasing of AFVs. In addition, the dataset permits the uncovering of more socio-economic factors of AFV adopters and non-adopters than reported in previous studies.

The Stockholm congestion tax is one of several national and local policies aimed at decreasing congestion but also increasing consumer adoption of AFVs and sales of alternative fuels such as bioethanol and gas. As an over-arching goal for the transport

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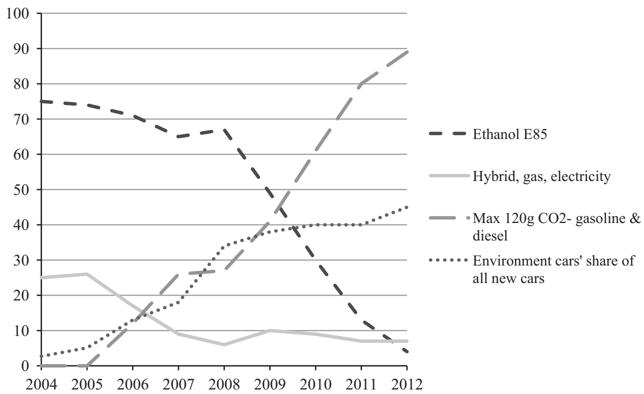

Fig. 1. The proportions of different types of environment cars of all environment car purchases in Sweden 2004–2012, and the total share of all environment car purchases of all car sales. New car registrations per year (Bil Sweden, 2013).

sector, the Swedish Parliament has set a target for zero greenhouse gas emissions in 2050 and a milestone of having a fossil oil independent car fleet by 2030 (Regeringskansliet, 2009). Furthermore, Sweden was the first country in Europe to create incentives for ethanol/E85[1] cars through tax breaks on the fuel as well as a law mandating fueling stations to invest in pumps for alternative fuels[2] (Riksrevisionen, 2011). According to a government regulation adopted in 2004, "environment cars[3]" are flexible fuel vehicles that can run on ethanol, electricity or biogas provided that they, when driven on gasoline, do not emit more than 218 g CO_2 per km (SFS, 2004: 1364). In addition, diesel cars and gasoline cars that emit less than 120 g CO_2 per km were also labeled "environment cars", but only cars that run on ethanol, electricity or gas were exempted from the Stockholm congestion tax. As shown in Fig. 1, at a national level these policies appear to have had a substantial effect on car purchases since 2004. Early on, ethanol cars dominated the "environment car" market. For example, in 2008 ethanol cars had a 68% share of the "environment car" market (corresponding to a 23% share of the total car purchases that year (Bil Sweden, 2013)). Since 2009, low CO_2-emitting diesel and gasoline cars have taken over as the most sold "environment cars" (e.g., Kågeson, 2012). Fig. 1 shows that the total market for "environment cars" expanded from 3% of all new car sales in 2004 to 45% in 2012, but it can also be concluded that ethanol cars have dropped over time as other types of "environment cars" have been introduced and become popular among consumers.

Although some evaluations of policies targeting the sales of biofuels and AFVs in Sweden have been conducted, most of them are partial or merely adopting a descriptive approach (e.g., City of Stockholm, 2009; Riksrevisionen, 2011). Hence, it is difficult to draw more specific conclusions as to how a specific policy such as the Stockholm congestion tax is linked to changes in the car fleet over time and about what factors that can explain the adoption of more environmentally friendly vehicles. From a research perspective, there is a wealth of published studies using different types of survey methods to clarify barriers and drivers of consumer adoption of AFVs (Diamond, 2009; Egbue and Long, 2012; Ozaki and Sevastyanova, 2011). Some studies have also utilized panel data (e.g., Ryan et al., 2009) to model the CO_2 intensity of the new car fleet, but this study did not analyze AFV adoption as such. However, there are no published studies based on register data that pool demographic and time series data in order to produce a more nuanced picture of how policies influence the car fleet depending on local or non-local policy to reduce environmental impact using alternative fuels.

To our knowledge there is yet no study of AFV adoption based on representative panel data with information on socio-economics and demographics. This type of analysis may add important insights to the existing knowledge of incentive mechanisms behind changes in AFV adoption. The purpose of the paper is to contribute to the understanding of how selective taxes and population characteristics influence the composition of the car fleet against this background. More specifically, our aim is to estimate the causal link between tax exemptions for AFVs and purchases of such vehicles, and to describe the socio-economic and demographic characteristics of AFV consumers. We do this by utilizing a natural experiment created by the introduction of the congestion tax in Stockholm (Sweden) in 2006. Since this tax was not introduced anywhere else in Sweden until 2013, and since ethanol/E85 cars were exempted from the tax, we are able to estimate how the tax affected incentives to purchase ethanol cars. Our rich register data further allows us to estimate the correlation between socio-economic and demographic characteristics and ethanol car purchases.

1.1. The Stockholm congestion tax and the exemption for AFVs: a natural experiment

Research has pointed towards policies as important factors behind the composition and development of the car fleet (e.g., de Haan et al., 2006; Potter and Parkhurst, 2005). Today, CO_2 taxation is well established in large parts of the European Union. Nineteen EU Member States (ACEA, 2012), among them Sweden, currently apply some form of CO_2 tax to the registration and/or ownership of passenger cars, based on the car's CO_2 emissions and/or fuel consumption. There are, for example, vehicle taxes such as the annual vehicle tax. These types of taxes affect the entire car fleet and aim to give incentives to choose more fuel-efficient cars (Ryan et al., 2009). In addition to the national taxation schemes there are also local taxes and subsidies implemented to attempt to steer the car fleet in less environmentally harmful and less fossil fuel intensive directions.[4] Local policies that affect the composition of the car fleet are exemption from congestion tolls and free parking for cars that pollute less.

During recent years, several policies have been implemented in Sweden in order to increase the adoption of AFVs and fuel-efficient cars. From 2007 to 2009 a national cleaner car purchase rebate was enacted that subsidized the purchase price of all new AFVs with SEK 10,000 (approximately 1000 Euros). Furthermore, a congestion tax was introduced in Stockholm in 2006, initially as a six-month trial. After close monitoring of traffic patterns and public opinions and a referendum in and around Stockholm city, the tax was made permanent in August 2007. According to Börjesson et al. (2012) the tax had both immediate and longer term effects on decreasing traffic congestion. In their study they also found that the tax had a considerable effect on the sale of AFVs due to the fact that these vehicles were exempted from the tax (to varying degrees) up until 2012 (Börjesson et al., 2012). In a national comparison they also show that the sales of AFVs in Stockholm were higher than the Swedish average in 2006 and

[1] E85 is a blend of 85% ethanol and 15% gasoline (summer quality; in the winter the mix is 75/25). It is the most commonly available blended fuel for use in flex-fuel vehicles (FFVs) in Sweden. In this paper we refer to cars that can run on E85 as ethanol cars.

[2] By the end of 2011 there were 2885 fueling stations in Sweden and 59% of these sold E85 (SBPI, 2013).

[3] The term "environment car" has been used by the Swedish legislators and is not a term invented or endorsed in this paper.

[4] It should be noted that these vehicle taxes impose a fixed cost on car ownership and therefore probably have very little effect on how the car is actually used, i.e., how much emission it produces. Hence, from an economics perspective, these policies are seen as second best; a unit tax on the CO_2 content in fuels would likely be a more cost-effective policy.

2008, and nearly the same for 2007. In total, exempting the AFVs from the tax seems to have had a positive effect on the sales of these vehicles together with other local (free residential parking) and national incentives (such as the tax exemption on renewable fuels and the national purchase subsidy for cleaner vehicles). This seems to be particularly the case on car sales to companies, which accounted for 91% of the bought “green cars” (AFVs and cars emitting less than 120 g of CO_2/km) according to Börjesson et al. (2012). Although the studies by Börjesson et al. (2012) and Eliasson and Jonsson (2011) concerning the Stockholm congestion tax are important for understanding Traffic Demand Management (TDM) measures and sales of so called “environment cars”, their estimation techniques do not allow for causal inference, since it does not include a counter-factual development. In other words, without an adequate control group, we cannot say to what extent congestion and the composition of the car fleet in Stockholm would have changed in the absence of the tax. Indeed, since Stockholm had a higher than the national average sale of “green cars” even before the introduction of the tax, the increase after 2006 may only represent a continuation of this trend. In addition, previous research does not offer insight into which types of consumers bought “environment cars”. Finally, Börjesson et al. (2012) and Eliasson and Jonsson (2011) study both private and company car purchases lumped together. Since the tax models for private and company purchase of cars differ, and since individual consumers and companies are likely to differ in terms of behavior, there are probably different driving forces behind car purchases in these two groups.

This paper contributes to the literature on AFV diffusion (and ethanol cars in particular) in three distinct ways. First, in contrast to previous research that commonly estimates correlations between AFV adoption and policy, we utilize the natural experiment created by the Stockholm congestion tax to estimate causal effects between policy and consumer behavior. Second, having access to a uniquely rich register dataset allows us to analyze previously uncovered factors, such as heterogeneity among consumers in terms of socio-economic and socio-demographic characteristics associated with AFV adoption. By focusing solely on private car purchases the third contribution refers to the analysis of the mechanisms behind adoption among private persons without interference from corporate sector purchases. This is important since company car purchases have different tax regulations and probably also involve other preferences compared to the household sector.

1.2. Consumer characteristics and the adoption of AFVs

As examples of AFVs we use ethanol cars, since they have accounted for a majority of new purchases of AFVs in Sweden during our period of investigation (2004-2008) see Fig. 1.

There are a wealth of studies on socio-economic factors on the household/family and individual levels related to consumer adoption (Hunecke et al., 2007) and how these affect car purchases. In this respect, income, gender, education, age and civil status appear to have some influence, although the explanatory ability of these factors is often found to be relatively low.

Previous research has found that high-income households value AFVs higher than conventional cars (Dagsvik and Liu, 2009) and that females, minorities, and residents in urban areas exhibit higher demands for fuel-efficient cars (McCarthy and Tay, 1998). Males have been found to have a higher stated choice of hydrogen vehicles (Ziegler, 2012), whereas females and owners of new cars are significantly more concerned with the environmental performance of the car (Johansson-Stenman and Martinsson, 2006). Moreover, old people seem to be significantly more concerned with the environmental performance of the car (Johansson-Stenman and Martinsson, 2006), but at the same time, age seems negatively related to greenhouse gas emissions from transportation (Hunecke et al., 2007). Finally, higher education seems to have a significant positive effect on the stated choice of hybrid vehicles (Potoglou and Kanaroglou, 2007) and AFVs (Jansson et al., 2011). Furthermore, in other studies there seems to be no effect of education on the willingness to choose an AFV (Zhang et al., 2011; Ziegler, 2012). According to a recent Eurobarometer (EC, 2011), Swedes are the most concerned about climate change in the EU and Swedish citizens are reported to have the most positive attitudes to environmentally friendly transportation in the EU. Thus, both the tax incentive schemes and the consumer preferences make Sweden an interesting case for a study of the diffusion of AFVs. Due to differences in preferences, there is probably a heterogeneity which can be examined by using register data. This approach will be further elaborated.

2. Material and methods

In order to evaluate the effect of the Stockholm congestion tax, we employ a Difference-in-differences approach (described in detail below) for the period 2004–2008. Our data consists of a random sample of individuals living in one of the three biggest cities in Sweden: Stockholm, Gothenburg or Malmö, where Gothenburg and Malmö function as control groups. The choice of control groups is partly justified by the resemblance in population size (all three being metropolitan areas as compared to other cities in Sweden), and partly by the fact that Gothenburg actually implemented a similar tax in 2013 while Malmö is still lacking congestion taxes. The difference in timing of implementation creates a natural experiment, which in turn enables a more accurate estimation of the effects of a congestion tax.

In order to capture effects on individuals that do not live in the city center in the metropolitan areas, but may be affected by the congestion tax (e.g., via work), we also include individuals living in neighboring municipalities. The choice of these neighboring municipalities follows the classification of Statistics Sweden. The distance between the three cities is: Stockholm-Malmö: 619 km; Stockholm–Gothenburg; 478 km, Malmö–Gothenburg; 276 km.

The dataset available for analyses is a compilation of register data of the entire Swedish population collected by Statistics Sweden. Individual-level record linkages between demographic and socioeconomic attributes in combination with car ownership make the foundation for the empirical analyses. This implies that car-related attributes like brand, model, registration date, fuel type, motor capacity, emissions etc. are linked to the individual (owner) and can be viewed together with his/her demographic (e.g. sex, age, and family situation) and socioeconomic (e.g. education level, earnings, housing, and labor market situation) characteristics. Since the dataset covers the entire population over the last 25 years we can observe car ownership of all private persons, which corresponds to a vast share of all cars in the country.

In 2012 there were about 4.4 million cars in Sweden, corresponding to 464 cars per 1000 inhabitants (480 in EU-25). Almost 80% of the cars in Sweden are owned privately. The regions of Stockholm, Gothenburg and Malmö account for 48% of these cars (Trafikanalys, 2013). Car owners in Sweden are predominantly male (65% in 2012), and the average annual driving distance is 12,118 km. The share of the population having a driver's license for passenger car was 78% at the end of 2011 (Stockholm: 69%, Gothenburg: 79%, Malmö: 76%). To enable an econometric analysis of the material, we use a random sample of 100,000 individuals in Stockholm, Göteborg and Malmö respectively. The population from which this sample is drawn is the total population of the three cities. These individuals are followed during the entire time period. Since only individuals over the age of 18 are eligible to drive a car in Sweden, we only conduct our analysis on individuals at or above the age of 18 in our sample. This implies that some individuals, who were below the age of 18 in 2004 but turns 18 sometime during the time period under study, enter into our sample in the year s/he comes of age. In combination with the fact that some individuals in the sample die during the time period this implies that our analysis is conducted on an unbalanced panel of individuals.

2.1. Econometric approach

To identify the possible impacts of the Stockholm congestion taxes on purchases of ethanol cars, we employ the Difference-in-differences approach, DiD (e.g., Wooldridge, 2002). The DiD approach enables us to compare the change in the probability to purchase an ethanol car in Stockholm (treatment group) before and after the introduction of the tax, with the corresponding change in Gothenburg and Malmö (control group). Hence, since we control for the potential "Stockholm" effect, this approach makes it possible to control for both observed and unobserved differences between the control and treatment group (Wooldridge, 2002). The empirical specification employed thereby increases the likelihood of capturing causal effects of the introduction of the congestion tax.

Our outcome variable is related to the choice to purchase an ethanol car, and thus dichotomous. This implies a limited dependent variable approach. To deal with unobserved individual heterogeneity, we employ a panel data probit approach (xtprobit) to estimate the model. The econometric model is specified in Eq. (1) below.

$$y_{it}^{*} = \alpha + \delta\boldsymbol{\tau}_t + \vartheta G_i + \phi\boldsymbol{\tau}_t G_i + \theta City_i + \mu\boldsymbol{\tau}_t G_i City_i + \boldsymbol{X}_{\boldsymbol{it}}'\varpi + \psi\Delta gdp_t + v_{it} \tag{1}$$

$$y_{it} = 1[y_{it}^{*} > 0]$$

$$v_{it} = c_i + u_{it}$$

In Eq. (1), y_{it} is a limited dependent variable taking the value one if individual i purchases an ethanol car at time t, i.e., if the latent variable $y_{it}^{*} > 0$, and zero otherwise. τ_t is a vector of time dummies. We use a different set of time dummies in different model specifications: In our *TIMEPERIOD* models, we want to estimate the total effect of the tax after its introduction, but also test for any additional effects in the year following the introduction. In these models we therefore have three time dummies. The first (2006–2008) takes the value one in the time period after the introduction of tax (2006–2008) and zero otherwise, the second takes the value one if the year is 2007, and the third takes the value one in the year 2008. In our *INDIVIDUAL YEARS* models, we analyze individual year effects. In these models, the time dummies thus consist of a full set of individual year dummies (2005, 20,062,007 and 2008). G_i is a dummy variable taking the value one if the individual belongs to the treatment group, in terms of residing in the Stockholm area, and zero otherwise. The coefficients on the interaction variables $\boldsymbol{\tau}_t G_i$ thus capture the effect of the congestion tax on the probability to purchase an ethanol car. Finally, we evaluate to what extent individuals living within the central city of Stockholm were differently affected by the tax than individuals living in the suburbs. We therefore include a "double" dummy interaction variable $\boldsymbol{\tau_t} G_i City_i$. This variable takes the value one in the time period after the introduction of the tax, if the individual lives in the city center in Stockholm, and zero otherwise.

The vector $\boldsymbol{X_i}$ consists of socio-economic and socio-demographic characteristics. Since we want to evaluate the change in consumption of ethanol cars between the *time period* before and after the introduction of the tax, we cannot include individual year dummies for the years before the tax in our TIMEPERIOD models. However, to capture the trend, we use the real growth in GDP per capita, Δgdp, between year $t-1$ and year t evaluated in year t. This variable thus captures time effects in the model. Finally, $v_{it} = c_i + u_{it}$ denotes the composite error term capturing the time invariant unobserved individual heterogeneity and the remainder disturbance that can vary over time as well as across individuals.

Now, in general, the estimated coefficients in non-linear models cannot be interpreted as easily as in linear models. This is especially true for interacted variables. However, Puhani (2012) shows that the estimated coefficient on the DiD variable ($\tau_t G_i$) is consistent and can be interpreted as the treatment effect on the treated. In addition, it is now possible to estimate marginal effects and unbiased coefficients of interaction variables in Stata (version 11 or later) by specifying the variables to be interacted and using the margins command. We employ this method for our double interaction variables $\tau_t G_i City_i$. In order to calculate the standard errors of the marginal effects for all variables, we employ the delta method.

We would like to alert the reader on our strategy to estimate the marginal effects. Although it, in practice, is possible to estimate the marginal effects with a panel model command, the statistical software will assume that the individual effects are zero, thus removing the value of the panel approach. In order to get some idea of the marginal effects, we therefore estimate a pooled probit (with standard errors adjusted for clustering on the individual level), and calculate the marginal effects resulting from this estimation. As a robustness check of this approach, we show that the estimated coefficients of the panel and pooled approach are very similar.

It should be noted that, in the above econometric specification, the group of individuals who purchased an ethanol car is compared to "everyone else" in the sample. In other words, the comparison group includes individuals that purchased another type of car, and individuals who did not purchase any type of car (regardless of whether they owned one previously or not). However, it is possible, and perhaps even plausible, that there are important differences between choices related to the type of car purchased and choices related to whether to buy a car in the first place. Most importantly, the decision to abstain from a car purchase may be related to environmental and/or congestion concerns and may thus constitute a response to the congestion tax. Hence, in order to not confound the effect of the tax with other effects, we also estimate Eq. (1) conditional on that the individual purchased a car.

As mentioned above, we employ a panel data probit approach to estimate Eq. (1). Panel data probit estimations are only available with random effects. However, a random effects approach is only valid if the independent variables are not correlated with the individual effects. If such a correlation exists, the estimated coefficients are biased. To deal with this problem, we use the Chamberlain's random effects probit model (Chamberlain, 1982, 1984; Mundlak, 1978), also known as the pseudo-fixed effects model. This approach implies that we explicitly model the relationship between the time-varying regressors and the unobservable effect in an auxiliary regression (Mundlak, 1978). The model is estimated under the assumption that:

$$c_i | X_{it} \sim Normal\left(\psi + \overline{\boldsymbol{X}}_{\boldsymbol{i}}\boldsymbol{\xi},\ \sigma_a^2\right) \tag{2}$$

where $\overline{X}_i$ is the average of the time varying explanatory variables $X_{it},\ t = 1, \ldots, T$ and σ_a^2 is the variance of the parameter σ_a^2 in the equation $c_i = \psi + \overline{X}_{it}^{'}\xi + a_i$. In other words, σ_a^2 is the conditional variance of the unobserved individual heterogeneity assumed to be independent of X_{it} (Wooldridge, 2002). In practice, the approach implies that, for each time varying variable and for each individual, we calculate the average over the full time period. The resulting variable is then added as an additional covariate in Eq. (1).

Finally, since probit models are sensitive to miss-specification, and since we have a large share of zeroes in our sample due to the relatively low presence of ethanol cars in the population, we also estimate a linear probability model and a complementary log log model.

As mentioned above, the DiD approach enables us to control for both observable and unobservable time-invariant differences between the treated and the non-treated groups. However, the approach relies on the, inherently untestable, assumption that the trend in the outcome variable, would have been parallel in the absence of treatment. If data is available for multiple time-periods before the introduction of treatment, one may validate this assumption by running regressions with "fake treatments", or placebo effects, in the years preceding the true treatment. If the coefficients on these placebo effects are insignificant, the belief in the validity of the parallel trend assumption is strengthened. However, if the coefficients on the placebo effects are significant, this increases the risk that the two groups develop differently with respect to the outcome variable over time. In this case, we cannot draw conclusions to what extent our estimation captures the true effect of the treatment (in our case the congestion tax).

In order to reduce the risk of a violated assumption of a common or parallel trend, in our treatment group, Stockholm, and our control groups, Malmö and Gothenburg, we match individuals on socio-economic characteristics by the use of propensity score matching.

The main purpose of the propensity score estimation is to balance the observed distribution of covariates across households in the control and treatment groups.[5] When exposure of the treatment is independent of outcomes, given the observables, then the relevant summary statistic to be balanced between the two groups is the conditional probability of being treated, called the "propensity score" (Rosenbaum and Rubin, 1983; 1985). The first step of computing a propensity score in propensity score matching is to estimate a standard probit or logit participation model with control variables.[6]

$$H_{it} = \alpha + K_{it} + v_{it} \tag{3}$$

where, for individual i and year t, H_{it} is a dummy variable representing exposure to treatment or not, K_{it} is a vector of variables used as determinants of the likelihood of treatment; and v_{it} is the error term. The predicted values are used to estimate the propensity score for each observation in the participant and the nonparticipant samples (Caliendo and Kopeinig, 2008). The comparison group is then formed by picking the "nearest neighbor" with similar characteristics for each participant. The propensity score is given by:

$$e(x) = \Pr(w = 1|X = x) = E(w|X = x) \tag{4}$$

where w is the indicator of exposure to treatment, and x is the multidimensional vector of pre-treatment characteristics. The choice of covariates to be included in the propensity score estimation is based on the principle of maintaining a balance in using common variables whilst at the same time meeting the common support criteria.

For each variable and propensity score, the standardized matching is computed before and after matching as:

$$SB(X) = 100 - \frac{\overline{X}_t - \overline{X}_{NT}}{\sqrt{\overline{V}_t(X) - \overline{V}_{NT}(X)/(2)}} \tag{5}$$

where $\overline{X}_t$ and $\overline{X}_{NT}$ are the sample means for the treatment and control groups, and

$\overline{V}_t(X)$ and $\overline{V}_{NT}(X)$ are the corresponding variance (Caliendo and Kopeinig, 2008).

Additional covariate balancing indicators that can be used in addition to the SB measure in this case are the likelihood ratio test of the joint significance of all covariates and the pseudo-R^2 from a logit of treatment status on covariates before matching and after matching on matched sample (ibid). After matching, there should be no systematic differences in the distribution of covariates between both groups. As a result, the pseudo-R^2 should be fairly low and the joint significance of all covariates should be rejected. We derive the propensity scores and the matched sample by the use of the command psmatch2 in Stata (Leuven and Sianesi, 2003). The matched sample is then used for the Difference-in-differences analysis.

2.2. Descriptive statistics

The descriptive statistics are presented in Table 1 below. As can be seen from the table, the matching procedure has given rise to a relatively high similarity between our sample in Stockholm and

Table 1
Descriptive statistics.

	Stockholm	Gothenburg	Malmö	Total
Gender				
% Male	45.85	45.57	45.64	45.67
% Female	54.15	54.43	54.36	54.33
Civil status				
% Unmarried	15.54	15.18	13.02	15.29
% Married	74.19	75.97	77.99	75.1
% Divorced	9.53	8.17	8.32	8.92
% Widow/Widower	0.74	0.68	0.66	0.69
Education				
% pre-highschool educ	16.19	17.62	17.25	16.63
% High school educ	41.96	42	40.61	41.58
% College, less than 3 years	6.42	6.37	5.75	6.3
% Bachelor degree	33.65	31.91	33.51	33.43
% Post graduate	1.77	2.09	2.87	2.07
Unemployment	6.77	6.26	7.52	7.18
Student	3.25	3.03	3.66	3.48
Early retirement	7.95	8.78	7.38	8.03
Pensioner	18.87	17.93	18.26	18.00
Age				
Mean	47.95	48.4	48.77	47.89
Std. dev	12.3	12.33	12.55	12.45
Min	18	18	18	18
Max	76	76	76	76
N children in household				
Mean	0.98	0.98	0.96	0.99
Std. dev	1.05	1.06	1.09	1.06
Min	0	0	0	0
Max	11	9	12	12
Income				
Mean	286826.1	276013.2	258818.6	276100.3
Std. dev	252344.9	205253.2	221367.4	232306.6
Min	0	0	0	0
Max	2,24E+07	1,40E+07	2,74E+07	2,74E+07
N	463 749	246 812	170 341	945 742

[5] The propensity score matching method is semi-parametric approach, which does not require an exclusion restriction or a particular specification of the selection equation to construct the counterfactual.

[6] Since the objective of the propensity score matching method is to identify a set of observations that are matched based on observables, our presentation of the method will remain brief.

Table 2
Analyzed ethanol and other car purchases 2004–2008.

	Year					
	2004	2005	2006	2007	2008	Total
Stockholm						
Ethanol	64	102	219	453	626	1464
Other	11177	11392	10420	9706	8001	50696
Gothenburg						
Ethanol	74	59	123	260	348	864
Other	6880	6729	6274	5853	4546	30282
Malmö						
Ethanol	14	25	38	85	186	348
Other	4567	4654	4526	4526	3452	21342
Total sample						
Ethanol	163	199	403	845	1236	2846
Other	24745	25103	23493	21885	17844	113070
Total	24908	25302	23896	22730	19080	115916

the samples from Gothenburg and Malmö. Women constitute roughly 54 percent of the sample in all three cities. The majority of the sample is married (between 74 and 78 percent). About 15 percent are unmarried and 9 percent divorced. The total sample consists of individuals between the ages of 18 and 76. The mean age is 48 in Stockholm and Gothenburg and 49 in Malmö. Individuals in our sample on average have one child under the age of 18 living in the household.

About 42 percent of the sample has some form of university education. The distribution of educational attainment is very similar between the three cities. Similarly, there are no striking differences in terms of income; mean income ranges from 258,819 SEK in Malmö to 286,826 in Stockholm.

The unemployment rate ranges from 6.3 percent in Gothenburg to 7.5 in Malmö. Malmö also has a slightly higher share of students, 3.7 percent, than Stockholm and Gothenburg (3.3 and 3 percent, respectively). Finally, the Gothenburg sample contains about 1 percentage point more early retirees and about 1 percentage point fewer pensioners than the samples in Stockholm and Malmö. Table 2 depicts the number of purchased ethanol cars in our sample, divided between Stockholm, Gothenburg and Malmö. As can be seen in the table, the number of ethanol cars is very small in the beginning of the time period, but rises sharply over the years.

3. Results

The main results of the empirical analysis are presented in Tables 3–5 below. In order to facilitate reading, we only present estimated coefficients and marginal effects of the main variables of interest (the full set of results can be found in Table A1 in the Appendix A). Differences in the results due to estimation technique are discussed in Section 3 below.

We start by describing the results of the tax variables. Table 3 presents estimated coefficients while Table 4 presents marginal effects (estimated with a pooled probit approach).

As described in Section 3.1 above, we have estimated four models relating to the probability to purchase an ethanol car. The first panels in Table 3 contain results for the panel probit estimation on the full sample (unconditional), i.e. regardless of whether an individual bought a new car or not, while the results in the second panels (conditional) relate to the probability of purchasing an ethanol car, given that the individual purchased any car in that year. Hence, the results in the second panels are conditional on purchasing a car. We further test to what extent the effect of the tax differs between different years. Consequently, the upper panel of Table 3 presents results for the overall effect of the tax (i.e., the entire time period since its introduction) and tests to what extent there were additional effects during the years following the introduction, while the lower panel presents results for each individual year.

Our results suggest that the congestion tax had a significant impact on ethanol car purchases in both 2006 and 2007 (lower panel of Table 3). There do not seem to be any significant lag effects as none of the coefficients on the year-specific effects are positive in the upper panel in Table 3.

However, our results also suggest that, although the tax had an overall positive effect on the probability of purchasing an ethanol car, the insignificant coefficient on the year-specific effect in 2008 may be interpreted as the tax effect fading away over time. In Table 4, we present the marginal increase in the probability of purchasing an ethanol car due to the tax in the time period 2006–2008, for the conditional sample.[7]

As can be seen in the table, in the absence of the congestion tax the average probability of purchasing an ethanol car (given that any car is purchased) would have been about 3.3 percent in the time period 2006–2008. The introduction of the tax increased this probability by 1.2 percentage points (i.e., to 4.5 percent) over the entire period. The right column in Table 4 depicts the marginal effects for the individual years. As can be seen, the tax increased the probability of purchasing an ethanol car by 1.3 percentage points in 2006 and 2007, but only by 0.8 percentage points in 2008. This reduction corresponds to the negative (but insignificant) marginal effect in the left column for 2008.

The marginal effects of the main socio-economic variables (individual year specification) are presented in Table 5 below. The full set of results is presented in the Appendix A.

As can be seen in Table 5, the marginal effects of the covariates are very small for the unconditional sample. This is not surprising, as we are not distinguishing between the choice to purchase a car and the decision to purchase an ethanol car. In this analysis we compare ethanol car purchasers to *all* other individuals, both those who purchased a non-ethanol car, and those who did not buy any car. Hence, we include all individuals who would not have bought a car regardless of policy. This, in turn, implies that the size of the marginal effects is expected to be small. If we focus our attention on the decision between a regular car and an ethanol car, we see that the single most important predictor for an ethanol car purchase is a past experience of ethanol car ownership: having owned an ethanol car in the previous period increases the probability of purchasing a new ethanol car by 8.6 percentage points.

The second most influential variable is education: having a post-graduate university degree increases the probability of purchasing an ethanol car by 2.5 percentage points in comparison to an individual who only attended elementary school. The effect may seem small, but considering that the probability of purchasing an ethanol car during 2004 to 2008 was only 2.7 percent, it implies that an individual with a post-graduate degree is almost twice as likely to purchase an ethanol car. It is interesting to note that even individuals with only high school education, a group with a relatively weak position on the labor market, are significantly more likely to purchase ethanol cars than individuals without high school education. Although we do not find any significant relationship between income and ethanol car purchases, this result may

[7] The average marginal effects for the entire time period 2004–2008 are smaller, as are the marginal effects for the unconditional sample. Results are available from the authors upon request.

Table 3
Main estimation results (xtprobit).

	Unconditional			Conditional		
	Coef.	Std. Err.	P > |z|	Coef.	Std. Err.	P > |z|
TIME PERIOD						
Tax 2006–2008	**0.109**	**0.054**	**0.043**	**0.154**	**0.065**	0.017
Sthlm_city#Tax2006–2008	0.020	0.068	0.765	0.059	0.085	0.487
Tax 2007	−0.014	0.048	0.769	−0.024	0.06	0.681
Sthlm_city#tax2007	0.030	0.058	0.603	0.09	0.077	0.242
Tax 2008	-0.043	0.045	0.344	−0.069	0.058	0.228
Sthlm_city#tax2008	−0,018	0.056	0.746	0.019	0.075	0.798
INIDIVIDUAL YEARS						
Tax 2006	**0.109**	**0.054**	**0.043**	**0.164**	**0.071**	**0.021**
Sthlm_city#Tax2006–2008	0.020	0.068	0.765	0.066	0.092	0.477
Tax 2007	**0.095**	**0.047**	**0.046**	**0.139**	**0.063**	**0.028**
Sthlm_city#tax2007	0.051	0.060	0.402	**0.160**	**0.083**	**0.054**
Tax 2008	0.066	0.045	0.143	0.091	0.061	0.133
Sthlm_city#tax2008	0.002	0.058	0.972	0.085	0.081	0.294
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Chamberlain–Mundlak effects	YES	YES	YES	YES	YES	YES
N	945730			115915		
Wald chi2	3313.89			2052.13		

Table 4
Marginal effects on the conditional probability of purchasing an ethanol car in 2006–2008.

	TIME PERIOD			INDIVIDUAL YEARS		
	Margin	Std.Err[a]	$P > z$	Margin	Std.Err[a]	$P > z$
Predict (ethanol car)						
No tax 2006–2008	0.033	0.001	0.000	0.033	0.001	0.000
	dy/dx	Std.Err	$P > z$	dy/dx	Std.Err	$P > z$
Tax 06–08	0.012	0.004	0.007			
Tax 06				0.013	0.005	0.011
Tax 07	−0.001	0.004	0.895	0.013	0.005	0.005
Tax 08	−0.005	0.004	0.197	0.008	0.004	0.063

[a] Delta-method.

indicate that individuals with a particularly low income are significantly different from individuals in other income segments, since the lack of upper secondary education is highly correlated with low income in Sweden. In accordance with this interpretation, we also find that individuals who do not work (unemployed, prematurely pensioners and students) are significantly less likely to purchase ethanol cars. However, it should be noted that these effects are relatively small: having an upper secondary education increases the probability of purchasing an ethanol car by 0.4 percentage points, while unemployment and early retirement reduce it by 0.5 and 1 percentage points respectively.

In contrast to previous studies, we do not find that women are consistently more prone to purchase ethanol cars. The negative and significant effect of gender in the unconditional sample is explained by a lower probability of women purchasing cars, but even when selection bias is controlled for, no significant pattern can be found (see Tables A2 and A3 in the Appendix A for the selection analysis). In 2004 and 2008 women are significantly more likely to purchase ethanol cars then are men, while in 2005–2007 there is no significant difference between the genders

Returning to our main estimation, we find that living in the city center is associated with about 1 percentage point increase in the probability of purchasing an ethanol car in Stockholm and Gothenburg, but with a reduction in the probability in Malmö. It is beyond the scope of this study to further analyze the cause of the

Table 5
Marginal effects of main socio-economic variables–Indivdiual years.

	UNCONDITIONAL			CONDITIONAL		
	dy/dx	Std.E[a]	$P > z$	dy/dx	Std. E[a]	$P > z$
Year 2005[b]	0.000	0.000	0.009	0.002	0.001	0.023
Year 2006	0.001	0.000	0.000	0.009	0.002	0.000
Year 2007	0.004	0.000	0.000	0.031	0.004	0.000
Year 2008	0.008	0.001	0.000	**0.071**	**0.012**	**0.000**
Stockholm	0.000	0.001	0.765	0.005	0.007	0.428
Stockholm city	0.000	0.000	0.759	0.009	0.002	0.000
Malmö city	−0.002	0.000	0.000	−0.008	0.002	0.000
Göteborg city	0.000	0.000	0.030	0.009	0.001	0.000
Work in city center	0.000	0.000	0.003	0.004	0.001	0.000
Owned ethanol car t-1	0.007	0.000	0.000	**0.086**	**0.004**	**0.000**
Female	−0.002	0.000	0.000	0.000	0.001	0.900
Age	0.000	0.000	0.039	−0.004	0.002	0.037
Civil status[c]						
Married	0.001	0.000	0.000	0.005	0.001	0.000
Divorced	0.000	0.000	0.582	−0.004	0.002	0.023
Widowed	0.000	0.001	0.640	−0.002	0.005	0.674
N children (0–18) in hh	0.000	0.000	0.486	0.002	0.001	0.077
Income (logged)	0.000	0.000	0.267	0.000	0.001	0.941
Education[d]						
Upper secondary education	0.000	0.000	0.002	0.004	0.001	0.001
College, less than 3 years	0.001	0.000	0.000	**0.015**	**0.002**	**0.000**
Bachelor degree	0.002	0.000	0.000	**0.019**	**0.001**	**0.000**
Post graduate degree	0.001	0.000	0.000	**0.025**	**0.004**	**0.000**
Unemployed	−0.001	0.000	0.027	−0.005	0.002	0.037
Student	−0.001	0.000	0.005	−0.008	0.004	0.046
Premature pensioner	−0.001	0.000	0.000	−0.010	0.002	0.000
Pensioner	0.000	0.000	0.035	0.002	0.002	0.366
Country of birth[e]						
Scandinavia except Sweden	−0.001	0.000	0.037	−0.004	0.003	0.145
Europe except Scandinavia	−0.001	0.000	0.129	−0.001	0.003	0.683
North America	−0.001	0.001	0.340	0.001	0.008	0.930
Other country of origin	−0.001	0.000	0.000	−0.008	0.001	0.000
Partner owns car	-0.003	0.000	0.000	−0.009	0.001	0.000
Mother's income. log	0.000	0.000	0.931	0.000	0.000	0.580
Father's income. log	0.000	0.000	0.332	0.000	0.000	0.793

[a] Standard errors estimated by delta method.
[b] 2004 is reference.
[c] Unmarried is reference.
[d] Lower secondary is reference.
[e] Sweden is the reference group.

deviating behavior in Malmö city center. However, if individuals living in Malmö are inherently different from individuals living in Gothenburg and Stockholm, their presence may bias the result. In an alternative estimation, we therefore excluded individuals from Malmö from our estimation. The results are presented in Table 6 below. As can be seen in the table, the qualitative results remain almost the same in this analysis. The main difference from the previous analysis is that, without Malmö, the tax had a significant effect in 2007 and 2008, and individuals living in the Stockholm city center were significantly more affected by the tax than individuals living outside the city limit.

Table 6
Main estimation results excluding Malmö (xtprobit).

	Unconditional			Conditional		
	Coef.	Std. Err.	$P>\lvert z\rvert$	Coef.	Std. Err.	$P>\lvert z\rvert$
TIME PERIOD						
Tax 2006–2008	**0.113**	**0.057**	**0.045**	**0.161**	**0.074**	**0.030**
Sthlm_city#Tax2006–2008	0.020	0.068	0.767	0,064	0.091	0.480
Tax 2007	−0.013	0.050	0.803	−0.026	0.068	0.704
Sthlm_city#tax2007	0.030	0.058	0.604	0.094	0.082	0.251
Tax 2008	0.005	0.048	0.920	−0.016	0.066	0.811
Sthlm_city#tax2008	−0.018	0.056	0.746	0.020	0.080	0.803
INIDIVIDUAL YEARS						
Tax 2006	**0,113**	**0.057**	**0.045**	**0.161**	**0.074**	**0.030**
Sthlm_city#Tax2006–2008	0.020	0.068	0.767	0.064	0.091	0.480
Tax 2007	**0.101**	**0.050**	**0.044**	**0.135**	**0.066**	**0.040**
Sthlm_city#tax2007	**0.050**	**0.060**	**0.404**	**0.158**	**0.082**	**0.053**
Tax 2008	**0.118**	**0.048**	**0.013**	**0.145**	**0.064**	**0,022**
Sthlm_city#tax2008	0.002	0.058	0.974	0.084	0.080	0.293
Control variables	YES			YES		
Year fixed effects	YES			YES		
Chamberlain–Mundlak effects	YES			YES		
N	775394			94225		
Wald chi2	2893.69			1896.17		

3.1. Sensitivity analysis

We use several techniques to test the robustness of our results. First, since ethanol car purchase is a relatively rare event, we estimate a Complementary log log model (cloglog). This estimation procedure allows a skewed distribution. Second, since probit models are highly sensitive for miss-specification, we estimate a random effects linear probability model (xtreg). The results for the main variables of interest are presented in Table 7, below. All models are corrected for potential correlation between exogenous variables and individual effects in terms of Chamberlain-Mundlak effects.

The coefficients resulting from the estimation of the Complementary log log model and the linear probability model cannot be directly compared to the probit estimates, but as can be seen in Table 7, the sign and significance level of the complementary log log estimation is similar to that of the panel probit (with the exception that the coefficient on the tax in 2008 is positive and

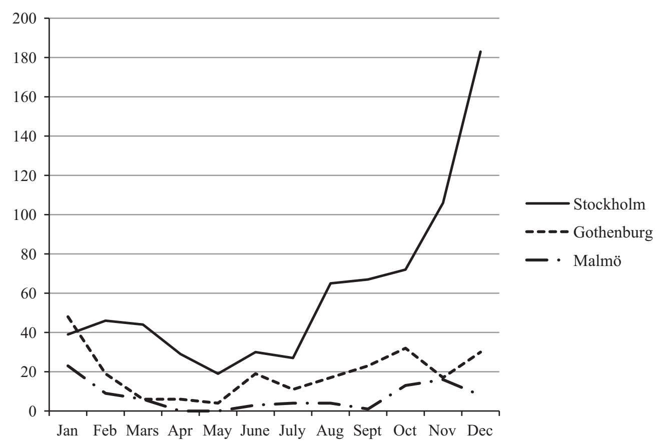

Fig. 2. Trend in privately purchased cars per month 2005 (full population ASTRID database, own computations).

Table 7
Model results: Probit, xtprobit, cloglog, xtprobit.

	UNCONDITIONAL				CONDITIONAL			
	probit	xtprobit	cloglog	xtreg	probit	xtprobit	cloglog	xtreg
TIME PERIOD								
Tax 2006–2008*	0.108**	0.109**	0.344**	0.000	0.154**	0.164**	0.372**	0.004
Sthlm_city#Tax2006–2008	0.020	0.020	0.018	0.000	0.059	0.066	0.036	0.008**
Tax 2007	−0.014	−0.014	−0.052	0.000	−0.024	−0.025	−0.052	0.002
Sthlm_city#tax2007	0.030	0.030	0.061	0.001*	0.090	0.094	0.112	0.019***
Tax 2008	−0.042	−0.043	−0.122	−0.000	−0.069	−0.073	−0.152	0.001
Sthlm_city#tax2008	−0.018	−0.018	−0.058	0.001	0.019	0.019	−0.047	0.024***
INDIVIDUAL YEARS								
Tax 2006*	0.108**	0.109**	0.344*	0.000	0.154**	0.164**	0.372**	0.004
Sthlm_city#Tax2006–2008	0.020	0.020	0.018	0.000	0.059	0.066	0.036	0.008**
Tax 2007	0.094**	0.095**	0.292**	0.001	0.130**	0.139**	0.320**	0.006**
Sthlm_city#tax2007	0.050	0.051	0.079	0.001***	0.150**	0.160*	0.148	0.027***
Tax 2008	0.065	0.066	0.222	0.000	0.085	0.091	0.22*	0.005*
Sthlm_city#tax2008	0.002	0.002	−0.041	0.001*	0.079	0.085	−0.011	0.033***
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Chamberlain–Mundlak effects	YES	YES	YES	YES	YES	YES	YES	YES
N	945730	945730	945730	945730	115915	115915	115915	115915
Wald Chi-2	3906.69	3313.89	5047.11	5433.2	3322.82	2052.13	4070.98	4469.93

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 8
Trend analysis xtprobit.

	UNCONDITIONAL			CONDITIONAL		
	Coef.	Std. Err.	$P>\|z\|$	Coef.	Std. Err.	$P>\|z\|$
Placebo03	0.065	0.092	0.483	0.093	0.112	0.407
sthlm_city#placebo03	**−0.379**	**0.172**	**0.028**	**−0.505**	**0.217**	**0.020**
Placebo04	−0.071	0.070	0.309	−0.083	0.088	0.346
sthlm_city#placebo04	**−0.197**	**0.100**	**0.050**	**−0.241**	**0.130**	**0.065**
Placebo05	0.033	0.069	0.629	0.027	0.085	0.753
sthlm_city#placebo04	**0.325**	**0.096**	**0.001**	**0.420**	**0.127**	**0.001**
Control variables	YES			YES		
Chamberlain–Mundlak effects	YES			YES		
N	745743			73882		

Table 9
Main estimation results excluding Stockholm city center (xtprobit).

	Coef.	Std. Err.	$P>\|z\|$	Coef.	Std. Err.	$P>\|z\|$
TIME PERIOD						
Tax 2006–2008	**0.109**	**0.053**	**0.040**	**0.166**	**0.071**	**0.019**
Tax 2007	−0.014	0.047	0.767	−0.025	0.065	0.699
Tax 2008	−0.042	0.045	0.347	−0.073	0.062	0.241
INIDIVIDUAL YEARS						
Tax 2006	**0.109**	**0.053**	**0.040**	**0.166**	**0.071**	**0.019**
Tax 2007	**0.095**	**0.047**	**0.043**	**0.141**	**0.063**	**0.025**
Tax 2008	**0.067**	**0.045**	**0.133**	0.093	0.060	0.124
Control variables	YES			YES		
Year fixed effects	YES			YES		
Chamberlain–Mundlak effects	YES			YES		
N	784514			101458		
Wald chi2	2781.39			1723.2		

significant in the individual year regression).[8] However, the results of the linear probability model give different results. Most importantly, the linear probability model estimation suggests that there was no overall effect of the tax if we consider the entire Stockholm region, but that the introduction of the tax affected individuals living in the city center to a significant extent, and that this effect persisted during the years following the introduction of the tax. If we look at the results for the individual years, we can further see that the linear probability model suggests that the lack of overall effect is caused by an absence of effect in 2006. This may be explained by the fact that Stockholmers seem to have prepared for the tax by purchasing ethanol cars before its introduction (see Fig. 2 below). We may thus expect a relatively low level of ethanol car consumption directly after its introduction. However, it should be noted that although the linear probability model is less sensitive to miss specifications, it is associated with other problems. One of these is that the model is not restricted to the 0 to 1 interval. Indeed, when we estimate the predicted values of the different models, we see that the linear probability model predicts negative probabilities (See Fig. A1 in the Appendix A).

As described in Section 3.1 the Difference-in-differences approach is able to account for observed and unobserved differences between the “treatment” and “control” groups. However, the approach rests heavily on the assumption of a common trend. In order to get an idea of the validity of the common trend assumption, we therefore ran a set of regressions with fake treatments (placebo effects) in the years preceding the introduction of the congestion tax. The results are presented in Table 8 below. As can be seen in the table, we find significant placebo effects for individuals living in Stockholm city center. However, the results do not consistently suggest that individuals in Stockholm City were on a different trend than individuals in Gothenburg and Malmö in terms of more rapidly becoming more prone to purchase ethanol cars. Indeed, the coefficient on the placebo effect in 2004 is negative.

The positive and significant effect of the placebo treatment in 2005 is at first glance disturbing. It might suggest that Stockholmers had developed preferences for more environmentally friendly cars even before the introduction of the tax, and thus that we are capturing an effect that does not pertain to the tax itself, but rather to a change of preferences unrelated to the tax. However, a look at the data shows that this effect is very likely to stem from an anticipation of the introduction of the tax and can therefore be called an anticipation effect. As can be seen in Fig. 3 below there was no clear difference in trend between Stockholm on the one hand and Gothenburg and Malmö on the other, before July 2005. However, after July 2005 sales of ethanol cars increased dramatically in the Stockholm area. It is thus highly likely that individuals in Stockholm, in anticipation of the tax, chose to buy ethanol cars before its introduction 6 months later.

Although Fig. 3 seems to present a relatively clear picture, one could conclude that the shift in the trend in Stockholm in July 2005 may be a seasonal effect. However, a closer look at the data reveals that the shift is relatively permanent, and arises first in 2005 (see Fig. 3).

[8] Based on the Akaike and Baysian Information Criteria, we do not find evidence that the Complementary log log model fits the data better than the probit model (results available upon request).

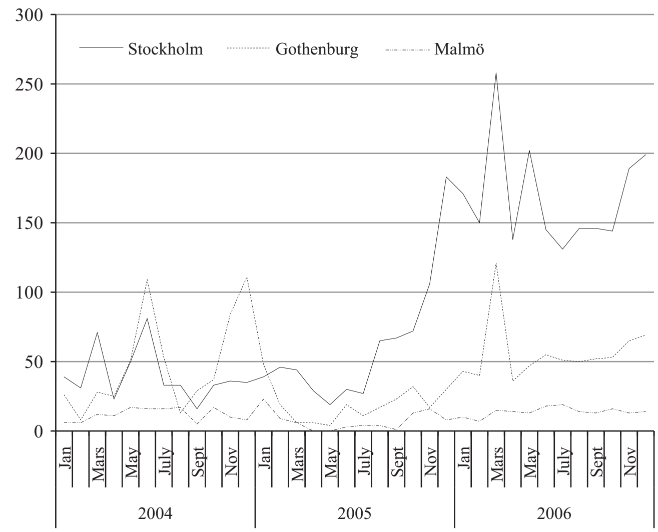

Fig. 3. Trend in purchased cars per month 2004–2006 (full population ASTRID database, own computations).

Free residential parking for green car owners was introduced in Stockholm city center during 2005. Consequently, a potential concern may be that the observed "anticipation effect" in reality is caused by the incentive to park freely rather than to avoid the congestion tax. Fortunately, since free parking only applied to individuals living in the city center, we can control for this effect. Reassuringly, re-running our estimations on a sample where individuals living in the city center are excluded does not change the results much (See Table 9, below). However, one interesting effect of excluding individuals living within the city limit is that our estimation results now show a significantly positive effect of the tax in 2008.

4. Discussion

The purpose of this paper has been to contribute to the understanding of how policy and population characteristics influence the composition of the car fleet. More specifically, we analyzed if and to what extent the Stockholm congestion tax affected private purchases of ethanol/E85 cars in Stockholm, and estimated to what extent socio-economic and demographic factors hold predictive power for the decision to purchase these types of cars.

Our analysis contributes to the existing literature in at least three ways. First, in contrast to previous research, which mainly relates to correlations between the congestion tax and car-related behavior, we approached the tax in Stockholm as a natural experiment and used the two other metropolitan cities in Sweden–Gothenburg and Malmö–to create a counterfactual course of events. Second, having access to unique register data enabled us to estimate the relationship between socio-economic and socio-demographic factors and ethanol car purchases. Thirdly, since corporate purchase of cars dominates the market, the coefficients emanating from studies of aggregated datasets are likely to be dominated by corporate behavior. Thus, since our dataset contains information on a representative sample of individuals, our analysis provides new information on the factors that determine the purchases of AFVs by households.

Our findings concerning the effects of the tax are consistent with the suggestive evidence in previous studies (Börjesson et al., 2012): the Stockholm congestion tax in our natural experiment had a significant impact on ethanol car purchases in both 2006 and 2007. In addition, our analysis points to a potential anticipation effect of the tax shortly before the introduction. Finally, although the reduction is insignificant, we see signs that the effect of the tax may have faded away over time.

Even though our results suggest a positive and significant initial effect of the congestion tax on the probability of purchasing an ethanol car, it should also be noted that the marginal effect of the tax is smaller than for example the effect of other covariates. The most important predictor is unsurprisingly previous ownership of an ethanol car, which increases the probability of a new purchase by 8.6 percentage points. However, we also find a relatively strong relationship between education and ethanol car purchase: seen over the entire study period (2004–2008), the Stockholm congestion tax increased the probability to purchase an ethanol car by 0.2 percent. This should be compared to having a post graduate education, which increases the probability to purchase an ethanol car by 2.5 percent. Hence, although the congestion tax is likely to have had a significant impact on car purchases, our analysis suggest that socio-demographic factors may be more important for the diffusion of AFVs.

Our result for education is consistent with previous research, which has found that higher education have a significant positive effect on the stated choice of hybrid vehicles (Potoglou and Kanaroglou, 2007) and AFVs (Jansson et al., 2011). However, while Dagsvik and Liu (2009) found that high-income households value AFVs higher than conventional cars, our results do not suggest that income has any significant effect on the probability of purchasing an ethanol car. This may be a consequence of a correlation between education and income, where the former determines the latter.

In contrast to previous research, our results do not lend support to the hypothesis that women buy environmental cars to a higher extent than men (Johansson-Stenman and Martinsson, 2006). Our results thus suggest that although females might view AFVs as more environmentally friendly than males (e.g., Jansson et al., 2009), their perceptions do not seem to carry over into actual behavior. This might also be an effect of the fact that males purchase and own the majority of cars and that although a car may be registered to a woman, the male in the household might have had an impact on the final choice of vehicle. However, our results indicate that in the years of 2004 and 2008 only, females did purchase a higher proportion of ethanol cars than males. The conclusion is that relationships between gender and purchases of ethanol cars are ambiguous and hard to predict.

Finally, by focusing solely on private car purchases our investigation also shows that not only corporate, but also private car purchases were positively affected by the congestion tax (see Börjesson et al., 2012 and Eliasson and Jonsson, 2011). This indicates that policies and incentives targeted at both corporate car purchases and private purchases are important for a transition of the car fleet into a less fossil-based one. Since we also find that previous ownership of an ethanol car is an important predictor of future ethanol car purchases, it can be argued that experience from driving a private car might spill over into the corporate domain and vice versa. However, more research on the relationships between the private and corporate car market is necessary in order to elucidate whether there is a causal relationship. Consumers who have purchased an AFV are more likely to re-purchase (i.e., confirming their decision), which has also been found in previous studies using survey data (Jansson et al., 2010). Our results confirm these findings using a wider sample and actual behavioral register data. The finding can be explained by pointing to the desire of individuals to re-confirm previously made adoption decisions in order to avoid cognitive dissonance, so it might not be a measure of satisfaction per se, although it is highly likely.

A limitation with our study is that it only concerns ethanol cars and not other types of AFVs such as electric vehicles or gas cars. This limitation is due to the incentives offered during the time period studied and also what types of cars that were adopted by consumers.

5. Conclusions and policy implications

Previous research has found that the Stockholm congestion tax was efficient in decreasing congestion over the short and long term (Börjesson et al., 2012, Eliasson et al., 2009). Our analysis shows that a policy with the main goal of reducing traffic congestion from cars also has an effect on the composition of the car fleet if AFVs are excluded from the congestion fee. This finding carries implications beyond the Swedish context. Currently, many cities have congestion charges, or consider implementation of such fees. Our analysis suggests that if these policy instruments are linked to less environmentally harmful vehicles, in terms of an exemption from the charge, this may prove doubly advantageous-less congestion and a less fossil fuel dependent car fleet. In this light, it is notable that Sweden has decided not to exempt electrical vehicles from the congestion charges in Stockholm and Gothenburg. In Norway these types of AFVs are exempted from road tolls, which is considered to be one reason why the electrical car market has lately taken off substantially (e.g., Klöckner et al., 2013).

However, our analysis also shows that the marginal effect of the congestion charge although significant, will not revolutionize the composition of the car fleet. In addition, we find that the effect may be temporary and that other factors, such as socio-economic variables, may prove equally or more important for changing the composition of the car fleet.

As described in the result section, we find that the exemption of the congestion charge is associated with an increase in the conditional probability to purchase an ethanol car corresponding to 1.2 percentage points. This is a relatively large increase considering that the conditional probability without the charge is only 3.3 percent. However, it also implies that even with the congestion fee in place, the probability to buy an ethanol car instead for a regular car is still just 4.5 percent. Hence, in order to substantially alter the composition of the car fleet, other measures are needed. Our finding that the effect of the tax falls over time suggests that although financial incentives similar to those in Stockholm may have an important effect in the short term, there may be a need to raise the tax over time to maintain the effect.

Concerning the effects of socio-economic determinants of ethanol car purchases, our results point to the importance of previous experience of ethanol cars, time effects and to the role of education. These results are likely related to preferences, social norms and awareness of the effect of cars on e.g., global warming. Our analysis does not go deep enough to generate any conclusive results on this topic, but it points to the continuant need to complement financial incentives with awareness-raising policies. Indeed, it is now relatively well known that financial incentives may crowd out intrinsic motivation to engage in pro-environmental behavior (Frey and Oberholzer-Gee, 1997). These are important aspects to consider when implementing environmental policies in the form of financial incentives or exemptions from taxes for less environmentally harmful alternatives.

In addition, congestion charges would probably be more effective were they not merely stand-alone measures. Other methods, such as improving public transportation, reviewing infrastructure for bicycling and walking, and considering the entire price structure of transports in a region become important (e.g., Gärling and Schuitema, 2007). In this sense, the effect of a congestion charge can be enhanced and positive environmental effects expected to last longer. In accordance, future research needs to consider infrastructure, cognitive factors and technological aspects in an integrated manner to better understand a more optimally constructed policy for reducing negative environmental consequences of transportation. The technological aspects bring us to the last point. During the last few years, cars have become more fuel-efficient and several types of AFVs have been developed. These technologies are likely to become more fuel-efficient and thus it becomes important to continually revise what types of vehicles will be exempted from congestion charges such as the one in Stockholm. All cars affect congestion and from this perspective it can be questioned if any types of cars should be exempted and for how long. Thus, our results indicate that policies aiming at reducing fossil fuel dependence, tailpipe emissions and congestion problems need to be considered in an integrated manner in order not to have positive effects in one area but simultaneously having adverse effects in another.

A final policy implication is the importance of monitoring the general public's view on both the congestion tax as such (e.g., Eliasson and Jonsson, 2011) and on AFVs. If AFVs are exempted from a tax but are not perceived as substantially less harmful for the environment by citizens and drivers, there might be risk of perceiving the tax as unjust between those who can afford to purchase an AFV and those who cannot. Since our results point at difference in adoption of AFVs among high and low income segments, these effects are important to consider when revising the policy and the type of vehicle exemption. In sum, since what is perceived as more or less environmentally harmful changes over time, a vital part for a successful policy is the constant revising of it as technology and behaviors change. One important topic for future research may therefore be to analyze how different socio-economic groups react to policy interventions of the kind analyzed in this paper.

Acknowledgments

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Appendix A

See Fig. A1 and Tables A1–A3.

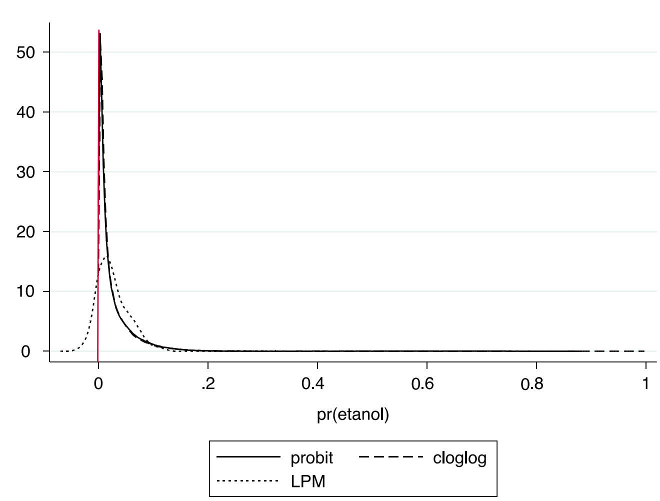

Fig. A1. Predicted values, probit, complementary log log and linear probability model.

Table A1
Estimated coefficients all variables.

	Unconditional			Conditional		
	Coef.	Std. Err.	P > |z|	Coef.	Std. Err.	P > |z|
TIME PERIOD						
Timeperiod = 2006–2010	0.331	0.086	0.000	0.419	0.127	0.001
Year 2007	0.179	0.058	0.002	0.267	0.078	0.001
Year 2008	−0.128	0.290	0.658	0.039	0.402	0.923
INDIVIDUAL YEARS						
Year 2005	0.094	0.048	0.051	0.116	0.069	0.091
Year 2006	0.318	0.080	0.000	0.402	0.119	0.001
Year 2007	0.631	0.112	0.000	0.835	0.170	0.000
Year 2008	0.846	0.145	0.000	1.251	0.224	0.000
Stockholm	0.035	0.106	0.742	0.115	0.141	0.417
Stockholm city	−0.001	0.049	0.986	0.132	0.066	0.044
Malmö city	−0.206	0.034	0.000	−0.183	0.047	0.000
Göteborg city	0.046	0.021	0.030	0.186	0.031	0.000
Work in city center	0.045	0.015	0.003	0.082	0.021	0.000
Owned ethanol car t-1	0.752	0.081	0.000	1.522	0.127	0.000
Female	−0.186	0.016	0.000	−0.004	0.022	0.837
Age	−0.046	0.036	0.197	−0.078	0.054	0.150
Age\widehat2	0.000	0.000	0.091	0.000	0.000	0.016
Civil status						
Married	0.107	0.021	0.000	0.113	0.030	0.000
Divorced	−0.018	0.033	0.576	−0.102	0.046	0.026
Widowed	0.042	0.084	0.614	−0.049	0.117	0.677
N children (0–18) in hh	0.012	0.018	0.487	0.040	0.024	0.095
Income (logged)	0.015	0.013	0.233	−0.001	0.016	0.948
Income*Stockholm	−0.013	0.012	0.290	−0.015	0.017	0.369
Education						
Upper secondary education	0.074	0.024	0.002	0.109	0.034	0.001
College, less than 3 years	0.178	0.033	0.000	0.348	0.048	0.000
Bachelor degree	0.222	0.025	0.000	0.416	0.039	0.000
Post graduate degree	0.189	0.044	0.000	0.514	0.068	0.000
Unemployed	−0.077	0.035	0.030	−0.098	0.048	0.040
Student	−0.165	0.059	0.005	−0.162	0.082	0.049
Premature pensioner	−0.162	0.036	0.000	−0.218	0.050	0.000
Pensioner	0.055	0.026	0.035	0.033	0.037	0.365
Country of birth						
Scandinavia except Sweden	−0.079	0.042	0.060	−0.081	0.059	0.168
Europe except Scandinavia	−0.072	0.052	0.170	−0.030	0.075	0.693
North America	−0.094	0.119	0.427	0.016	0.173	0.928
Other country of origin	−0.112	0.027	0.000	−0.186	0.039	0.000
Partner owns car	−0.345	0.017	0.000	−0.199	0.025	0.000
Mother's income. log	0.001	0.007	0.935	0.005	0.009	0.592
Father's income. log	−0.006	0.007	0.341	−0.002	0.009	0.786
Real growth	−0.134	0.069	0.051	−0.165	0.098	0.091
average age	0.053	0.036	0.138	0.063	0.054	0.243
average child hh	−0.092	0.024	0.000	−0.148	0.034	0.000
average income	0.090	0.013	0.000	0.116	0.018	0.000
average mother's inc	0.002	0.007	0.796	0.000	0.010	0.980
average father's inc	0.012	0.007	0.098	0.013	0.010	0.188
Constant	−3.541	0.274	0.000	−3.041	0.390	0.000
/lnsig2u	−3.784	1.411		−1.814	0.571	
sigma_u	0.151	0.106		0.404	0.115	
rho	0.022	0.031		0.140	0.069	
N	945730			115915		
Wald Chi2	3313.890			2052.530		

Table A2
First stage selection estimation: decision to purchase a car.

	2004			2005			2006			2007			2008		
	Coef.	Std. Err	P > z	Coef.	Std. Err	P > z	Coef.	Std. Err	P > z	Coef.	Std. Err	P > z	Coef.	Std. Err	P > z
Owned car t-1	**0.476**	**0.009**	**0.000**	**0.451**	**0.009**	**0.000**	**0.444**	**0.009**	**0.000**	**0.463**	**0.009**	**0.000**	**0.421**	**0.010**	**0.000**
Stockholm	**−0.104**	**0.034**	**0.002**	**−0.135**	**0.034**	**0.000**	**−0.146**	**0.036**	**0.000**	**−0.182**	**0.038**	**0.000**	**−0.102**	**0.040**	**0.011**
Sthlm city center	**−0.168**	**0.012**	**0.000**	**−0.140**	**0.012**	**0.000**	**−0.160**	**0.013**	**0.000**	**−0.184**	**0.013**	**0.000**	**−0.136**	**0.014**	**0.000**
Malmo city center	**−0.115**	**0.015**	**0.000**	**−0.104**	**0.015**	**0.000**	**−0.104**	**0.015**	**0.000**	**−0.099**	**0.016**	**0.000**	**−0.070**	**0.016**	**0.000**
Gbg city center	**−0.112**	**0.012**	**0.000**	**−0.125**	**0.012**	**0.000**	**−0.117**	**0.013**	**0.000**	**−0.091**	**0.013**	**0.000**	**−0.129**	**0.014**	**0.000**
Work city center	0.013	0.009	0.138	**−0.021**	**0.009**	**0.014**	**−0.019**	**0.009**	**0.033**	**−0.023**	**0.009**	**0.010**	**−0.031**	**0.010**	**0.001**
Female	**−0.260**	**0.008**	**0.000**	**−0.274**	**0.008**	**0.000**	**−0.272**	**0.009**	**0.000**	**−0.283**	**0.009**	**0.000**	**−0.276**	**0.009**	**0.000**

Table A2 (*continued*)

	2004			2005			2006			2007			2008		
	Coef.	Std. Err	$P>z$	Coef.	Std. Err	$P>z$	Coef.	Std. Err	$P>z$	Coef.	Std. Err	$P>z$	Coef.	Std. Err	$P>z$
Age	**0.028**	**0.003**	**0.000**	**0.032**	**0.003**	**0.000**	**0.026**	**0.003**	**0.000**	**0.027**	**0.003**	**0.000**	**0.020**	**0.003**	**0.000**
Age squared	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Civil status															
Married	−0.011	0.011	0.314	−0.006	0.011	0.571	**0.019**	**0.011**	**0.089**	**0.030**	**0.012**	**0.010**	**0.034**	**0.013**	**0.006**
Divorced	**0.080**	**0.016**	**0.000**	**0.054**	**0.016**	**0.001**	**0.087**	**0.016**	**0.000**	**0.099**	**0.017**	**0.000**	**0.104**	**0.018**	**0.000**
Widowed	**0.097**	**0.045**	**0.032**	0.048	0.046	0.294	**0.144**	**0.046**	**0.002**	**0.128**	**0.047**	**0.007**	**0.102**	**0.049**	**0.039**
N. children (0–18) in household	−0.006	0.004	0.206	**−0.018**	**0.004**	**0.000**	−0.006	0.005	0.226	**−0.026**	**0.005**	**0.000**	**−0.012**	**0.005**	**0.015**
Income (logged)	**0.028**	**0.003**	**0.000**	**0.033**	**0.003**	**0.000**	**0.025**	**0.003**	**0.000**	**0.017**	**0.003**	**0.000**	**0.021**	**0.004**	**0.000**
Education															
High school	**−0.031**	**0.011**	**0.005**	0.016	0.011	0.161	0.008	0.011	0.462	−0.013	0.012	0.253	**−0.022**	**0.012**	**0.081**
College, < 3 years	**−0.136**	**0.018**	**0.000**	**−0.059**	**0.018**	**0.001**	**−0.089**	**0.018**	**0.000**	**−0.098**	**0.019**	**0.000**	**−0.135**	**0.020**	**0.000**
Bachelor degree	**−0.123**	**0.012**	**0.000**	**−0.090**	**0.012**	**0.000**	**−0.089**	**0.012**	**0.000**	**−0.110**	**0.013**	**0.000**	**−0.130**	**0.013**	**0.000**
Post graduate degree	**−0.286**	**0.030**	**0.000**	**−0.268**	**0.030**	**0.000**	**−0.251**	**0.030**	**0.000**	**−0.243**	**0.030**	**0.000**	**−0.321**	**0.032**	**0.000**
Income*Live in Sthlm	0.000	0.004	0.991	0.004	0.004	0.374	0.004	0.005	0.402	**0.012**	**0.005**	**0.012**	0.001	0.005	0.876
Country of birth															
Scandinavia except Sweden	−0.017	0.021	0.407	0.003	0.021	0.894	−0.009	0.021	0.670	0.029	0.022	0.182	0.022	0.023	0.331
Europe except Scandinavia	**−0.148**	**0.029**	**0.000**	**−0.073**	**0.028**	**0.009**	**−0.060**	**0.028**	**0.036**	**−0.109**	**0.030**	**0.000**	**−0.087**	**0.031**	**0.006**
North America	**−0.201**	**0.070**	**0.004**	**−0.165**	**0.065**	**0.011**	**−0.241**	**0.070**	**0.001**	−0.090	0.069	0.189	**−0.139**	**0.075**	**0.064**
Other country of origin	0.012	0.013	0.363	0.010	0.013	0.427	−0.004	0.013	0.763	**0.043**	**0.013**	**0.001**	**0.054**	**0.014**	**0.000**
Unemployed	**0.036**	**0.013**	**0.007**	**0.038**	**0.013**	**0.005**	**0.029**	**0.015**	**0.043**	0.007	0.017	0.670	0.013	0.020	0.505
Student	**−0.136**	**0.022**	**0.000**	**−0.112**	**0.022**	**0.000**	**−0.116**	**0.023**	**0.000**	**−0.084**	**0.025**	**0.001**	**−0.083**	**0.029**	**0.004**
Premature pensioner	0.003	0.015	0.850	0.002	0.015	0.899	0.003	0.015	0.839	−0.018	0.016	0.243	−0.013	0.017	0.419
Pensioner	**0.041**	**0.016**	**0.009**	**0.065**	**0.015**	**0.000**	**0.037**	**0.016**	**0.018**	**0.038**	**0.016**	**0.016**	**0.038**	**0.017**	**0.020**
Partner owns car	**−0.222**	**0.009**	**0.000**	**−0.243**	**0.009**	**0.000**	**−0.247**	**0.009**	**0.000**	**−0.214**	**0.009**	**0.000**	**−0.225**	**0.010**	**0.000**
Mother's income. log	0.002	0.001	0.258	−0.001	0.001	0.514	**−0.004**	**0.001**	**0.002**	0.001	0.001	0.292	**−0.006**	**0.001**	**0.000**
Father's income. log	−0.002	0.001	0.232	**−0.004**	**0.001**	**0.001**	**−0.002**	**0.001**	**0.085**	**−0.005**	**0.001**	**0.000**	**−0.005**	**0.001**	**0.001**
Constant	**−1.559**	**0.068**	**0.000**	**−1.654**	**0.066**	**0.000**	**−1.479**	**0.070**	**0.000**	**−1.466**	**0.076**	**0.000**	**−1.377**	**0.082**	**0.000**
N	189272.0			196661.0			191333.0			185294.0			183170.0		
Wald Chi2	98.95			193.3			417.34			645.89			617.46		
LogLikelihood	−69208.23			70979.56			−68646.77			−67223.99			−61275.73		

Table A3
Second stage selection estimation: Decision to purchase an ethanol car.

	2004			2005			2006			2007			2008		
	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$
Owned car t-1	−0.398	0.519	0.443	0.090	0.374	0.810	0.292	0.287	0.309	**0.719**	**0.277**	**0.009**	0.168	0.187	0.370
Stockholm	0.003	0.101	0.973	**0.246**	**0.087**	**0.005**	**0.197**	**0.065**	**0.003**	**0.319**	**0.048**	**0.000**	**0.239**	**0.044**	**0.000**
Sthlm city center	**−0.455**	**0.182**	**0.012**	0.086	0.124	0.485	**−0.207**	**0.117**	**0.076**	**−0.166**	**0.083**	**0.046**	**−0.123**	**0.063**	**0.051**
Malmo city center	**0.206**	**0.076**	**0.006**	**0.225**	**0.091**	**0.014**	**0.256**	**0.068**	**0.000**	**0.231**	**0.050**	**0.000**	**0.129**	**0.046**	**0.005**
Gbg city center	0.083	0.061	0.171	−0.040	0.061	0.515	**0.092**	**0.048**	**0.053**	**0.098**	**0.035**	**0.005**	**0.106**	**0.031**	**0.001**
Work in city center	**1.793**	**0.505**	**0.000**	**2.129**	**0.269**	**0.000**	**2.260**	**0.179**	**0.000**	**1.706**	**0.135**	**0.000**	**1.199**	**0.119**	**0.000**
Female	**0.181**	**0.068**	**0.008**	−0.021	0.075	0.776	0.053	0.061	0.384	0.033	0.046	0.473	**0.095**	**0.039**	**0.016**
Age	−0.022	0.023	0.341	−0.023	0.023	0.308	−0.026	0.017	0.135	**−0.033**	**0.013**	**0.014**	**−0.024**	**0.011**	**0.036**
Age squared	0.000	0.000	0.190	0.000	0.000	0.265	**0.000**	**0.000**	**0.077**	**0.000**	**0.000**	**0.009**	**0.000**	**0.000**	**0.004**
Civil status															
Married	−0.046	0.074	0.528	−0.071	0.074	0.339	0.086	0.066	0.194	**0.203**	**0.053**	**0.000**	**0.148**	**0.045**	**0.001**
Divorced	**−0.333**	**0.131**	**0.011**	−0.179	0.128	0.164	−0.040	0.098	0.682	−0.016	0.077	0.839	**−0.138**	**0.066**	**0.038**
Widowed	−3.146	108.214	0.977	**0.403**	**0.234**	**0.085**	−0.227	0.273	0.406	−0.089	0.201	0.657	−0.043	0.178	0.812
N. children (0–18) in hh	0.004	0.033	0.908	**−0.089**	**0.036**	**0.012**	**−0.073**	**0.027**	**0.007**	**−0.069**	**0.021**	**0.001**	−0.019	0.017	0.283
Income (logged)	0.032	0.036	0.374	0.040	0.035	0.256	0.031	0.029	0.283	**0.111**	**0.029**	**0.000**	**0.049**	**0.018**	**0.007**
Education															
High school	**0.174**	**0.098**	**0.075**	0.200	0.126	0.111	0.187	0.081	0.021	0.048	0.054	0.379	**0.096**	**0.046**	**0.037**
College. less than 3 years	**0.316**	**0.131**	**0.016**	**0.557**	**0.146**	**0.000**	**0.457**	**0.104**	**0.000**	**0.215**	**0.077**	**0.005**	**0.379**	**0.064**	**0.000**
Bachelor degree	**0.344**	**0.100**	**0.001**	**0.588**	**0.126**	**0.000**	**0.509**	**0.081**	**0.000**	**0.395**	**0.055**	**0.000**	**0.392**	**0.047**	**0.000**
Post graduate degree	**0.454**	**0.186**	**0.014**	**0.599**	**0.206**	**0.004**	**0.772**	**0.133**	**0.000**	**0.484**	**0.104**	**0.000**	**0.559**	**0.099**	**0.000**
Income*Live in Sthlm	0.049	0.065	0.451	−0.002	0.046	0.960	−0.011	0.036	0.760	**−0.069**	**0.034**	**0.044**	−0.010	0.023	0.667
Country of birth															
Scandinavia except Sweden	0.151	0.137	0.271	−0.091	0.186	0.624	0.025	0.123	0.841	**−0.230**	**0.104**	**0.028**	−0.102	0.085	0.230
Europe except Scandinavia	−0.011	0.238	0.962	0.115	0.198	0.563	0.025	0.156	0.875	−0.144	0.132	0.274	0.053	0.107	0.621
North America	−3.382	1030.819	0.997	0.217	0.407	0.594	0.032	0.416	0.939	−0.026	0.264	0.921	0.129	0.252	0.610
Other country of origin	−0.078	0.109	0.472	**−0.370**	**0.142**	**0.009**	−0.125	0.081	0.124	**−0.410**	**0.064**	**0.000**	**−0.117**	**0.049**	**0.018**
Unemployed	−0.013	0.105	0.898	−0.136	0.121	0.262	−0.117	0.098	0.234	−0.061	0.082	0.457	**−0.182**	**0.082**	**0.027**
Student	−0.288	0.291	0.322	−0.116	0.194	0.549	0.044	0.151	0.771	−0.042	0.132	0.748	**−0.339**	**0.144**	**0.019**
Premature pensioner	−0.186	0.145	0.201	−0.269	0.171	0.115	**−0.274**	**0.115**	**0.017**	**−0.181**	**0.081**	**0.025**	**−0.177**	**0.069**	**0.010**

Table A3 (*continued*)

	2004			2005			2006			2007			2008		
	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$	Coef.	Std.Err	$P>z$
Pensioner	0.059	0.107	0.583	−0.047	0.114	0.679	0.118	0.081	0.143	−0.012	0.060	0.847	0.014	0.054	0.797
Partner owns car	−0.097	0.080	0.223	−0.150	0.078	0.054	**−0.135**	**0.065**	**0.036**	**−0.101**	**0.046**	**0.028**	**−0.100**	**0.042**	**0.018**
Mother's income. log	0.004	0.009	0.695	0.013	0.010	0.188	0.005	0.007	0.487	−0.008	0.005	0.163	**0.015**	**0.005**	**0.002**
Father's income. log	0.008	0.009	0.380	**0.024**	**0.009**	**0.008**	0.007	0.007	0.319	0.005	0.005	0.301	**0.009**	**0.005**	**0.040**
Constant	**−1.947**	**0.704**	**0.006**	**−2.888**	**0.627**	**0.000**	**−2.182**	**0.541**	**0.000**	**−1.799**	**0.440**	**0.000**	**−1.369**	**0.361**	**0.000**
/athrho	**−0.459**	**0.168**	**0.006**	0.140	0.179	0.434	−0.195	0.139	0.162	−0.359	0.101	0.000	−0.417	0.096	0.000
Rho	−0.429	0.137		0.139	0.176		−0.192	0.134		−0.344	0.089		−0.395	0.081	
N	189272			196661			191333			185294			183170		
Wald chi2	98.950			193.300			417.340			645.890			617.460		
LogLik	−69208			−70980			−68647			−67224			−61276		
LR test (rho=0):	$p=0.0096$			$p=0.4261$			$p=0.1704$			$p=0.0006$			$p=0.0000$		

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