Eco-driving training and fuel consumption: impact, heterogeneity and sustainability

Philippe BARLA, CREATE-Transport Université Laval, Département d'économique, Pavillion J.-A. DeSève, 1025 avenue des sciences humaines, Québec, Québec, Canada, G1V 0A6, tel : 418-656 7707, fax : 418-656 7412 email : philippe.barla@ecn.ulaval.ca (corresponding author)

Mathieu GILBERT-GONTHIER, CREATE-Transport, Université Laval, Département d'économique, Pavillion J.-A. DeSève, 1025 avenue des sciences humaines, Québec, Québec, Canada, G1V 0A6, tel : 418-656 2131, email : mathieu.gilbert-gonthier.1@ulaval.ca

Marco Antonio LOPEZ CASTRO, CRAD, Université Laval, Pavillon Félix-Antoine-Savard, 2325 rue des Bibliothèques, Québec, Québec, Canada G1V 0A6, tel : 418-656 2131 email : marco-antonio.lopez-castro.1@ulaval.ca

Luis MIRANDA-MORENO, CREATE-Transport, McGill University, Department of Civil Enineering, Macdonald Engineering Building, 817 Sherbrooke Street West, Montreal, Quebec, Canada, H3A 0C3, tel: 514-398 6589, email: luis.miranda-moreno@mcgill.ca

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Abstract

In this paper, we assess the impact of an eco-driving training session on fuel consumption using weekly data for 59 drivers over a one year period. A random coefficient model is estimated to measure the effect of the course over a ten-month period, controlling for confounding factors and individual heterogeneity. We find that eco-driving training induced average city and highway fuel consumption reductions of 4.6% and 2.9% respectively. The effects are highly heterogeneous between individuals, with standard deviations of about 5%. Drivers' socio-demographic characteristics are not helpful to explain these discrepancies but we find that drivers of vehicles with manual transmissions achieve significantly larger reductions: 10% on city roads and 8% on highways. Finally, we show that reductions faded gradually after the course. City reductions go from 4.7% to 2.8% within ten months. Highway fuel use decreases average 3.3% in the first ten weeks after the course but become statistically insignificant after about twenty weeks.

Keywords: Eco-driving; fuel consumption

1. Introduction

In many countries, transportation accounts for a large share of greenhouse gas (GHG) emissions. In 2005, transport-related emissions represented 26% of Canada's total GHG issues – increasing by 33% from 1990 –, with cars being the main source of emissions (Environment Canada, 2007). Cutbacks in fuel consumption and the related GHG emissions can be achieved by reducing usage and/or improving the fuel efficiency of vehicles. For the latter, several countries have adopted regulations to foster technological improvements in the fuel economy of new vehicles (e.g. CAFE standards in the U.S.). Alternatively, it may also be possible to improve actual fuel economy of existing vehicles by promoting the adoption of eco-driving techniques. It is indeed well documented that driving habits significantly affect fuel consumption (Ross 1994; Ericsson, 2001; Saboohi & Farzaneh, 2009). In fact, some public agencies such as Natural Resources Canada claim that the use of five fuel-efficient driving techniques can lead to a 25% lower fuel consumption rate compared to an "average driving style". Obviously, the actual performance of a program promoting eco-driving is likely to be smaller as it will depend upon the rate of compliance of drivers.

In this paper, we assess the impact of an eco-driving training program on the fuel consumption of 45 drivers over a ten-month period. The training involves six consecutive hours in theoretical and practical application of eco-driving techniques such as accelerating and decelerating smoothly, shifting gears optimally, maintaining a moderate and steady speed, anticipating traffic, avoiding idling and insuring good maintenance of vehicles. These techniques have been documented and evaluated by Santos et al., 2010; Barkenbus, 2010; Barth & Boriboonsomsin, 2009; af Wåhlberg, 2007. In our study, the fuel efficiency gains are evaluated using pre-training observations for the 45 drivers as well as observations for a control group of 14 drivers. We isolate the impact of the program by estimating a random coefficient model which accounts for heterogeneity in the effect of the program across participants. We also explore the determinants of the program's effectiveness based on drivers and vehicle characteristics and analyze the sustainability of its impact over time.

This study contributes to a relatively small literature on eco-driving training. This type of program has, for the most part, been tested on public transportation drivers and city workers (Zarkalouda et al., 2007; af Wåhlberg, 2007; Rutty et al., 2013), but its effect on private car owners has also drawn interest, albeit to a lesser extent (Beusen et al., 2009; Degraeuwe & Beusen, 2013). It has been found that eco-driving training has the potential to yield average decreases ranging between 2% and 7%. However, most existing studies only measure the short term benefits of eco-driving training. A few studies have pointed out that the impact of these measures is much weaker in the long run (af Wåhlberg, 2002, 2007; Degraeuwe & Beusen, 2013). Our study contributes by measuring the impact for a period of up to ten months following the training session and estimating variations of the effect through time. Our empirical strategy also accounts for the effect of confounding factors and explore heterogeneity in the program's effectiveness across drivers.

We find that eco-driving training induced average reductions in fuel consumption of approximately 4.6% on city roads and 2.9% on highways over a ten-month period. Our results also show a substantial amount of individual heterogeneity in the impact of the course, with standard deviations of about 5%. These discrepancies are not readily explained by individual or vehicle characteristics, although we find that manual transmissions do provide a consistent and significant advantage for drivers applying eco-driving techniques. We also find that the average effect of the course becomes weaker as weeks pass. City fuel efficiency gains are reduced by about 40% within ten months while highway reductions become statistically insignificant around the twentieth week after the eco-driving course.

The rest of our discussion unfolds as follows. Section 2 provides a review of the relevant literature. The data and methodology are discussed in sections 3 and 4, respectively. Results are presented in section 5 and section 6 contains concluding remarks.

2. Literature review

Table 1 presents the results of a small but growing number of studies measuring the impact of eco-driving training programs on fuel consumption. Most studies use small-scale experiments comparing “before and after” fuel consumption rates. Only a limited number of researches also use the performance of a control group of drivers to better assess the impact of the programs. Overall, all but one study find significant but relatively small reductions ranging from 2% to 7%. Table 1 also reports the results of a few studies examining the impact of on-board devices that provide drivers with dynamic feedback to help reduce their fuel consumption. While dynamic feedbacks are somewhat different from eco-driving training programs, the results of these studies are still relevant to confirm the impact of eco-driving techniques on fuel consumption. Moreover, they indicate, as expected, that eco-driving techniques are more effective in congested urban environments.

Among the contributions of our study to this literature, we use a somewhat larger sample of drivers and regression techniques that allow us to control for the effect of other explanatory factors and heterogeneity across drivers. In that respect, our analysis is closest to the methodology used by Degraeuwe and Beusen (2013).

Zahabi et al. (2014) uses the same data source as ours. Their study differs however in several dimensions. First, their main focus is on the impact of low temperatures on the fuel economy of hybrid vehicles. They only include eco-driving of one of the control variable. Second, the sample of drivers is different: they include hybrid and sedan non-hybrid vehicles while we work with all the non-hybrid vehicles. Third, they work with observations at the road-segment level while we use data averaged by driver-week. Finally, they do not address the issue of heterogeneity through time and across drivers of the effect of training.

Table 1: Summary of studies about the effect of eco-driving on fuel consumption

Reference	Data (duration)	Methodology	Eco-driving effect on fuel consumption
Training			
Zarkalouda et al. (2007)	3 bus drivers in Greece (experimental run before and after training)	Before-after difference in means	4.35% reduction
af Wåhlberg (2007)	400 bus drivers in Sweden (12 months)	Before-after difference in means	2% reduction (+2% when combined with feedback)
Beusen et al. (2009)	10 private car owners in Belgium (4 months)	Three-way ANOVA	5.8% reduction
Degraeuwe & Beusen (2013)		Random coefficient model	6.7% reduction (fades with time)
Rutty et al. (2013)	15 municipal fleet drivers in Calgary, Canada (1 month)	Before-after difference in means	Significant effect (CO_2 emissions reduced by 1.7 kg per vehicle per day)
Zahabi et al. (2014)	74 private/company car drivers in Quebec, Canada	Random-effects model	3-4% reduction for non-hybrid sedans
Dynamic feedback			
Barth & Boriboonsomsin (2009)	2 vehicles on experimental runs	Difference in means between “device” and “no-device” vehicles	10-20% reduction (only in congested areas)
Larsson & Ericsson (2009)	20 postal delivery cars drivers (6 weeks)	Difference in means between “device” and “no-device” vehicles	No significant effect
Boriboonsomsin et al. (2010)	20 private car owners (2 weeks)	Before-after difference in means	Reductions of 6% in city conditions and 1% on highways
Kurani et al. (2013)	118 drivers (2 months)	Mixed effect model	2.7% reduction
Strömberg & Karlsson (2013)	20 bus drivers (3 weeks)	Before-after difference in means	6.8% reduction

3. Data

Most of our data was collected for a pilot project that was launched in 2009 by the Quebec government’s *Agence de l’efficacité énergétique* (AEE). A third party service provider FPInnovations (a Canadian non-profit research organization) carried out the data collection. The experiment was designed to assessment the impact of an eco-driving training program that could eventually be offered in the province. The pilot involved employees of five companies. Of the 95 subjects who took part in the project, 59 were kept for the current analysis. A preliminary check of the data led us to drop part of the sample to avoid irregularities. This led us to drop all participants from three other cities considered in the sample as well as other participants for whom the number of observations was deemed insufficient. Furthermore, hybrid vehicles were excluded from the sample to avoid misleading results caused by technical differences with respect to non-hybrids. In particular, hybrid vehicles are particularly affected by cold temperatures, as found by Zahabi et al. (2014).

All of these participants were residents of the province's two major cities namely Montreal and Quebec City. Potential participants had to satisfy a few conditions in order to take part in the experiment. They had to be the only driver of a car that was recent enough to have an Onboard Diagnostic Port (OBD-II) using CAN communication protocol and sensors that measure instantaneous fuel consumption. They also needed to be the only person to drive their car during the experiment. Participants were selected as to include a wide array of car types (e.g. sedans, SUVs, hatchbacks) in the sample. About half of the cars were owned by the participants while the other half was the property of the employers.

The experiment was conducted from July 2009 to July 2010. Monitoring devices were installed in each participant's vehicle. The device is a BOXV80-FMS by ISAAC Instruments. It is plugged into the OBD port and records several parameters such as instantaneous fuel consumption, speed and accelerations at a rate of 5 readings per second. The information is sent on a regular basis by the cellular network to a server where the data are processed. There was a reference period of two months during which participants were monitored without receiving any training or advice about eco-driving. Spanning over the third and fourth months of the experiment, waves of training took place. Out of the 59 participants included in our sample, 45 were trained and the remaining 14 formed a control group. The training activities were followed by another six to ten months of monitoring, depending on the date on which participants received their training. The course lasted about six hours and involved both theoretical and practical teaching as well as evaluation activities. Each participant was trained by the same instructor. No further instructions or feedback was provided to participants after training day.

In the final steps of the program, the data collected by the devices were compiled and averaged over each week of the monitoring phases. Thus, the full database contains weekly fuel consumption rate observations for each participant, with missing values for weeks when participants were either not monitored or drove less than 30 kilometers. The monitoring devices also measured several other parameters, including speed and ambient temperature. To complement the data compiled by the monitoring devices, official city and highway fuel consumption rates for each car in our sample were collected. These data were obtained from the Fuel Consumption Guide published by Natural Resources Canada's Office of Energy Efficiency (OEE). These rates are measured in laboratories by manufacturers using standardized protocols. They are used to construct standardized consumption rates, as discussed below in section 5.

In addition to providing data via the monitoring devices, participants responded to a survey inquiring about their age, gender, income and motivation to pursue the eco-driving course (i.e. obligation, saving of fuel expenses and/or environmental concern). Information about each car driven during the experiment was also collected, including make, model, year and technical specifications. Table 2 provides a description of the sample by group, based on the information on participants and the vehicles they used. Note that one participant preferred not to specify her age and six participants opted to keep their annual income confidential.

Table 2: Number of participants by group and category

Category	Number of participants			Total
	Treatment	Control	Missing	
Montreal	20	7	0	**27**
Quebec City	25	7		**32**
Male	35	11	0	**46**
Female	10	3		**13**
< 30 years old	2	2	1	**4**
30-44 years old	15	2		**17**
45-59 years old	27	8		**35**
≥ 60 years old	0	2		**2**
$25 000-$49 999/year	14	4	6	**18**
$50 000-$74 999/year	15	5		**20**
≥ $75 000/year	11	4		**15**
Automatic / CVT / automated manual	40	13	0	**53**
Manual	5	1		**6**
weight ≤ 1700 kg	24	6	0	**30**
weight > 1700 kg	21	8		**29**
Company-owned cars	22	10	0	**32**
Personal cars	23	4		**27**
Total	**45**	**14**	**-**	**59**

It should be noted that our sample is not quite representative of Quebec's actual vehicle fleet and pool of drivers. First of all, our sample is mostly composed of company-owned cars (54% versus less than 10% for the Quebec fleet), which could have an effect on the behavior of drivers. There is also a relatively large proportion of heavy vehicles (49% versus less than 20% in the fleet) due to the high number of commercial vans in the sample. A vast majority of participants are men (78% versus 48% in the population of drivers) and very few individuals are aged less than 30 (7% versus about 11% in the population of drivers) or 60 years or older (3 % versus about 18% in the population of drivers). Because of the composition of the sample, inference about the magnitude of the effect of eco-driving training is tricky. Although we cannot provide a precise estimate of the effect of a widespread eco-driving training policy, our results should nonetheless indicate whether eco-driving training can be an effective measure to reduce fuel consumption.

4. Methodology

We estimate a random coefficient model of the following form:

$$\log\left(\frac{FCR_{it}}{FCR_{it}^{OEE}}\right) = (\beta_0 + u_{0i}) + (\beta_1 + u_{1i})training_{it} + \boldsymbol{X}_{it}\boldsymbol{\delta} + \sum_{t=1}^{T} \gamma_{ct}(city_{ci} \times I_t) + \varepsilon_{it} \qquad (1)$$

where (FCR_{it}/FCR_i^{OEE}) is the ratio of actual fuel consumption over the rate estimated in laboratories by manufacturers (both in liters per 100 km) for individual i at week t. The ratio is a “standardized” measure of fuel use to account for differences in baseline consumption from one vehicle to another. As such, model (1) provides estimates of the marginal effect of each explanatory variable on actual fuel consumption net of their impact on the rate reported by the OEE. The marginal effect of an explanatory variable x is $\frac{\partial \log\left(FCR_{it}/FCR_i^{OEE}\right)}{\partial x} = \frac{\partial \log(FCR_{it})}{\partial x} - \frac{\partial \log(FCR_i^{OEE})}{\partial x} \approx \frac{\%\Delta FCR_{it} - \%\Delta FCR_i^{OEE}}{100}$, the difference of percent changes in actual and estimated consumption rates induced by a unit change in x.

The model is estimated using city and highway fuel consumption rates separately, since fuel consumption shows different relationships with, for instance, speed and temperature in these two different driving cycles (Zahabi et al., 2014). The distinction between city and highway driving is based on speed: all driving below 70km/h is used to compute city fuel rates while driving above that threshold is used for highway fuel rates.

$training_{it}$ is a dummy variable equal to one if individual i has taken the eco-driving course at week t. Note that generally speaking, coefficients of dummy variables in a linear semi-logarithmic model cannot be interpreted as percent changes in the dependent variable induced when the dummy equals one. However, when these coefficients are relatively small (less than 0.1 in absolute value is a safe threshold), estimates are good approximations of percent variations (Halvorsen & Palmquist, 1980). We expect eco-driving training to have an impact that is small enough, so there is no major issue here.

$\mathbf{X}_{it}$ is a vector of variables that determine standardized fuel consumption and $\boldsymbol{\delta}$ is the corresponding vector of parameters. Potential determinants of fuel use are temperature, road congestion, vehicle characteristics (type of transmission and weight), motivational factors (environmental concern and financial savings) and socioeconomic characteristics (age, gender, income and level of education) of drivers. Most of these variables are dummies, but some are continuous (temperature and the share of driving with a speed between 0 and 30 km/h which is an indicator of congestion).

($city_{ci} \times I_t$) are city fixed effects for each week. Thus, $city_{ci}$ is a dummy variable equal to one if individual i lives in city c and I_t is a dummy variable equal to one at week t. These terms are included to capture the effect of any unobserved conditions affecting fuel consumption in city c at week t (e.g. winter storm, slowdown of traffic due to road construction). Finally, ε_{it} is a zero-mean, normally distributed disturbance.

This model resembles the classical linear regression case, except for two random idiosyncratic parameters, u_{0i} and u_{1i}. These parameters are introduced into the model to capture heterogeneity across individuals. The β parameters capture the average (or "fixed") effects while u_{0i} and u_{1i} are random deviations from β_0 and β_1, respectively. The u_i parameters are assumed to be normal with mean zero so that the idiosyncratic effects in brackets are also normal with means β_0 and β_1. The model is estimated using maximum likelihood. The random coefficients are not directly estimated, but their covariance matrix is estimated along with the other parameters of the model. Once these random components have been estimated, it is possible to predict idiosyncratic effects for each participant. For a detailed description of the estimation process and prediction of the random parameters, see Bates & Pinheiro (1998). The result is usually referred to as best linear unbiased predictions (BLUPs), meaning that the predictor used has minimum mean squared error among all other linear unbiased predictors (Robinson, 1991).

Several explanatory variables to include in $\mathbf{X}_{it}$ were tried. These comprise ambient temperature ($temp_{it}$), the share of driving time spent at speeds between 0 and 30 km/h ($share(0,30)_{it}$), dummies for the presence of a manual transmission in the vehicle ($manual_i$), vehicles with a dry weight of more than 1700 kg ($heavy_i$), vehicle ownership (own_i), gender ($female_i$), individuals under the age of 45 ($young_i$) and those with a university degree (uni_i) or an annual income of $50 000 or higher ($highinc_i$) and motivation due to environmental concerns ($reason_i^{ENV}$) or fuel savings ($reason_i^{FE}$). Final results displayed in next section are those obtained when excluding control variables that had no statistically significant effect on standardized fuel consumption. Moreover, their exclusion had a negligible impact on significant coefficients.

The inclusion of ($city_{ci} \times I_t$) was tested using an F-test. We reject the null hypothesis that all city-specific time effects are simultaneously equal to zero. They are therefore included in the model, although the coefficients are not reported below. We also tested if the individual effects (u_{0i}) should be treated as fixed or random parameters by testing for the presence of correlation between the individual effects and the explanatory variables. The test results indicate that the random effect model is more appropriate. Finally, a likelihood ratio test confirms that the inclusion of a random coefficient for $training_{it}$ significantly improves the model fit.

5. Results

5.1 Base model

Results obtained by estimating (1) are shown in Table 3**.** Eco-driving training has a negative and statistically significant effect on both dependent variables. Over the ten-month post-training period, city and highway fuel consumption dropped on average by 4.6% and 2.9%, respectively. These figures are in the range of values found in the literature. In city conditions, temperature, congestion and manual transmissions have significant impacts on standardized fuel consumption. The effect of temperature is well approximated by a second degree polynomial, since fuel consumption tends to increase in particularly cold or hot conditions. This is reflected in the positive and significant estimate of the coefficient for $temp_{it}^2$. The share of driving time spent between 0 and 30 km/h, which controls for the effect of congestion, also has a strong positive effect on fuel use. Conversely, having a manual transmission decreases city fuel consumption by approximately 12%. Highway fuel use has different determinants. Temperature still has a significant effect, but it is considerably smaller compared to its effect in city conditions. Manual transmissions have no impact, but weight appears to matter as heavier vehicles tend to consume more on average than their official rates, as indicated by the positive and significant coefficient of $heavy_i$. Somewhat surprisingly, none of the socio-demographic or motivational variables had a statistically significant impact on fuel consumption. It is indeed usually expected that driving habits vary with age or gender, for example. The absence of significant effects could be due to a lack of diversity in the sample (small number of young people and women).

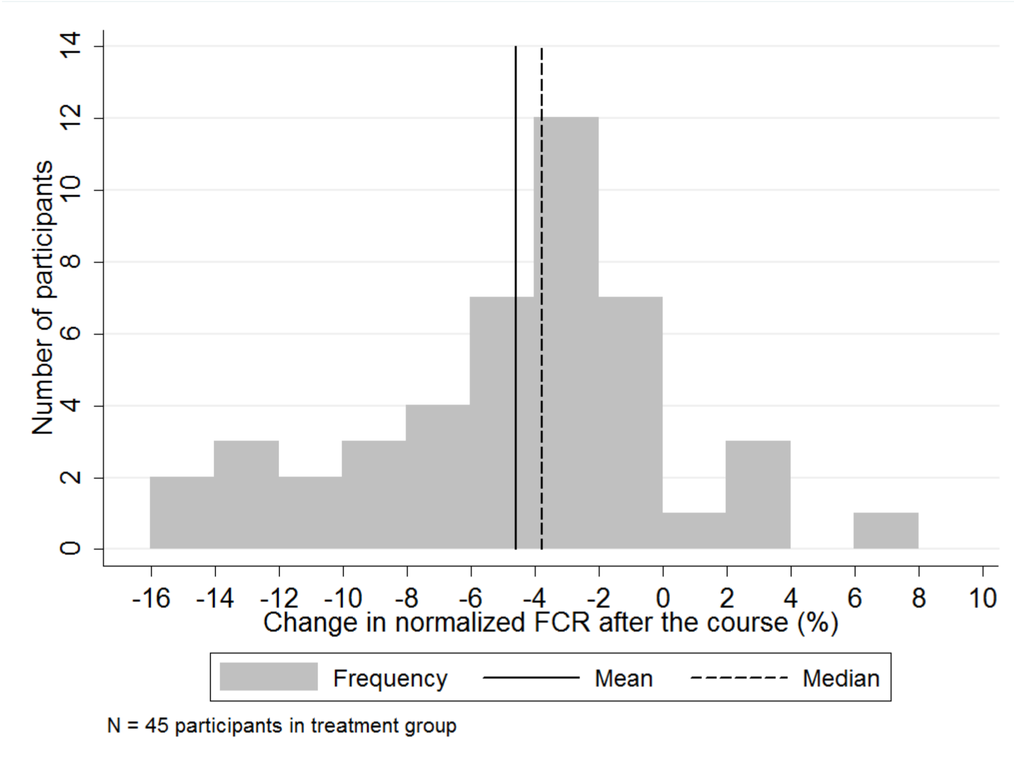
The inclusion of random parameters allows us to take the analysis one step further and examine individual heterogeneity in baseline consumption and the eco-driving effect. As shown at the bottom of Table 3, the constant term has standard deviations of 0.104 and 0.087. Both parameter estimates are statistically significant, suggesting that unobservable individual factors vary considerably from one driver to another and have a substantial impact on fuel consumption. Heterogeneity is also observed in the participants' responses to the eco-driving course. In both models, the standard deviation for the impact of eco-driving training is estimated at about 5%, meaning that some participants achieved very steep reductions in fuel use while others made no decrease at all or even increased their consumption. Histograms of predicted individual eco-driving training effects – the sum of the fixed and predicted random coefficients – are shown in Figure 1. Panel (a) shows that 7 out of 45 trained participants achieved fuel use reductions of 10% or more, but most decreased their consumption much less or even increased it. In fact, only 14 participants showed statistically significant reductions at the 5% level, meaning that 31% of trained drivers effectively applied eco-driving techniques. Similar dispersion is observed in the highway model and effective application of the techniques is much alike with 13 (28%) participant exhibiting significant reductions. An additional random parameter, the correlation between the constant term and the training effect, is statistically insignificant in city conditions but negative and highly significant in highway conditions. Such a correlation suggests that higher standardized fuel uses before the eco-driving course may be associated with larger post-training reductions in fuel consumption. However, the correlation is not particularly strong at -0.4.

Table 3: Results from the base model

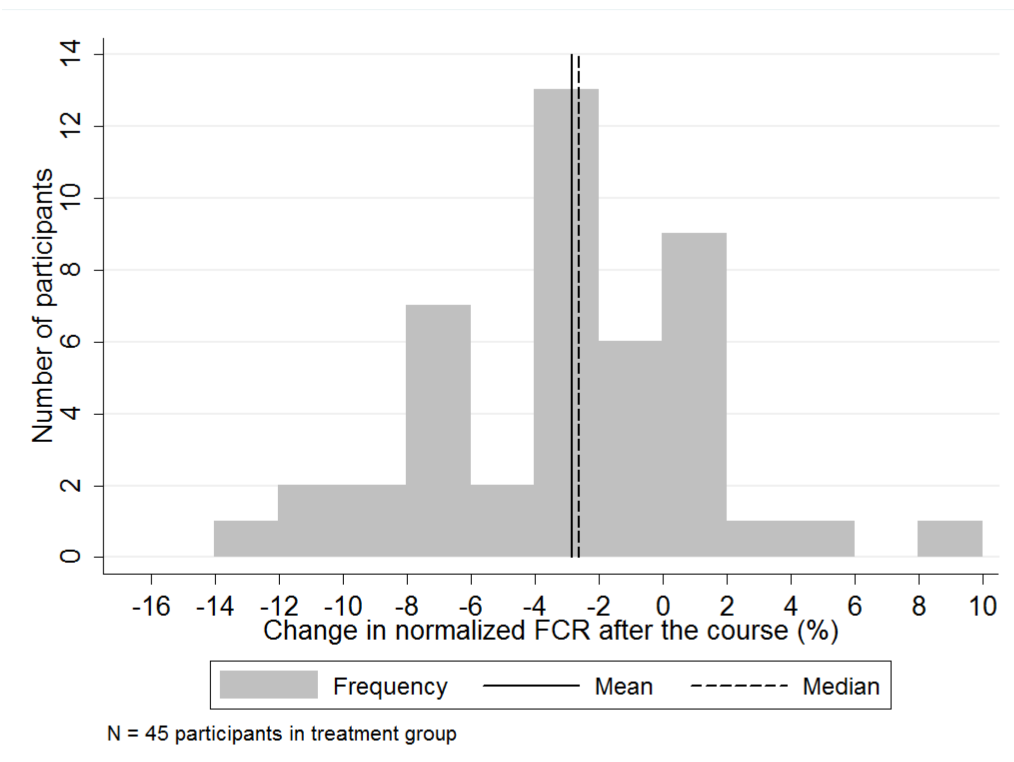
Explanatory variable	**Coefficient estimate (standard error)**	
	City	**Highway**
Fixed parameters		
Constant	0.109*** (0.028)	0.047** (0.021)
$training_{it}$	-0.046*** (0.010)	-0.029*** (0.008)
$temp_{it}$	-	-0.002*** (0.0007)
$temp^2_{it}$	0.0002*** (0.00002)	0.0001*** (0.00002)
$share(0,30)_{it}$	0.732*** (0.030)	-
$manual_i$	-0.112** (0.045)	-
$heavy_i$	-	0.082*** (0.022)
Random parameters		
Standard deviations		
Constant	0.104***	0.087***
$training_{it}$	0.053***	0.045***
Correlations		
Constant, $training_{it}$	-0.023	-0.406***
N	2494	2459

Significance levels: p(>|t|) *** ≤ 0.01 ** ≤ 0.05 * ≤ 0.1
Coefficients of the city-week effects are not shown.

Figure 1: Distributions of estimated individual eco-driving effects



(a) City



(b) Highway

5.2 Heterogeneity and sustainability of the eco-driving effect

Using a variant of our base model, we attempt to find significant determinants of individual discrepancies in the eco-driving effect. This is done by introducing interaction terms in (1). Specifically, new variables of the form $training_{it} \times X_i$ are generated, where X_i is a dummy variable corresponding to an individual characteristic or a feature of the participant's vehicle. Therefore, interaction terms capture the difference in the eco-driving impact between the participants who share the characteristic and those who do not. Consequently, the coefficient of $training_{it}$ captures the eco-driving effect for participants who correspond to none of the characteristics represented in the set of interactions. The total effect for participants sharing a given characteristic is the sum of the coefficient of $training_{it}$ and that of the corresponding interaction term. The set of individual and vehicle characteristics that were tested is the same as that of potential control variables (see section 5.1). Only statistically significant interaction terms are retained.

Coefficient estimates for the interactions model are shown in Table 4. In city conditions, the coefficient on training is no longer statistically significant. However, participants with a manual transmission reduced their fuel use by approximately 12% on average and those who were motivated by environmental concerns, by about 5%. On highways, individuals with a manual transmission also performed better, achieving average fuel consumption reductions of approximately 7% (compared to less than 2% for participants with automatic transmission). Female drivers also decreased their fuel use significantly more, by about 5%. No other interaction term had a statistically significant coefficient estimate. Random parameter estimates show standard deviations around 4% for the training effect in both models. Thus, much of the individual heterogeneity cannot be explained by observable individual characteristics or vehicle attributes. Our results however clearly indicate that drivers using manual transmissions have a considerable advantage when it comes to effectively applying eco-driving techniques.

With a second variant of the base model, we address the issue of sustainability, which has been an important concern in the eco-driving literature. As seen in section 2, the impact of eco-driving courses has been found to fade in a matter of months. To determine whether it has been the case with our sample, we modify our base model in (1) by using four dummies instead of $training_{it}$: $training_{it}^{(1)}$, $training_{it}^{(2)}$, $training_{it}^{(3)}$ and $training_{it}^{(4)}$. Each of the dummies captures the eco-driving effect in a ten-week interval in the post-training period. Thus, $training_{it}^{(1)}$ is equal to one if week t corresponds to the first ten weeks after the course, $training_{it}^{(2)}$ equals one in weeks 11 to 20, and so on.

Table 4: Results from the interactions model

Explanatory variable	Coefficient estimate (standard error) City	Highway
Fixed parameters		
Constant	0.108*** (0.028)	0.052*** (0.022)
$training_{it}$	-0.018 (0.012)	-0.017** (0.008)
$training_{it} \times manual_i$	-0.103*** (0.024)	-0.052*** (0.018)
$training_{it} \times reason_i^{ENV}$	-0.037** (0.015)	-
$training_{it} \times female_i$	-	-0.031** (0.014)
$temp_{it}$	-	-0.002*** (0.0007)
$temp^2_{it}$	0.0002*** (0.00002)	0.0001*** (0.00002)
$share(0,30)_{it}$	0.731*** (0.030)	-
$manual_i$	-0.099** (0.045)	-
$heavy_i$	-	0.069*** (0.022)
Random parameters		
Standard deviations		
Constant	0.103***	0.087***
$training_{it}$	0.043***	0.038***
Correlations		
Constant, $training_{it}$	-0.105	-0.392***
N	2494	2459

Significance levels: p(>|t|) *** ≤ 0.01 ** ≤ 0.05 * ≤ 0.1
Coefficients of the city-week effects are not shown.

Estimation results for the sustainability model are displayed in Table 5. In both the city and highway model, the effect of eco-driving training appears to fade with time. In the city model, trained participants achieved an average reduction of 4.7% in the first ten weeks of the post-training period, but this decrease shrinks steadily to 2.8% (significant only at the 10% level) in weeks 30 to 40. The effect erodes in highway conditions as well. Initial reductions average 3.3%, but the effect of the course becomes statistically insignificant between weeks 20 and 30 of the post-training period. The estimated time patterns for the eco-driving effect are shown in Figure 2. At the bottom of Table 5, random parameter estimates show that the effect of the eco-driving course is about as heterogeneous in every post-training period. Correlations are quite strong between consecutive periods and weaker between distanced intervals, further indicating that the eco-driving effect gradually changed with time. The share of trainees sustaining statistically significant fuel use reductions also decreases with time in both models. In city conditions, it goes from 38% (17) in the first post-training period to 29% (13), 18% (8) and 9% (4) in the following time intervals, respectively. A similar erosion occurs in the city model: the rate of effective application goes from 33% (15) to 29% (13), 11% (5) and 9% (4).

Table 5: Results from the sustainability model

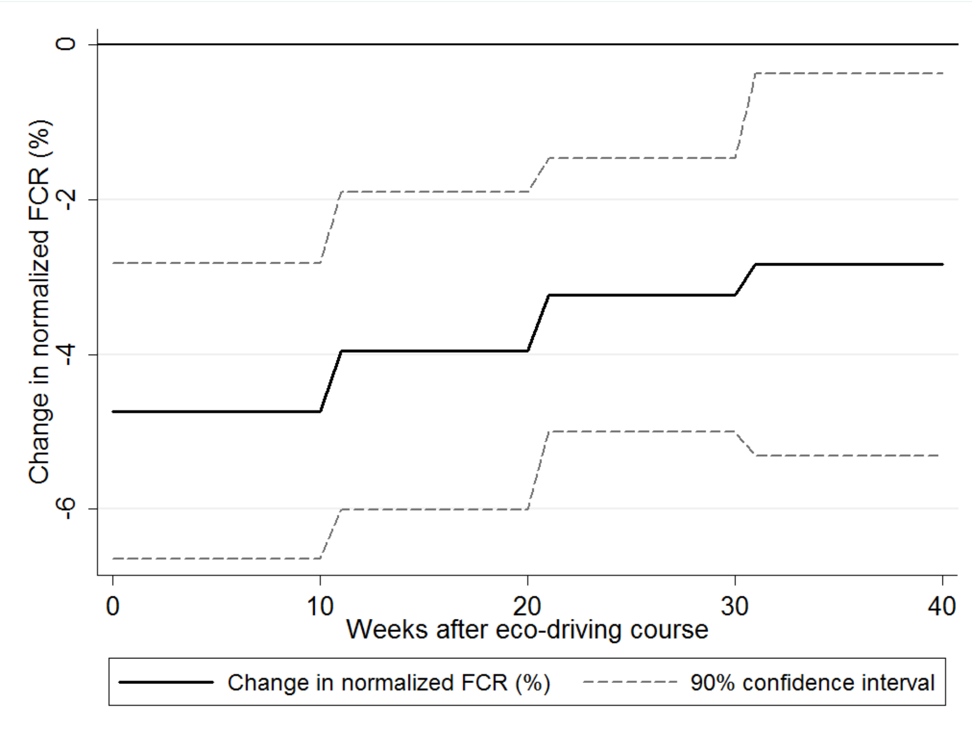
Explanatory variable	**Coefficient estimate (standard error)**	
	City	**Highway**
Fixed parameters		
Constant	0.100*** (0.027)	0.035* (0.021)
$training_{it}^{(1)}$	-0.047*** (0.012)	-0.033*** (0.008)
$training_{it}^{(2)}$	-0.040*** (0.013)	-0.027*** (0.009)
$training_{it}^{(3)}$	-0.032*** (0.011)	-0.010 (0.010)
$training_{it}^{(4)}$	-0.028* (0.015)	-0.0004 (0.013)
$temp_{it}$	-	-0.003*** (0.0007)
$temp^2_{it}$	0.0002*** (0.00002)	0.0001*** (0.00002)
$share(0,30)_{it}$	0.708*** (0.029)	-
$manual_i$	-0.093** (-0.043)	-
$heavy_i$	-	0.074*** (0.021)

Random parameters*		
Standard deviations		
Constant	0.104***	0.087***
$training_{it}^{(1)}$	0.067***	0.048***
$training_{it}^{(2)}$	0.072***	0.054***
$training_{it}^{(3)}$	0.048***	0.053***
$training_{it}^{(4)}$	0.065***	0.068***
Correlations		
$training_{it}^{(1)}$, $training_{it}^{(2)}$	0.872***	0.706***
$training_{it}^{(1)}$, $training_{it}^{(3)}$	0.429**	0.454**
$training_{it}^{(2)}$, $training_{it}^{(3)}$	0.692***	0.888***
$training_{it}^{(2)}$, $training_{it}^{(4)}$	0.425**	0.657***
$training_{it}^{(3)}$, $training_{it}^{(4)}$	0.747***	0.857***
N	2494	2459

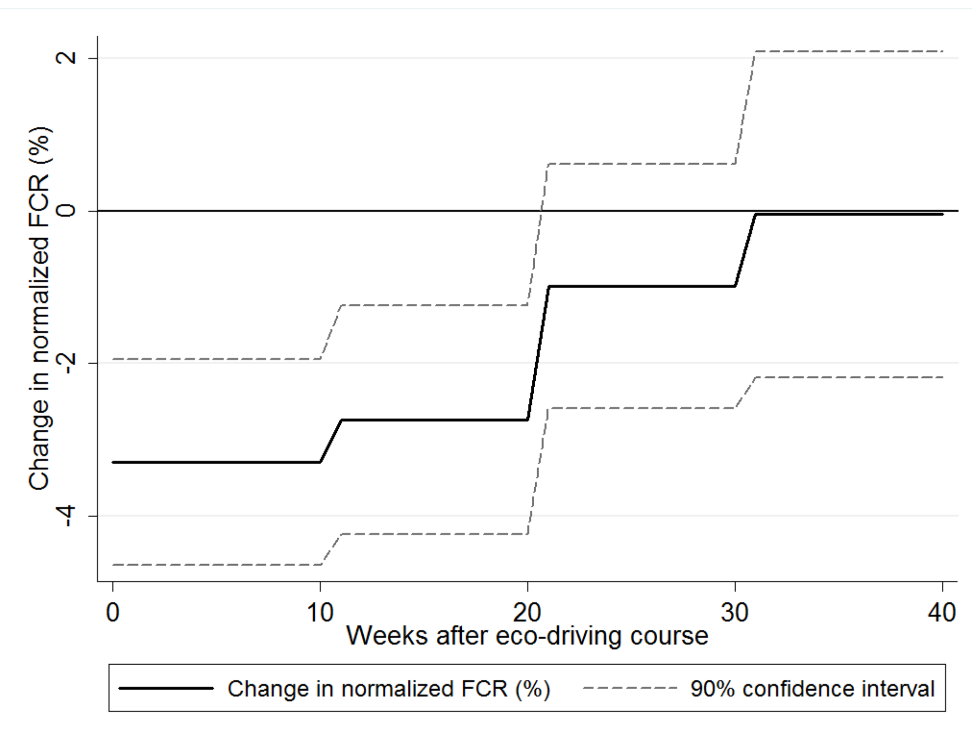
Significance levels: p(>|t|) *** ≤ 0.01 ** ≤ 0.05 * ≤ 0.1

Coefficients of the city-week effects are not shown. * Only statistically significant random parameters are shown to reduce the size of the table.

Figure 2: Time patterns of the eco-driving effect



(a) City



(b) Highway

6. Conclusion

In this study, we assessed the impact of eco-driving training on fuel consumption as well as its sustainability and heterogeneity. In the ten-month period covered by our sample, a short eco-driving course induced average decreases of 4.6% and 2.9% in city and highway fuel consumption, respectively. We further find that these effects have large standard deviations of approximately 5%, indicating that individuals respond to eco-driving training very heterogeneously. Our results show that only about one third of participants achieved statistically significant fuel use decreases. Socio-demographic and vehicle characteristics do not help to explain this heterogeneity except for manual transmissions which seem to provide more opportunities to save on fuel by applying eco-driving techniques. Furthermore, our analysis suggests that the impact of the training declines over time. In fact, highway fuel consumption reductions became statistically insignificant around week 20 of the post-training period while the average benefits of eco-driving on city roads were cut by almost half within ten months. The share of participants achieving statistically significant fuel consumption reductions also fades with time and becomes rather marginal at about 9% in the last ten weeks of the experimental period.

Eco-driving techniques can help reduce fuel consumption, at least moderately. As our analysis and others before us show, the issue is to favor the large and sustained application of these techniques by drivers. Short training sessions are probably the simplest and most direct way to inculcate eco-driving techniques in drivers. However, the resulting benefits appear rather modest, especially from an individual point of view. Using the mean regular gasoline price in Montreal for the period covered by the experiment, we estimate that the "average driver" in our sample – with mean fuel consumption rate and kilometers driven in city and highway conditions– would save around 60$ in fuel expenses over a year. Therefore, it might be preferable to combine eco-driving training with other types of initiatives in order to increase these benefits. Other means of encouraging eco-driving exist and there is some evidence showing that they might be promising. For instance, on-board dynamic feedback devices – such as dashboard interfaces often found in hybrid cars – provide a constant assessment of fuel efficiency and encourage sustained eco-driving. Barth & Boriboonsomsin (2009) find that a traffic sensing device providing dynamic information to drivers can induce fuel efficiency gains ranging between 10 and 20%. Furthemore, af Wåhlberg (2007) shows that dynamic feedbacks led to an additional 2% decrease over twelve months in the fuel consumption of bus drivers who were given eco-driving training.

While eco-driving training – even coupled with the use of on-board devices – may not be sufficient to achieve significant long-run reductions in GHG emissions, it may still prove to be beneficial as part of broader initiatives aiming to make eco-driving the norm rather than the exception. Such policy has been proposed by Barkenbus (2010) who suggests more complete, multi-dimensional intervention including regulation, fiscal incentives and social norm enforcement. Further research assessing the worth of broader and more ambitious policies would be undoubtedly interesting as they would help reveal the true potential of eco-driving.

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