The rebound effect through industrial ecology's eyes : the case of transport eco-innovation

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Environmental rebound effects from past transport innovations in Europe

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Abstract

The term eco-innovation has been coined to label those innovations expected to reduce the life cycle environmental burdens resulting from their use. Claims of environmental superiority are usually supported by technology-oriented analyses, such as product-level life cycle assessment. However, the environmental superiority of an innovation depends not only on its technical characteristics but also on technology-demand interactions. In this article, such interactions are incorporated through the concept of the environmental rebound effect. Using the Dynamic IPAT-Life cycle assessment with Environmental Rebound effect or DILER model, environmental superiority claims of seven alleged transport eco-innovations were evaluated by comparing alternative macro-level scenarios (with and without innovation) for Europe. The results support the claims of environmental superiority of only three out of seven studied innovations. That is, a majority of innovations actually induced increases in various environmental pressures. Such increases can be attributed mostly to the influence of generally noteworthy environmental rebound effects. The magnitude of the rebound effect is found to be highly correlated with two variables: the total change in effective income resulting from the use of the innovation and the difference between the environmental pressures per monetary unit of the studied innovations and that of the rest of consumption. The article contributes to the literature by (a) applying a comprehensive approach to the rebound effect and its relationship with the eco-innovation concept, (b) by calculating original rebound estimates of specific transport innovations and assessing these in absolute terms, as well as by (c) obtaining novel insights into the drivers behind the rebound effect. The counterintuitive results of this study also invite to re-assess the use of technology-oriented tools for guiding environmental policy. Other policy implications of this study relate to the relevance of transport cost differences, the targeted promotion of actual eco-innovations and its combination with broader policies as well as the achievement of higher quality mobility.

Keywords: Rebound effect, eco-innovation, transport innovation, sustainable transport, life cycle assessment, Europe.

1. Introduction

A number of past innovations have been labelled as eco-innovations, as they were expected to reduce the life cycle environmental burdens resulting from their use (EIO, 2012). In the context of transport, some examples of alleged eco-innovations are motor engines with increased fuel efficiency or modal shifts towards greener transport modes (e.g. bicycle or public transport). Claims of environmental superiority, particularly from industry, are usually supported by the results of technology-oriented assessments, many of them based on traditional product-level life cycle assessment (LCA) (Dangelico and Pujari, 2010). However, the environmental performance of a given transport innovation, even at the micro-level, is not only the outcome of its technical characteristics, but also of its interactions with the rest of elements of the transport system (vehicles, infrastructure and operations), which together deliver the transport function of mobility. For instance, a passenger car with a more fuel-efficient motor engine can induce extra driving due to lower travel costs, thus describing a link between the vehicle (car) and the operations (car driving). Moreover, since not all liberated income will be spent on extra driving, but eventually be spent also on other consumption, the entire socioeconomic system should also be factored in to capture changes in the overall demand for products. The environmental performance of transport innovations will thus depend upon the interaction between the transport system elements as well as between these and other elements of the socioeconomic system (e.g. consumer behaviour, market prices or technology availability).

The inclusion of causal relationships between system elements in the environmental assessment of products has been explored in the literature through a variety of approaches, all of which were influenced by the systems thinking theory (Bertalanffy, 1968; Cole, 2005; Sterman, 2012). Among these, technology-demand interactions have been studied mostly through the so-called rebound effect framework (Brookes, 1990; Greening et al., 2000; Khazzoom, 1980; Saunders, 1992). In short, the rebound effect in the context of transport can be defined as the change in overall demand for transport as well as other products resulting from the liberated or bound consumption factors (e.g. income) as a result of a technical change in a transport system (e.g. more fuel-efficient vehicle). Many single effects can be included within the rebound effect umbrella. Among these, methodological advances and data availability have favoured the study of microeconomic price effects, also known as direct and indirect price effects (Sorrell, 2007). These effects encompass comparative-static microeconomic changes in demand resulting from changes in the effective prices of providing mobility.

In the field of industrial ecology, the term environmental rebound effect (ERE) is often used to differentiate those studies dealing with various environmental aspects instead of only energy use and related pressures (greenhouse gas emissions [GHG]). The ERE concept, which was initially coined by Goedkoop et al. (1999), entails a re-interpretation of the traditional energy rebound effect not only in how the rebound estimates are expressed (multiple environmental indicators) but also in how the technical change is defined (Font Vivanco and van der Voet, 2014). While energy economics generally defines the technical change leading to the rebound effect as an improvement in the energy efficiency of the provision of an energy service, the ERE allows to define the technical change more broadly, as a change in the environmental efficiency of a product. Under this interpretation, one can study the rebound effect of innovations that are not primarily aimed at improving the energy efficiency, but at reducing specific environmental pressures (e.g. GHG or toxicity efficiency).

The rebound effect is a focus of growing attention in transport studies, due to the fact that the existing body of scientific research suggests that its magnitude can be considerable (Chakravarty et al., 2013; Greening et al., 2000; Sorrell et al., 2009). It sometimes can even outweigh any environmental improvements, a case that is commonly known as backfire effect (Saunders, 2000). Rebound studies in the field of transport, however, generally fail to address a number of relevant issues. First, rebound studies seem to be generally biased towards purely technological innovations, particularly regarding developments in fuel efficiency. Thus, other types of innovation, such as organizational innovation (e.g. bicycle sharing systems [BSS]) or normative innovation (e.g. parking systems), have generally been overlooked. Some examples of rebound studies of organizational transport innovation can be found in the works of Briceno et al. (2004) for car-sharing schemes and Ornetzeder et al. (2008) for a car-free housing project. Second, rebound estimates are rarely calculated by means of LCA data (Chakravarty et al., 2013), thus overlooking possible trade-offs between indicators and/or stages as well as disregarding other advantages of using this method (Font Vivanco and van der Voet, 2014). Examples of life cycle rebound estimates for transport, including such trade-offs, can be found in the works of Murray (2013), Briceno et al. (2004), Takase et al. (2005) and Girod et al. (2011). Third, rebound studies often present their results as a percentage of the environmental savings that are "taken back". Consequently, the overall impact of the rebound effect at the macro-level generally remains unknown since absolute changes in environmental pressures are ignored. However, information about the absolute impact of the rebound effect is crucial in order to identify those innovations that merit policy attention.

This paper aims to contribute to the growing field of research of the rebound effect by studying the effects of microeconomic ERE at the macro-level of a number of past transport innovations that were claimed to be eco-innovations in Europe. Such an analysis is expected to provide insights into their overall environmental life cycle performance, which will provide evidence for critically evaluating claims of environmental superiority.

2. Methods

This section describes the methods used to address the aim of the article, as well as the case studies to which this method will be applied to. First, the case studies are presented in Section 2.1. Following, an overview of the main model is described in Section 2.2, and this is further developed in Sections 2.3 and 2.4. Lastly, methods to perform scenario, sensitivity and uncertainty analyses are presented in Sections 2.5 and 2.6.

2.1. Case studies

A number of relevant transport innovations were selected for the study of the ERE. All innovations

present overall environmental improvements at the product-level (determined by means of LCA data from the literature, see Section 2.3) and diffused in the EU-27 region. The relevance of the innovations was determined on the basis of the following criteria:

a) High past innovation diffusion.

b) Evidence from literature of considerable transport cost changes due to the use of the innovation.

c) Substantial organisational changes in transport systems.

According the these criteria, seven transport innovations were selected, which are presented in Table 1. Short technological descriptions of each innovation are presented in sections 1-7.1 of supplementary data S1.

Table 1. Selected transport innovations for the case studies according to the defined criterion scores.

Selected transport innovations	Criterion scores		
	a) High diffusion	b) Considerable changes in transport cost	c) Organisational changes
Bicycle sharing system (BSS)	-	-	+
Car sharing scheme (CSS)	-	-	+
Catalytic converter in passenger cars	+	-	-
Diesel engine in passenger cars	+	+	-
Direct fuel injection (DFI) in passenger cars	+	+	-
High speed rail (HSR)	+	+	-
Park-and-ride (P+R)	-	-	+

2.2. Method overview

To evaluate claims of environmental superiority, two macro-level ex-post scenarios were compared: a scenario in which the innovation was not introduced (without innovation) and a scenario in which the innovation diffused and caused an ERE (with innovation). The scenarios were modelled with the Dynamic IPAT-LCA with Environmental Rebound Effect or DILER model. The DILER model combines the dynamic IPAT-LCA approach described by Font Vivanco et al. (2014b) (see Section 2.3) with an ERE model based on econometric estimates (see Section 2.4). An overview of the method is described in Fig. 1.

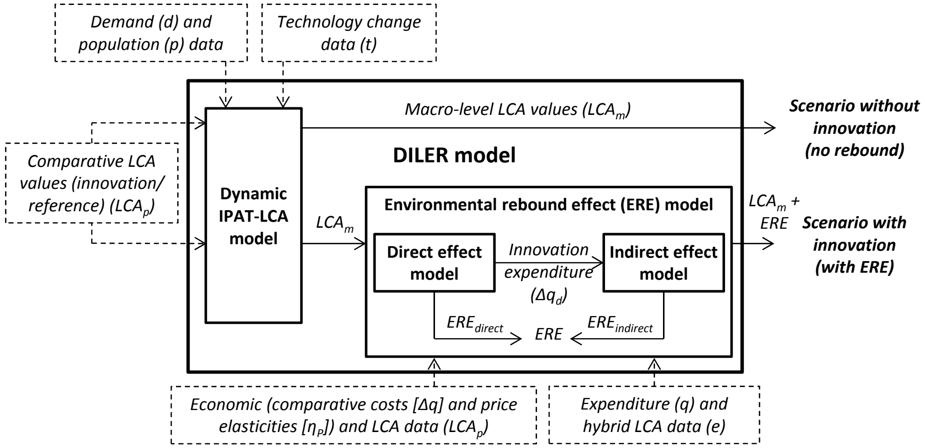


Fig. 1. Graphic overview of the DILER model. Solid boxes represent models, whereas dashed boxes represent data inputs. Solid arrows represent endogenous modelled data flows, whereas dashed arrows represent literature data flows. LCA: life cycle assessment.

2.3. Dynamic IPAT-LCA model

The dynamic IPAT-LCA model was proposed by Font Vivanco et al. (2014b) and is characterized by two main features. First, it scales up product-level LCA results to the macro-economic level using population growth data and product demand data, based on the concept of the IPAT equation (see Equation (1)). Second, it adds a temporal dimension to static LCA results by using technology change and diffusion data (see Equation (2)). In mathematical notation:

$$LCA_m = LCA_p * d * p \quad (1)$$

$$LCA_{m,y} = (LCA_p * t_y) * d_y * p_y \quad (2)$$

where *LCA* is the LCA result value of a given environmental indicator (expressed as pressures per demand unit), the subscripts *m* and p represent the macro and the product-level respectively, *d* is the relative product demand (in demand units per inhabitant), *p* is the total number of inhabitants, the subscript *y* describes the year of the value and *t* is a unit-less scaling factor representing technology change with respect to a reference value. For each innovation, the values of the variables and further details are presented in sections 1-7.2 of supplementary data S1. Environmental indicators and time periods may vary between innovations due to data availability.

2.4. Environmental rebound effect model

The ERE model describes how the consumption patterns of innovation users will change as a result of the cost changes resulting from the use of the new product. In other words, it describes how income that was liberated or bound due to cost changes will or will not be re-spent over the various consumption categories. Microeconomic rebound effects have been studied in the literature mainly by means of econometric models, which offer robust analyses and flexible data requirements (Sorrell, 2007). Among these, two main approaches stand out: the use of a single re-spending model that treats all products equally (see, for instance, the work by Murray (2013)) and a combined model in which the direct and indirect effects are calculated separately. The latter approach has been applied in the works of Freire-Gonzalez (2011) and Thomas and Azevedo (2013) and presents the advantage of providing with more accurate estimates of the direct effect. For this study, the latter approach was chosen and estimates for the direct and indirect ERE were calculated using two submodels (described in the following sections). Following the approach described by Font Vivanco et al. (2014a), each submodel is composed of a demand component and an environmental modelling component. The outcome of both submodels were aggregated to describe the ERE expressed as environmental pressures per functional unit:

$$ERE_y = ERE_{direct,y} + ERE_{indirect,y} \quad (3)$$

A common way to express the ERE is as a percentage of the environmental savings that are "taken back", as follows:

$$\%ERE_y = \left(\frac{PS_y - AS_y}{|PS_y|}\right) * 100 \quad (4)$$

with

$$AS_y = PS_y - (PS_y + ERE_y) \quad (5)$$

$$PS_y = LCA_{m,y,a} - LCA_{m,y,e} \quad (6)$$

PS are the potential or engineered environmental savings (in pressure units) resulting from the studied technology with respect to its alternative, considering only their technological characteristics, *AS* are the actual savings (in pressure units) considering the ERE, and the subscripts *e* and *a* represent the innovation and its alternative, respectively. It is worth noting that, as pointed out by Font Vivanco et al. (2014a), the denominator in Equation (4) must be an absolute value if PS < 0 values are possible. In the context of the ERE, PS < 0 values can occur in case of an increase of other environmental vectors not improved by the technical change. For example, a catalytic converter reduces certain air pollutants, but it increases other pressures related to its manufacture and recycling (Amatayakul and Ramnas, 2001).

2.4.1. Direct effect model

The direct effect has been defined in different ways in the literature (Becker, 1965; Berkhout et al., 2000; Greene et al., 1999; Juster and Stafford, 1991; Khazzoom, 1980; Sorrell and Dimitropoulos, 2008). In the context of transport, a definition that is commonly used by researchers is the one that defines the direct effect (RE_{direct}) as[16]:

$$RE_{direct} = -\eta_{P_T}(T) - 1 \quad (7)$$

16. For further details on the assumptions behind this definition, see: Sorrell and Dimitropoulos, 2008. The rebound effect: Microeconomic definitions, limitations and extensions. Ecological Economics 65, 636-649.

Where $\eta_{PT}(T)$ is the own transport price elasticity of transport demand, expressed as the percentage change in quantity demanded in response to a one percent change in price. RE_{direct} is thus expressed in percentage units. For example, if transport costs are 1% lower and η_{PT} is -0.10, transport demand increases by 0.10%. Price elasticities of demand depend on the time horizon, usually split into short-term and long-term. Between the two, long-term elasticities present the advantage of describing greater responsiveness of users (e.g. involving capital depreciation and new investments creating the possibility to switch to other transport modes), and would thus be preferred for this study. Differences in transport cost between innovations and their respective alternatives were calculated using both operation and capital costs. The inclusion of capital costs is consistent with the life cycle approach of the proposed model and is an established approach in rebound studies (Chitnis et al., 2012a; Mizobuchi, 2008; Nässén and Holmberg, 2009). All η_{PT} and transport cost values used for each case study can be found in sections 1-7.3 of supplementary data S1.

To add the direct effect to the original macro-level LCA results ($LCA_{m,y}$), direct effect estimates (RE_{direct}) must be converted first to demand units (using relative demand and population) and then to environmental pressure units (using LCA values). This new variable is referred to in this study as the environmental direct rebound effect (ERE_{direct}):

$$ERE_{direct,y} = (RE_{direct} * d_y * p_y) * (LCA_p * t_y) \tag{8}$$

2.4.2 Indirect effect model

A common approach to modelling the indirect effect is based on expenditure elasticities or Engel curves. This approach has been applied by Murray (2013), Chitnis et al. (2012b), Druckman et al. (2011) and Brännlund et al. (2007) and has proven to be more consistent than other approaches, such as the income-shifting model (Alfredsson, 2004; Thiesen et al., 2008), which has been applied mainly within the environmental assessment field (Font Vivanco et al., 2014a). In short, Engel curves describe how expenditure on a given consumption category varies with household income. Total expenditure is usually taken as a proxy of total income “to separate the problem of allocating total consumption to various goods from the decision of how much to save or dissave out of current income” (Lewbel, 2006:1). The use of Engel curves to model the indirect effect thus assumes that cost changes from using a particular product are effectively translated into changes in total expenditure. The functional form of the Engel curve describes real expenditure (q) on product i as a function (f) of total expenditure (z) as:

$$q_i = f(z) \tag{9}$$

On the other hand, an Engel curve can also be expressed as proportional expenditure changes with respect to total expenditure, also referred to as marginal budget shares (MBS), as follows (Goldberger, 1969):

$$MBS_i = w_i = \frac{\partial q_i}{\partial z} \tag{10}$$

Where w_i is the fraction of z that is spent on product or consumption category i. MBS thus provide a way to model the indirect effect by describing how consumers will or will not allocate the marginal liberated or bound income to the rest of consumption categories (other than the innovation under investigation). The indirect effect can thus be defined as:

$$RE_{indirect,i,y} = q_{i,y} - q_{n,i,y} \tag{11}$$

with

$$q_{n,i,y} = q_{i,y} + \Delta q_{r,y} * w_i \tag{12}$$

$$\Delta q_{r,y} = \Delta q_y - \Delta q_{d,y} \tag{13}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{14}$$

Where q_n is the new total expenditure (in monetary units), Δq is the change in total expenditure due to cost differences resulting from using the innovation with respect to its alternative (in monetary units), the subscript d is the share of Δq spent on the use of the innovation (direct effect) (in percentage units) and the subscript r is the remaining share of Δq (in monetary units). $RE_{indirect}$ is thus expressed in monetary units. The q_n complies with the Walras' Law by reallocating all liberated or bound income across consumption categories. Engel curves are time-horizon-dependent, but for practical reasons this time element is usually disregarded, reckoning with data on changes as they are available.

Engel curves can adopt many functional forms, which determine how the MBS are calculated. In this study, the most appropriate functional form was selected following two criteria: (1) goodness of fit and (2) types of goods described. The first criterion is based on maximizing the goodness of fit of the functional form, which was evaluated using the R-squared test. The second criteria follows the premise that all consumption categories should describe normal goods, as is expected when assessing general consumption categories (Barten and Böhm, 1982). Normal goods are goods for which demand increases when income increases. These criteria were applied to four pre-selected functional forms commonly used in household demand models: linear, semi-logarithmic, double semi-logarithmic and Working-Leser forms. Among these, the linear form offered the best fit for a description of marginal consumption consisting only of normal goods (see supplementary data S2). Using the linear form, the MBS can be calculated using equations 8 and 9 as follows:

$$q_i = \alpha_i + \beta_i y \tag{15}$$

$$MBS_i = w_i = \beta_i \tag{16}$$

Where α and β are unknown parameters. A list of all MBS for each consumption category is presented in supplementary data S2. Engel curves were calculated using household mean consumption expenditure (HMCE) data for the EU27 member states derived from Eurostat (2014a, 2014b). The data corresponds to the year 2005 and is structured by detailed classification of individual consumption according to purpose (COICOP) level (division, group and class) and income quintiles.

Lastly, the indirect effect expressed as a change in expenditure can be translated to environmental pressure units to express the environmental indirect effect ($ERE_{indirect}$) by using an environmental intensity factor (e):

$$ERE_{indirect,y} = \sum_{i=1}^{n} (RE_{indirect,i,y} * e_i) \tag{17}$$

The e values (expressed as environmental pressures per €) for each consumption category can be obtained from environmentally-extended input-output tables (EEIOT). For this study, the E3IOT database (Universiteit-Leiden, 2014b) was used. The E3IOT contains a high resolution EEIOT for the EU25[17], which covers production, consumption and waste management sectors (with effects of imports and exports covered by technology assumptions). The E3IOT has a resolution of 282 consumption categories based on the comprehensive environmental data archive (CEDA) 3.0 classification (Tukker et al., 2006). The environmental pressures per monetary unit of all the consumption categories were calculated using CMLCA, an LCA software developed by the Institute of Environmental Sciences (CML) at Leiden University (Universiteit-Leiden, 2014a). Since CMLCA is fully matrix-based, its combination with the E3IOT makes it a true hybrid LCA approach (Heijungs et al., 2006; Heijungs and Suh, 2002). Moreover, the proposed model is based on COICOP expenditure categories, reason why a correlation between CEDA 3.0 and COICOP categories was established (see supplementary data S3). A list of the e values for all case studies can be found in supplementary data S4.

2.5. Scenario building

The results of the DILER model are used to calculate the scenarios with and without innovation. In the scenario without innovation, it is assumed that the innovation was never introduced, whereas in the scenario with innovation, it is assumed that the innovation diffused and caused an ERE. Moreover, the scenario without innovation postulates that the demand for the innovation is shifted to its (single) alternative, whereas in the scenario with innovation, the demand for both the innovation and its alternative diffused as described by empirical evidence. Both scenarios were defined as follows:

$$Scenario\ without\ innovation = LCA_{m,y,a} + LCA_{p,y,a} * d_{y,e} * p_y \tag{18}$$

$$Scenario\ with\ innovation = LCA_{m,y,a} + LCA_{m,y,e} + ERE_y \tag{19}$$

17. Because MBS are calculated using EU27 data, full geographical consistency is not possible..

2.6 Sensitivity and uncertainty analyses

For completeness, sensitivity and uncertainty analyses of the results were conducted. The sensitivity analysis reveals to what extent the results of the model are responsive to changes in its input variables. The responsiveness of the results were studied using proportional sensitivities or point elasticities. A point elasticity (E) describes the % change of the model result (r) as a result of a % change of an input variable (v). In this study, r corresponds to the difference between the scenarios with and without innovation. Point elasticities were calculated as follows (Sloman and Garratt, 2010):

$$E = \frac{v}{r} * \frac{dr}{dv} \tag{20}$$

The uncertainty analysis describes how uncertain the results of the model are. Uncertainty is determined by attributing confidence levels to highly sensitive input variables. For each case study, the five most sensitive input variables were selected (see supplementary information S1, sections 1-7.4). Confidence levels were determined according to the representativeness of the data (see table 2). Due to the outcome of the uncertainty analysis, the results of the model will be presented as a range of values, with mean, maximum and minimum values.

Table 2. Confidence levels according to the source and type of the input variables.

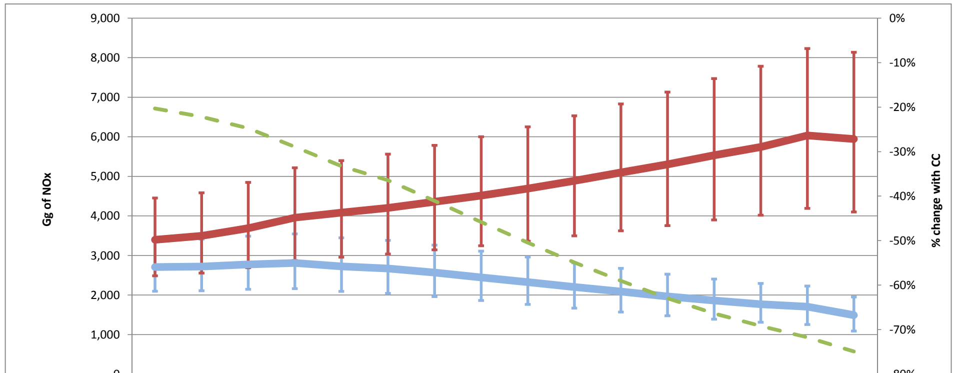
Data types/sources	Confidence level
Reported data with European scope	**Very high** – ±5%
Estimated data with European scope	**High** – ±10%
Estimated/reported data with national scope	**Moderate** – ±15%
Informed guess	**Fair** – ±25%

3. Results and discussion

In this section, the results of the DILER model for the seven case studies are presented. The focus is on the results in terms of overall macro-level environmental pressures for the scenarios with and without innovation. Intermediate results of interest (e.g. ERE estimates or cost changes) may be presented to support the discussion. Complete datasets of intermediate results for each case study are presented in supplementary data S1. Relevant environmental indicators for each innovation were chosen according to the targeted improvements, with particular attention to GHG emissions. Due to data availability, indicators and time periods can vary among case studies.

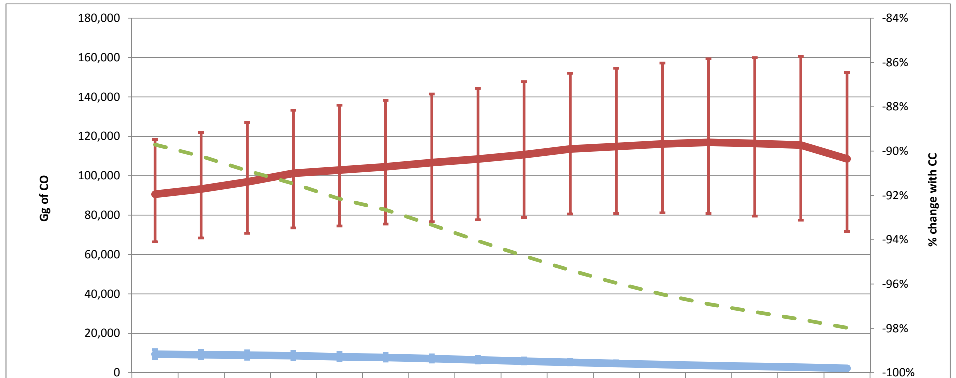
3.1. Catalytic converters in passenger cars

Figs. 2-4 present the scenario results for nitrogen oxides (NO_x), carbon monoxide (CO) and hydrocarbons (HC) air emissions, respectively, from passenger cars with and without catalytic converter. The results describe a general absolute improvement of these environmental vectors as a consequence of the introduction of catalytic converters. The ERE is assumed to be zero, as the change in transport costs can be considered to be negligible (see supplementary data S1-1.3). Technological characteristics were thus the main driver of changes in the relative environmental performance of catalytic converters. For the studied environmental vectors, CO emissions show the largest accumulated emission reduction, with an average of more than 1620 tonnes avoided, followed by 38 and 8 tonnes for NO_x and HC, respectively. In relative terms, on average, emissions were 94%, 91% and 48% lower for the scenario with catalytic converters for CO, HC and NO_x emissions, respectively.



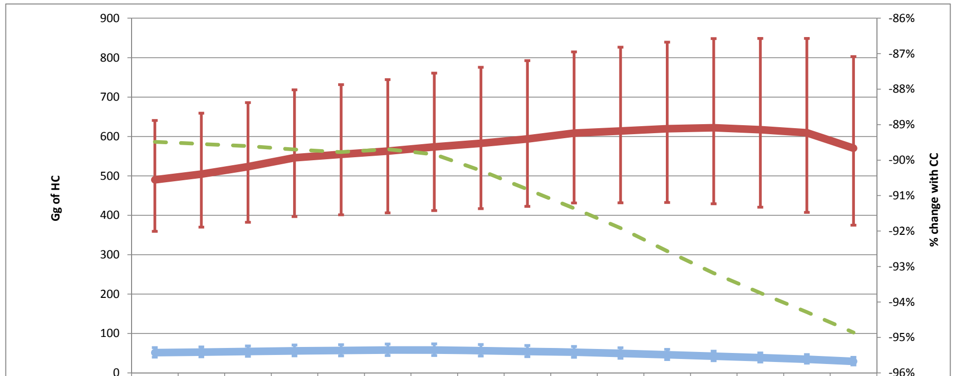
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
With CC	2705.6	2719.7	2774.7	2810.9	2724.5	2670.0	2568.5	2445.7	2323.9	2204.3	2087.4	1966.0	1861.3	1768.5	1706.4	1490.8
Without CC	3395.7	3495.0	3687.8	3954.9	4083.4	4200.7	4358.7	4513.1	4690.6	4890.0	5096.7	5303.3	5534.4	5741.2	6035.1	5941.2
% change	-20%	-22%	-25%	-29%	-33%	-36%	-41%	-46%	-50%	-55%	-59%	-63%	-66%	-69%	-72%	-75%

Fig. 2. Calculated scenarios with and without innovation for catalytic converters (CC) and percentage change in nitrogen oxides (NO_x) emissions due to the use of CC.



	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
With CC	9322.7	9104.4	8827.3	8628.5	8064.6	7685.3	7110.4	6451.9	5826.0	5243.7	4638.3	4097.5	3612.2	3189.1	2773.6	2198.1
Without CC	90605.	93257.	96852.	101201	102884	104542	106632	108482	110657	113535	114789	116152	116910	116395	115500	108549
% change	-90%	-90%	-91%	-91%	-92%	-93%	-93%	-94%	-95%	-95%	-96%	-96%	-97%	-97%	-98%	-98%

Fig. 3. Calculated scenarios with and without innovation for catalytic converters (CC) and percentage change in carbon monoxide (CO) emissions due to the use of CC.



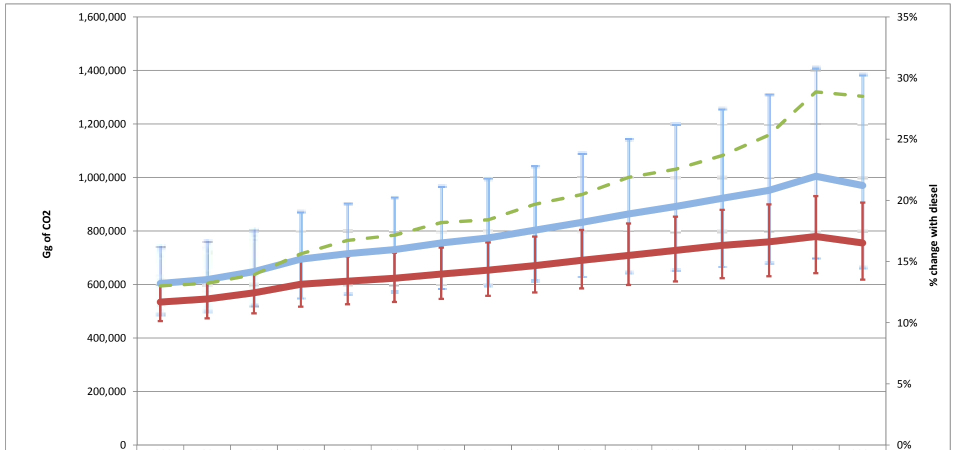
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
With CC	51.529	52.747	54.411	56.226	56.699	58.004	58.274	56.550	54.485	52.564	49.622	46.061	42.368	38.597	34.843	29.314
Without CC	490.07	504.41	523.34	545.93	554.46	562.93	573.53	582.77	593.68	608.43	613.79	619.78	622.07	617.27	609.52	570.43
% change	-89%	-90%	-90%	-90%	-90%	-90%	-90%	-90%	-91%	-91%	-92%	-93%	-93%	-94%	-94%	-95%

Fig. 4. Calculated scenarios with and without innovation for catalytic converters (CC) and percentage change in hydrocarbons (HC) emissions due to the use of CC.

3.2. Diesel engine in passenger cars

The scenario results for diesel engines are presented in Fig. 5. They show that the introduction of diesel engines caused an overall increase in CO_2 emissions during the studied period, even though both diesel engines and its alternative present very similar environmental profiles (see Table S2-2.1 in supplementary data S2). On average, emissions were 20% higher in the scenario with diesel cars than in the scenario without innovation, and the accumulated extra CO_2 emissions were about

2200 tonnes. Therefore, the ERE did not only offset any environmental improvements, but caused an absolute increase in emissions. The magnitude of the ERE was on average about 7000%, which would explain such a counterintuitive outcome. Moreover, the ERE was mainly driven by the indirect effect, which had an average contribution of about 87% (see Table S1-2.4 in supplementary data). Such a notable magnitude can be explained primarily by two aspects. First, since the transport costs of diesel cars are on average 35% lower, on average, more than 1200 euros are liberated per user and year, which represents more than 6% of the total income (see Table S1-2.5). Second, using Equation (4) as a guide, a large ERE magnitude is to be expected because the potential savings (denominator) are very small and the difference between these and the actual savings (numerator) is quite large.

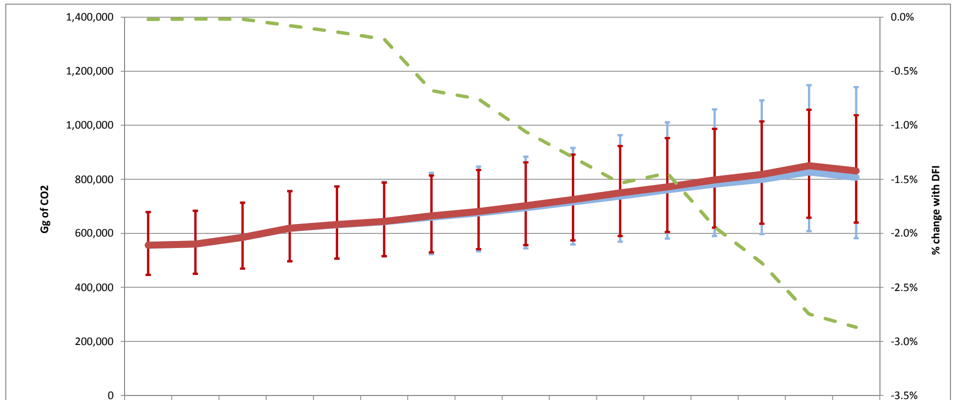


	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
With diesel	603614.	618019.	648191.	694424.	715065.	730309.	754879.	774014.	802589.	831799.	863595.	891161.	922326.	951620.	1004342	970185.
Without diesel	534100.	545858.	568969.	600543.	612556.	623416.	638706.	653684.	670578.	690463.	708541.	727253.	745814.	759197.	779367.	754940.
% change	13%	13%	14%	16%	17%	17%	18%	18%	20%	20%	22%	23%	24%	25%	29%	29%

Fig. 5. Calculated scenarios with and without innovation for diesel engines and percentage change in CO_2 emissions due to the use of diesel engines.

3.3. Direct fuel injection systems in passenger cars

The scenario results for direct fuel injection (DFI) systems are presented in Fig. 6. The results show a moderate decrease in CO_2 emissions as a result of the diffusion of DFI systems. Emissions decreased from -0.02% to -2.87% in the period 1990-2005 and caused an average accumulated absolute decrease of about 133 tonnes. The average magnitude of the ERE is about 63% (see Table S1-3.4 in supplementary data), so environmental savings remained at the macro-level, yet an important share was taken back. This figure can be explained by the fact that DFI systems entail a moderate reduction in transport costs of about 9%, liberating an average of 238 euro per year and user (see Table S1-3.5 in supplementary data). Moreover, the liberated income was spent on consumption with a 58% higher environmental intensity (see Table S1-3.6 in supplementary data).



	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
With DFI	555869.	560323.	584676.	618650.	631671.	642972.	659938.	675459.	694716.	715868.	737863.	760753.	781885.	799272.	826930.	807127.
Without DFI	555975.	560412.	584779.	619129.	632534.	644286.	664444.	680610.	702158.	725271.	749370.	771893.	797361.	817882.	850290.	830968.
% change	-0.02%	-0.02%	-0.02%	-0.08%	-0.14%	-0.20%	-0.68%	-0.76%	-1.06%	-1.30%	-1.54%	-1.44%	-1.94%	-2.28%	-2.75%	-2.87%

Fig. 6. Calculated scenarios with and without innovation for direct fuel injection (DFI) and percentage change in CO_2 emissions due to the use of DFI.

3.4. High speed rail

Figs. 7-9 present the scenario results for high speed rail (HSR) in terms of global warming potential (GWP), land use change (LUC) and abiotic depletion potential (ADP), respectively.[18] The results show that the introduction of HSR systems increased environmental pressures for all indicators during the studied period. The increase is overall significant, ranging from 13% to 50%, resulting in accumulated increases in GWP, LUC and ADP of 123 tonnes, 12 km^2 and 0.5 tonnes, respectively. The ERE magnitude is found to be 91% for LUC and 215% and 227% for GWP and ADP, respectively. This means that, in the case of LUC and GWP, the ERE offset any environmental improvements. Given the moderate change in income (0.3% from total income, see Table S1-4.5 in supplementary data), the differences in the environmental intensity play an important role. Thus, higher rebound estimates are presented by those indicators in which the use of HSR systems has a lower environmental intensity than that of general consumption. Concretely, GWP and ADP present an environmental intensity that is 94% and 68% lower than that of general consumption. Considering that the indirect effect is the main contributor to the ERE, every marginal liberated income unit would thus have a considerable effect on driving up emissions, since each unit would be spent on extra consumption that has a higher environmental intensity than the use of HSR systems.

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18. Selected indicators have been chosen for being relevant according to own criteria. Multiple other indicators are also possible yet impractical to analyze.

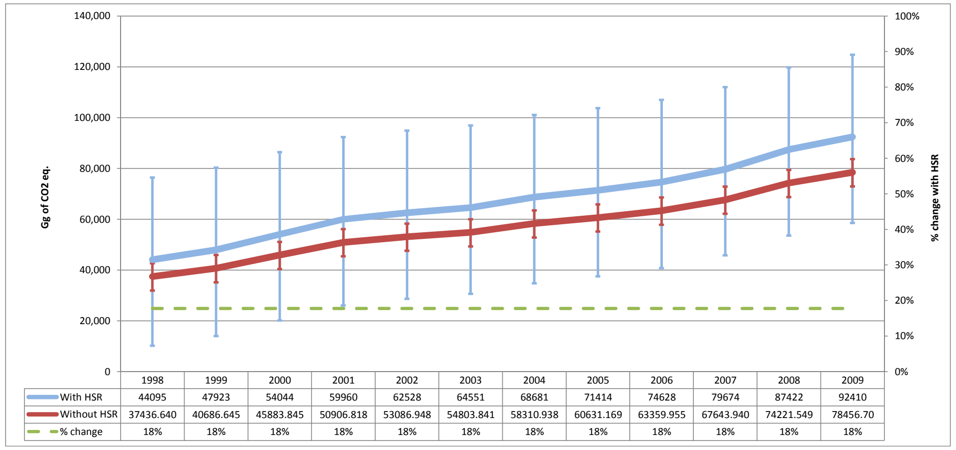

Fig. 7. Calculated scenarios with and without innovation for high speed rail (HSR) and percentage change in emissions for global warming potential due to the use of HSR.

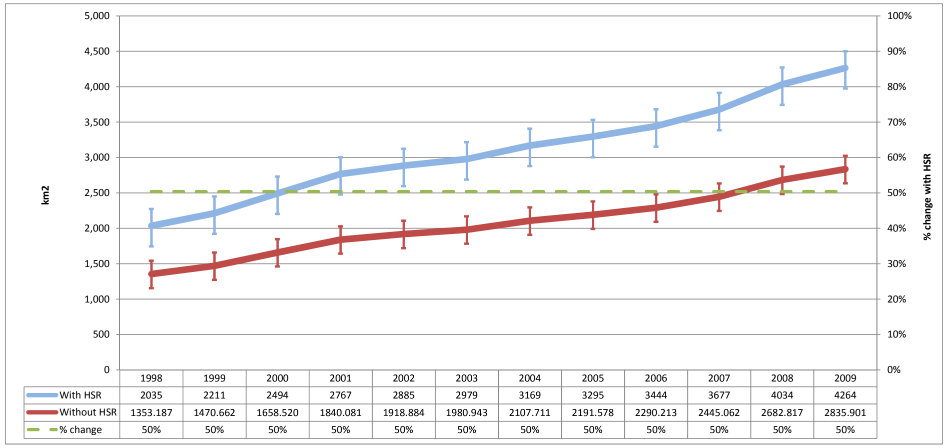

Fig. 8. Calculated scenarios with and without innovation for high speed rail (HSR) and percentage change in land use due to the use of HSR.

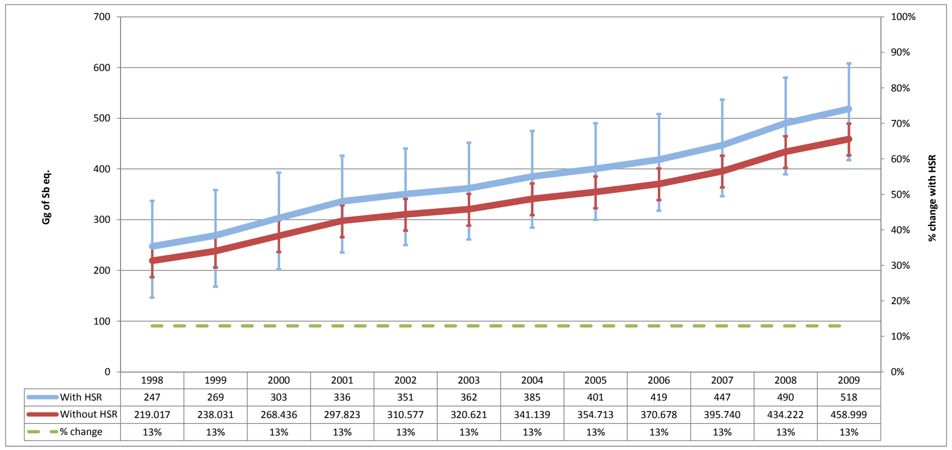

Fig. 9. Calculated scenarios with and without innovation for high speed rail (HSR) and percentage change in emissions for abiotic depletion potential due to the use of HSR.

3.5. Park-and-ride facilities

The scenario results for park-and-ride (P + R) facilities show an overall reduction in GWP emissions as a result of their introduction, with an accumulated decrease in emissions of more than 166 tonnes (see Fig. 10). Besides having a better environmental profile, the use of P + R facilities entails higher transport costs for commuters (32% with respect to its alternative, see Table S1-5.5 in supplementary data), which translates into a negative ERE. Concretely, the magnitude of the ERE is -1224%, mostly driven by the indirect effect (see Table S1-5.4 in supplementary data). This notable magnitude is mainly due to a notable change in the available income (-2420 € per year, see Table S1-5.5). Similarly to the previous case studies, the use of P + R facilities has a lower environmental intensity than that of other consumption categories, thus magnifying the ERE.

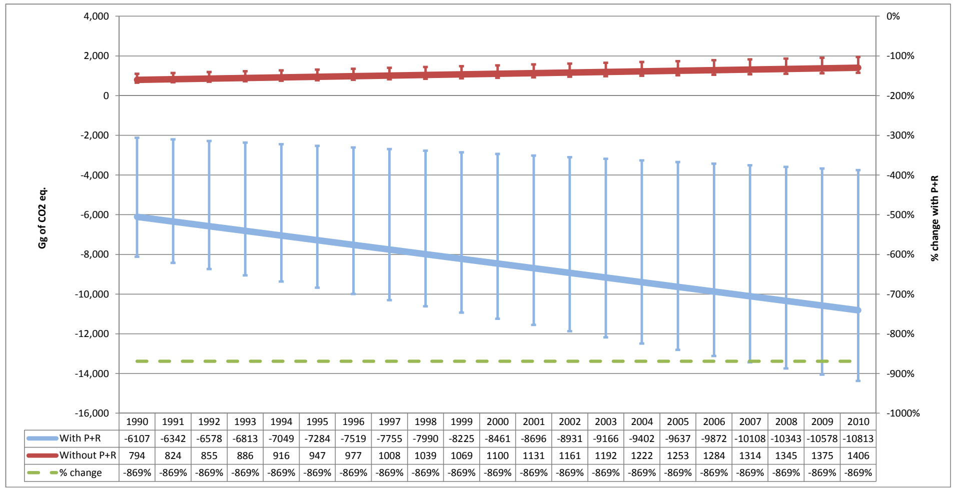

Fig. 10. Calculated scenarios with and without innovation for park-and-ride (P + R) and percentage change in emissions for global warming potential due to the use of P + R.

3.6. Car sharing schemes

The introduction and diffusion of car sharing schemes (CSS) in Europe caused an overall increase in GWP emissions, with an average increase of 40% and an accumulated increase of about two tonnes of CO_2 eq (see Fig. 11). The ERE, driven by the indirect effect, thus offset environmental improvements with a magnitude of 135%. The ERE was induced by the lower transport costs of CSS (42% lower), which liberated 391 € per year and user (see Table S1-6.5 in supplementary data). The liberated income was then spent on consumption with higher environmental intensities (see Table S1- 6.6 in supplementary data), which explains the high magnitude of the ERE.

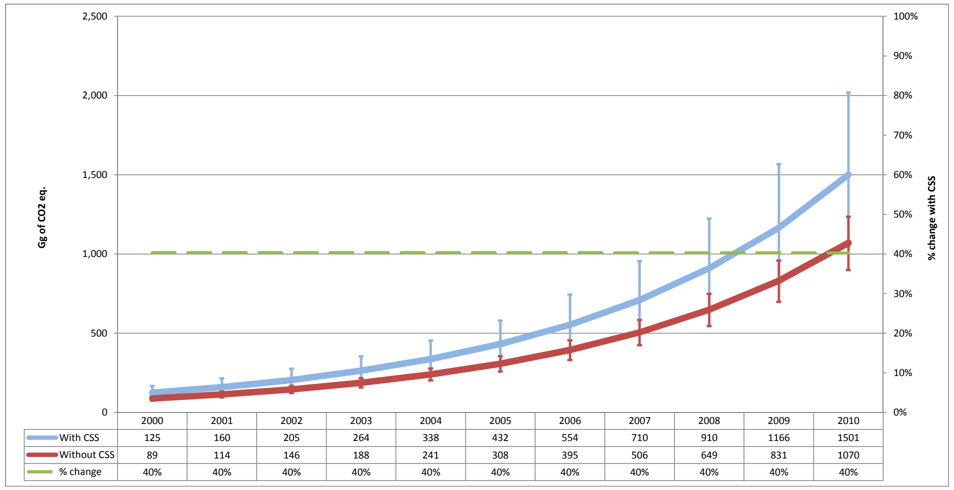

Fig. 11. Calculated scenarios with and without innovation for car sharing schemes (CSS) and percentage change in emissions for global warming potential due to the use of CSS.

3.7. Bicycle sharing systems

The scenario results for bicycle sharing systems (BSS) show a notable increase in emissions following their diffusion in Europe (see Fig. 12). Concretely, emissions increased 673% on average, with an accumulated increase of 0.25 tonnes of CO_2 eq. Similarly to other case studies, the ERE was responsible for offsetting environmental improvements at the product-level, with a magnitude of almost 900%. Again, the notable magnitude of the ERE is explained by the significantly lower transport costs (about 60% lower than its alternative, see Table S1-7.5 in supplementary data) and the lower environmental intensity compared to that of general consumption (95% lower, see Table S1-7.6 in supplementary data).

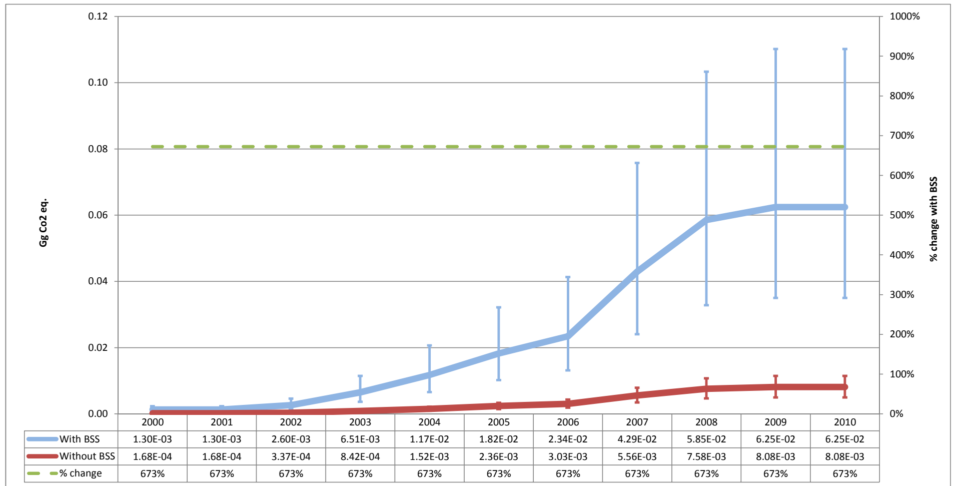

Fig. 12. Calculated scenarios with and without innovation for bicycle sharing systems (BSS) and percentage change in emissions due to the use of BSS.

4. Discussion

The aim of this paper is to study the effects of microeconomic ERE at the macro-level of a number of past transport innovations that were claimed to be eco-innovations. From the results of the seven case studies analysed, a number of general insights can be drawn. First, while the studied transport innovations generally present better environmental profiles than their alternatives, emissions increased in most cases as a result of their introduction because of the ERE. The exceptions are catalytic converters, DFI and P + R facilities, which achieved overall absolute emission reductions. The varying trends can be largely explained by the change in transport costs; The majority of the studied transport innovations (5 out of 7) are cost-reducing (thus liberating money that will be spent on extra consumption), whereas cost changes were negligible for catalytic converters and costs even increased for P + R facilities. For DFI systems, the cost reductions were moderate and the ERE, while positive, did not attain a backfire effect.

In absolute terms, the changes in emission trends are largely influenced by macro-level diffusion levels. Diffusion levels translate relative changes in transport costs to absolute changes in available income, which magnifies the effect of the ERE at the macro-level. That is, those innovations with higher diffusion rates contributed the most to absolute changes in emissions. To depict the absolute change in emissions for all the studied innovations, the average values of GHG emissions are presented in Fig. 13. It is worth noting that indicators and time spans are not fully consistent and thus this exercise serves only to observe general trends. From the results, it can be concluded that diesel engines contributed the most to the overall increase in GHG emissions, mostly due to the high ERE and their extensive diffusion in Europe. The other innovations diffused comparatively less, and therefore their contribution was comparatively modest. The only innovations that contributed to decrease GHG emissions were P + R facilities and DFI. The reasons why P + R and DFI did not counteract the overall increase in emissions are a low diffusion and a modest negative ERE, respectively.

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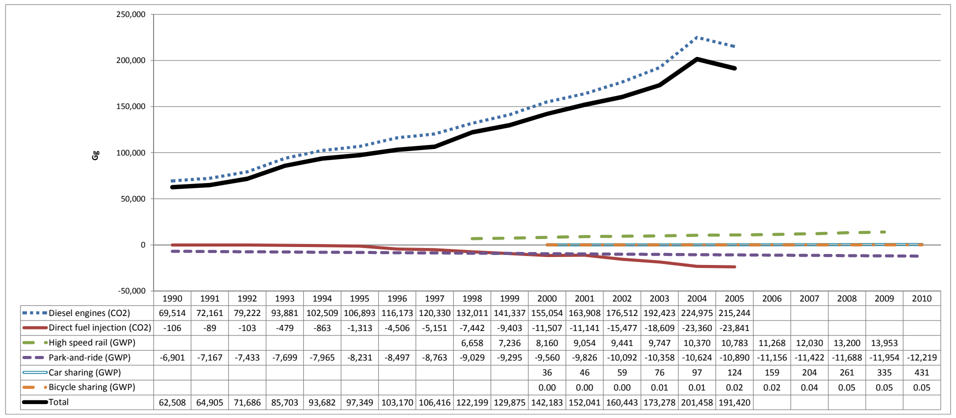

Fig. 13. Absolute change in greenhouse gas emissions (indicator in brackets) due to the diffusion of the studied transport innovations. GWP: global warming potential, in CO_2 eq.

Another finding from the analysis of the results is that the notable magnitude of the ERE can be largely attributed to differences in environmental intensity between the studied innovations and that of the rest of consumption. In general, the environmental intensity of the studied innovations is lower than that of the other consumption categories to which liberated or bound income is allocated or unallocated. Thus, liberated or bound income entails large changes in environmental pressures since it is spent or no longer spent on consumption categories with higher environmental intensity. This aspect is in line with the findings of Font Vivanco et al. (2014a), and can largely be explained by the fact that the studied innovations are aimed at reducing environmental pressures (e.g. by switching to greener transport modes), thus setting a low reference environmental intensity value. This leads to the conclusion that innovations with low environmental intensities will be prone to a larger ERE.

Given the notable influence on final results of both the changes in available income and the differences in the environmental intensity of the use of the innovations with respect to that of general consumption, a two-variable indicator can be constructed. This indicator can aid in predicting whether the magnitude of the ERE can be expected to be relevant (see Fig. 14). Four areas are defined in this indicator, each one describing the low or high potential of the ERE to offset or enhance environmental improvements. Plotting each studied innovation confirms that the magnitude of the ERE is highly correlated with the two variables: those innovations situated far away from the axis cross show higher ERE magnitudes. As rebound modelling exercises can be time consuming and data intensive, this indicator can be useful for screening among multiple innovations and identifying which ones would merit further study as well as policy attention.

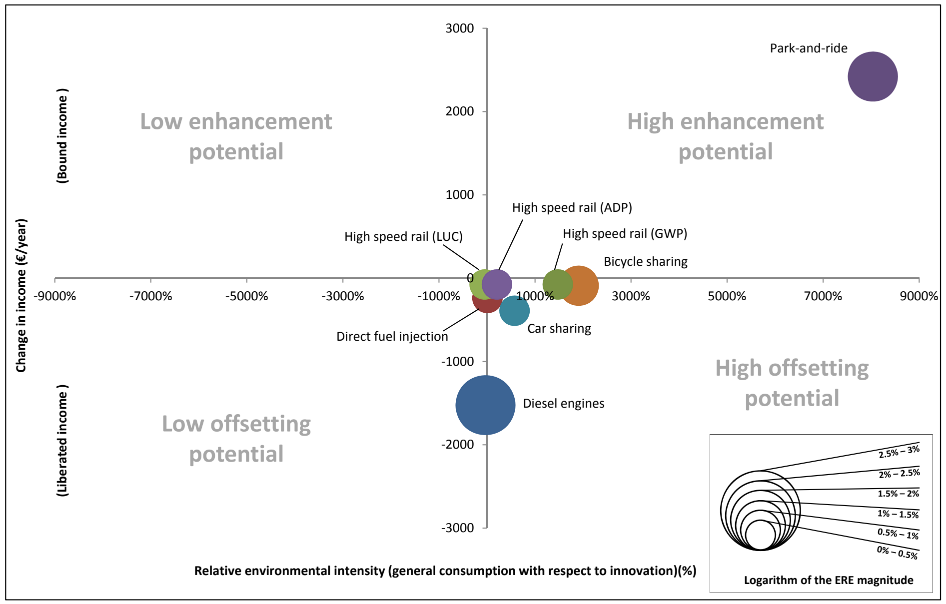

Fig. 14. Potential of the environmental rebound effect (ERE) to enhance or offset environmental improvements for the assessed transport innovations.

Another important aspect to mention is that the results are surrounded by high uncertainty. Therefore, while the results provide valuable insights and reveal general trends, they should be interpreted with caution. One of the aspects contributing the most to overall uncertainty is data quality. Concretely, data on innovation diffusion at the European level is scarce for some innovations, reason why assumptions have been made (e.g. by using country-level diffusion data). Choosing an appropriate comparable alternative has also proven to be a challenge. For instance, in the context of innovations promoting transport mode shifts, there is a lack of studies dealing with diversion factors of previous transport modes at the European level. Similarly, technology change data is also found to be scarce, limiting the application of the dynamic IPAT-LCA method. Technology change data has been found only for catalytic converters, diesel engines and DFI systems, whether via technology shares (e.g. diesel versus gasoline) or developments in product technology (e.g. fuel efficiency). The influence of technology changes on the other studied innovations is thus ignored.

An additional limitation of the study relates to the re-spending model applied. Concretely, since new expenditure patterns were derived from statistical data rather than from personalised surveys (see, for instance, the work of de Haan et al. (2007)), it is not possible to correlate such patterns with variables of interest, such as the use of a particular innovation. For instance, it is not possible to differentiate the new expenditure patterns of diesel car users from those that drive a gasoline car. While the use of a particular innovation may have a considerable influence on consumption patterns (e.g. a BSS user may have a "greener" attitude towards consumption), such a limitation is hard to overcome in broad-scoped studies like this (multiple countries and innovations under investigation), as differentiating between innovation users would require either very detailed statistical data or comprehensive personalised surveys.

Lastly, it is worth explaining why the ERE magnitude found in the case studies differs from the findings of other studies that also studied the magnitude of microeconomic rebound effects (Sorrell, 2007). Often, the ERE magnitude found in this study is higher than 100% (including both positive and negative ERE), whereas such magnitudes are rarely found in the mainstream literature. For instance, Briceno et al. (2004) and Spielmann et al. (2008) found a rebound magnitude in terms of GWP emissions of up to 75% and 114% for CSS and HSR, respectively, whereas the present study identified average magnitudes of about 900% and 227%. Also, for increases in energy efficiency in road transport, Barker et al. (2007) calculated a total rebound effect of about 30%, which is significantly lower than, for instance, the average magnitude of 7000% in terms of CO_2 emissions found in this study for diesel cars. Following Font Vivanco et al. (2014a), these differences can be explained by four important characteristics of the present study. First, the study of specific products instead of whole sectors can lead to higher rebound magnitudes, as their technical and economic characteristics can differ widely from that of the sectorial technology mix. Second, the ERE definition allows for broader rebound analyses by including multiple environmental aspects instead of only energy use. It is thus possible to study the rebound effects of a broader set of technical changes, not only those changes aimed at increasing energy efficiency. This definition also has repercussions on the differences in the environmental intensity of the studied innovations and the general consumption, the importance of which has been discussed before. Thus, energy intensity is generally found to be much more uniform among consumption categories due to its extensive use (also in upstream processes), whereas other environmental vectors (e.g. land use) present a much less uniform distribution (Tukker et al., 2006). Third, by adopting a life cycle perspective, the present research could account for environmental flows that could otherwise remain hidden. Lastly, by accounting for capital costs, transport costs that are sometimes treated as “sunk costs” could be included, potentially leading to greater changes in income and, consequently, larger rebound magnitudes.

5. Conclusions

The high environmental rebound effect (ERE) magnitude found in this study highlights the importance of considering technology-demand interactions in the environmental assessment of alleged eco-innovations. The results cast a critical light on the application of technology-oriented approaches, such as traditional product LCA, for informing environmental policy. While the application of LCA is still appropriate for determining product environmental profiles that can be used for some applications such as industrial eco-design (Millet et al., 2007), it is not an adequate guide to base policy on, since it ignores absolute environmental changes. While product-level LCA estimates indicated that all the studied innovations generally present a better environmental performance, the applied micro-to-macro model showed that environmental pressures would actually have increased in most cases due to the introduction and diffusion of the innovations, mostly because of the ERE. Only those innovations in which the change in transport costs is negligible or positive (bound income) show decreases in environmental pressures. In these cases, the ERE does not outweigh the technology improvements or even enhances them. Based on these results, it can be concluded that claims of environmental superiority of the seven alleged eco-innovations studied are only supported in their actual economic functioning in three cases: catalytic converters, direct fuel injection systems and P + R facilities.

Overall, this study contributes to the literature in a number of ways. First, by applying a comprehensive approach to assess potentially detrimental secondary effects of transport innovation by means of the ERE concept, and its relation with the eco-innovation concept. Second, by calculating original rebound estimates of specific transport innovations rather than at the sector level, which shows that specific technical and economic characteristics can notably differ from that of the sectorial technology mix, leading to potentially larger rebound estimates. Third, by assessing ERE estimates of transport innovations in absolute terms by means of diffusion data, thus showing the impact of the ERE at the macro-level. Lastly, by obtaining novel insights into the drivers behind the rebound effect, especially the relevance of the differences in environmental intensities in the case of certain innovations and environmental indicators.

As pointed out in the discussion section, incomplete supporting information led to considerable uncertainty in the results. To reduce this uncertainty and obtain more accurate rebound estimates, the knowledge base needs to be improved. Further academic research can be directed towards the comprehensive study of innovation diffusion, diversion factors, technology change data and expenditure patterns. Moreover, the method and scope applied may also have introduced uncertainty

about the actual rebound magnitude. Indeed, the method applied consists of a microeconomic, partial equilibrium approach, and it only considered income effects of households since only changes in expenditure were accounted for. Applying a macroeconomic approach would provide the opportunity to study effects related to endogenous prices, income and factor supply. Deeper changes in consumers’ preferences, social institutions or feedbacks from adoption (e.g. economies of scale and learning, see Sandén and Karlstrom (2007)), which can be captured through the so-called transformational effect, have been neither studied. Thus, the study of macroeconomic and transformational rebound effects seems a logical next step in order to assess the full environmental consequences of the introduction and diffusion of new technologies.

This research also has implications for policy and business decisions, as the study of rebound effects can be an informative tool for managerial strategies targeting absolute environmental improvements. In Europe, and in the context of transport, aspects related to rebound effects and other causal effects seem to be generally overlooked by the main sustainable mobility strategies, such as the White Paper 2011 (EC, 2011). Moreover, the transport industry is rarely interested in secondary effects that fall out of their sphere of influence (Mayyas et al., 2012). Instead, policy and business strategies seem to focus primarily on technology developments related to efficiency (Figge et al., 2014). The study of rebound effects of transport innovations can thus contribute to developing more informed sustainable mobility strategies and policies. For instance, the results of this study reaffirm the importance of avoiding perverse marketing campaigns that shift economic savings towards environmentally intensive products (Maxwell et al., 2011). The results also suggest the promotion of innovations that entail minimal changes or even increases in transport costs, including non-technological (e.g. organisational) innovations. The aim is to minimise positive ERE so that environmental savings are still achieved, or even to induce negative ERE (bound income). It is worth noting, however, that increased transport costs are not necessarily related with decreases in general welfare, and that better mobility (e.g. reduced travel time or increased comfort) is also possible. For optimal solutions, the targeted promotion of innovations must be combined with broader policy measures, such as those aimed at increasing the prices of environmentally intensive transport products. An effective carbon pricing scheme for transport but also for non-transport products could have a desired impact in this respect. The greenness of innovation depends importantly on economic aspects.

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Supporting information

Supporting information may be found in the online version of this article (http://www.sciencedirect.com/science/article/pii/S0959652615003625) and is available upon request.