Economy-wide rebound makes UK's electric car subsidy fall short of expectations

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Abstract

Environmental policies often underperform due to so-called rebound effects, namely behavioural and systemic responses to technical change leading to additional consumption and environmental damage. While evidence of rebound is abundant, studies generally focus on technical changes that are neither associated with specific technologies nor their production costs, making it difficult to connect these changes with the policies governing them. To overcome this limitation, this study proposes to combine a technology-rich model based on life cycle assessment and a behaviour-optimising model for the global economy based on computable general equilibrium modelling. This approach allows to quantify policy-induced economy-wide rebound effects for four relevant environmental impacts: climate change, acidification, photochemical ozone formation, and particulate matter. We apply this approach to evaluate the effectiveness of the United Kingdom's subsidy on electric cars. The results show notable economy-wide rebound effects associated with this subsidy: over or close to 100% (no environmental benefits) for acidification and particulate matter impacts, and a lower, yet notable, magnitude for climate change (~20-50%) and photochemical ozone formation (~30-80%) impacts. The results also show the important role of macro-economic effects from price changes, particularly how the shift from petrol to electricity triggered additional demand for cheaper petrol.

Keywords: rebound effect; electric cars; policy impact assessment; life cycle assessment; computable general equilibrium; integrated modelling.

Abbreviations: Acidification (A), climate change (CC), computable general equilibrium (CGE), greenhouse gas (GHG), Global Trade Analysis Project (GTAP), input-output (IO), input-output analysis (IOA), input-output table (IOT), land use change (LUC), life cycle assessment (LCA), life cycle impact assessment (LCIA), life cycle inventory (LCI), multi-regional input-output (MRIO), multi-regional input-output table (MRIOT), particulate matter (PM), photochemical ozone formation (POF), United Kingdom (UK), vehicle-kilometres (vkm).

Word count: 7,359

1. Introduction

Energy and broader environmental policies often underperform due to so-called rebound effects [1–3]. Rebound effects relate to behavioural and systemic responses to technical change leading to additional consumption and environmental pressures, such as energy use and greenhouse gas (GHG) emissions [4–6]. Rebound effects are generally classified into two broad types, namely micro-economic or partial equilibrium and macro-economic or general equilibrium rebound, together adding to the so-called economy-wide rebound [7]. The first type relates to situations where increases in effective income/profits from consumers/producers are re-invested leaving prices constant [8,9], whereas the second type accounts for changes in output and factor prices which lead to further changes in market composition and economic growth [10]. Micro-economic rebound is generally divided into direct and indirect effects [4], for instance when economic savings from energy-efficient light bulbs lead users to increased luminosity and burn time (direct effect) [11] and additional consumption of other commodities (indirect effect). An example of macro-economic rebound is the widespread fuel efficiency improvements in transport driving down oil prices and triggering further demand for energy services worldwide [7]. Rebound effects are gaining attention among policymakers and are even regarded in policy impact assessments and policy design guidelines [12].

While quantitative evidence of rebound is abundant [4,7,13], studies generally focus on broad and costless technical changes that are unrelated to the policies that govern their diffusion, technical standards, financing, etc. [14,15]. For instance, many studies analyse the implications of costless and arbitrary improvements in resource productivity [2,10,16].

Moreover, the few studies that have explicitly addressed policy-induced rebounds do not address adequately four key aspects relating to the (1) scope of analysis, (2) product properties, (3) rebound mechanisms, and (4) indicators [17]. First, technical changes are poorly connected to particular policies and lack a sufficient technological detail to assess specific technologies. It is thus common to analyse resource productivity improvements in broad economic sectors without considering the specific technical changes needed to achieve these [18]. Second, and in the same vein, changes in product attributes and capital costs are often ignored or estimated with a broad brush. For instance, a specific technology can be associated with specific behaviours [19] as well as capital costs [20]. Third, macro-economic rebound effects related to market price, composition, and economic growth [7] are generally not addressed. Most policy-induced rebound analyses thus focus solely on how additional income is re-spend while keeping prices constant [17]. Lastly, studies often express rebound magnitudes mostly via direct energy and energy-based emissions, disregarding trade-offs between life cycle stages and/or environmental pressures. This limitation is often imposed by the models used, such as macro-economic models lacking the use and end-of-life stages as well as environmental extensions other than energy.

To overcome the above limitations, we here propose a novel life cycle general equilibrium approach to quantify policy-induced rebound effects for various environmental pressures. Our approach combines two popular modelling traditions in rebound analysis, namely life cycle assessment (LCA) and computable general equilibrium (CGE) modelling (see supporting information S1 for an introduction), using consistent benchmark data and partly consistent assumptions. LCA has been used to calculate rebound effects for specific products and technologies, from cheese [21] to electric car models [22] and biofuel crop production [23]. This approach, sometimes referred to as the environmental rebound effect, is characterised by the possibility to incorporate a high technology detail and costs through a life cycle perspective, and to express rebound in terms of multiple environmental indicators [24]. Rebound studies using LCA, however, often suffer from truncation issues when describing economic systems [25], namely leaving out processes that complete global supply chains. LCA studies also systematically ignore broader economic consequences of technical change beyond supply chain effects, such as price, distributive, and growth effects [26–28].

Modelling the consequences of the complex interactions between economic agents is possible with macro-economic models, such as growth, econometric, and CGE models [29]. Among these, CGE models offer clear advantages with respect to other models [30] despite obvious limitations [31]. In particular, CGE models are *ex ante* in nature (compared, for example, to the *ex post* focus of econometric approaches) and offer great flexibility in terms of modelling the interactions and specific characteristics of different economic agents, for example regarding different possible closures (e.g. tax and income closures), and so they can be adapted to address future consequences of a wide range of shocks. Moreover, CGE models have been widely used for rebound analysis [29,32] and have been applied to estimate the so-called 'general equilibrium rebound' [10], which incorporates the effects of changes in output and factor prices. Standard CGE models, however, generally lack technology detail and environmental extensions [27,33]. Following previous works that linked macroeconomic and systems engineering models [34], some studies combine LCA and CGE to exploit their strengths. Such hybrid LCA-CGE approaches combine the technology detail of LCA with the economic behaviour of CGE models without loss of information nor modelling power, generally at the expense of ontological discrepancies that can be only partially solved currently [27,35,36]. Two main LCA-CGE approaches can be identified in the literature (see supporting information S1 for a detailed review). One approach is to incorporate LCA concepts and data into a CGE modelling framework, as done in the works of Pothen [28], Bosello et al. [45], and the United States Environmental Protection Agency [37]. An alternative approach is to focus on using parameters and/or results from CGE models to inform an LCA, as done in the works of Kløverpris et al. [38–40], Nguyen et al. [41], Dandres et al. [42,43], and Igos et al. [44]. The review shows that each approach provides different and valuable insights according to given research questions and scope of analysis. Further, the study of rebound effects via LCA-CGE approaches is scarce and, in any case, does not allow for a deep analysis of its causes and implications. In this study, we develop an original hybrid LCA-CGE approach specifically tailored to quantify policy-induced rebound effects.

We apply our method to the case of the promotion of electric passenger cars in the United Kingdom (UK) via governmental subsidies for illustration purposes. Our research question is thus: do UK government's economic incentives to promote electric car uptake led to significant economy-wide rebound effects? While car electrification is seen as a central action to cut transport GHG emissions by the UK government, for instance as described in the *UK Low Carbon Transition plan* [45] and the UK Renewable Energy Roadmap [46], the impact of such action as a policy package nor its policy components (such as the studied subsidy) have not been calculated, neither in terms of GHG emission nor other environmental impacts. This study can thus provide valuable new insights into the effectiveness of this and similar policies, both in the UK and internationally. More generally, this research contributes to the current body of knowledge by (1) developing a novel technology-rich life-cycle based macro-economic model suited to comprehensively assess the environmental performance of any given technology-oriented policy and (2) complementing the limited literature on rebound effects associated with electric car adoption [22,47] by providing, for the first time, estimates of both micro and macro-economic rebound effects.

2. Methods and data

2.1 Case study and modelling set-up

Our case study focuses on the life cycle environmental assessment of the UK government's subsidy on electric cars, with a special focus on the detrimental impact of rebound effects. The policy intervention under investigation is the 'Plug-in Car Grant', which is in place since 2011 to cover for 35% of the purchase price of full battery electric cars, limited at 4,500£ per vehicle (https://www.gov.uk/plug-in-car-van-grants). To assess the consequences of this subsidy, we designed three scenarios in order to estimate the rebound effect (see section 2.4): (1) a counterfactual 'no subsidy' scenario where the subsidy would have not been implemented, (2) a 'subsidy without rebound' scenario with the subsidy implemented in the UK, and (3) a 'subsidy with rebound' scenario were the sales of electric cars associated with the subsidy lead to a rebound effect. For the 'no subsidy' scenario, we assume a shift from electric to comparable petrol cars through a one-to-one substitution, whereas both 'subsidy' scenarios include electric car sales as reported. The effect of the subsidy on total car sales is thus captured by the difference between the reported electric car sales ('subsidy' scenarios) and the modelled sales of both electric and petrol cars in the hypothetical absence of the subsidy ('no subsidy' scenario).

We focus on the effects of the subsidy on private demand of electric cars for the period 2011-2022. Passenger cars in the UK are driven about 12,760 vehicle-kilometres (vkm) per year [48] which, assuming a lifespan of 150,000 vkm from the corresponding datasets of the ecoinvent database (see section 2.4.2), means they are driven for about 12 years. Hence, the studied period would cover the entire lifespan of cars bought in 2011 and allow for certain structural changes in the economy. No dynamic technical changes are considered during the studied period, such as improvements in fuel efficiency, battery production, waste treatment, etc. The only technical change considered is thus the substitution between electric and petrol cars caused by the subsidy. Relative differences in the environmental performance of these scenarios will be the basis for the rebound calculations (see section 2.4).

2.2 Method overview and rebound calculation

Our proposed method departs from a policy intervention (a subsidy in this case) which generates four effects: (1) technical change, (2) economic incentives, and (3) technology diffusion and (4) consumption shifts (see column A in Figure 1). The technical change effect will be active in all scenarios, as electric cars were sold before the policy intervention in this case. Both economic incentives and technology diffusion and consumption shifts will be active only in the 'subsidy' scenarios. These effects are then assessed with various interdependent models (column B) to obtain numerical results for various environmental indicators which will be the basis for the rebound calculations (column C). The models used are a hybrid IO-LCA model (see section 2.3.1), a CGE model coupled with a multi-regional input-output (MRIO) model (see section 2.3.2), and a multiple regression and household demand models (see section 2.3.3). The hybrid IO-LCA model offers a high technology detail where car technologies can be assessed, while the CGE model allows to account for a wide array of economic responses to the subsidy, especially the consequences of price changes. The MRIO model is used to simulate the effect of the subsidy with fixed prices to isolate price effects (see section 2.3.2). With this modelling set-up, three rebound effects can be quantified in various ways: micro-economic, macro-economic, and economy-wide effects (see section 1). With this approach, we are able not only to apply the two mainstream approaches in the literature independently, namely technology-rich micro-economic (LCA) and general equilibrium macro-economic (CGE) approaches, but also to combine them in a pseudo-consistent way. We first describe the models and their relationships as well as the required calibration data (section 2.3), followed by the implementation of policy effects (section 2.4).

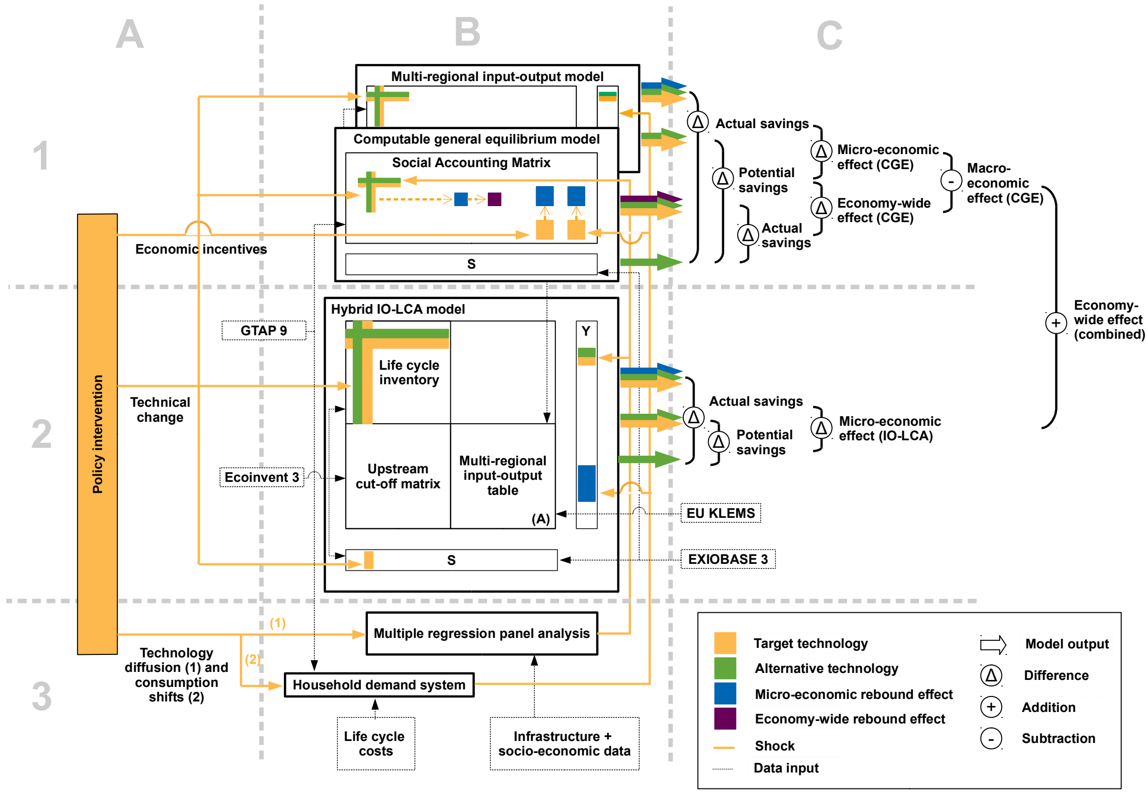

Figure 1. Overview of the proposed method to calculate policy-induced rebound effects.

Following convention, the (environmental) rebound effect can be calculated as the percentage of potential environmental benefits that are ‘taken back’ [22], as

$$rebound\ effect = \left(\frac{potential\ environmental\ benefits - actual\ environmental\ benefits}{|potential\ environmental\ benefits|}\right) * 100 \qquad (equation\ 1)$$

In this study, potential environmental benefits correspond to the difference in environmental impacts between the ‘subsidy without rebound’ and ‘no subsidy’ scenarios, whereas actual environmental benefits correspond to the difference between the ‘subsidy with rebound' and 'no subsidy' scenarios. Three types of rebound effects will be calculated: micro-economic, macro-economic, and economy-wide rebound. The micro-economic rebound can be calculated independently with both the IO-LCA and the MRIO models. The macro-economic rebound can only be calculated by the difference between the economy-wide rebound calculated with the CGE model and the micro-economic rebound calculated with the MRIO model (see column C in Figure 1). The economy-wide rebound can be calculated with the CGE model as is standard in the literature [1,18,29,49] or, alternatively, by adding the macro-economic rebound (calculated by subtracting the micro-economic rebound [MRIO model] from the economy-wide rebound [CGE model]) to the micro-economic rebound from the IO-LCA model, an approach we refer to as the 'combined approach'.

The environmental rebound effect can be expressed through multiple indicators that are relevant to the analysed technical change [24]. Given both their relevance and availability across models, we have chosen the following midpoint impacts: climate change (in CO_2 equivalents), particulate matter (in PM2.5 equivalent), photochemical ozone formation (in C_2H_4 equivalents), and acidification (in H+ equivalent). Results in terms of pressures, such as CO_2 emissions, can be converted to midpoint impacts, such as climate change in CO_2 equivalents, using characterisation factors. The characterisation factors for ecoinvent's elementary flows (used in the hybrid IO-LCA model) have been obtained from the International Reference Life Cycle Data System 2011 midpoint method (ILCD 2011 method for short) [50]. The characterisation factors for EXIOBASE's environmental extensions (used in the hybrid IO-LCA, the CGE, and the MRIO model), also according to the ILCD 2011 method, have been obtained from the adaptation done by Huysman et al. [51]. The ILCD 2011 method is based on internationally-accepted existing environmental impact assessment models and factors based on both domain expertise and stakeholder consultations [52].

In order to make the results of all the models comparable, we exogenously add combustion emissions from the LCIs to the results of the CGE and MRIO models, where the use phase is missing.

2.3 Model description

2.3.1 Hybrid IO-LCA

The hybrid IO-LCA model (see coordinate 2B in Figure 1) is a pseudo-consistent representation of the world economy using two levels of detail: a technology-rich system at the level of processes and their products based on LCI data, and a comprehensive system at the level of industries based on a multi-regional input-output table (MRIOT). Both systems can be interconnected via so-called cut-off matrices and integrated into a single input-output matrix [53]. This approach is commonly known as integrated hybrid LCA. The cut-off matrices represent industry inputs into processes (upstream cut-off matrix) and product inputs into industries (downstream cut-off matrix) [25]. This integrated approach therefore minimises truncation of the LCI system boundary by extending supply chains using information from the IOT.

The hybrid IO-LCA model is made up of three matrices, which follow standard IOA notation [54]: an input-output matrix of technical coefficients A, a stressor matrix S, and a final demand matrix Y. The A matrix contains normalised data based on Leontief coefficients on the interdependencies between economic activities, namely processes and industries. The S matrix contains environmental extensions in coefficient form (in physical unit per monetary unit of output) for each process/industry. The Y matrix is used to shock the system using arbitrary levels of final demand from households, government, etc. for product/industry outputs. The hybrid IO-LCA model is solved using the standard demand-pull Leontief model [54], briefly described in the supporting information S1.

The A and S matrices are populated using three different datasets. The process data, comprising the LCI system in the A matrix and the corresponding extensions in S, corresponds to the "allocation at the point of substitution" system model of the ecoinvent 3.4 database [55]. The IOT within the A matrix corresponds to the GTAP 9 global database [56], the latest available at the time of writing from the GTAP project. The databases from the GTAP project are widely used in the research community to address international economic policy issues and its members include prominent global governance and policy research institutions like the World Bank, European Commission, and World Trade Organization. The construction of a MRIOT using the GTAP database has been done following the procedure described by Peter et al. [57], specifically the variant with endogenous international transport pool. The specific tool used, 'GDX_to_MRIOT_GTAPinGAMS', written with the programming language R, can be found in the following repository: https://github.com/dfontv/Rtools. Note that the MRIOT is updated yearly according to the results of the CGE model (see section 2.3.2). The corresponding environmental extensions of the IOT in the S matrix have been constructed using the EXIOBASE 3 database [58], the latest available at the time of writing from the EXIOBASE project. The EXIOBASE project generates one of the most extensive environmentallyextended multi-regional input-output systems available worldwide. Using extensions from EXIOBASE instead of those from GTAP, which are currently limited to CO_2 emissions, allows to compute a broader and more complete set of environmental impacts [59]. The many-to-one mapping between EXIOBASE and GTAP industries has been obtained from Winning et al. [33] and the new extensions in absolute terms have been built by simple aggregation .

Combining LCI and IOT data can however lead to inconsistent systems where the economy is heterogeneously described. Notably, LCI systems are known to overlook some services, such as professional, scientific, and technical services [60]. To increase the overall consistency of our modelling framework, we have tried to homogenise the treatment of services by largely following the method described by Font Vivanco [61], with the exception that we here use GTAP instead of EXIOBASE and thus require of original sectorial concordances (see supporting information S2). In short, the proposed method adds those service inputs which are not present in an LCI system by using service inputs per output from an input-output table while correcting for economic imbalances.

2.3.2 Computable general equilibrium and multi-regional input-output model

The CGE model (see coordinate 1B in Figure 1) is based on the mathematical programming system for general equilibrium analysis (MPSGE) [62], a subsystem within Generalized Algebraic Modeling System (GAMS) [63]. MPSGE is a modelling language designed for solving Arrow-Debreu economic equilibrium models [64], and is based on nested constant elasticity of substitution production functions. The underlying agent behaviour is based on the cost minimisation of firms and utility maximisation of households. The implementation of the MPSGE model is done through the GTAP6inGAMS package (see supporting information S2 for additional details), an array of programs based on the GTAP model [65,66]. The model is calibrated using the GTAP 9 database for the year 2011 [56], and runs in a recursive-dynamic setting from 2011-2023. Both the standard versions of the GTAP6inGAMS model [66] and GTAP 9 database have been used except otherwise specified. For modelling the proposed shocks (see section 2.4), the original regions have been aggregated into to two regions – UK and rest-of-the-world (RoW) – by means of the GTAPAgg2 tool [67]. Because GTAP 9 only includes CO_2 emissions in the core data set, we have integrated a set of environmental extensions from EXIOBASE 3.4 by defining sectorial concordances between both databases and aggregating the extensions accordingly to match the GTAP classification (see section 2.3.1).

Given the need to isolate the effect of dynamic prices in the CGE model to estimate the macro-economic rebound effect (see section 2.4), we have built a mirror static model using the same benchmark data. The static model is a MRIO model and is equivalent to that used in the hybrid IO-LCA model and described in section 2.3.1. By using the mirror MRIO model, we intend to isolate the macro-economic rebound by controlling for the micro-economic rebound, which is assumed to correspond to the re-spending of economic savings by households on both additional electric cars (direct rebound effect) and other commodities (indirect rebound effect) [7]. This step is required given the modelling discipline imposed by the MPSGE, where the ability to change prices is a precondition of the model to find numerical solutions to economic shocks. Our intention is thus to produce a similar shock on the MRIO model and estimate the effect of dynamic prices alone – the macro-economic rebound – by calculating the difference between the results of the economy-wide rebound from the CGE model and the micro-economic rebound from the MRIO model (see Figure 1).

2.3.3 Multiple regression and household demand analysis

Multiple regression panel and household demand analysis (see coordinate B3 in Figure 1) are used, respectively, to estimate the effect of the subsidy on electric car sales and the shifts in consumption patterns in response to changes in effective income. Multiple regression analysis has been used to measure the effects of regional policies by isolating the effect of a given policy from other covariates [68–70]. According to Yong and Park [71], electric car deployment can be explained by both policy factors, such as purchase subsidies and tax benefits, and environmental factors, such as charging infrastructure and socio-economic status. Accordingly, we gathered panel data on both policy and environmental factors for the 28 EU countries and for the period 2014-2017 (see supporting information S2). After different tests, we have specified the following fixed effects model to conduct the econometric estimates:

$$ECSHARE_{it} = \mu_i + c_{it} + \beta_1 CHARG_{it} + \beta_2 POP_{it} + \beta_3 COMPTAX_{it} + \beta_4 SUBS_{it} + \beta_5 VAT_{it} + u_{it}$$

Where $ECSHARE_{it}$ is the endogenous variable 'electric car sales share' of country *i* at year *t*; μ_i is the specific fixed effect for country *i*; c_{it} is the common fixed effect, or constant, for all the countries*;* $\beta_{1\ldots n}$ represents the coefficients accompanying the different variables; $CHARG_{it}$ is the number of public charging stations (both fast and normal charging); POP_{it} is the population; $COMPTAX_{it}$ is the level of tax benefits for companies (from 0 to 100%);

$SUBS_{it}$ is the maximum purchase subsidy available; VAT_{it} is the level of value-added tax benefits (from 0 to 100%), and u_{it} is the error term.

The outcome of estimating the model using the described panel data can be found in the supporting information S2. We have used the Generalized Least Squares method (EGLS) with cross-section weights. We observe that all estimated coefficients are statistically significant at 5% or 10% levels. Regression shows a good adjustment, with a weighted adjusted R-Squared of 0.92, meaning that most of the variability of the endogenous variable is captured by exogenous variables. The EGLS estimation method avoids heteroskedasticity or autocorrelation problems. The resulting model describes an average decline in electric car sales in the UK of about 40% with respect to reported sales in 2011 by removing the purchase subsidy (see supporting information S2). Such result is then imposed into the CGE model via the substitution elasticity as described in section 2.4.3.

Regarding the household demand analysis, GTAP6inGAMS uses a Cobb-Douglas utility function to represent final demand [65]. Final demand is first composed of a Cobb-Douglas aggregate of energy and non-energy consumption, and these are in turn aggregates of different energy and non-energy goods. The corresponding substitution elasticities are included in the GTAP database. Any price and/or income change could thus result in a corresponding shift in final demand.

2.4 Policy intervention effects

2.4.1 Technical change

To assess the comparative environmental performance of electric car uptake, we first need to make both electric and petrol cars explicit in our models. Both electric and petrol cars can be found in the LCI system through the processes ‘transport, passenger car, electric’ from the global geography and the comparable ‘transport, passenger car, medium size, petrol, EURO 5’ from the European geography, both delivering one vkm. The individual LCIs also include the corresponding electricity and petrol requirements.

As with the rest of technologies, vehicle technologies are highly aggregated in GTAP, which is the basis of both the CGE and MRIO models. In order to make both electric and petrol cars explicit in these models, we use the physical inventories for the vehicle construction from the LCI system (kg of steel, meters of cable, etc.) to disaggregate the sector ‘mvh - Motor vehicles and parts: cars, lorries, trailers and semi-trailers’ into three subsectors: ‘evh – Electric car vehicles’,’pvh – Petrol car vehicles’, and ’ovh – Other vehicles’. We first transform the physical inventories for electric and petrol cars to monetary units by using price data for reference products as provided by ecoinvent 3.4 [72]. Currency exchanges and inflation rates for the UK are taken from Eurostat to match GTAP units, namely 2011 US dollars. We then transform the monetary inventories to GTAP classification using a sectorial concordance (see supporting information S2). Lastly, we scale the inventories to reflect a baseline scenario were the subsidy under study did not take place (see section 2.4.3). That is, the original inventory per vkm is scaled to the predicted number of vehicles for a ‘no subsidy’ scenario. Such scaling ensures an appropriate weight of the new sectors in the global economy. The disaggregation is carried out with Splitcom, an array of programs to split a given GTAP sector while preserving the GTAP accounting identities [73]. For full details on the weights applied to carry out the disaggregation in Splitcom, namely partial shares for new columns and intersection of national matrix, shares for new rows of national matrix, and shares for new commodities in trade matrix, see supporting information S2. Furthermore, electricity and petrol are included, respectively, in the broader sectors 'ely - Electricity: production, collection and distribution' and 'trd - Trade: all retail sales; wholesale trade and commission trade; hotels and restaurants; repairs of motor vehicles and personal and household goods; retail sale of automotive fuel'.

2.4.2 Economic incentives

The analysed subsidy of 35% of the purchase price of electric cars is introduced in the CGE model via a reduction in both 'rtpd – Private domestic consumption tax rate' and 'rtpi – Private import consumption tax rate' of electric cars sold in the UK. Considering the original tax rates for both domestic and imported vehicles of about 9%, the resulting sales tax rates including the subsidy would be -12.8%. A negative tax means that no tax is charged to consumers and a share of the purchase cost is effectively subsidised by the government. Given that tax rates are defined as exogenous in the standard GTAP6inGAMS model [66], this effectively means that our model will seek to compensate such subsidy via a reduction in government expenditures (see section 3.2).

2.4.3 Technology diffusion and consumption shifts

To calculate the technology diffusion (sales of both electric and petrol cars) in the 'subsidy' and 'no subsidy' scenarios, we depart from sales data in the UK, which describe sales of 749 electric cars and 925,183 petrol cars in 2011 [74]. According to the results of the multiple regression panel analysis described in section 2.3.3, we define the 'no subsidy scenario' in all models with the sales of 449 (749 * (1-0.4)) electric cars and 925,857 (925,183 + (749-449)) petrol cars. Next, we calibrate the CGE model so that it responds to the subsidy by endogenously adjusting the sales of electric vehicles to the reported sales in 2011. To achieve this, we introduce a nested structure in the household utility function (see Figure 2) and calibrate the CGE model via the substitution elasticity between the production of electric and petrol cars, which is estimated at 10,5 so as to match the expected shift in sales in response to the subsidy according to the regression model. This substitution elasticity reflects the preferences of consumers for both technologies, so such a high elasticity means a high willingness to shift between the two according to relative prices. The magnitude of this substitution elasticity will have an impact on the absolute environmental benefits achieved, but not on the (relative) rebound results, which are the main focus of our analysis. This is because such substitution does not take place at a large scale within the economy as a whole nor leads to meaningful structural changes, unlike the substitution between energy and non-energy inputs typically used in energy rebound studies [75,76].

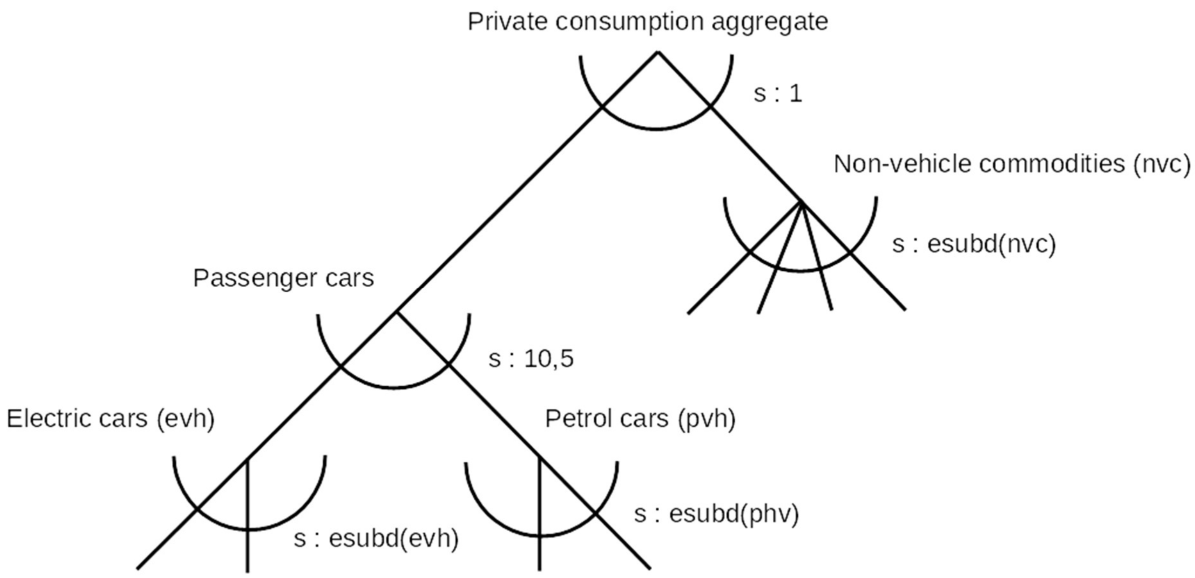

Figure 2. Nested structure of household utility; s: elasticity of substitution, esubd: Armington elasticity of domestic-import substitution.

Once the CGE model is calibrated, we calculate the stock of electric and petrol cars for all scenarios and years and use it for the MRIO and IO-LCA models consistently. The MRIO and the hybrid IO-LCA models are based on the standard demand-pull Leontief model (see supporting information S1), which means that the final demand can be arbitrarily set with the stock results. Moreover, both electricity and petrol are endogenously linked to the use of vehicles in the IO-LCA model, but they are not in the CGE model. We therefore impose the consumption of both electricity and petrol by means of a subsistence or fixed demand. Specifically, we impose an initial consumption in 2011 in the 'no subsidy' scenario according to the vehicle stock and consumption per vehicle and year from the LCIs. This consumption is then linked to the vehicle stock so that electricity/petrol consumption will change proportionally to any change in electric/petrol car stock.

For the micro-economic rebound, we first estimate the life cycle economic savings for households associated with the subsidy by calculating both purchase and operation savings based on the original LCIs. Using the household demand model (see section 2.3.3), we calculate additional expenditures and impose them in the IO-LCA model. For the MRIO model, we assume for simplicity that differences in the domestic consumption by households of the newly created evh (electric cars) and pvh (petrol cars) sectors between the 'subsidy' and 'no subsidy' scenarios correspond to the effect of the subsidy (price effect) and the direct rebound (income effect) alone. This implicitly assumes that changes in relative prices other than the purchase price of electric cars have no effect on the sales of both electric and petrol cars, a necessary assumption in this case. We then estimate the remaining savings (indirect rebound) by calculating the difference between life cycle savings and the direct rebound. Life cycle savings must therefore be fully allocated to either additional electric cars (direct rebound effect) and other commodities (indirect rebound effect). A high direct rebound entails a high-income elasticity of demand for electric car driving, meaning low saturation for such demand. Note that the calculated micro-economic rebound in the MRIO model will in fact correspond to the indirect effect alone, a limitation with modest effects given that the indirect effect is generally the top contributor of the micro-economic rebound for electric cars [22,47].

3. Results

This section presents the results of the proposed approaches: the IO-LCA model (section 3.1) and the CGE model and combined approach (section 3.2). The results are presented for four impact categories: climate change (CC), acidification (A), photochemical ozone formation (POF), and particulate matter (PM). The complete set of results can be found in the supporting information S2.

3.1 Input-output-life-cycle-assessment model

The IO-LCA model describes a noteworthy micro-economic rebound effect associated with the studied subsidy, ranging across impacts from 6% (POF) to 13% (A) (see Figure 3). In other words, about a tenth of all the potential environmental benefits would be offset due to this type of rebound effect. The micro-economic rebound stems mostly from the indirect effect, which contributes about 90% for all the studied impacts (see supporting information S2). Within the indirect effect, the top contributing sectors are ‘other manufacturing’ (7% from total micro-economic rebound), ‘other vehicles’ (6%), and ‘wearing apparel’ (5%). Overall, the subsidy achieved rather modest absolute decreases of about 0.2% for all impact categories both with and without the rebound. Such an impact is in line with the small technical change induced, where the subsidy caused a shift of only about 0.04% of petrol car sales towards their electric counterparts.

The proposed integrated IO-LCA approach, which harmonises the treatment of services via a dynamic IO system that is re-calculated yearly based on the results of the CGE model, also allows to test the effect of both including additional services and considering dynamic elements. First, additional services can be disregarded by simply turning the downstream cut-off matrix into a zero matrix (see section 2.3.1). Under this scenario, the rebound effect would increase slightly, ranging from 8% (POF) to 48% (A), and similar absolute reductions would be achieved. The reasons behind higher rebound magnitudes is that, according to our method, electric cars would require, on a life-cycle basis, a higher proportion of services than their petrol counterparts, especially financial, business, and trade services, and these are to a large extent related to electricity transmission and distribution. The impacts associated with these additional services reduce the environmental benefits associated with electric cars, thus reducing the importance of the rebound effect when using the integrated approach. Second, using a static rather than a dynamic IO system causes minimal changes for all scenarios and impacts, specifically about 8% lower rebound effects: from 5% (POF) to 12% (A). The dynamic IO system reflects higher requirements of some commodities, such as chemical rubber products, which can be partly attributed to a decrease in the price of imported oil products (see section 3.2 and the supporting information S2).

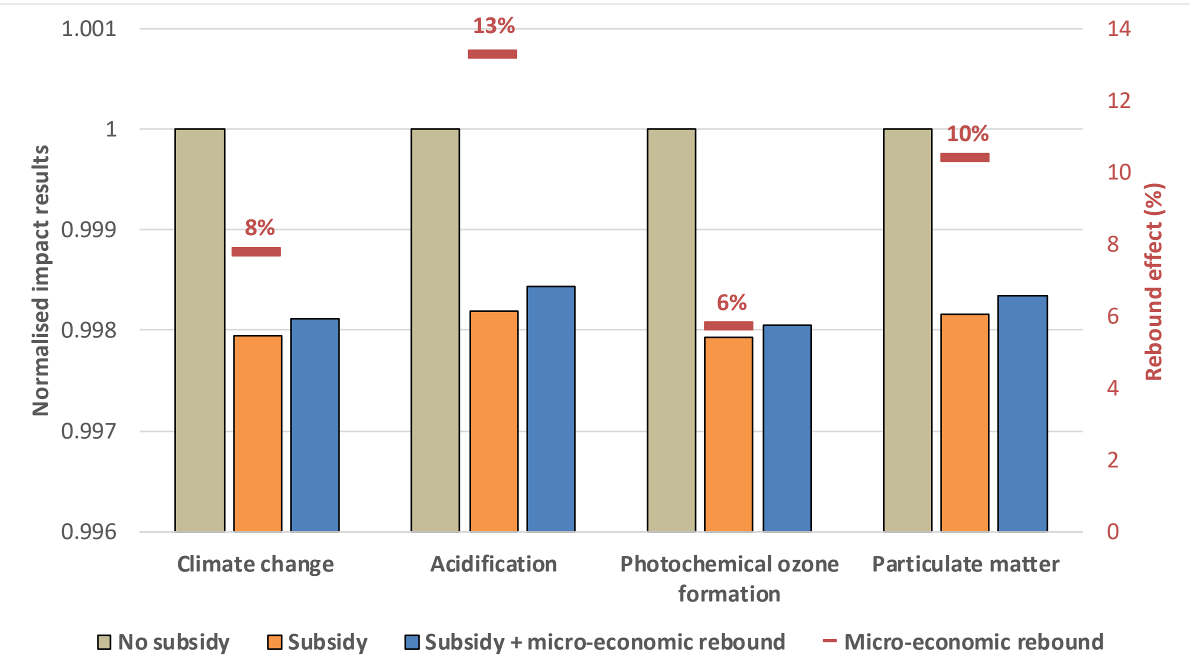

Figure 3. Life cycle impacts associated with a subsidy on electric cars sold in the UK during 2011-2022 according to the input-output-life-cycle-assessment model. The left axis and the

bars represent impact results normalised to the reference 'no subsidy' scenario, while the right axis and the horizontal lines with percentages represent the rebound effect associated with the 'subsidy + rebound' scenario as the percentage of environmental benefits that are 'taken back'.

3.2 Computable General Equilibrium model and combined approach

The results of the CGE model describe notable both micro-economic and economy-wide rebound effects, the first ranging from 24% (PM) to 30% (CC) and the latter ranging from 52% (CC) to 99% (A) (see Figure 4). Note that a rebound effect higher than 100% or the so-called backfire effect [77] entails that any potential environmental benefits would be fully offset, rendering the subsidy ineffective from an environmental standpoint. In this sense, the economy-wide rebound effect for all impact categories except CC would be close to backfiring. Focusing on the macro-economic rebound, it originates largely from the increase in the household domestic demand for trade retail sales (see Figure 5). Note that the demand for petrol fuel associated with the stock of petrol cars has been included in the retail trade sector as it originally includes automotive fuel (see section 2.4.3). This increase can be largely attributed to the reduction in the domestic price of automotive fuel, a consequence of the original decrease in petrol fuel demand from the decline in the petrol car stock. A similar mechanism, albeit of smaller magnitude, takes place regarding imported petrol fuel (see supporting information S2). Overall, the subsidy increased global gross domestic product by 0.001% during the studied period, mostly led by the increase in household domestic demand in the UK (392% contribution to total change). Conversely, UK's government domestic demand decreased notably (-242% contribution to total change) to compensate for the subsidy. Specifically, UK's government domestic purchases and imports decreased in value terms by 0.34% and 0.01%, respectively.

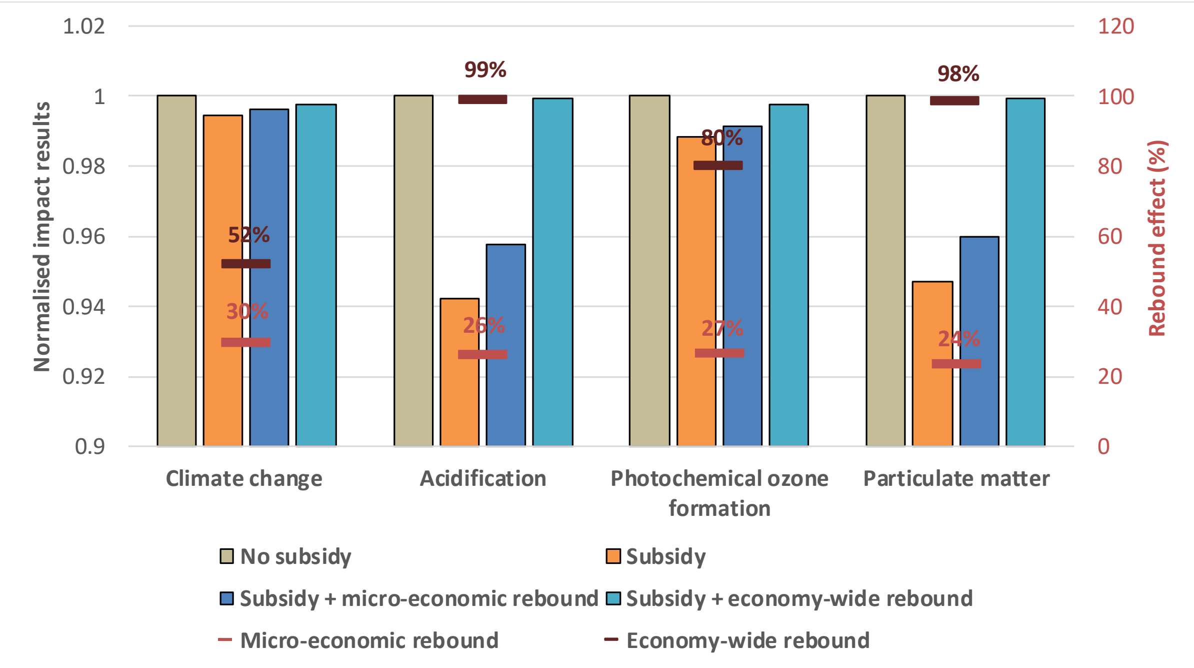

Figure 4. Life cycle impacts associated with a subsidy on electric cars sold in the UK during 2011-2022 according to the computable general equilibrium model. The left axis and the bars represent impact results normalised to the reference 'no subsidy' scenario, while the right axis and the horizontal lines with percentages represent the rebound effect associated with the 'subsidy + rebound' scenarios as the percentage of environmental benefits that are 'taken back'.

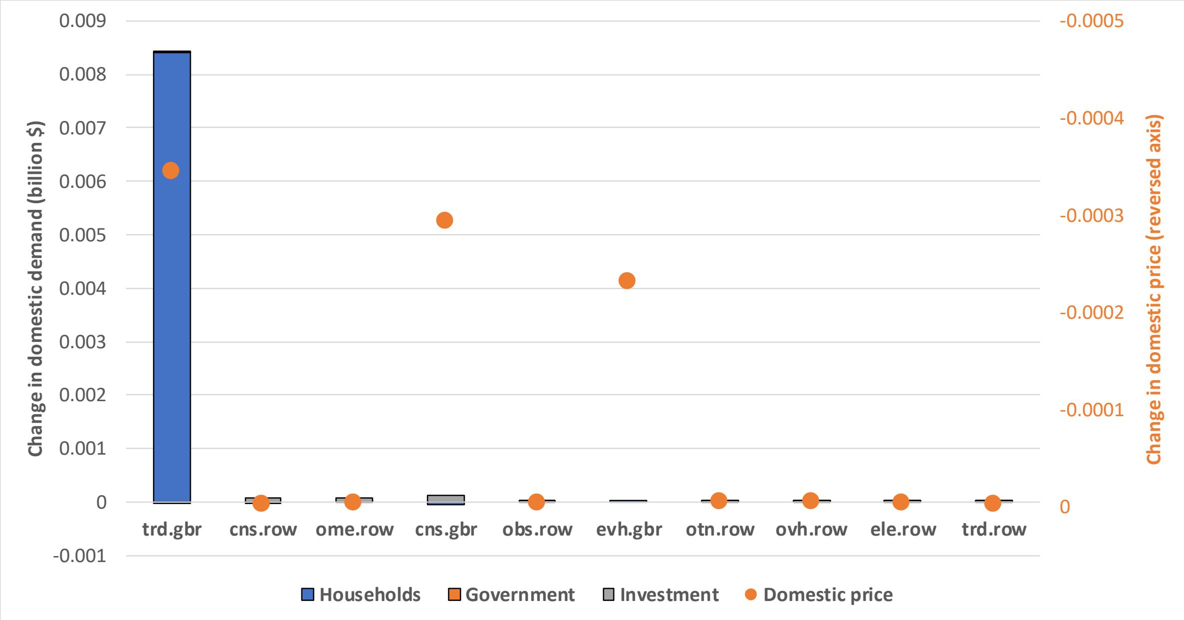

Figure 5. Change in domestic demand (left axis and bars) and change in domestic price (right axis and dots) associated with a subsidy on electric cars sold in the UK during 2011-2022 according to the computable general equilibrium model. Only the top ten sectors in terms of positive changes in domestic demand are shown. Trd: trade services; cns: construction; ome: other machinery & equipment; obs: other business services; evh: electric vehicles; otn: other transport equipment; ovh: other vehicles; ele: electronic equipment; gbr: united kingdom; row: rest-of-the-world.

With respect to the results of the IO-LCA model, the micro-economic rebound from the CGE model is significantly larger, with relative increases ranging from a factor 1.16 (A) to a factor 4.04 (POF) (see Figure 6). The results of the combined approach (see section 2.3.2) describe a notable economy-wide rebound effect, ranging from 22% (CC) to 102% (A) (see Figure 7).

These magnitudes are generally lower than those from the CGE model (see Figure 6). Even so, backfire or near backfire mechanisms can be observed for both A and PM impacts.

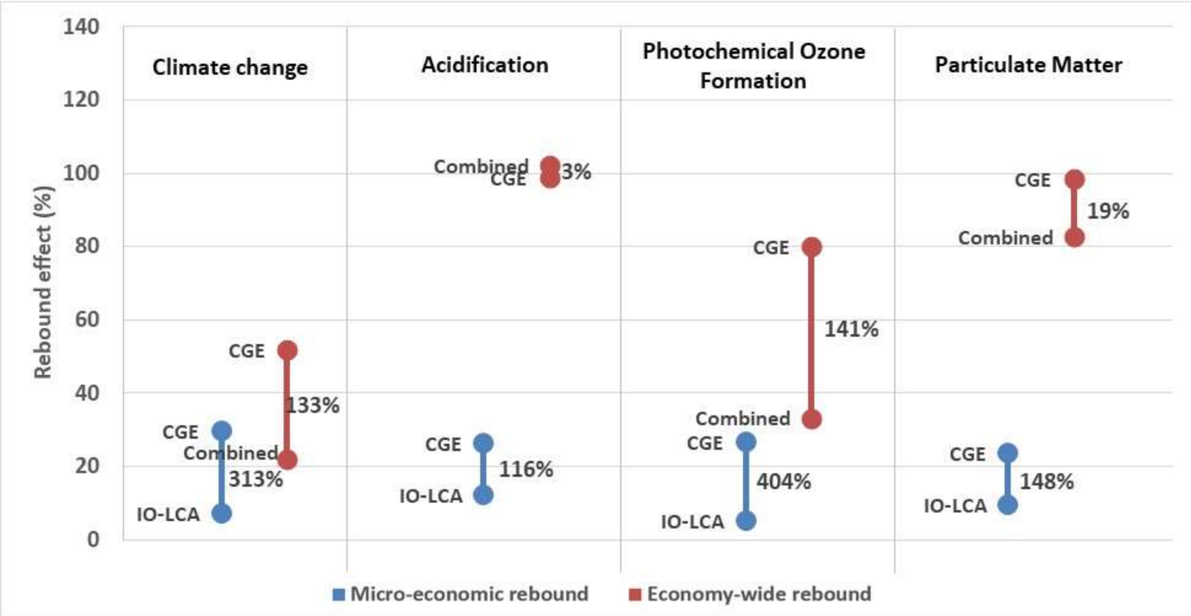

Figure 6. Overview of the magnitude of the micro-economic and economy-wide rebound effects (as the percentage of environmental benefits that are 'taken back') calculated with the input-output-life cycle assessment model (IO-LCA), the computable general equilibrium model (CGE), and the combined approach. The percentages within the graph indicate the relative change between the results of the different models.

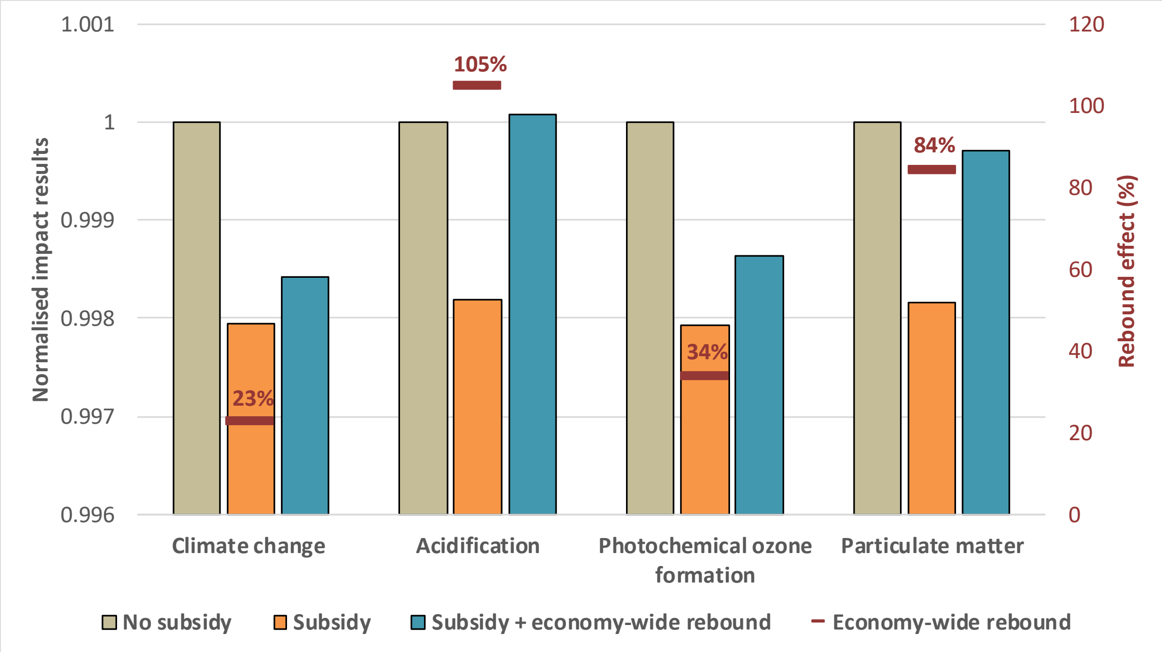

Figure 7. Life cycle impacts associated with a subsidy on electric cars sold in the UK during 2011-2022 according to an approach combining the input-output-life cycle assessment and the computable general equilibrium models. The left axis and the bars represent impact results normalised to the reference 'no subsidy' scenario, while the right axis and the horizontal lines with percentages represent the rebound effect associated with the 'subsidy + rebound' scenario as the percentage of environmental benefits that are 'taken back'.

4. Discussion

Our results suggest that the subsidy on electric cars implemented in the UK from 2011 may be associated with notable economy-wide rebound effects that negate a large share, and in some cases even the entirety, of life cycle environmental benefits in terms of climate change, acidification, photochemical ozone formation, and particulate matter impacts. Furthermore, the two components of the economy-wide rebound, namely the micro-economic and macro-economic effects, both contribute importantly across impacts and modelling configurations. The relevance of the macro-economic rebound, namely that arising from price changes alone, is a valuable addition to the literature as it has not been isolated before. In this case, the decrease in the price of petrol fuel from lower demand has been a major factor behind the macro-economic rebound. This effect is similar, for example, to that observed by Dandres et al. [43], where a shift from coal to biofuels triggered additional demand for cheaper coal. Both the effective environmental benefits and the magnitude of the rebound effect are modest in absolute terms, yet this is in line with the trivial technical change achieved, with only about a few hundred users switching from petrol to electric models. It is thus expected that, with increasing sales of electric vehicles in the UK and in the presence of economic incentives, the rebound effect could take back considerable future environmental benefits in absolute terms.

The proposed modelling approach, which combines a technology-rich model based on life cycle assessment and a behaviourally-realistic model for the global economy based on computable general equilibrium modelling, allows to calculate a wide array of results as well as to test some modelling assumptions for the first time. Among those studies dealing with the environmental implications of rebound effects, two important approaches are those based on either LCA or CGE models. We have been able not only to calculate estimates with each model individually, but also with a combined approach based on consistent benchmark data and partly consistent assumptions. The results describe some important discrepancies across models (see Figure 6), where the CGE model generally yields larger rebound estimates than those of both the IO-LCA and the combined approach. Key reasons for such discrepancies are aggregation errors of input-output tables [78] and the incompleteness of LCI systems [61]. Specifically, the reduced technology detail of the CGE model, where industry averages are used, sometimes leads to overestimating certain environmental impacts, such as approximating a specific metal product with the wider metal products sector. Also, LCI systems suffer from systemic truncation issues where certain inputs are omitted, which have been here only partially solved by including service inputs. In any case, it merits noting that (1) rebound effects are constructs that are modelled and attributed to certain shocks rather than being empirically measured, (2) it is incorrect to assume any 'true value' due to modelling trade-offs, and (3) the results in any case allow for some general interpretations. First, any type of rebound effect is the result of a modelled counterfactual scenario where the rebound mechanisms are isolated at the discretion of the modeller. This fact prevents rebound effect estimates to be validated against empirical evidence and thus cross-validate the different existing rebound models. Second, trade-offs between technology detail and (economic) behaviour realism are mostly unresolved due to missing data, computational capacity, ontological discrepancies, etc [27,35,36]. A suitable alternative is thus to seek for convergence in the results from different models, in line with how ensemble modelling is used for decision-making in climate modelling, clinical research, etc [79]. In this sense, our results indicate that the economy-wide rebound would likely cause a backfire or near-backfire effect for acidification and particulate matter impacts, and a lower, yet notable, magnitude for climate change (~20-50%) and photochemical ozone formation (~30-80%).

Our approach to calculate the economy-wide rebound of a specific technical change instead of a costless and exogenous change is unparalleled in the literature, which makes contextualising our results difficult. Even so, some similar results include those from Barker et al. [18] and Broberg et al. [80], who found an economy-wide rebound for road transport, respectively, of about 30% and 18%. These results, which are focused on energy and/or carbon emissions, are close or within the range found here for climate change impacts, yet other impacts show higher magnitudes and even describe backfire in some cases. As explained in previous studies [22,81], energy is relatively uniformly used across sectors, which lowers the rebound magnitude. Being able to describe the rebound magnitude through multiple environmental impacts is thus key for identifying trade-offs and hidden hotspots [24]. In any case, cases of backfire in economy-wide rebound estimates are not rare in the literature (see, e.g., Freire-González [82] and Hanley et al. [83]).

Our modelling approach suffers from a number of limitations, of which we highlight the most relevant in the following. First, both electric and petrol cars are modelled via generic vehicles based on European or global conditions. To better reflect the actual car models sold and UK conditions, such as the electricity mix, specific LCIs would need to be built. Second, the technology detail of the CGE model is relatively poor, and so the specific effects of battery construction, fuel use, etc, are not well captured. To solve this issue, one could either further disaggregate (and calibrate) the underlying database [33] or chose a more detailed database [84]. Third, and related to the previous one, modelling changes in demand for automotive fuel as changes in demand for the broader sector of retail trade is also problematic, yet leads to conservative results. Specifically, the own-price elasticity of demand for the UK's retail trade sector from GTAP (-0.85) is generally more elastic than that of automotive fuel, estimated at about -0.53 according to a meta-analysis carried out by Brons et al. [85]. This higher elasticity leads to an overestimation of demand for retail trade, a sector associated with low environmental impact multipliers, with respect to other sectors when estimating the macro-economic rebound. Fourth, a very high elasticity of substitution of 10,5 between electric and petrol cars has been exogenously forced into our model to achieve the expected short-term shift in sales in response to the subsidy according to the regression model (see section 2.4.3). Such a high elasticity is however rather unrealistic compared to existing vehicle choice models and thus limits the application of our model to address long-term effects and/or other shocks. To avoid having to re-calculate this elasticity for each shock, a more consistent and flexible approach would be to integrate a full vehicle choice model into the CGE model as done in Schmelzer et al. [86] and Karplus et al. [87]. Fifth, endogenizing final demand in the CGE model, namely including final users as an additional economic sector, could avoid the issue of exogenously modelling electricity/fuel use and associated combustion emissions. Lastly, our approach does not capture technology change over time, which may overestimate future impacts. For example, the current trend of decarbonisation of the UK's electricity mix will likely cause a reduction of future rebound effects.

More generally, it merits noting that we conducted a short-term analysis of a single policy in isolation, which can lead to misleading conclusions on large-scale and long-term policy strategies both nationally and internationally. In other words, a subsidy on electric cars is often just a component of a broader long-term strategy towards systemic change to decarbonise an economy (e.g., together with other stimulus on infrastructure, regulatory instruments, voluntary approaches, etc.), and so it may contribute to kick-start and/or facilitate broader changes on technology, institutions, consumer behaviour, etc., even beyond national borders. While greatly challenging, further work should ideally focus on long-term policy packages that explicitly address trans-boundary effects.

5. Conclusion and policy implications

This study aims at evaluating the effectiveness of UK government's economic incentives promoting electric car uptake for reducing various environmental impacts, with a focus on the role of rebound effects. The results describe notable economy-wide rebound effects that partly or completely offset environmental benefits for all studied impact categories. These results, which can be generalised beyond the UK context to other countries following similar policies, have important policy implications given the high expectations placed on transport electrification to mitigate climate change and air pollution. Further policy implications relate to the potential manifold applications of the proposed model, with pertinent adaptations, to assess the environmental performance, including economy-wide rebound effects, of other policy instruments and policy packages internationally.

A fiscal policy resulting in both environmental benefits and increased gross domestic product can be interpreted to effectively achieve a 'double dividend' [88,89]. In the presence of a notable rebound effect, however, this interpretation may conceal the fact that significant potential environmental benefits are being lost due to a combination of policy and market failures. The identification and quantification of rebound mechanisms carried out in this study can help to redesign UK government's economic policy for promoting electric car uptake and further environmental benefits by minimising such policy and market failures. Regarding policy failures, the studied subsidy could have been overdimensioned by offering too high economic incentives to purchasers. There could also be more efficient alternative policies, with the results of our regression analysis in fact showing that various other alternatives, such as public charging stations and company tax benefits, could achieve similar results. A lower subsidy in favour of higher investment in charging stations would have likely offered a better performance. Regarding market failures, it has been long discussed that an energy (or carbon) tax on the most energy-intensive industries or products would mitigate the magnitude of energy rebound effects [12,90], and the same principle could be applied to address other environmental issues according to policy objectives. Thus, the electric car subsidy would have been much more effective were it to be accompanied by a broader fiscal policy were the price of air-polluting products and activities such as fossil fuels and private transport incorporates negative externalities related to climate change, urban air pollution, etc.

Avoiding policy and market failures is paramount for achieving environmental goals, yet their specific implications are often difficult to assess with tools that rely almost exclusively on particular modelling assumptions, such as life cycle assessment or computable general equilibrium models. The approach presented here tries to overcome such limitations by combining different modelling traditions in a pseudo-consistent analytical framework. In this sense, we address recent calls to reconcile bottom-up and top-down modelling traditions [36] via common ontologies [35] and in the context of trans-disciplinary research [91]. Such reconciliation is also expected to increase the value of industrial ecology tools for policy making and evaluation [28]. Future applications and extensions of this approach could be used to evaluate the effects of a manifold of policies and technologies, such as pollution taxes, tradable quotas, emission standards, and policy mixes targeting renewable energies, bioplastics, etc.

Acknowledgements

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