



Can active follow-ups and carrots make eco-driving stick? Findings from a controlled experiment among truck drivers in Norway

Daniel Ruben Pinchasik^{a,*}, Inger Beate Hovi^a, Eirill Bø^b, Christian S. Mjøsund^a

^a Institute of Transport Economics, Department of Economics, Gaustadalléen 21, N-0349 Oslo, Norway

^b BI Norwegian Business School, Department of Accounting, Auditing and Business Analytics, Nydalsveien 37, N-0484 Oslo, Norway

ARTICLE INFO

Keywords:

Road freight transport
Eco-driving training
Driving behavior
Fuel consumption
Eco feedback
Non-monetary rewards
Long-term effects

ABSTRACT

This article presents results from a randomized controlled eco-driving experiment with differential treatment between two groups of truck drivers in Norway. Using data from in-vehicle devices, we investigate whether eco-driving interventions (a course, active monthly follow-ups, and non-monetary incentives) reduce fuel consumption by inducing more efficient driving behavior for drivers in a treatment group, compared to a control group. Hereby, we consider persistence of effects over time and the relative importance of eco-driving factors, while controlling for fixed vehicles, routes, drivers, and weather.

We find significant fuel consumption reductions, persisting over a longer period of time than in most previous studies (where effects fade or disappear), that weather conditions are important, and evidence of an ‘eco-driving learning curve’. This might result from monthly follow-ups and driver rewards. Further, we find spill-over effects through significant fuel savings for drivers in the control group (undergoing no interventions). These are likely the result of them becoming aware that ‘something eco-driving related’ is going on.

Our analysis suggests that improvements on engine and gear management contribute most to fuel savings. We estimate the potential for fuel savings to lie between 5.2 and 7.5% (lower bound, control group) and 9% (upper bound, treatment group). This implies a potential for significant cost savings and emission reductions, which might to some extent be scalable and transferable to other settings. As such, eco-driving may play one part in reducing emissions from road freight, for which much-needed emission reductions are challenging to achieve, especially in the shorter run.

1. Introduction

Climate change is one of the major issues of our time, and tackling it requires large efforts across different economic sectors. A key and common feature for pathways in which global warming is limited to 1.5 °C, is that sizable emission cuts from transport are indispensable [1]. In addition, and following from the notion of a global carbon budget, emission cuts from transport have to take place urgently, because delaying them, even just a few years, has detrimental effects (see e.g. [1,2,3,4]).

Within transport, a segment identified as particularly challenging is freight transport by road [3,5]. Already, road freight stands for about 50% of all global diesel consumption and is a major driver of emissions [6]. More importantly, however, both diesel consumption and CO₂ emissions are projected to keep increasing strongly over the coming decades, with road freight surpassing passenger cars as the world’s

largest oil consuming sector [4,6]. Besides its climate impact, fuel consumption within road freight is also an important consideration from a cost perspective: depending on the size of the freight vehicle and the transport segment (e.g. distribution or long-haul), fuel expenses can easily make up 30% of per-km costs, wages excluded [7]. The above illustrates that reductions in fuel consumption are desirable both for freight operators and society as a whole.

Reducing fuel consumption from road freight, however, is not straightforward. This is due to the sector’s high expected demand growth and fossil fuel dependency [5], alongside a lagging uptake of low and zero emission technologies relative to the passenger car, van and bus segments; particularly when it comes to electric propulsion [7]. This lagging uptake is attributed to the demanding requirements set by freight transport (e.g. regarding driving range, engine power, and tradeoffs between vehicle weight, payload and charging needs), and which have thus far yielded high investment costs. Also the market

* Corresponding author.

E-mail addresses: drp@toi.no (D.R. Pinchasik), ibh@toi.no (I.B. Hovi), eirill.bo@bi.no (E. Bø), esm@toi.no (C.S. Mjøsund).

<https://doi.org/10.1016/j.erss.2021.102007>

Received 5 May 2020; Received in revised form 18 December 2020; Accepted 24 February 2021

Available online 23 March 2021

2214-6296/© 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

availability of electric propulsion trucks, particularly in heavier classes, has so far been very limited and largely consisted of converted diesel trucks rather than series-produced vehicles [3,5,6]. Whilst these barriers are expected to be resolved in the medium- to longer term, they imply that for road freight, the achievement of emissions reductions at scale will take time [8]. The same goes for other promising developments (such as e-highways, platooning and connected and automated vehicles (e.g. [3,6,9])). Also many other determinants of fuel consumption are largely given in the short- to medium term and/or beyond the control of transport operators and their drivers, with main examples including vehicle characteristics, road infrastructure, traffic and driving conditions, and load rates [10,11].

One of the main remaining determinants of fuel consumption is driving behavior [12]. Compared to other determinants of fuel consumption, driving behavior can be influenced more immediately, through the concept of eco-driving. Stimulating eco-driving is further regarded as low-cost and scalable approach [12,13,14,15,16,17], and in the present research studied in the context of trucks and truck drivers, through an eco-driving experiment carried out in Norway (see 'Present research').

Besides the particular challenge of reducing emissions from road freight, focusing on eco-driving for truck drivers is also warranted for other reasons. Although a number of studies have been performed on effects of eco-driving interventions for drivers of passenger cars (and buses), the number of studies regarding eco-driving within freight transport and for heavy-duty vehicles (HDVs) has been more limited [18,19,20,21]. Relative to drivers of passenger cars, professional truck drivers further spend much more time and kilometres behind the wheel, and fuel consumption per kilometre is also considerably higher both per km and in total for HDVs [22]. This implies that the same relative improvement in fuel efficiency yields larger absolute savings for truck drivers in terms of diesel, costs, and emissions [18]. Hence, a euro spent on eco-driving training is potentially (much) more cost effective for truck drivers than for passenger car drivers.

2. Literature review and theoretical background

2.1. Eco-driving: Concept and strategies

Definitions of eco-driving vary in scope, and the broadest definitions encompass factors that affect fuel consumption and which can be addressed either prior to, during, or post trips [8,13]. Most eco-driving studies and initiatives, however, focus on factors which can be addressed while driving, and which can be controlled directly through driving behavior [17,23].

In its core, driving can be divided into acceleration, cruising, and braking. During each of these stages, fuel consumption is affected by how the driver operates the vehicle [10]. Simply put, eco-driving theory recognizes that most drivers operate vehicles in a way that is sub-optimal for fuel efficiency [10] and provides insights into how driving behavior can be improved to minimize tank-to-wheel energy losses, fuel consumption, and emissions [19,24]. In general terms, eco-driving is often described as the adoption of a less aggressive or smoother driving style (e.g. [13,14,16,18,19,25]), and the main eco-driving strategies include driving at a moderate, constant speed, anticipating traffic, gentle acceleration and deceleration, optimizing gear changes, minimizing unnecessary braking and stops, and avoiding unnecessary idling [8,10,13,17,18,19,20,22,25,26,27,28,29,30]. Because these definitions are not standardized and strategies are interrelated, overlap, and may have somewhat different optimums under different road conditions [16,31], eco-driving strategies should be viewed somewhat generically.

Looking at the different strategies, limiting unnecessary idling is one of the most intuitive, as idling uses fuel without contributing to vehicle movement (e.g. [17,19,29]). With regard to speed choice, the eco-driving rationale is that vehicles have an optimal speed or speed range in which they are most fuel efficient. This optimum varies between

vehicles and is also dependent on topography and driving conditions, but tends to lie at around 70–80 km/h for trucks [17,19]. In most cases, it is therefore advisable to drive at a moderate pace and to avoid over-speeding [10]. Fuel consumption is further lower when maintaining steady speeds, which can be achieved either manually or through the use of cruise control [17,18,19,25].

Better anticipation, or 'planning ahead' is pointed out as eco-driving strategy because it helps avoid unnecessary braking and stopping, and thereby reduces the amount of energy that is lost [10,26,28,30]. Looking further ahead also allows the accelerator pedal to be released earlier, meaning that the vehicle can roll on using its existing momentum, rather than through additional fuel consumption that is later wasted in braking [10]. Better anticipation can also be seen as a way to reduce fuel inefficient 'stop-and-go'-driving [13].

The rationale behind optimal gear use, and particularly shifting up early, is that fuel consumption is lower when appropriate speeds are achieved at low RPM (revolutions per minute) (e.g. [16,18,22,25,26,27,29]). Similarly, eco-driving theory recognizes that hard acceleration and braking result in higher energy losses than mild or smoother operation, making the latter preferable from a fuel efficiency perspective (e.g. [8,14,16,19,27,28,30]).

For many of the above eco-driving strategies, connected and automated vehicles could in the medium- to long term reduce much of today's suboptimal human performance, both by excelling at situational awareness and by more accurately following the most energy-efficient driving trajectory in any situation [24, p.558]. Until this is technologically and financially feasible, and implemented at scale, however, eco-driving may contribute to reduce the gap to optimal vehicle operation, albeit within human limitations.

2.2. Eco-driving analysis and interventions

Eco-driving has been researched in several settings. To date, the main approaches for stimulating eco-driving have been training programs and driver support systems [10,17,28,32,33]. Training programs usually consist of knowledge-based training, but can also include practical training or combine both elements [17]. Driver support systems usually revolve around providing drivers with eco-driving feedback, either as part of stand-alone interventions or as follow-ups to training sessions. Feedback can be given in real-time, through in-vehicle devices, shortly after trips (e.g. through online portals), or with a longer time lag between trip and feedback [10,20,33]. Other related and partially overlapping approaches to eco-driving stimulation include information campaigns and gamification initiatives [12,13]. Research methods evaluating the effects of eco-driving interventions, in turn, have predominantly consisted of laboratory or simulator studies, field trials (on-road driving on test tracks or real-world routes), and numerical modelling [14,17].

2.3. Effects of eco-driving on fuel consumption

Both eco-driving training and in-vehicle devices have shown to result in rapid and significant improvements in driving behavior, with estimates on fuel efficiency improvements varying between 1 and 40%, depending on the study [14,16,17,18,34]. While most of these estimates stem from studies involving drivers of passenger cars and buses, the fewer studies on freight vehicles suggest that results are similar for truck drivers (e.g. [11]). In a review, Boriboonsomsin [19] finds that for larger truck studies, eco-driving interventions usually yield fuel efficiency improvements of between 5 and 15%.

Although effects of eco-driving interventions thus tend to be significant and often considerable in the short term after an intervention, effects are found to fade markedly or even disappear in a longer run as a result of drivers returning towards previous behavior [8,12,13,14,16,17,26,35,32,36,37]. This decline is seen both after eco-driving training and in studies using in-vehicle devices [17], although

its extent is dependent on the quality and nature of interventions, and whether or not interventions are followed up with reinforcements [13]. Thus, with some exceptions (e.g. [22]), the challenge seems to be to make behavioral changes from eco-driving interventions more permanent.

At the same time, it should be noted that both effects and persistence vary considerably between individuals [18,26,29]. In some cases, driving behavior has for example been seen not only to improve immediately after an eco-driving intervention, but to follow a progressive trend or 'learning curve'. This has been observed both for individual drivers and driver groups, although in the latter case, effects wore off in the longer term [18,29]. Other reasons for exercising caution when comparing results across studies are the often considerable differences in methodology, vehicles, type of eco-driving interventions, evaluation settings (e.g. closed course vs real routes), drivers, baseline driving behavior, and other sample characteristics [19,20]. Fuel efficiency improvements found in field trials are for example typically smaller than what modelling and laboratory tests would suggest [14,16,17]. This implies either an untapped potential [17] or suggests that achieving major results is difficult in practice. Several studies point out that the simplified and artificial setting of laboratory and modelling studies may not adequately reflect real-world driving, and thereby overestimate the fuel saving potential (e.g. [17,18,22]). Examples of oversimplification include inadequate representation of real-world traffic conditions and road state, noting that different driving behavior is optimal under different conditions [31], and the dependency of laboratory and modelling results on congestion assumptions [14]. Also stress levels and safety risks may be significantly higher in real traffic and limit a driver's focus on driving fuel efficiently [17,31]. More generally, it is noted that modelling results tend to be less accurate and reliable, and may lack external validity [17,27].

2.4. Fuel savings contributions of different eco-driving strategies

In terms of contributions of different eco-driving strategies to fuel savings, results too, are difficult to compare directly, amongst others due to the lack of consistent definitions of eco-driving strategies between studies, as well as the overlap and interrelations between strategies [16].

Nevertheless, some overarching insights can be inferred. Boriboonsinsin [19] points to fuel 'waste' for typical trucks being 33% due to speeding, 25% due to hard acceleration, 20% due to idling, 16% due to hard turns, and 6% due to hard braking. Based on a summary of multiple studies, Huang et al. [17, p. 600] conclude that 'acceleration and deceleration' is the most important eco-driving factor, with improvements yielding a fuel savings potential of between 3.5 and 40%. Driving speed, in turn, could reduce fuel consumption by 2–29%, while reductions in idling could contribute between 6 and 20%. In another summary, Sivak and Schoettle [25] find that effects from reducing idling vary, that overspeeding can increase fuel consumption by 30%, not using cruise control by 7% (under highway conditions), and aggressive driving styles by 20–30%.

Schall and Mohnen [29, p. 292] conclude that both optimal speed choices and less aggressive driving styles (through acceleration and deceleration behavior) can improve fuel efficiency by 10%, while holding speeds constant and anticipating stops can give an 8% improvement and reductions in idling an improvement of between 4 and 10%. As such, the authors point out speed and driving aggressiveness as the most important factors, but note that effects may vary, depending on specific circumstances.

Finally, from a truck field study by Walnum and Simonsen [11], it can be derived that among different eco-driving factors, driving with high engine loads is most detrimental for fuel efficiency, while driving in the highest gear has the largest positive influence. This is followed by idling and high speeds (negative effects) and coasting (positive effects). Increased use of cruise control and automatic gear shift have relatively smaller, but positive effects on fuel efficiency. From the above,

improvements in speed choice and acceleration/deceleration behavior seem to be the main contributors to fuel reduction, followed by avoiding unnecessary idling.

2.5. Reinforcing and maintaining effects of eco-driving interventions

Existing studies suggest that eco-driving interventions limited to training are not sufficient to sustain long-term effects, and that the main challenge seems to be to make behavioral changes from eco-driving interventions both more permanent and large enough [13,16,26]. Indeed, several studies point out that the repetitive and habitual nature of driving implies that purely information-based approaches are likely to have a limited impact and that some form of reinforcement or long-term driver support is required after completion of eco-driving training (e.g. [8,12,19,27]). Several approaches have therefore been proposed aimed at incentivizing and/or reinforcing eco-driving behavior. These include different forms of feedback and driver support after training, as well as different types of reward incentives [8,19,27,32].

With regard to feedback, a number of approaches have been tried, spanning from real-time feedback using in-vehicle devices or online feedback directly after trips, to regular feedback at varying intervals [12,16,34]. Both regular feedback and different types of in-vehicle feedback have been shown to be effective tools for reinforcing eco-driving behavior, and evidence suggests that instantaneous feedback might be somewhat more effective to maintain eco-driving behavior [16,34,38]. However, instantaneous feedback is also associated with driver distraction [16].

Reward incentives, in turn, have been proposed to address the behavioral aspect of driving [32], and it is recognized that monetary and non-monetary rewards may have different effects, because they tend to impact motivation and behavior in different ways [27]. Using reward incentives as a reinforcement for energy conservation behavior has demonstrated mixed results [27]. For eco-driving specifically, non-monetary rewards have been shown to give stronger effects than monetary rewards, but still with attenuation of effects over time [29].

2.6. Moderating factors

When evaluating effects of eco-driving interventions, one moderating factor that should be considered is weather. Fuel consumption is affected by weather conditions such as ambient temperature, precipitation, air pressure, etc. Generally, precipitation increases fuel consumption, amongst others by increasing friction, while fuel consumption is lower at higher ambient temperatures, up to a certain optimum [11,27,28,39]. An illustration of the importance of weather is provided by Allison and Stanton [16], who discuss a study which found significant fuel consumption reductions both in the short and a longer term after an eco-driving intervention, but when data were reanalyzed controlling for temperature, evidence for a long-term effect was no longer significant.

The strength and effects of eco-driving initiatives and strategies are further thought to be influenced by a range of driver and situational characteristics, such as gender, age, driving experience, pressure experienced under driving, knowledge, and attitudes [33,39]. Eco-driving incentives and motivation may for example be stronger in private settings than when driving for an employer [33,40]. Positive attitudes to the environment, as well as attitudes towards, knowledge about, and perceived usefulness and satisfaction from eco-driving, may also positively affect results [33,40]. With regard to driving experience, theoretical eco-driving training has been found to be more effective for inexperienced drivers than for experienced drivers, whose ingrained habits are thought to be more difficult to change through training [37]. In another study, it was found that new drivers with eco-driving as part of their mandatory license training had a better understanding of eco-driving techniques than experienced drivers who lacked this training, and also converted this understanding to more efficient driving in practice [40]. As addressed later, most of the latter factors fall beyond

the scope of the present article.

2.7. Limitations of existing studies

While interesting and relevant, most existing eco-driving studies exhibit one or more limitations. As pointed out above, most eco-driving studies have focused on drivers of passenger cars and buses, while studies on eco-driving within freight transport and HDVs have been more scarce [18,19,20,21]. Generally, most eco-driving evaluations have been based on comparisons of fuel efficiency pre- and post- an eco-driving intervention [26]. Few studies, however, have employed a control group [18,26,35], a gap that is especially apparent among the limited research on truck drivers [22]. Further, most studies are based on small-scale samples [22,26] and have been limited to evaluations of short-term benefits, while research on effects after more than a few months has been scarce [22,26,27,35]. Additionally, many studies have been based on artificial driving conditions [22], and many fewer on natural experiments [27]. This may reduce the external validity of results if factors independent of the driver, but with a considerable impact on fuel consumption, are not adequately controlled for, e.g. road geometry, vehicle type, traffic conditions, and loading factors [12].

2.8. Potential side-effects of eco-driving

In addition to fuel consumption, emissions, and costs reductions, eco-driving is associated with side-effects related to traffic safety, vehicle maintenance, and driver fatigue (e.g. [31,41]). Many of the main eco-driving strategies overlap with strategies for safe driving [13,19,28]. Anticipation, driving at consistent and appropriate speeds [13], smoother acceleration and deceleration, fewer gear changes, and less braking, for example, tend to be beneficial both from a fuel efficiency and safety perspective [17,18]. Smoother driving may additionally reduce wear, and thereby expenses on maintenance and repair, and is associated with less stress and driver fatigue, which might be a traffic safety benefit in itself [18]. However, driving behavior involving less braking and use of high gears may also have opposite effects by reducing headway and vehicle control [28]. It has further been pointed out that while beneficial at the individual level, eco-driving behavior could yield opposite effects at a network level through changes in headway, speed and congestion [14]. Some eco-driving approaches, particularly those involving active in-vehicle feedback, have further raised safety concerns as a consequence of driver distraction (e.g. [14,16,39,42]). These potential side-effects have not been a focus area in the present research, but are mentioned in light of some feedback which we report as part of our discussions.

3. Present research

The present research builds on a randomized controlled eco-driving experiment with differential treatment between two groups of truck drivers, working within freight distribution in the South-Eastern part of Norway. In short, the experiment subjected drivers in a treatment group to an eco-driving course, monthly eco-driving evaluations, and ‘carrots’ in the form of non-monetary rewards, while drivers in a control group were left alone. Details on the experimental design and specifics are described extensively in the next chapter.

Objectives behind the experiment were to shed light on the following overarching research questions:

- Do eco-driving interventions have the potential to reduce fuel consumption by inducing more efficient driving behavior among truck drivers, and if so, to what extent?
- Are changes in driving behavior temporary, or do they persist when an eco-driving course is reinforced with additional interventions?
- Which eco-driving strategies contribute most to reductions in fuel consumption?

- How are results affected by weather conditions?

From the literature, we expect to find significant short-term improvements in driving behavior and fuel efficiency following an eco-driving course (with fuel and emissions savings likely in the 5–15% range). We further expect to observe considerable variation between individual drivers, and possibly a ‘learning curve’ with a progressive trend in effect strength, up to a certain peak (cfr. [18,29]). Without follow-ups, however, effects of the eco-driving course would be expected to attenuate or disappear in the longer run, likely in the course of several months. Both regular and non-monetary rewards could potentially strengthen the persistence of effects, but most likely only delay the fading of effects, rather than completely avoiding it (e.g. [16,29,34]). Due to the many ways and extents in which feedback and rewards can be implemented, the latter expectation is particularly uncertain.

Of different eco-driving strategies, we expect improvements in behavior related to driving speed and acceleration/deceleration to yield the largest potential for fuel savings, followed by reduced idling. Finally, we expect to find significant effects of weather conditions on fuel efficiency through ambient temperatures (positive relationship) and precipitation (negative relationship).

4. Methodology

4.1. Study design

As mentioned, the current study, performed in 2019, was designed as a randomized controlled eco-driving experiment with differential treatment between two groups of seven truck drivers: a treatment and a control group. All fourteen drivers work for the same firm (a large Norwegian freight forwarder operating about 130 trucks), and take shifts driving the same regional freight distribution rounds in the South-Eastern part of Norway. As part of their employment, all drivers had previously been informed about and consented to the potential use of data from their employer’s fleet management system (FMS) for analytical objectives. This made it possible to use such data in the current experiment, and in other parts of an overarching ‘LIMCO’ research project, for which data utilization additionally was cleared with the Norwegian Centre for Research Data.

Because of the arrangement of driving into work shifts (e.g. two weeks on, two weeks off), the fourteen drivers were first divided into ‘complementary pairs’, driving the same routes and vehicle types. Thereafter, one driver from each pair was assigned to a control group and the other to a treatment group by means of random draws.

Although the above leaves a relatively small sample size, the strength of this design compared to many previous studies, is that it allows an assessment of eco-driving in a real-world setting, while to a large extent controlling for the same vehicles (see also data collection), fixed routes (regular and predictable distribution routes, predominantly fulfilling the same order types for the same clients every week), and fixed drivers (the experimental participants). As such, the design attempts to control for effects of driver-independent factors which may have a considerable effect on fuel consumption and might otherwise lead to unfair comparisons between drivers [12].

4.1.1. Participants

The participants in our experiment were all male, professional truck drivers. From information provided by the freight forwarder, we know that within their driver pool of ca. 225 drivers, around half is aged between 30 and 39 and another quarter between 40 and 49, while 16% of drivers are 50 + and 10% are aged under 30. Regarding driving experience, we were provided with a rough split-up of tenure (45% between 0 and 3 years, 13% between 3 and 6 years and 42% with tenure of 6+ years). However, these numbers indicate tenure only at the current freight forwarder, disregarding truck driving experience at previous employers which most drivers were said to have. The freight forwarder

further provided information indicating an average annual mileage per driver of ca. 45.000 km. Because we have not had access to more detailed information for drivers in the experimental sample specifically, the above factors fall beyond the scope of the present research, as is also mentioned in our discussions. However, it can be noted that the freight forwarder has indicated that the base sample of fourteen drivers was intended to have a very homogeneous composition (attempting to avoid e.g. socio-economic differences).

4.1.2. Experimental baseline and eco-driving course

During the first three months of the experiment, none of the drivers knew that they participated in an experiment. This was done to have them continue their work as usual, so that driving behavior and fuel consumption baselines could be established both for drivers in the control and treatment group, and unaffected by any intervention. Three months into the experiment, in early April 2019, an intervention was arranged for the treatment group. Drivers in this group were given a course in eco-driving, while the control group was not. The eco-driving course was held by Cognia, a Norwegian supplier of the FMS-solution used in our experiment (details in next section). During a one evening session, drivers were taught eco-driving theory closely linked to the eco-driving strategies discussed earlier, and how they could improve their performance.

4.1.3. Monthly follow-ups for the treatment group

After the course, drivers in the treatment group started receiving monthly performance reports, covering a total eco-driving score, scores on 'anticipation', 'engine and gear use', 'speed adaption' and 'idling', and their respective sub-components (also explained in detail in the next section). Performance reports were actively followed up through individual monthly evaluation sessions between driver and manager, and with focus on (further) improvement of driving behavior.

4.1.4. Non-monetary rewards for the treatment group

Around 2.5 months after the eco-driving course, non-monetary awards were introduced to give drivers in the treatment group an additional performance incentive: Drivers who achieved a minimum monthly (total) score of 85 (out of a possible 100; see data collection) could earn a t-shirt or fleece jacket with respective texts 'Certified Eco-driver' and 'Perfect Eco-driving skills', depending on their performance. The use of non-monetary rewards was inspired by the eco-driving experiment carried out by Schall and Mohnen [27], and for which results suggested that non-monetary rewards might be a more effective follow-up than monetary rewards.

4.1.5. Potential spill-overs to the control group

While the experiment was intended to have a pure treatment group (with eco-driving interventions) and a pure control group (no interventions), the experiment's implementation gave rise to two potential sources for spill-over effects. Firstly, the non-monetary rewards for drivers in the treatment group may have revealed to the control group that some eco-driving activity was ongoing. Secondly, we were informed in retrospect that between August-December 2019, drivers in the control group were also sent an eco-driving performance report, together with their monthly pay check. Both these potential sources of spill-over effects are addressed in our analysis and discussion. While unintended and unfortunate, it is important to clarify that at no point did drivers in the control group receive any active follow-ups, evaluations, reviews or explanations of performance report contents, nor were they taught or given information on eco-driving, eco-driving strategies, or how to improve their driving behavior and scores. Because of the latter, changes or improvements to driving behavior are most likely associated with driver's own belief of what would constitute good eco-driving behavior.

4.2. On data collection

Modern trucks are increasingly equipped with different sensors, which log data on a number of driving performance indicators. Although many of these indicators vary between vehicle manufacturers and models, examples include (comparable) data on various trip characteristics and driving behavior (e.g. speed, distance, fuel consumption, eco-driving indicators, etc.), as well as other factors, such as geographical conditions [43].

Depending on ownership arrangements, owners or operators of trucks may have access to a variety of valuable indicators, which allow for the follow-up of daily, weekly and monthly behavior through scores on different driving performance indicators in FMS systems. In practice, however, relatively few organizations have so far actively started utilizing logged data more than superficially, and in fact, experience in the overarching LIMCO project indicates that many lack active subscriptions to such data (which form an expense). Further, even when active subscriptions are in place and information could be valuable for research on transport and driving behavior, a challenge remains that data from FMS systems are normally kept in-house. In the current experiment, however, cooperation with both the freight forwarder and FMS provider ensured access to such data.

Overall, data collected in our study cover driving with 15 Volvo trucks (all 3-axled distribution trucks with closed chapel and max. allowed total gross weight of 27 t). Nearly all driving was done with seven of these trucks (all basically identical Volvo FH trucks from 2014 with 460 HP engine and the same dimensions and characteristics), while the remaining eight trucks (including more near identical models from the same year) were only driven over very short total distances by participants in our experiment. Since our sample consists entirely of Volvo trucks, data for most indicators of interest could have been extracted through Volvo's own FMS system (Dynafleet). However, for generalizability, repeatability, and as source for the monthly follow-ups with drivers from the treatment group, we chose to extract data through Cognia's FMS solution, 'Linx'. This solution is developed to be universal across vehicle brands, based on the least common multiple information from different manufacturers' factory-fitted FMS-API, making it possible to capture data from a huge number of trucks and enterprises (as is currently done in the LIMCO project).

In addition to direct engine performance indicators, Linx reports scores on four eco-driving performance indicators mentioned earlier (anticipation, engine and gear, speed adaption and idling), as well as a total score (all with possible range from 0 to 100, where 100 is best). Sub-components used by Linx to calculate these scores are indicated in Table 1.

Data was collected for the period between January 1st and December 31st, 2019. Data on driving behavior performance is available at the daily level, while GPS-tracking usually is available at a (much) higher time frequency. However, the frequency of GPS data from Volvo trucks can easily be set by the driver and therefore varies more in frequency than for other brands: this is for example seen for Scania trucks tracked in the LIMCO project. Unfortunately, GPS-data for the vehicles in the current sample are scarce and therefore not actively utilized in this study.

4.3. Data compilation and quality

After data collection, data quality was checked and certain outlier observations removed (3.2% of observations). For example, all observations where drivers had a daily driving distance below 10 km were excluded, because rather than covering distribution routes, such observations are typically related to the moving and rearranging of vehicles. This comes with high average fuel consumption, predominantly influenced by starts and stops, rather than driving performance. Since each daily observation has the same weight in our analysis, regardless of the daily fuel consumption or mileage, these observations were

Table 1
Descriptives for selected variables included in the data set.

Variable	Description	Descriptives
Average fuel consumption while driving	In liters per 100 km. Only fuel consumption while driving.	Avg: 36.1 L/100 km; Min: 19.1 L/100 km; Max: 59.3 L/100 km.
Distance	Distance driven in km on day of observation	Avg: 313 km; Min: 13 km; Max: 673 km.
Anticipation score (0–100 range)	Derived by Linx from coasting and braking parameters.	Avg: 80.3; Min: 40; Max: 100 Calculated based on percentage of distance spent coasting (Avg: 16%; Min: 0%; Max: 46%) and braking score (Avg: 92.2; Min: 42; Max: 100)
Engine & gear score (0–100 range)	Derived by Linx from parameters on use of automatic gear and power	Avg: 98.8; Min: 56; Max: 100 Calculated based on percentage of distance using automatic gear (Avg: 99.4%; Min: 83%; Max: 100%) and power take-off (data on this individual component was missing in the data set).
Speed adaptation score (0–100 range)	Derived by Linx from parameters on (over)-speeding and use of cruise control	Avg: 73.9; Min: 0; Max: 100 Calculated based on percentage of distance spent speeding (Avg: 16.4%; Min: 0%; Max: 81%) and using cruise control (Avg: 40.5%; Min: 0%; Max: 91%)
Idling score (0–100 range)	Derived by Linx from parameter on idle running	Avg: 49.3; Min: 0; Max: 100 Calculated based percentage of time with idle running (Avg: 23%; Min: 1%; Max: 97%).
Total score (0–100 range)	Calculated by Linx as weighted average of scores on the above four eco-driving parameters.	Avg: 80.3; Min: 40; Max: 100

removed. Further, all observations with a total score of 0 were also removed, because a score of 0 as a monthly weighted average across four different driving performance indicators is most likely a result of an error.

As complement to data collected from the vehicles, the data set was expanded with a number of (dummy) variables. These variables were constructed to indicate whether drivers were part of the treatment group (1) or control group (0), and whether observations were from a date after the eco-driving course (1) or during the baseline period (0), in addition to an interaction dummy (treatment group, after treatment). Further, we added dummy variables representing time passed after the eco-driving course in 6-week intervals (0–6 weeks, 6–12 weeks, etc.). This approach was chosen for a combination of reasons. Firstly, two independent providers of eco-driving tracking solutions provided feedback that meaningful eco-driving performance changes should be considered at time scales of 1–2 months (citing e.g. random variations in traffic, such as traffic jams, road closures, etc., and weather (see below) as reasons). Secondly, while we expect changes in eco-driving scores and fuel consumption over time, these changes may have different strength, direction, persistence and timing (cfr. our discussion of [18,26,29]). This makes it difficult to specify suitable functional forms for regression analyses with time as metric variable (see Section 4.4). Using time period dummies additionally allows us to test differences in effects at different intervals after treatment.

Further, we added variables on average daily temperature, as well as precipitation (in mm) on the observation day. These data were collected from the Norwegian Meteorological Institute, for a measurement location in Oslo (i.e. centrally located relative to the trucks' distribution routes), and were intended to control for effects of weather conditions on fuel consumption (cfr. e.g. [16]).

The resulting data set yielded 1,523 daily observations in total, for all drivers, covering the whole of 2019, and for a total driving distance of over 475,000 km and fuel consumption over 178,000 L of diesel. Drivers in the treatment group stood for 58% of both the observations and total mileage. Further, at 314 and 312 km, average distances driven per day were almost equal between the treatment and control group. This suggests that distribution routes driven in practice were indeed similar between the two groups, as was intended and expected in the study design.

Table 1 provides a summary of the most important variables in the data set. It should be noted that the four Linx-scores on eco-driving parameters are not stand-alone scores, but are derived (by Linx) from 1 or 2 sub-parameters per score, as indicated in the table, while the total score in turn is derived from the four eco-driving parameters. In addition to parameters in the table, the data set includes amongst others anonymized IDs to distinguish vehicle and driver, date, week number, parameters on weather conditions, a number of vehicle characteristics such as age and weight, as well as the dummy variables discussed above.

4.4. Analysis and modeling of effects

To analyze effects of the eco-driving intervention and follow-ups for the treatment group, we constructed two multivariate regression models with daily average fuel consumption (per 100 km) as the dependent variable. The reason for constructing two models is A) to measure how performance on different eco-driving aspects affects fuel consumption (the driving performance score model), and B) to investigate whether there is a difference between the treatment and control group before and after the eco-driving course takes place (the dummy model) - as outlined through our research questions.

Both models were tested using different sub-specifications through inclusion of different independent variables. Before presenting these models and specifications, Table 2 illustrates correlations between fuel consumption, and trip-specific, vehicle-specific and driving behavior parameters. Correlation coefficients were calculated according to Spearman's rank-order approach, as this methodology provides better robustness to outliers than Pearson correlations, and because underlying assumptions for Pearson correlations might not be met across all pairs of variables and all samples. The table reports correlations within three different sub-sets, for all observations in 2019 related to 'driver and vehicle days'. The three sub-sets consist of 1) all vehicles for which the LIMCO project has data capture through Linx ('the LIMCO sample'; this includes both vehicles of the freight forwarder in the study and vehicles of a range of other firms); 2) a sub-set of 'the LIMCO sample', limited to those vehicles that are owned by the freight forwarder ('the full freight forwarder sample'); and 3) only those vehicles driven by drivers in either the treatment or control group ('the study sample', i.e. a subset of both 'the LIMCO sample' and 'the full freight forwarder sample'). The purpose of this approach is to compare observations in the study sample with larger samples with more variability both for vehicles and driving behavior, and thereby to validate the representativeness of the study sample. In the table, positively correlated parameters are shaded blue, and negatively correlated variables are shaded in red, with shading intensity representing the degree of correlation.

For trip-specific parameters, the table indicates negative correlations between average fuel consumption and trip average speed, which is as expected from eco-driving theory, as average fuel consumption usually decreases up to an optimal speed. Fuel consumption and distance have a positive correlation, albeit very weak. Here, we had expected a negative correlation, because fuel consumption tends to be lower for long-haul transport than e.g. urban distribution (e.g. [3]). For the full freight forwarder sample and the study sample, this is likely a result of less variation in routes driven, with longer trips more likely taking place in areas with harsher driving conditions (elevation and/or winding roads, see also [11]).

Of vehicle-specific parameters, several are positively correlated with fuel consumption for both the LIMCO sample and the full forwarder

Table 2

Spearman’s correlations between average fuel consumption and different trip-specific, vehicle-specific, and driver behavior parameters, for three different sub-groups of vehicles and drivers. Rounded to two decimals. GW = Max. allowed vehicle gross weight. N represents number of observations in 2019 related to driver and vehicle days.

		LIMCO sample N = 48 278	Full freight forwarder sample N = 6 046	Study sample N = 1 523
Trip	Distance in km	0.01	0.08	0.09
	Average speed	-0.23	-0.24	-0.22
Vehicle	Age	-0.26	0.24	-0.01
	Engine power	0.49	0.50	-0.03
	Engine displacement	0.41	0.42	0.02
	Vehicle front area	0.02	0.10	-0.36
	Vehicle own weight	0.20	0.31	0.19
	GW vehicle	0.37	0.48	-0.09
	GW vehicle + trailer	0.16	0.54	-0.18
	Number of axles	0.25	0.62	
<i>Driving behavior:</i>				
Engine and gear	Use of automatic gear	-0.11	-0.08	-0.24
	Power take-off (PTO)	0.29	0.18	
Anticipation	Coasting	-0.02	0.23	-0.09
	Braking	-0.09	-0.21	-0.08
Speed adaptation	(Over-)speeding	-0.13	-0.19	0.07
	Cruise control	-0.21	-0.10	-0.08
Idling	Idle running	0.15	0.31	0.40

sample: engine power, engine displacement, vehicle front area (vehicle width times height in m²), the vehicle’s own weight, allowed maximum vehicle weight and maximum allowed gross weight for vehicle and trailer, and the number of axles. This is as expected, as larger and heavier vehicles usually consume more fuel (see e.g. [11]). However, for observations within this study’s sample, many of the vehicle-specific parameters have the opposite sign. This is most likely caused by the trucks in the study being very similar, resulting in too little variation to give plausible correlation coefficients. Vehicle age has a negative sign also for the LIMCO sample, opposite of what can be expected from e.g. engine inefficiencies increasing with age. Only for observations in the full freight forwarder sample do we find the expected positive correlation between age and fuel consumption.

The four eco-driving behavior indicators from Linx consist of different sub-parameters. From the table, we find negative correlations between average fuel consumption and use of automatic gear, coasting, braking score, and use of cruise control. This is as expected from our discussion on eco-driving strategies in Section 2.1. Surprisingly, we also find a negative correlation between (over-)speeding and fuel consumption for the LIMCO sample, while for the study sample, we do find the expected positive correlation between (over-)speeding and fuel consumption. Further, we find positive correlations between power take-off (PTO or engine load) and idling, with fuel consumption. This too, is as expected from the literature. For drivers in the study sample, we only have ‘engine and gear scores’, but lack separate underlying data on the use of PTO. In all, the correlation matrix illustrates that we can expect that improved driver behavior will reduce fuel consumption through increased focus on the use of automatic gear, cruising, braking, and cruise control, and less use of PTO, (over-)speeding and idling.

4.4.1. The dummy model

As pointed out, the main objective of the dummy model is to identify differences in fuel consumption between the treatment and control group, as well as differences before and after the eco-driving course. The number of independent variables in the model is increased stepwise to analyze partial effects of various exogenous variation and how coefficients are affected by controlling for additional variables, as well as to analyze the longer-term effects of the eco-driving course and follow-ups.

In its base specification (Model I), the dummy model is constructed as follows:

$$FC_{i,t} = \beta_0 + \sum_{n=1}^3 \beta_n * D_{n,(i),t} + \epsilon_{i,t} \tag{I}$$

where FC_{i,t} is driver i’s average fuel consumption on day t in liters per 100 km, D_{1,i} is a dummy variable equal to 1 when a driver i is part of the treatment group and 0 otherwise, D_{2,t} is a dummy variable equal to 1 for observations occurring (t) after the eco-driving course has taken place and 0 otherwise, and D_{3,i,t} is an interaction dummy equal to 1 for cases when both the driver i is part of the treatment group and the observation is for a day (t) after the eco-driving course has taken place, and 0 otherwise. Finally, ε_{i,t} is the random error term, while β_n represent parameters that we seek to estimate.

In its second specification (Model II), dummies for eco-driving course completion and the interaction dummy are replaced by dummies for 6-week intervals after course completion, while the third specification (Model III) adds to this two control parameters: average temperature and precipitation on the day of observation:

$$FC_{i,t} = \beta_0 + \sum_{n=1}^7 \beta_n * D_{n,(i),t} + \epsilon_{i,t} \tag{II}$$

$$FC_{i,t} = \beta_0 + \sum_{n=1}^7 \beta_n * D_{n,(i),t} + \sum_{n=1}^2 \gamma_n * \chi_{n,t} + \varepsilon_{i,t} \quad [III]$$

where $FC_{i,t}$, and dummy $D_{1,i}$ have the same meaning as before, while $D_{2...7,t}$ are different dummies equal to 1 for respective 6-week intervals after the eco-driving course (0–6; 6–12...30 + weeks) and 0 before this course has taken place. The variables χ_1 and χ_2 in Model III indicate average temperature and precipitation on day t, respectively. As before, β_n (and in Model III also γ_n) represent the parameters we seek to estimate.

The fourth specification (Model IV) is similar to Model III, but while using observations from both groups for the period before the eco-driving course, the six-week interval dummies after the eco-driving course are only included for the treatment group, while for the control group, a new dummy variable is introduced for the full period after the eco-driving course (D_8).

$$FC_{i,t} = \beta_0 + \sum_{n=1}^8 \beta_n * D_{n,(i),t} + \sum_{n=1}^2 \gamma_n * \chi_{n,t} + \varepsilon_{i,t} \quad [IV]$$

4.4.2. The driving performance score model

The purpose of the driving performance score model is to investigate how changes in driving performance influence fuel consumption. Driving performance is measured by the four eco-driving score indicators or strategies discussed in Section 4.3, and variables are transformed to a logarithmic scale. This has the advantage that elasticities constant of scale can be deduced, and yields the following base specification:

$$\ln(FC_{i,t}) = \beta_0 + \sum_{n=1}^4 \beta_n * \ln(\chi_{n,i,t}) + \varepsilon_{i,t} \quad [A]$$

where $FC_{i,t}$ is the driver i's average fuel consumption on day t in liters per 100 km, χ_1 through χ_4 are a driver i's respective Linx-scores on anticipation, engine and gear, speed adaptation, and idling, on day t, and $\varepsilon_{i,t}$ is a random error term. β_n represent the parameters we seek to estimate.

In its second specification (Model B), the base specification is expanded with control parameters for average temperature ($\chi_{5,t}$) and precipitation ($\chi_{6,t}$) on the day (t) of observation. To enable a logarithmic scale, temperature (which can include negative values) is converted from Celsius to Kelvin. In the third specification (Model C), a further parameter is added for distance, ($\chi_{7,i,t}$, again in logarithmic transformation, for driver i on day t). This can be summarized as follows:

$$\ln(FC_{i,t}) = \beta_0 + \sum_{n=1}^6 \beta_n * \ln(\chi_{i,t}) + \varepsilon_{i,t} \quad [B]$$

$$\ln(FC_{i,t}) = \beta_0 + \sum_{n=1}^7 \beta_n * \ln(\chi_{i,t}) + \varepsilon_{i,t} \quad [C]$$

5. Results

5.1. Developments in eco-driving and fuel consumption

Before moving results from our regression, we first look at developments in eco-driving and fuel consumption throughout 2019. Fig. 1 illustrates developments in the average monthly total driving performance score (0–100) for both the treatment group and control group, i.e. the weighted average of the four score sub-indicators from Linx. The dotted curve represents drivers in the control group who participated throughout the entire period, i.e. excluding the drivers that quitted their positions and for whom data is missing towards the end of the period.

From the figure, it can be seen that drivers in the treatment group on average started out from lower total scores than the control group. A significant increase started immediately after the eco-driving course in the beginning of April, for both groups of drivers, but this increase leveled out in May. While this increase is not unexpected for the treatment group, observations for the control group are less intuitive. We expect the latter to be a result partially of the transition from winter to spring, and partially of score variation internally in the control group (combined with the sensitivity of group averages to relatively small group sizes). While we discussed potential sources of spill-overs from treatment to control group, these are likely first relevant after the introduction of rewards in June or performance reports unintentionally being sent out also to control group drivers, from August onwards.

For the treatment group, a new increase is visible from May to June, and further on to July, while the control group had a stable score level until June, with a sharp increase from June to July. This distinctive increase can partially be explained by the fact that three of the drivers, whereof two with the lowest scores in the control group, quitted their positions from the start of July. However, the dotted line also illustrates that the rest of the control group had an increase in score from June to July, most likely a result of the differential treatment becoming visible because of the introduction of non-monetary awards at this time. From July onwards, the treatment group maintained a relatively stable average total score level, while scores for the control group exhibited

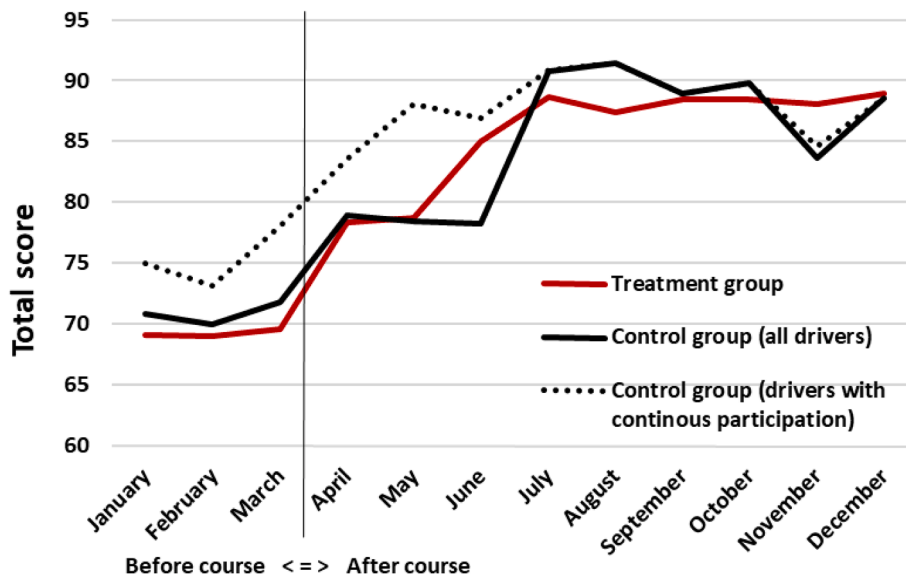


Fig. 1. Development in average monthly total driving performance score for the treatment and control groups, before and after the eco-driving course in early April 2019.

more variation. The control group reached its maximum average total score level in August and later exhibited a seemingly temporary decrease in November.

Fig. 2 presents average driving performance scores before and after the eco-driving course, and well as corresponding percentage changes, for individual drivers in both groups.

From the figure, it is seen that all drivers in the treatment group increased their average total scores by 10% or more after the eco-driving treatment. The figure further shows that most drivers in the control group also increased their scores; only one driver exhibited a score reduction, while another maintained nearly the same average level.

On the other hand, two of the three drivers with the highest percentage improvements are in the control group. While one of the drivers in the treatment group increased his score to nearly the maximum of 100, this increase is from a high initial level, yielding a percentage change of less than 15%. The driver with the largest relative improvement showed an increase in average score of nearly 40%. In line with several previous studies (e.g. [18,26,29]), the figure further confirms considerable variation between individual drivers.

A similar illustration is given in Fig. 3, but now for average fuel consumption before and after the eco-driving course.

This figure shows that two of the drivers in the treatment group had a slight increase in average fuel consumption in the period after treatment, and one of these is the driver who achieved a nearly perfect average total driving score after treatment. This is a case in point, illustrating that fuel consumption is affected by more than eco-driving parameters (e.g. weather), and one reason for studying partial effects in more detail. All other drivers show a reduction in average fuel consumption after treatment. With a reduction of nearly 15%, the largest reduction in average fuel consumption after treatment is found for a driver in the treatment group.

5.2. Differences in fuel consumption between treatment and control group

Table 3 summarizes regression results for different specifications of the dummy model, with coefficients being the β - and γ -values in the respective sub-specifications according to equations I, II, III and IV given above.

Using these results, we further carried out a series of Wald tests comparing coefficients between all pairs of time period dummies, with the null hypothesis that coefficients are not significantly different. Results of these comparisons are presented in Table 4, for Models II, III and IV respectively, and indicate whether effects (change in average fuel consumption) are significantly different between time periods, e.g.

indicating a learning curve, progressive increases, or effect fading (cfr. [18,29]).

From Table 3, Model I has an adjusted R-squared of 0.078, i.e. around 8% of variation in average fuel consumption can be explained by the independent variables in the regression model. While this value is low, it is not unexpected given that fuel consumption is affected by many variables not included here (cfr. [10]). The positive and statistically significant coefficient on the treatment group dummy indicates that before the eco-driving course, the fuel consumption for drivers in the treatment group was on average 2.3 L/100 km higher than for drivers in the control group, who had an average fuel consumption of 37.1 L/100 km.

Further, fuel consumption after the eco-driving course is significantly lower (on average 2.9 L/100 km) than before the course. Although the coefficient on the interaction dummy for treatment group and completion of the eco-driving course is negative (suggesting that the post-course reduction in fuel consumption is larger for drivers in the treatment group than in the control group), this difference is not found to be significantly different from zero.

In Model II, we take a closer look at changes in fuel consumption in a short and a longer term. As seen from Table 3, coefficients on all variables are significant at the 99% level, and the share of variation explained by the model is slightly higher. In the reference (all timing dummies equal to zero, i.e. before the eco-driving course), fuel consumption for drivers in the treatment group was on average 1.9 L/100 km higher than for drivers in the control group. The largest reductions in fuel consumption are found from weeks 12 to 24 after the treatment, but also in the last period for which we have data (i.e. up to a whole 9 months after the eco-driving course), we find that fuel consumption is lower than before the course (99% significance). Results from Wald tests comparing coefficients between pairs of dummies in Table 4 further suggest that drivers may experience a learning curve: effects between 12 and 30 weeks after the course are namely significantly stronger than in the first 12 weeks (98–99% confidence). In the last time period, fuel consumption is still significantly lower than before the eco-driving course, but the effect is significantly smaller than in the peak time intervals 12–24 weeks after the course (99% confidence) and 24–30 weeks after the course (95% significance).

In model III, average daily temperature and precipitation (in mm) are included as control variables. The negative coefficient on temperature indicates that higher average temperatures might reduce fuel consumption (but not significantly), while the positive and significant coefficient on precipitation indicates that increases in precipitation on average increase fuel consumption. The latter is as expected due to

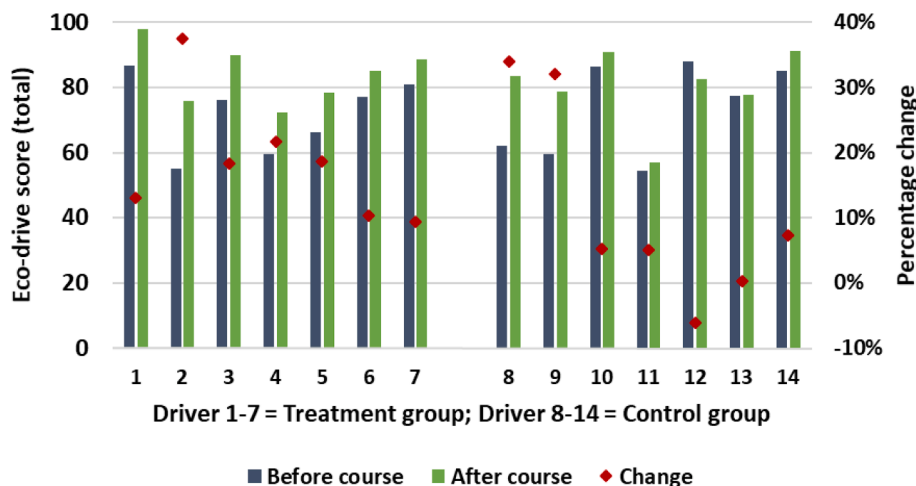


Fig. 2. Average driving performance score before and after the eco-driving course, for each driver in the treatment group (driver 1–7) and the control group (driver 8–14), and corresponding percentage changes (right axis).

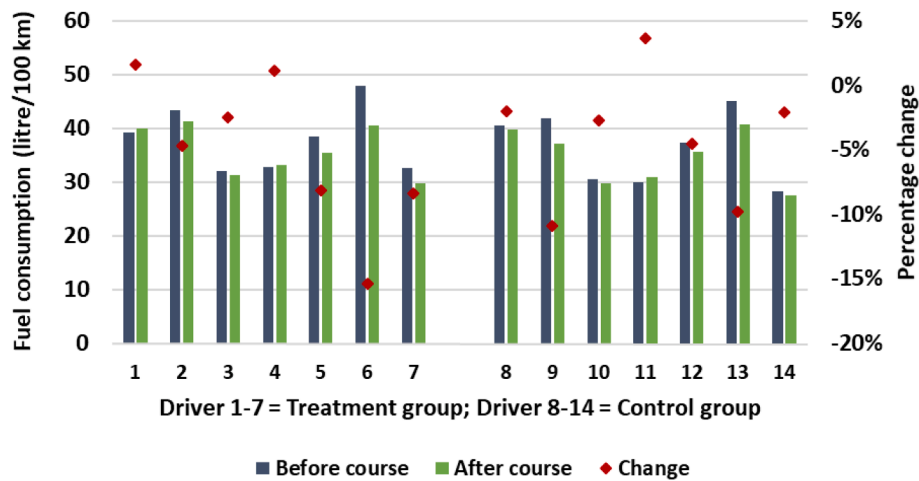


Fig. 3. Average fuel consumption before and after the eco-driving course, for each driver in the treatment group (driver 1–7) and the control group (driver 8–14), and corresponding percentage changes (right axis).

Table 3

Results from four different specifications of the dummy model for avg. fuel consumption (liters per 100 kms) for the treatment group and the control group, before and after the course, the short and long-term effects, and how weather conditions influence fuel consumption.

		Model I	Model II	Model III	Model IV
β_0	Intercept	37.09 ***	37.17 ***	37.03 ***	36.88 ***
β_1	Dummy treatment group	2.34 ***	1.91 ***	1.92 ***	2.26 ***
β_2 (in I)	Dummy eco-driving course	-2.91 ***			
β_3 (in I)	Interaction dummy treatment group & eco-driving course	-0.82			
β_2	0-6 weeks after treatment		-1.78 ***	-1.40 **	-1.50 **
β_3	6-12 weeks after treatment		-2.43 ***	-2.01 **	-1.45 *
β_4	12-18 weeks after treatment		-4.36 ***	-3.57 ***	-3.73 ***
β_5	18-24 weeks after treatment		-5.11 ***	-4.48 ***	-3.96 ***
β_6	24-30 weeks after treatment		-3.99 ***	-3.84 ***	-3.95 ***
β_7	30+ weeks after treatment		-2.34 ***	-2.39 ***	-2.85 ***
β_8	Dummy control group after eco-driving course				-2.12 ***
γ_1	Average temperature			-0.04	-0.07 **
γ_2	Precipitation (in mm)			0.06 **	0.06 **
	Adjusted R-squared	0.078	0.095	0.097	0.092

increased rolling resistance from rain. Remarkable is that controlling for weather conditions reduces the coefficient values of the short and longer-term changes in fuel consumption, except for the last time interval, which is in winter time. Results in Table 4 show that effects are stronger between 12 and 30 weeks after the course than during the first 12 weeks (95–99% significance), again suggesting a learning curve. After controlling for weather conditions, we further find fewer indications of effects fading over time. Fuel consumption in the last time interval for which we have data is still found to be significantly lower than before the eco-driving course, and the fuel reduction effect is no longer significantly different from the effect in the time interval 12–18 weeks after the course (β_4), while differences compared to peak reductions in the intervals 18–30 weeks after treatment (β_5 and β_6) become less statistically significant (at 95% and 90% level vs. 99% and 95% in Model II).

Model IV is similar to model III, but uses only observations from the treatment group for the estimation of differences in effects in the long term, while for the control group, a new dummy variable is introduced for the period after the eco-driving course. The dummy for the treatment

group still indicates that drivers in this group have a significantly higher initial fuel consumption than the control group. All coefficients are significant at the 95–99% level, except for the period 6–12 weeks after treatment, where fuel consumption is significantly different at the 90% level (for later intervals, statistically significant reductions found lie between 2.8 and 4.0 L/100 km). Further, both temperature and precipitation coefficients are statistically significant (95%), and have the same signs as in Model III. The last series of Wald test results in Table 4 shows that for the treatment group, effects early on (0–6 weeks after the course, β_2) are significantly different from effects in the intervals 12–30 weeks after the treatment (95–99% confidence). Further, effects from 6 to 12 weeks after the eco-drive course are found to be different from effects between 12 and 30 weeks after the course (99% significance). This suggests a learning curve effect specifically for drivers in the treatment group. However, unlike for Model II and III (including long-term observations for the control group) we find no statistically significant differences between effects after 12–18 weeks and later intervals, and hence, no evidence of fading effects for drivers in the treatment group.

Table 4

Results from Wald tests comparing coefficients between all pairs of time periods, with null hypotheses that coefficients are not significantly different, for each individual pair. Table reports test statistics (F) with corresponding degrees of freedom and p-values indicating statistical (in)significance.

			Model II		Model III		Model IV				
			F _{1,1515}	p-value	F _{1,1513}	p-value	F _{1,1512}	p-value			
β ₂	vs	β ₃	1,3	0,258		0,9	0,343	0,0	1,00		
β ₂	vs	β ₄	18,1	0,000	***	8,1	0,004	***	6,5	0,01	**
β ₂	vs	β ₅	27,4	0,000	***	18,2	0,000	***	7,5	0,01	***
β ₂	vs	β ₆	12,7	0,000	***	15,0	0,000	***	10,3	0,00	***
β ₂	vs	β ₇	0,8	0,371		2,0	0,156		2,6	0,11	
β ₃	vs	β ₄	9,8	0,002	***	5,8	0,017	**	7,3	0,01	***
β ₃	vs	β ₅	17,2	0,000	***	14,3	0,000	***	8,0	0,00	***
β ₃	vs	β ₆	6,1	0,014	**	7,1	0,008	***	9,0	0,00	***
β ₃	vs	β ₇	0,0	0,888		0,2	0,663		2,0	0,15	
β ₄	vs	β ₅	1,3	0,262		1,8	0,185		0,1	0,79	
β ₄	vs	β ₆	0,3	0,572		0,1	0,740		0,1	0,81	
β ₄	vs	β ₇	9,4	0,002	***	1,3	0,247		0,7	0,39	
β ₅	vs	β ₆	2,7	0,101		0,7	0,400		0,0	1,00	
β ₅	vs	β ₇	16,3	0,000	***	4,8	0,028	**	1,2	0,28	
β ₆	vs	β ₇	6,1	0,014	**	3,7	0,054	*	1,6	0,20	

5.3. Results from the driving performance score model

Table 5 show results from three specifications of the driving performance score model, assessing how different eco-driving scores and weather conditions influence fuel consumption and corresponding elasticities. Coefficients represent the β-values in the respective sub-specifications according to equations A, B and C given above.

All parameter coefficients in the three model specifications are significant at the 99% level (except for the coefficient on rainfall in Models B and C, which is significant at the 90% and 95% level respectively), and differences stemming from introducing additional variables to the base specification are not large. Further, adjusted R-squared values indicate that between 14.5 and 17.2% of the variation in average fuel consumption can be explained by the independent variables. Of the four driving performance factors, it can be seen that improvements in ‘engine and gear score’ reduce fuel consumption most, followed by improvements in ‘speed adaptation score’ and ‘idling score’. These results seem consistent with eco-driving theory and conclusions in previous research (Section 2.4), although differences in definitions and score compositions make direct comparisons difficult. On the other hand, the coefficient for ‘anticipation score’ has a positive sign. This implies that higher scores lead to increased fuel consumption, and is the opposite of what was expected. An explanation could be that the anticipation score is composed of the two variables for coasting and braking, which are

expected to be correlated with the topography of the area where the truck is driving. Higher coasting scores could be related to more opportunities for coasting due to downhill driving on a route, but when such routes also imply more uphill driving, this could result in a net fuel consumption increase.

Also in the driving performance score model, average temperature and precipitation significantly influence average fuel consumption, and have the expected signs (Model B and C). At the same time, temperature and precipitation do not influence coefficients or significance of coefficients on the score parameters particularly.

In the specification of Model C, the coefficient on the parameter for ‘distance’ has a positive sign, again contrary to what was expected. However, it is important to note that the study data contain a limited number of distribution routes. Increased fuel consumption for the longest routes can therefore be the result of these longer distribution routes to a larger extent taking place in areas with harsher topography and curvature than the shorter routes in the Central South-Eastern parts of Norway.

Total elasticities (i.e. the sum of elasticities for the score parameters) of between -0.322 and -0.350 indicate that an increase of 10% in total driving performance score leads to a decrease in average fuel consumption of between 3.2 and 3.5%. As was shown in Fig. 1, drivers in the treatment group on average increased their (rounded) total driving performance scores from 69 in January to March, to 89 in October to

Table 5

Results from three regression specifications of how performance on different eco-driving indicators and weather conditions influence fuel consumption, and corresponding elasticities.

		Model A	Model B	Model C
β ₀	Intercept	5.121 ***	8.868 ***	8.268 ***
β ₁	LN(anticipation score)	0.050 ***	0.060 ***	0.069 ***
β ₂	LN(engine and gear score)	-0.328 ***	-0.344 ***	-0.321 ***
β ₃	LN(speed adaptation score)	-0.036 ***	-0.036 ***	-0.038 ***
β ₄	LN(idling score)	-0.033 ***	-0.030 ***	-0.032 ***
β ₅	LN(average temperature)		-0.662 ***	-0.616 ***
β ₆	LN(rainfall in mm)		0.006 *	0.007 **
β ₇	LN (distance)			0.037 ***
	Adjusted R-squared	0.145	0.173	0.172
	Sum elasticity	-0.348	-0.350	-0.322

December, i.e. a score increase of 28% on average. Combining this information with the estimated elasticities indicates that the eco-driving intervention results in a decrease of 9.0% in average fuel consumption from January to December, taking into account differences in temperature and precipitation. This can be interpreted as ‘upper bound potential’ for savings from the eco-driving interventions in the current study.

Also the control group had an increase in total score, from (rounded) 71 in January to March, to 87 in October to December, or 23%. Correcting for the drivers that quitted their positions during the summer, this improvement is 16%. Combining this information with the estimated elasticities indicates that the reduction in average fuel consumption from January to December was between 5.2% and 7.5% for the control group. This is despite the control group not participating in the eco-driving course and not receiving follow-ups, and might be the result of spill-overs from the treatment group. The 5.2% reduction might be interpreted as ‘lower bound potential’, given that eco-driving is not actively addressed for these drivers and driving behavior improvements might be induced by an indication that ‘something is going on’. Active follow-ups should be expected to strengthen this effect.

The freight forwarder reports a total annual fuel consumption of 3.4 million liters of diesel in 2018. This corresponds relatively well with the fuel consumption in our dataset for 2019 (2.9 million liters of which 179,000 L by drivers in our experiment). The average score level for all drivers of the freight forwarder was 78 in 2019. This is below the annual average for both the treatment group in 2019 (85) and the control group (83, not corrected for drivers quitting their position, or 86 for drivers in the control group with continuous participation in 2019).

As can be seen from Fig. 4, the monthly score level for drivers not participating in the study was more constant throughout the year than for the other two groups, with a peak in July. This indicates that also drivers at the company that weren’t part of this study might have a potential for improved driving behavior. However, this improvement potential is smaller than for the treatment group, which started from a lower initial score level in January. The score level of other drivers at the forwarder is more in line with the initial level of the control group. This suggests a potential for increasing total scores by between 16% and 28%, corresponding to a reduction in fuel consumption of between 5.2% and 9.0%. For the freight forwarder as a whole, this would correspond to potential annual diesel savings of between 178 and 306 thousand liters, a reduction in CO₂ emissions of between 454 and 779 tonnes (based on the Norwegian biodiesel blend-in in 2019 [7]), and savings on fuel

expenses of between 2 and 3.5 million NOK (ca. 205–350 thousand EUR or 230–393 thousand USD at 2019 average exchange rates and Norwegian diesel prices (cfr. [7]).

6. Discussion

6.1. Summary of results

In summary, our results indicate that an eco-driving course, combined with active follow-ups and ‘carrots’ in the form of non-monetary rewards, might induce more efficient driving behavior among truck drivers, and thereby significantly reduce fuel consumption. Although considerable variation is observed between individual drivers, results indicate that driving behavior improves progressively up to a peak, suggesting an eco-driving ‘learning curve’. Results further indicate that effects do not disappear or fade significantly over time, and suggest that follow-up evaluations and non-monetary rewards may reinforce or strengthen effects of a theoretical eco-driving course. Based on improvements in driving behavior found for the treatment group, and potential spill-overs of effects to the control group, we estimate a potential for fuel savings between a lower bound of 5.2% and an upper bound of 9.0% on a yearly basis (for driving in comparable settings).

Of four driving performance factors, representing eco-driving strategies, results indicate that improvements in ‘engine and gear’ management (consisting of automatic gear use and power take-off) may contribute most to reductions in fuel consumption, followed by improvements in ‘speed and adaptation’ (consisting of cruise control use and avoidance of speeding) and ‘idling’ behavior. Better ‘anticipation’ (consisting of coasting and braking behavior) is not found to contribute to fuel savings, a finding that might be the result of the topography of the routes driven. Weather conditions are found to be significant and largely as expected, with lower fuel consumption at higher ambient temperatures and higher fuel consumption with increased precipitation. Controlling for weather also makes our finding that effects do not fade significantly over time, more robust.

6.2. Implications

Reducing emissions from road freight transport is seen as highly necessary and urgent, but also very challenging due to large projected increases in demand and the high fossil fuel dependency of road freight. At the same time, it is expected that large-scale adoption of both low-

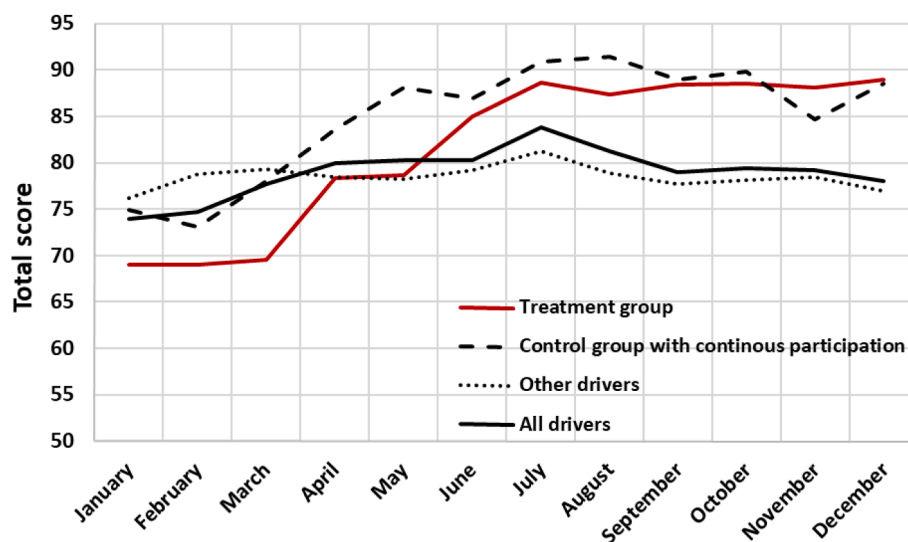


Fig. 4. Monthly averages in total score for treatment group, control group, other drivers of the freight forwarder, and on average for all drivers of the forwarder (treatment and control group, and others).

and zero-emission technologies and other solutions with considerable emission reduction potential (such as connected, automated vehicles, platooning, etc.) will take time. Also many other main determinants of road freight's fuel consumption are largely given in the short- to medium term, or beyond the control of transport operators and their drivers. Inducing more fuel efficient driving behavior, eco-driving, is therefore often seen as one of the few veins through which fuel consumption can be reduced both significantly and in a shorter term [3]. In addition, eco-driving is regarded as a low-cost and scalable approach [13,14,17]. However, the effect of eco-driving initiatives tends to fade over time, and the challenge seems to be to make improved driving behavior more permanent [13,16,26].

Through its approach and results, the present research has several implications for this latter challenge and future eco-driving initiatives and research. Although we acknowledge a number of limitations in the next section, our results are promising with regard to the effectiveness of combining eco-driving training with active follow-ups and rewards. While different settings might moderate results, it is not unlikely that significant fuel savings are achievable also at other firms and by other drivers, and at relatively low cost. Our research also implies that future interventions could benefit from designs where knowledge training is followed up with reinforcement mechanisms. Our research further provides insights into the importance of different eco-driving strategies, which may contribute to increased focus in eco-driving interventions and potentially lower the threshold for implementing such initiatives. In addition, if spill-overs indeed took place, this strengthens the view that eco-driving might be a rather low-hanging fruit.

Compared to previous literature, a number of findings and observations are confirmed or supported. Examples include the rapid materialization of effects (e.g. [17]), the size of effects (falling within the 5–15% fuel savings range compiled by [19]), the possibility of a 'learning curve' [18,29], considerable variation between drivers [18,26,29], the importance of including weather, and direction of effects [most notably 16], and possibly the materialization of spill-overs (related example in [35]). To a large extent, our results also seem consistent with findings on the relative importance of (improvements on) different eco-driving factors for fuel consumption [11,17,19,25,29]. Different from many previous studies is that effects are not found to fade significantly in the longer term. While both feedback and non-monetary rewards have been found to be effective in reinforcing effects after eco-driving training [16,34,38], effects are usually still expected to fade in the longer term (e.g. [29]).

In addition to contributing to the relatively limited body of literature on truck eco-driving, and particularly real-world studies on longer-term effects and reward incentives [12,26,27], our research added some new elements. For example, we combined real-world conditions with a design in which trucks, routes and drivers are relatively fixed. As opposed to some laboratory experiments or eco-driving evaluations on dedicated testing tracks, real-world examples are scarce, but needed, to increase external validity of results. Further, we utilize data from in-vehicle FMS-devices. Such data are currently often underutilized, but have a large potential for detailed future data collection and utilization given that FMS-devices have become a 'standard' in new trucks and are increasing rapidly in number [43].

6.3. Limitations, strengths and suggestions for future research

Despite best efforts, our study revealed a number of challenges. One of these challenges was related to potential spill-overs of effects to the control group, once treatment group rewards became visible, or after control group drivers unintentionally started receiving feedback reports. This challenge implies that the control group might not fully reflect what would have happened without any eco-driving interventions, and indeed, developments in scores from drivers at other departments of the freight forwarder suggest that some spill-overs may have taken place. At the same time, spill-overs are unlikely to have affected effects for drivers

actually undergoing eco-driving interventions. These effects could be regarded as 'upper bound potential' and provide an indication of what can be achieved through the interventions in our experiment.

Further, even though our experiment aims to control for fixed routes, drivers, and trucks, the sign of some estimated coefficients is not as expected. This is particularly true for improvements on coasting and braking, which are generally assumed to improve fuel efficiency. We believe this is rather the result of some critical factors not being included in the analysis because of data availability issues. Examples are the lack of information about dynamic on-board cargo weight and the topography and curvature of roads in areas where transports are carried out. Even though the selection of routine distribution routes and sample of trucks and drivers likely reduces these deficiencies, there will still be some day-to-day variations in payload, and occasional variations in routes. Our attempt to control for these factors as much as possible also put a natural limit to the sample size that could be included, which was exemplified by some attrition due to drivers in the control group quitting their position. Similarly, drivers could not be compared at the exact same time because distribution routes were driven in shifts. Any differences between shifts are particularly thought to relate to weather, which we controlled for in our analyses. In all, eco-driving experiments such as the one described here must balance between the representativeness of experiments for real-life driving, the ability to control for external factors, availability of and access to sufficiently comprehensive data covering sufficiently long periods, and sample size.

The above challenges also point out the critical moment for using FMS data for transport analyses, because factory-fitted FMS-APIs do not provide access to dynamic vehicle weight information. For information on actual payload, access is required also to order system data, but these are rarely available and not easily coupled to vehicle data. Ideally, information on driver behavior, fuel consumption, payload, and GPS data should be available at a high and similar frequency, i.e. usually every 2–3 min or preferably more frequently, or at least event-based. In the current study, controls for topography could not be included due to the very low (driver-set) frequency of GPS data logging, but this challenge could be addressed in future studies.

Another limitation of our research is that we were unable to consider several driver and situational characteristics, which are thought to potentially moderate effects. For example, we lacked access to sample-specific information on factors such as age, driving experience, average mileage, or eco-driving knowledge and attitudes. At the same time, the freight forwarder indicated that the study sample was intended to have a very homogeneous composition and that it was believed that differences between drivers would be small.

Although our experiment did not explicitly consider potential side-effects of eco-driving, e.g. on safety (other than giving feedback post-trip, rather than in-vehicle), a few points are worth noting. Both the supplier of Linx and an independent other supplier of FMS solutions claim that eco-driving improvements in practice also yield reductions on maintenance and damage costs for their clients. Anecdotal evidence from the freight forwarder also suggests that drivers with good eco-driving performance have had reduced maintenance expenses, damages and other deviations (e.g. vehicle/goods damages or administrative breaches). For future research and experiments, it could therefore both be interesting and relevant to more explicitly consider eco-driving and traffic safety in conjunction. Further, although not explored in detail, observations during our analyses suggest that real-world data on fuel consumption from in-vehicle FMS-systems may deviate considerably from factors or averages often used in research and transport policy analyses, and as such have a potential to contribute to better calibrated analyses in future. The increasing prevalence of such systems might contribute to future studies being able to study driving behavior over longer time periods than before, and at larger scale.

Finally, it is worth mentioning that right before the eco-driving course, drivers in the treatment group completed a survey asking them to characterize their own performance and prioritization of coasting,

speed adaptation, idling, use of cruise control, engine and gear, and anticipating behavior. This was done in connection with a Master Thesis on short-term effects of the eco-driving course, within the same project [44]. Although the sample size was very small, survey results suggested that driver perception on some eco-driving factors was closer to performance scores than on other factors, but that overall, drivers overestimated their driving performance compared to objective score data (e.g. how much they used cruise control or their coasting performance). When the same survey was repeated towards the end of May, perceptions were more consistent with Linx score data, but overall still an overestimation of driving performance. This could suggest that some further effectiveness gains may be possible by further closing the gap between perceptions and reality (e.g. more frequent or real-time feedback).

6.4. Conclusions

Through the present research, we demonstrated that eco-driving training can give significant fuel savings for truck drivers, and that effects can be maintained longer than is often assumed, when training is combined with active monthly follow-ups and non-monetary rewards. We shed light on the importance of different eco-driving strategies, the progression of effects over time, and the importance of controlling for weather conditions. This is done through a real-world, or naturalistic, randomized controlled experiment, which contributes to the existing literature in several ways, including its design, controls, and use of reinforcement mechanisms after completion of an eco-driving course, but also through the way data are used. Our research points to eco-driving being a relatively low-hanging fruit for the road freight sector, for which emissions reductions are very challenging, especially in the short term. Until emission reduction solutions are technologically and economically feasible at a large enough scale, eco-driving can be a scalable, immediate, and not insignificant part of strategies towards (urgent) emissions reductions from the road freight sector. In addition, eco-driving interventions can yield beneficial results also from the financial perspective of freight operators, which contributes to eco-driving acceptance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The current study was carried out within the LIMCO project (Logistics, Environment and Costs), a so-called knowledge-building project for industry, funded by the Norwegian Research Council (grant number 283333), and collaborating with nine enterprises from the transport and logistics industry.

References

- [1] IPCC, 2018, 'Global Warming of 1.5 °C', Special Report, Accessed on 10-12-2020 via: <https://www.ipcc.ch/sr15/>.
- [2] C. Figueres, H.J. Schellnhuber, G. Whiteman, J. Rockström, A. Hobley, S. Rahmstorf, Three years to safeguard our climate, *Nature* 546 (7660) (2017) 593–595, <https://doi.org/10.1038/546593a>.
- [3] A. McKinnon, *Decarbonizing Logistics: Distributing Goods in a Low-Carbon World*, Kogan Page, London, 2018.
- [4] ITF: International Transport Forum, 2019, 'ITF Transport Outlook 2019', OECD report, Accessed on 10-12-2020 via: https://www.oecd-ilibrary.org/sites/transp_outlook-en-2019-en/index.html?itemId=/content/publication/transp_outlook-en-2019-en.
- [5] ALICE: Alliance for Logistics Innovation through Collaboration in Europe, 2019, 'A framework and process for the development of a roadmap towards zero emissions logistics 2050', Accessed via: <https://www.etp-logistics.eu/?p=3152>.
- [6] ITF, 2018, 'Towards Road Freight Decarbonisation Trends Measures and Policies', ITF Policy Papers, OECD Publishing, Paris.
- [7] I.B. Hovi, D.R. Pinchasik, E. Figenbaum, R.J. Thorne, Experiences from battery-electric truck users in Norway, *World Electric Vehicle Journal* 11 (1-5) (2020) 1–21, <https://doi.org/10.3390/wevj11010005>.
- [8] A. Zavalco, Applying energy approach in the evaluation of eco-driving skill and eco-driving training of truck drivers, *Transportation Research Part D* 62 (2018) 672–684, <https://doi.org/10.1016/j.trd.2018.01.023>.
- [9] Giovanni Delnevo, Pietro Di Lena, Silvia Mirri, Catia Prandi, Paola Salomoni, On combining Big Data and machine learning to support eco-driving behaviours, *Journal of Big Data* 6 (1) (2019), <https://doi.org/10.1186/s40537-019-0226-z>.
- [10] R. Thijssen, T. Hofman, J. Ham, Ecodriving acceptance: An experimental study on anticipation behavior of truck drivers, *Transportation Research Part F* 22 (2014) 249–260, <https://doi.org/10.1016/j.trf.2013.12.015>.
- [11] H.J. Walnum, M. Simonsen, 'Does driving behavior matter? An analysis of fuel consumption data from heavy-duty trucks, *Transportation Research Part D* 36 (2015) 107–120, <https://doi.org/10.1016/j.trd.2015.02.016>.
- [12] H. Liimatainen, Utilization of fuel consumption data in an ecodriving incentive system for heavy-duty vehicle drivers, *IEEE Transactions on Intelligent Transportation Systems* 12 (2011) 1087–1095, <https://doi.org/10.1109/ITITS.2011.2142182>.
- [13] I. Wengraf, Easy on the gas – The effectiveness of eco-driving', RAC-foundation report, 2012, Accessed on 10-12-2020 via: https://www.racfoundation.org/assets/rac_foundation/content/downloadables/easy_on_the_gas-wengraf-aug2012.pdf.
- [14] M.S. Alam, A. McNabola, A critical review and assessment of Eco-Driving policy & technology: Benefits & limitations, *Transport Policy* 35 (2014) 42–49, <https://doi.org/10.1016/j.tranpol.2014.05.016>.
- [15] T. Savkovic, P. Gladovic, M. Milicic, P. Pitka, S. Ilic, Effects of eco-driving training: A pilot program in Belgrade public transport, *Technicki vjesnik* 26 (4) (2019) 1031–1037, <https://doi.org/10.17559/TV-20180704091922>.
- [16] C.K. Allison, N.A. Stanton, Eco-driving: the role of feedback in reducing emissions from everyday driving behaviours, *Theoretical Issues in Ergonomics Science* 20 (2) (2019) 85–104, <https://doi.org/10.1080/1463922X.2018.1484967>.
- [17] Y. Huang, E.C.Y. Ng, J.L. Zhou, N.C. Surawski, E.F.C. Chan, G. Hong, Eco-driving technology for sustainable road transport: A review, *Renewable and Sustainable Energy Reviews* 93 (2018) 596–609, <https://doi.org/10.1016/j.rser.2018.05.030>.
- [18] M.A. Symmons, G. Rose, 2009, Ecodriving training delivers substantial fuel savings for heavy vehicle drivers, *Proceedings of Driving Assessment 2009 Conference*, pp. 46–53, <https://dx.doi.org/10.17077/drivingassessment.1301>.
- [19] K. Boriboonsomsin, Reducing the Carbon Footprint of Freight Movement through Eco-Driving Programs for Heavy-Duty Trucks, White Paper, UC Davis, 2015.
- [20] K. Ayyildiz, F. Cavallaro, S. Nocera, R. Willenbrock, Reducing fuel consumption and carbon emissions through eco-drive training, *Transportation Research Part F* 46 (2017) 96–110, <https://doi.org/10.1016/j.trf.2017.01.006>.
- [21] J. Díaz-Ramírez, N. Giraldo-Peralta, D. Flórez-Ceron, V. Rangel, C. Mejía-Argueta, J.I. Huerfano, M. Bernal, Eco-driving key factors that influence fuel consumption in heavy-truck fleets: A Colombian case, *Transportation Research Part D* 56 (2017) 258–270, <https://doi.org/10.1016/j.trd.2017.08.012>.
- [22] M.J.M. Sullman, L. Dorn, P. Niemi, Eco-driving training of professional bus drivers – Does it work? *Transportation Research Part C* 58 (2015) 749–759, <https://doi.org/10.1016/j.trc.2015.04.010>.
- [23] J. Olstam, V. Bernhardsson, C. Choudhury, G. Klunder, I. Wilmink, M. van Noort, Modelling eco-driving support system for microscopic traffic simulation, *Journal of Advanced Transportation* 2019 (2) (2019) 1–17, <https://doi.org/10.1155/2019/2162568>.
- [24] Jihun Han, Ardalan Vahidi, Antonio Sciarretta, Fundamentals of energy efficient driving for combustion engine and electric vehicles: An optimal control perspective, *Automatica* 103 (2019) 558–572, <https://doi.org/10.1016/j.automatica.2019.02.031>.
- [25] M. Sivak, B. Schoettle, Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy, *Transport Policy* 22 (2012) 96–99, <https://doi.org/10.1016/j.tranpol.2012.05.010>.
- [26] P. Barla, M. Gilbert-Gonthier, M.A. Lopez Castro, L. Miranda-Moreno, Eco-driving training and fuel consumption: Impact, heterogeneity and sustainability, *Energy Economics* 62 (2017) 187–194, <https://doi.org/10.1016/j.eneco.2016.12.018>.
- [27] D.L. Schall, A. Mohnen, Incentivizing energy-efficient behavior at work: An empirical investigation using a natural field experiment on eco-driving, *Applied Energy* 185 (2017) 1757–1768, <https://doi.org/10.1016/j.apenergy.2015.10.163>.
- [28] M.S. Young, S.A. Birrell, N.A. Stanton, Safe driving in a green world: A review of driver performance benchmarks and technologies to support 'smart' driving, *Applied Ergonomics* 42 (2011) 533–539, <https://doi.org/10.1016/j.apergo.2010.08.012>.
- [29] Dominik L. Schall, Menas Wolf, Alwine Mohnen, Do effects of theoretical training and rewards for energy-efficient behavior persist over time and interact? A natural field experiment on eco-driving in a company fleet, *Energy Policy* 97 (2016) 291–300, <https://doi.org/10.1016/j.enpol.2016.07.008>.
- [30] G. Goes, R. Bandeira, D. Goncalves, M. de Almeida D'Agosto, C. Oliviera, The effect of eco-driving initiatives toward sustainable urban waste collection, *International Journal of Sustainable Transportation* 14 (8) (2020) 569–578, <https://doi.org/10.1080/15568318.2019.1584933>.
- [31] D. Lois, Y. Wang, A. Boggio-Marzet, Andres Monzon, Multivariate analysis of fuel consumption related to eco-driving: Interaction of driving patterns and external factors, *Transportation Research Part D* 72 (2019) 232–242, <https://doi.org/10.1016/j.trd.2019.05.001>.

- [32] W.-T. Lai, The effects of eco-driving motivation, knowledge and reward intervention on fuel efficiency, *Transportation Research Part D* 34 (2015) 155–160, <https://doi.org/10.1016/j.trd.2014.10.003>.
- [33] M. Günther, C. Kacperski, J.F. Krems, 'Can electric vehicle drivers be persuaded to eco-drive? A field study of feedback, gamification and financial rewards in Germany, *Energy Research & Social Science* 63 (2020), 101407, <https://doi.org/10.1016/j.erss.2019.101407>.
- [34] A. Sanguinetti, E. Queen, C. Yee, K. Akanesuvan, Average impact and important features of onboard eco-driving feedback: A meta-analysis, *Transportation Research Part F* 70 (2020) 1–14, <https://doi.org/10.1016/j.trf.2020.02.010>.
- [35] A.E.af Wählberg, Long-term effects of training in economical driving: Fuel consumption, accidents, driver acceleration behavior and technical feedback, *International Journal of Industrial Ergonomics* 37 (2007) 333–343, <https://doi.org/10.1016/j.ergon.2006.12.003>.
- [36] M. Zarkadoula, G. Zoidis, E. Tritopoulou, Training urban bus drivers to promote smart driving: A note on a Greek eco-driving pilot program, *Transportation Research Part D* 12 (6) (2007) 449–451, <https://doi.org/10.1016/j.trd.2007.05.002>.
- [37] Y. Wu, X. Zhao, J. Rong, Y. Zhang, The effectiveness of eco-driving training for male professional and non-professional drivers, *Transportation Research Part D* 59 (2018) 121–133, <https://doi.org/10.1016/j.trd.2018.01.002>.
- [38] Y. Yao, X. Zhao, J. Ma, C. Liu, J. Rong, Driving simulator study: Eco-driving training system based on individual characteristics, *Transportation Research Record* 2673 (8) (2019) 463–478, <https://doi.org/10.1177/0361198119843260>.
- [39] M.C. Chen, C.T. Yeh, Y.S. Wang, Eco-driving for urban bus with big data analytics, *Journal of Ambient Intelligence and Humanized Computing* 83 (2020) 1–13, <https://doi.org/10.1007/s12652-020-02287-2>, in press.
- [40] M. Günther, N. Rauh, J.F. Krems, How driving experience and consumption related information influences eco-driving with battery electric vehicles – Results from a field study, *Transportation Research Part F* 62 (2019) 435–550, <https://doi.org/10.1016/j.trf.2019.01.016>.
- [41] G. Wang, K. Makino, A. Harmandayan, X. Wu, Eco-driving behaviors of electric vehicle users: A survey study, *Transportation Research Part D* 78 (2020), 102188, <https://doi.org/10.1016/j.trd.2019.11.017>.
- [42] S.G. Dehkordi, G.S. Larue, M.E. Cholette, A. Rakotonirainy, H.A. Rakha, Ecological and safe driving: A model predictive control approach considering spatial and temporal constraints, *Transportation Research Part D* 67 (2019) 208–222, <https://doi.org/10.1016/j.trd.2018.11.010>.
- [43] A. Sozzi, H. Luomaranta, S. Amdam, J. Fosen, ESSnet Big Data II, Work package L, Deliverable L4: Description of the findings regarding Task 4: Smart Traffic, 2019, Accessed on 04-03-2020 via: https://webgate.ec.europa.eu/fpfi/mwikis/essnetbigdata/images/d/d5/WPL_Deliverable_L4_Description_of_the_findings_regarding_Task_4_Smart_Traffic_2019_11_01.pdf.
- [44] J. Loennechen, F. Tennøy, Transport efficiency through driving behavior, Master thesis BI Norwegian Business School, 2019.