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What Drives Decarbonization of New Passenger Cars?

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Abstract

Transition towards a low-carbon transport sector fundamentally depends on decarbonization of the passenger car fleet. Therefore, it is critically important to understand the driving factors behind decreasing CO₂ emissions of new passenger cars. This paper develops a new decomposition method to break down the change in the average CO₂ emissions of new passenger cars into components representing changes in available technology, carbon efficiency of consumer choices, vehicle attributes, fuel mix, and the gap between type-approval and on-road CO₂ emissions of passenger cars. Our decomposition draws insights from the traditional index decomposition analysis and frontier-based decomposition of productivity growth. It satisfies such desirable properties as factor reversal, time reversal, and zero-value robustness. An empirical application to a unique data set that covers all registered passenger cars in Finland sheds light on why and how the CO₂ emissions of new cars decreased from year 2002 to year 2014.

Keywords: Data envelopment analysis; Carbon tax; Decomposition analysis; Nonparametric regression; Sustainable transportation

1. Introduction

Passenger cars are a major contributor to carbon dioxide (CO₂) emissions, the most important greenhouse gas contributing to climate change. In the European Union (EU), there were 251 million passenger cars on the road in 2015, producing 770 million metric tons of CO₂ emissions (Mock, 2015), 22.2% of the EU total CO₂ emissions of the year.¹ Reducing CO₂ emissions of passenger cars is critical for the EU to achieve its abatement targets.

To promote the transition towards a low-carbon passenger car fleet, the EU has stipulated a series of policy measures to decarbonize new passenger cars. One important supply-push strategy is that manufacturers' new cars sold on the EU market are subject to mandatory CO₂ emission targets: the average CO₂ emissions of new cars need to be no higher than 130 g/km (grams per kilometer) by year 2015—which was already met—and no higher than 95 g/km by year 2021 (European Parliament and the Council of the EU, 2009). On the demand-pull side, for example, the EU directive on car labeling requires disclosure of the CO₂ information (among others) to

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¹The percentage 22.2% is own calculation based on data from Mock (2015) and Olivier et al. (2016).

consumers (European Parliament and the Council of the EU, 2000) and there are various forms of CO₂-based vehicle taxation in EU member states aiming to shift consumer preferences towards low CO₂-emitting cars.²

What are the mechanisms through which regulatory measures and social-economic environment influence CO₂ emissions from new passenger cars? Empirical studies have identified such pathways as consumer choices (with regard to vehicle attributes in particular) and available technology (e.g., Meyer & Wessely, 2009; Kok, 2013; MacKenzie & Heywood, 2015) as well as test manipulation (e.g., Dings, 2013; Tietge et al., 2016; Fontaras et al., 2017). However, no systematic decomposition of changes in the CO₂ emissions to these pathways is available in the literature. This is clearly a research gap that needs to be filled, as a comprehensive understanding of the driving factors is critically important for evidence-based policy making.

This paper addresses the research gap by developing a novel decomposition of the average CO₂ emissions of new passenger cars, which includes the following components:

- Available Technology
- Carbon Efficiency of Consumer Choices
- Vehicle Attributes
- Fuel Mix
- Test Manipulation

From the methodological point of view, our novel decomposition draws insights from the traditional index decomposition analysis (Ang & Choi, 1997) and the frontier-based decomposition of the Malmquist index (Färe et al., 1994). The proposed method yields a comprehensive, robust, and flexible decomposition of changes in the average CO₂ emissions of new passenger cars, and satisfies such desirable properties as factor reversal, time reversal, and zero-value robustness. However, the main difference to the existing frontier-based decomposition is that our decomposition does not include any scale efficiency component, the interpretation of which has caused a lot of debate in the productivity literature (Lovell, 2003). By measuring the change in absolute scale (g/km) rather than in a unit-invariant index number, we effectively avoid the use of constant returns to scale benchmark technology.

Finland was among the first in the world to introduce a CO₂-based tax on car registration as of January 1, 2008. Since then, there has been a significant decrease in the average CO₂ emissions of new registered passenger cars in Finland (see Figure 1). An average new car emitted 117.4 g/km of CO₂ in 2018, 34.3% (or 61.3 g/km) lower than the 2007 level. The Finnish new car fleet achieved the 2015 EU target already in year 2014, but further reduction is needed to reach the next target in year 2021. We apply the proposed decomposition to a

²See, for example, a summary of CO₂-based vehicle taxes levied by EU member states at: <http://www.acea.be/publications/article/overview-of-co2-based-motor-vehicle-taxes-in-the-eu>.

Figure 1: Average CO₂ Emissions (g/km) of New Registered Passenger Cars in Finland; 2002–2018.

Data sources: The Finnish Information Centre of Automobile Sector and own calculations based on open data from the Finnish Transport Safety Agency.

unique data set that covers all registered passenger cars in Finland. This empirical application casts light on why and how the average CO₂ emissions of new passenger cars decreased from year 2002 to 2014. We hope that Finland’s pioneering experience can also help other states and countries to develop better policy measures.

The rest of this paper is organized as follows. Section 2 overviews the decomposition literature and elaborates our specific contribution beyond previous studies. Section 3 introduces our novel decomposition framework and discusses its properties. Estimation of the decomposed components is described in Section 4. Section 5 presents the empirical application to the Finnish new car fleet. In the final section we conclude the paper, discuss policy implications, and suggest revenues for future research. Proofs of formal statements, a detailed description of data preparation, and additional tables and results are provided in Appendices A–C.

2. Overview of Existing Decomposition Literature

The conceptual distinction of *decomposition* in different contexts is worth emphasizing prior to the literature overview. Decomposition can be generally understood as a process by which a complex (aggregate) thing is broken down into simpler (disaggregate) component parts. This may refer to the process of biological or chemical decomposition, the process of factoring in algebra, or the process of splitting a large-scale programming problem into achievable block structures. In the current context, however, we reserve the term decomposition for the process by which we break down the change in an aggregate indicator into various driving factors.

Understanding what drives the change in an environmental, economic, or socioeconomic variable has long

been a topic of great interest in such fields of operational research, econometrics, energy and environmental economics, among others. The literature on this subject is too vast to review in full. Instead, the objective of this section is to summarize two categories of commonly used methodological approaches: *decomposition analysis* and *productivity and efficiency analysis*.

The most standard decomposition analysis techniques include the index decomposition analysis (IDA) based on index numbers (Ang & Choi, 1997), the structural decomposition analysis (SDA) drawn from input-output tables (Rose & Casler, 1996), and the production decomposition analysis (PDA) rooted in the production theory (Zhou & Ang, 2008). Compared to the more traditional IDA and SDA, the PDA literature has recently seen several new methodological developments, particularly the PDA model with heterogeneity (see, e.g., Wang et al., 2018a, 2019). The above techniques decompose changes in aggregate indicators (absolute quantities or index numbers) into several predefined components. Examples of such indicators include, just to name a few, energy demand (e.g., Du & Lin, 2015; Dai & Gao, 2016), CO₂ emissions (e.g., Lakshmanan & Han, 1997; Löfgren & Muller, 2010; Fan & Lei, 2016; Sueyoshi et al., 2019), energy intensity (e.g., Choi & Ang, 2012; Lin & Du, 2014), and carbon intensity (e.g., Liu et al., 2017; Wang et al., 2018b). In particular, several decomposition analysis studies have investigated driving factors behind the change in CO₂ emissions (or fuel consumption) of the entire stock of passenger cars in one or more countries/regions (e.g., Great Britain in Kwon, 2005, Greece and Denmark in Papagiannaki & Diakoulaki, 2009, France in D’Haultfoeuille et al., 2014).

Another branch of the literature focuses on the decomposition of total-factor productivity (TFP) growth, particularly the Malmquist index (Färe et al., 1994).³ The estimated TFP growth can be decomposed into components representing technical change, efficiency change, and/or scale efficiency change (Lovell, 2003). Built upon a solid foundation of the production theory, the Malmquist index can measure and decompose TFP (especially green TFP in recent years) growth in production units from consumer durables (e.g., Zhou, 2018) to individual firms or establishments (e.g., He et al., 2013; Arabi et al., 2014; Boussemart et al., 2019), sectors (e.g., Kuosmanen, 2013; Emrouznejad & Yang, 2016), and regions or countries (e.g., Aparicio et al., 2017; Du et al., 2018). In addition to TFP measures, the decomposition of economic efficiency to allocative, technical, and scale efficiency components has received continuous and significant attention (see, e.g., Färe et al., 2019).

However, the existing approaches are not directly applicable in the context of the present study; no single method can completely characterize the potential driving factors (as described in Section 1) for the decarbonization of new passenger cars. To be specific: IDA and SDA are able to assess the effect of fuel mix change but cannot capture the production technology-associated components such as available technology and carbon efficiency of consumer choices. In contrast, PDA and the TFP measure are the opposite in this regard. Although

³Compared to the classic index numbers such as Laspeyres, Paasche, Fisher, and Törnqvist indices, the Malmquist index is a TFP measure based on the production possibility frontier. Other frontier-based TFP measures include, e.g., the additive Luenberger indicator (Chambers et al., 1996) and the Malmquist-Luenberger index that takes undesirable outputs explicitly into account (Chung et al., 1997).

PDA gives algebraically perfect decomposition results (Zhou & Ang, 2008), it tends to yield some practically unnecessary components in terms of the change in the average CO₂ emissions of new cars, and the TFP measure considers the relative performance rather than the absolute change in CO₂ emissions in grams per km.

The above discussion demonstrates the need for a new decomposition that can systematically break down the change in average CO₂ emissions to the driving factors that explain the decarbonization of new passenger cars. To this end, we draw insights from the traditional IDA approach and a frontier-based decomposition analysis adapted from the Malmquist TFP measure.⁴ Further, our decomposition inherits several desirable properties from the IDA approach and the frontier estimation, including factor reversal, time reversal, and zero-value robustness.

3. A Novel Decomposition Framework

Consider that the fleet of new registered passenger cars in a country/region in year t comprises cohorts of new cars differentiated by fuel type. In our empirical application, we draw distinction between gasoline and diesel cohorts (the mainstream of new-car sales in Finland for 2002–2014), but our decomposition can be readily extended to include, for example, electric, biofuel, and gas cohorts. Further, it is straightforward to generalize our decomposition to the entire stock of passenger cars, by considering additional components as to the fleet size and the average mileage per car per year.

This novel decomposition framework employs a bottom-up procedure (as illustrated in Figure 2) to determine the driving factors behind the decarbonization of new passenger cars. We start with developing a frontier-based decomposition analysis to distribute the change in cohort average CO₂ emissions—separately for the gasoline and diesel cohorts—into the changes in available technology, carbon efficiency of consumer choices, and vehicle attributes. Next, we use the traditional IDA approach to aggregate the changes in average CO₂ emissions occurred at the cohort level and simultaneously examine the structural change in fuel mix. Therefore, this bottom-up procedure leads to a decomposition of the change in the fleet average CO₂ emissions into components representing the changes in available technology, carbon efficiency of consumer choices, vehicle attributes, and fuel mix.

In recent years, the test manipulation has provoked several scandals around the world. The CO₂ emissions data for new cars are drawn from official records of type-approval values, but various sources indicate that there has been a widening gap between type-approval and real-world CO₂ emissions for passenger cars (see, e.g., Dings, 2013; Tietge et al., 2016; Fontaras et al., 2017).⁵ To take the test manipulation into account, we

⁴Some recent studies, for example, Lin & Du (2014); Du & Lin (2015); Wang et al. (2018b), have combined IDA with PDA to investigate driving factors behind the change in energy demand, energy intensity, or carbon intensity at the sectoral or provincial level. However, as noted above, PDA tends to generate some redundant or implausible components for the change in the average CO₂ emissions of new cars.

⁵To narrow the gap between type-approval and on-road CO₂ emissions, a new type-approval test procedure, the Worldwide

Figure 2: Pathways of Change in the Average CO₂ Emissions of New Passenger Cars.

could either try to adjust the official CO₂ data prior to the decomposition analysis, or alternatively, to adjust the estimated results afterwards. In this study, we adhere to the second approach because comparable data of the real-world CO₂ emissions are currently not available for all models.

3.1. Decomposition at the Cohort Level

For a given type of cohort (either gasoline or diesel), consider the model

$$x_{it} = f_t(\mathbf{y}_{it}) + \epsilon_{it} \quad (1)$$

where x denotes the type-approval CO₂ emissions (measured in g/km), $\mathbf{y}$ is the vector of vehicle characteristics influencing CO₂ emissions (e.g., total mass, engine power), f is an increasing and convex emissions generating function, and ϵ represents the carbon inefficiency term. Subscript t refers to the cohort of year t , and $i = 1, \dots, n_t$ is an index of new cars. We can equivalently write Equation (1) in terms of car models as

$$x_{mt} = f_t(\mathbf{y}_{mt}) + \epsilon_{mt} \quad (2)$$

where each $m = 1, \dots, m_t$ characterizes a subset of identical new cars (i.e., car models) within the cohort (m_t is the number of car models). We will return to the estimation of function f_t in more detail in Section 4.

The average CO₂ emissions in the cohort of year t are

$$\bar{x}_t = \sum_{i=1}^{n_t} x_{it} / n_t \quad (3)$$

Harmonized Light Vehicle Test Procedure, has been adopted by the EU since September 2017 to replace the outdated New European Driving Circle. See, e.g., Dimaratos et al. (2016) and <http://wltf facts.eu/>, for more information.

Note that the average emissions are calculated over individual vehicles $i = 1, \dots, n_t$. Equivalently, we can calculate the average CO₂ emissions of the cohort as the weighted average of model specific emissions

$$\bar{x}_t = \sum_{m=1}^{m_t} w_{mt} x_{mt} \quad (4)$$

where w_{mt} is the number of new cars belonging to model m in the cohort of year t divided by the size of the cohort n_t .

3.1.1. Available Technology

Technological progress can help to decrease average CO₂ emissions of a cohort. To quantify technological change, we apply insights from the productivity analysis literature and measure the shift in the emissions generating function f over time. Note that we can measure the shift of function f given the average vehicle characteristics in year t , that is, $f_{t+1}(\bar{\mathbf{y}}_t)/f_t(\bar{\mathbf{y}}_t)$, or alternatively, we could equally well consider the average $\mathbf{y}$ in year $t+1$, that is, $f_{t+1}(\bar{\mathbf{y}}_{t+1})/f_t(\bar{\mathbf{y}}_{t+1})$. Since there is no reason to prefer the average vehicle attributes of the base year or the target year, we define our measure of the Available Technology component as the geometric mean⁶

$$\Delta AT = \left[\frac{f_{t+1}(\bar{\mathbf{y}}_t)}{f_t(\bar{\mathbf{y}}_t)} \times \frac{f_{t+1}(\bar{\mathbf{y}}_{t+1})}{f_t(\bar{\mathbf{y}}_{t+1})} \right]^{1/2} \quad (5)$$

While in the productivity literature the frontier shift is interpreted as technological change, by the choice of the term Available Technology we want to highlight the fact that the emissions generating function not only captures technological innovation, but also policy measures such as technical standards and regulations that directly influence the diffusion of innovation to the retail market. Note that the Available Technology component depends on car models available in the market, but not on popularity of models among consumers. Therefore, the Available Technology component reflects both the technical progress of the car industry and the tightened regulatory standards.

3.1.2. Carbon Efficiency of Consumer Choices

Secondly, the change in the cohort average CO₂ emissions from year t to $t+1$ can be due to the change in carbon efficiency. Formally, we can define the average efficiency of the cohort in year t as $\bar{x}_t/f_t(\bar{\mathbf{y}}_t)$. In other words, we use the carbon efficiency of the average new car in year t to represent the carbon efficiency of consumer choices. Therefore, the measure of carbon efficiency change is then given by

$$\Delta CE = \frac{\bar{x}_{t+1}/f_{t+1}(\bar{\mathbf{y}}_{t+1})}{\bar{x}_t/f_t(\bar{\mathbf{y}}_t)} \quad (6)$$

At the level of individual new cars, the average CO₂ emissions of a cohort depend on the market share of CO₂ efficient models. Therefore, the component ΔCE is not affected by the car industry, but relies on the change in the popularity of carbon efficient cars. It captures changes in the consumer behavior, whether due to changes in consumer preferences or incentives set by the government (e.g., CO₂-based vehicle taxes).

⁶Note the analogue with the Laspeyres and Paasche indices and the Fisher index as the geometric mean of two periods.

3.1.3. Vehicle Attributes

Thirdly, the change in the cohort average CO₂ emissions over time also depends on the change in vehicle attributes. For example, as new cars become more fuel efficient, consumers may switch to bigger cars with more powerful engines.⁷ Given the emissions generating function f of the cohort in year t , the change in vehicle attributes could be quantified as $f_t(\bar{\mathbf{y}}_{t+1})/f_t(\bar{\mathbf{y}}_t)$, which measures the impact of characteristics changes in new cars on the average CO₂ emissions given the benchmark technology f_t . We could equally well take the technology of year $t + 1$ as the benchmark and measure the change in vehicle attributes as $f_{t+1}(\bar{\mathbf{y}}_{t+1})/f_{t+1}(\bar{\mathbf{y}}_t)$. Since there is no reason to prefer the emissions generating function of year t or $t + 1$, we define our measure of the Vehicle Attributes component as the geometric mean

$$\Delta VA = \left[\frac{f_t(\bar{\mathbf{y}}_{t+1})}{f_t(\bar{\mathbf{y}}_t)} \times \frac{f_{t+1}(\bar{\mathbf{y}}_{t+1})}{f_{t+1}(\bar{\mathbf{y}}_t)} \right]^{1/2} \quad (7)$$

Like the change in carbon efficiency of consumer choices, the change in vehicle attributes depends solely on the consumer behavior. The difference here is that ΔCE measures the change in the popularity of carbon efficient models given the vehicle characteristics, whereas ΔVA measures the change in vehicle attributes and amenities. For instance, if a consumer trades an old car to a new SUV, it is possible that the carbon efficiency improves but the emissions increase due to the increased vehicle attributes.

It is also important to note the conceptual distinction between the terms Vehicle Attributes and Available Technology. Although the term Available Technology could also be broadly seen as a vehicle attribute, we must stress that we reserve the term Vehicle Attributes for the technical parameters $\mathbf{y}$ that influence car emissions such as total mass and engine power.

3.1.4. Synthesis

Having introduced these three components, the following Proposition ties them back to the quantity of interest, that is, the change in the cohort average CO₂ emissions from year t to $t + 1$.

Proposition 1. *The change in the cohort average CO₂ emissions from year t to $t + 1$ is the product of the components of available technology, carbon efficiency of consumer choices, and vehicle attributes, formally,*

$$\frac{\bar{x}_{t+1}}{\bar{x}_t} = \Delta AT \times \Delta CE \times \Delta VA.$$

PROOF. Multiply the three components to verify that their product is $\frac{\bar{x}_{t+1}}{\bar{x}_t}$. $\square$

This frontier-based decomposition is similar to the decomposition of the Malmquist TFP measure in the context of production (Färe et al., 1994). However, an important difference here is that our decomposition

⁷Consumers may also drive more mileage as cars become more CO₂ efficient, but the driving behavior of consumers is not related to the average CO₂ emissions of new passenger cars.

measures the change in absolute scale (g/km) rather than in a unit-invariant index number. Therefore, our decomposition does not include any scale efficiency component as there is no need to measure the technical change relative to the constant returns to scale benchmark technology (cf. Ray & Desli, 1997; Färe et al., 1997, for a critical exchange on this matter). Another important difference here is that our decomposition defines the components based on the sales-weighted average CO₂ emissions, instead of each car model analogous to the traditional decompositions in productivity analysis where the entry and exit of evaluated units are often ignored (Olley & Pakes, 1996). Therefore, our decomposition allows the possibility of taking into account the change in popularity of car models.

3.2. Aggregation of Cohorts to the Fleet Level

We begin the aggregation by expressing the average CO₂ emissions of the new car fleet in year t as the weighted average of cohort average emissions

$$\bar{X}_t = \sum_h S_t^h \bar{x}_t^h = S_t^g \bar{x}_t^g + S_t^d \bar{x}_t^d \quad (8)$$

where the capitalized $\bar{X}_t$ denotes the fleet average CO₂ emissions in year t , the superscript $h = g, d$ is an index of fuel type (g and d represent the gasoline and diesel cohorts, respectively), and S_t^h is the market share of new passenger cars of fuel type h in year t .

Therefore, following the spirit of the traditional IDA approach (Ang & Zhang, 2000), the change in the fleet average CO₂ emissions from year t to $t + 1$ can be decomposed into two components associated with the change in average CO₂ emissions at the cohort level (termed ‘cohort-average change’) and the structural change in fuel mix. This decomposition can be expressed in a multiplicative form as

$$\frac{\bar{X}_{t+1}}{\bar{X}_t} = \Delta CC \times \Delta FM \quad (9)$$

where ΔCC and ΔFM denote the cohort-average change and the change in fuel mix, respectively.

There are multiple index techniques available to approximate the two components in Equation (9). According to Ang (2004), however, the logarithmic mean Divisia index method proposed by Ang & Choi (1997) (LMDI-II)⁸ is preferred for multiplicative decomposition over other indices (e.g., Laspeyres, Paasche, arithmetic mean Divisia). The LMDI-II method uses a logarithmic mean weight function (Törnqvist, 1935) to estimate the two components and thus gives a complete decomposition of the quantity being considered, i.e., leaving no residual (see Ang & Choi, 1997 for a formal proof).

Formally, the logarithmic mean weight function for cohort h from year t to $t + 1$ is defined as

$$\omega_{t,t+1}^h = \frac{L(\psi_{t+1}^h, \psi_t^h)}{\sum_h L(\psi_{t+1}^h, \psi_t^h)} \quad (10)$$

⁸There are two versions of LMDI: while LMDI-II specializes in multiplicative decomposition, LMDI-I (Ang & Liu, 2001) is developed for additive decomposition. See, e.g., Ang (2004); Wang et al. (2017), for further discussion on this matter.

where $\psi_t^h = \bar{x}_t^h n_t^h / \sum_h \bar{x}_t^h n_t^h$ is the CO₂ emissions share of cohort h in year t and function $L(\cdot)$ is the logarithmic mean. Then the measures of cohort-average change and fuel mix change are given by

$$\Delta CC = \prod_h \left(\frac{\bar{x}_{t+1}^h}{\bar{x}_t^h} \right)^{\omega_{t,t+1}^h} \quad (11)$$

$$\Delta FM = \prod_h \left(\frac{S_{t+1}^h}{S_t^h} \right)^{\omega_{t,t+1}^h} \quad (12)$$

By inserting Proposition 1 into Equation (11), we can rewrite Equation (9) as

$$\frac{\bar{X}_{t+1}}{\bar{X}_t} = \prod_h \left(\Delta AT^h \right)^{\omega_{t,t+1}^h} \times \prod_h \left(\Delta CE^h \right)^{\omega_{t,t+1}^h} \times \prod_h \left(\Delta VA^h \right)^{\omega_{t,t+1}^h} \times \Delta FM \quad (13)$$

where the first three terms on the right-hand side use the logarithmic mean weight function $\omega_{t,t+1}^h$ to aggregate the changes in available technology, carbon efficiency, and vehicle attributes, respectively, over different cohorts from year t to $t + 1$.

The above equation synthesizes the traditional IDA approach applied at the fleet level with the frontier-based decomposition analysis developed at the cohort level.⁹ This synthesis yields a decomposition of the change in the fleet average CO₂ emissions into the changes in available technology, carbon efficiency of consumer choices, vehicle attributes, and fuel mix. Properties of the new decomposition method are discussed in the next subsection.

3.3. Properties

Following Ang & Zhang (2000) and Zhou & Ang (2008), there are three desirable properties directly relevant to a meaningful decomposition method,¹⁰ as defined below:

- Factor reversal: multiplying all the decomposed components together yields exactly the aggregate ratio of change.
- Time reversal: each decomposed component estimated from year $t + 1$ to t is the reciprocal of that estimated from year t to $t + 1$.
- Zero-value robustness: zero values can be tolerated by replacing zeros with extremely small positive values.

⁹It is possible to replace the index decomposition part with a frontier-based approach where we can compare and aggregate the gasoline and diesel cohorts (see, e.g., Camanho & Dyson, 2006; Aparicio et al., 2017; Aparicio & Santin, 2018). This opens an interesting avenue for future research.

¹⁰Despite not being directly relevant here, for those who are concerned with the properties of productivity indices, see Althin (2001) for a list of the most usual tests for productivity analysis.

Note that the zero-value robustness property ensures the flexibility to extend the new decomposition method to incorporate carbon-free vehicles such as electric cars powered by renewable energy. The following Proposition demonstrates that our proposed decomposition satisfies all the three desirable properties (the proofs are given in Appendix A).

Proposition 2. *The decomposition of the average CO₂ emissions of a cohort stated in Proposition 1 satisfies the properties of factor-reversal, time-reversal, and zero-value robustness.*

The following Corollary confirms that the properties of the cohort-level decomposition carry over to the fleet level as well.

Corollary 1. *The decomposition of the average CO₂ emissions of the fleet stated in Equation (13) satisfies the properties of factor-reversal, time-reversal, and zero-value robustness.*

In addition, it is worth noting that since our decomposition takes the multiplicative form, a component contributes to decreasing (increasing) the average CO₂ emissions when the component is less than (greater than) unity.

3.4. Adjustment for Test Manipulation

Finally, we adjust the estimated decomposition by considering the discrepancy between type-approval and real-world CO₂ emissions of passenger cars.

Let the superscript asterisk denote the real-world CO₂ values. Formally, we can define the discrepancy in terms of the fleet average emissions in year t as $\bar{X}_t^*/\bar{X}_t$. The measure of the Test Manipulation component is then given by

$$\Delta TM = \frac{\bar{X}_{t+1}^*/\bar{X}_{t+1}}{\bar{X}_t^*/\bar{X}_t} \quad (14)$$

Taking Equations (13) and (14) together, we can express the change in the ‘actual’ fleet average CO₂ emissions from year t to $t + 1$ as

$$\frac{\bar{X}_{t+1}^*}{\bar{X}_t^*} = \underbrace{\Delta AAT \times \Delta TM}_{\text{Real technical change}} \times \Delta ACE \times \Delta AVA \times \Delta FM \quad (15)$$

where ΔAAT , ΔACE , and ΔAVA refer to the aggregate changes in available technology, carbon efficiency, and vehicle attributes, respectively.

Due to somewhat scattered empirical evidence, we assume for simplicity that the emissions discrepancy was identical for both gasoline and diesel cohorts. Thus, Available Technology would be the component that was offset to some extent by the change in the test manipulation.

4. Frontier Estimation

In the TFP literature, the components of the Malmquist index are typically estimated by deterministic data envelopment analysis (DEA), which is a classic OR tool. However, alternative econometric approaches are also available. We emphasize that our decomposition is applicable to any estimation method. In this paper we resort to convex nonparametric least squares (CNLS) (Kuosmanen, 2008), which can be interpreted as a generalized version of DEA (Kuosmanen & Johnson, 2010). The CNLS regression provides a consistent estimator for the emissions generating function f without the need to specify *a priori* the functional form but with stochastic noise explicitly taken into account (see, e.g., Kuosmanen et al., 2015, for further discussion).

It is important to emphasize that we estimate the emissions generating function f based on car models, i.e., Equation (2), and not based on individual vehicles, i.e., Equation (1), to avoid the influence of consumer choices or popularity of car models on our estimates. To estimate Equation (2), we only assume that f is a monotonic increasing and convex function. Further, we assume that ϵ_{mt} is a random variable with a zero mean and a finite variance, uncorrelated with the vector $\mathbf{y}_{mt}$. For a given cohort, the CNLS estimator of function f_t is obtained by solving the following quadratic programming problem (Kuosmanen, 2008)

$$\begin{aligned}
& \min_{\gamma, \alpha, \beta, \epsilon} \sum_{m=1}^{m_t} \epsilon_{mt}^2 \\
& s. t. \\
& f_t(\mathbf{y}_{mt}) = \alpha_{mt} + \beta'_{mt} \mathbf{y}_{mt} \quad \forall m \\
& x_{mt} = f_t(\mathbf{y}_{mt}) + \epsilon_{mt} \quad \forall m \\
& \alpha_{mt} + \beta'_{mt} \mathbf{y}_{mt} \geq \alpha_{kt} + \beta'_{kt} \mathbf{y}_{mt} \quad \forall m, k \\
& \beta_{mt} \geq \mathbf{0} \quad \forall m
\end{aligned} \tag{16}$$

where the first set of equality constraints specifies the emissions generating function f_t based on car models, the second set of equality constraints represents Equation (2), the third set of inequality constraints imposes convexity, and the fourth set of inequality constraints ensures monotonicity. Coefficients α_{mt} and β_{mt} represent the intercept and slope parameters that define the tangent hyper-planes to the estimated piece-wise linear frontier of f_t . They are specific to each car model m rather than being the same throughout the cohort. As such, the heterogeneity of different car models can be properly modeled. This is an advantage of the CNLS regression compared to linear regression models such as ordinary least squares. Further, α_{mt} is an indicator of the returns-to-scale property of each car model: car model m exhibits constant, decreasing, or increasing returns to scale in terms of CO₂ emissions when α_{mt} takes a value equal to, greater than, or less than zero, respectively. β_{mt} can be interpreted as the marginal CO₂ emissions of the vehicle characteristics $\mathbf{y}_{mt}$.

Under the assumptions of zero-mean of ϵ_{mt} and no correlation between ϵ_{mt} and $\mathbf{y}_{mt}$, the CNLS estimator of function f_t gives the expected CO₂ emissions of car model m in the cohort of year t given the vehicle

characteristics $\mathbf{y}_{mt}$, constituting an average-practice frontier. Note that CNLS is a consistent estimator of f_t if ϵ_{mt} has zero mean (Kuosmanen et al., 2015). Further, if ϵ_{mt} has a non-zero mean $\mu(t)$ that is time invariant, i.e., $\mu(t) = \mu(t + 1)$ for all t , then the constant $\mu(t)$ does not influence the decomposition. Note also that it is possible to apply the second stage of stochastic nonparametric envelopment of data (StoNED), which includes CNLS as the first stage (Kuosmanen & Kortelainen, 2012; Kuosmanen et al., 2015). However, this comes at the cost of imposing parametric distributional assumptions, which seems rather arbitrary. Therefore, in the present study we prefer to adhere to a fully nonparametric CNLS estimator and use the average-practice f_t as the benchmark technology.

A practical advantage of the proposed estimation approach compared to the classic DEA implementation of the Malmquist index concerns the possible infeasibility of observations of period $t + 1$ in period t . While in theory it is possible that the representative model in period $t + 1$ is infeasible in period t , in practice this is extremely unlikely to occur in our approach because we compare the average car model to the frontier estimated by all models.

Along this line of thought, we further find it promising to apply convex quantile regression (CQR) (Wang et al., 2014; Kuosmanen et al., 2015; Kuosmanen & Zhou, 2018) to estimate the components of the frontier-based decomposition, using, for example, the 90th or 75th quantile for all time periods. Although this would then involve a debatable choice of quantiles if different quantiles yield different decomposition results, the CQR approach might help to establish the impact of the choice of quantiles.

5. Application to the Finnish New Car Fleet

5.1. Data and Specification

In this section we apply the proposed decomposition to a unique data set that includes all passenger cars registered in Finland in October 2015.¹¹ The data set details registration information on every individual car in Finland, such as its classification, year, make, model, fuel type, total mass, engine power, and type-approval CO₂ value. Decomposing the change in the average CO₂ emissions of new passenger cars taken in use each year during the period of 2002–2014 enables us to quantify the driving factors behind the decarbonization of the Finnish passenger car fleet.

New cars registered each year during 2002–2014 were classified into two cohorts consisting of gasoline- and diesel-powered cars, respectively.¹² Recall that we estimate function f using data of car models rather than individual vehicles. Therefore, we identified subsets of identical new cars and classified them as a single car model. See Appendix B for a detailed description of the data preparation procedure.

¹¹The original data were retrieved from the Finnish Transport Safety Agency (Trafi) website: http://www.trafi.fi/en/information_services/open_data on 23 October 2015.

¹²As noted earlier, new cars powered by alternative fuels were rare during this time period, and were excluded from the analysis.

Regarding the specification of function f , the vehicle characteristics ($\mathbf{y}$) of car models that influence the type-approval CO₂ emissions (x) include two technical parameters, total mass (kg) and engine power (kW). These two technical parameters are widely used in the literature to characterize the capability of passenger cars to provide transportation services and amenities to consumers (e.g., Kok, 2013). Descriptive statistics of the three variables considered are reported in Table 1 for the gasoline and diesel cohorts in years 2002, 2008, and 2014. Note that the average CO₂ emissions decrease in both cohorts despite the notable increase in engine power and the modest increase in total mass. The average CO₂ emissions were somewhat lower in the diesel cohorts than in the gasoline cohorts, even though the diesel cars were on average heavier than gasoline vehicles.

To adjust our estimates for the well-known gap between the type-approval and on-road CO₂ emissions of passenger cars, we complement the official registration data with aggregate level estimates reported by Tietge et al. (2016). They summarize a variety of sources reporting emissions discrepancies observed in several European countries from year 2001 to 2015. Since there is no reason to prefer any of the sources, we make use of aggregate data based on all data sources to adjust the estimated decomposition.

Table 1: Descriptive Statistics of Gasoline and Diesel Cohorts in Years 2002, 2008, and 2014.

Year	CO ₂ Emissions (g/km)				Total Mass (kg)				Engine Power (kW)			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Gasoline Cohort												
2002	217.4	47.7	113	499	1,461.6	258.1	736	2,560	116.7	49.1	33	380
2008	196.2	47.2	103	495	1,472.4	264.0	825	2,684	126.0	63.0	40	471
2014	149.8	36.2	78	361	1,459.0	276.7	750	3,835	127.2	67.2	46	460
Diesel Cohort												
2002	189.4	41.3	86	340	1,665.9	297.6	805	2585	98.4	26.4	30	230
2008	180.3	42.0	88	333	1,717.1	343.6	845	3080	112.5	34.6	33	368
2014	138.8	35.0	86	295	1,719.0	359.7	730	2920	116.1	41.3	40	283

5.2. Empirical Results at the Fleet Level

In this subsection we report and discuss our empirical results for yearly fleets of new passenger cars, obtained by aggregating the gasoline and diesel cohorts as discussed in Section 3.2. The cohorts of gasoline and diesel cars will be examined in more detail in Section 5.3. For the sake of brevity, we use graphical illustrations to highlight important findings. Precise numerical estimates as well some additional results are reported in Appendix C.

Figure 3 illustrates how different driving factors affected the decarbonization of new passenger cars in Finland during years 2002–2014 by breaking down the cumulative change in the average (type-approval) CO₂

emissions of the Finnish new car fleet (green line) according to our proposed decomposition, setting year 2002 as the base year. Compared to the 2002 level, the average (type-approval) CO₂ emissions of the Finnish new car fleet (green line) decreased by 54.3 g/km by year 2014, with the average annual reduction rate of 2.9%. Note that the green line is just a re-scaled version of the line plotted for years 2002–2014 in Figure 1.

It is clearly evident from Figure 3 that the decrease in average emissions was primarily due to technical progress that occurred in the car models available in the market. Recall that the Available Technology component is calculated based on the emissions generating function f estimated for all models in period t without any sales weights, and therefore, this component is unaffected by the consumer choices. The cumulative contribution of the Available Technology component between 2002 and 2014 was a decrease of 55.5 g/km in the fleet average emissions.

Figure 3: Cumulative Contributions of Different Pathways to the Decarbonization of the Finnish New Car Fleet (g/km); 2002–2014.

Consider next the carbon efficiency of consumer choices. Recall that we assume ϵ_{mt} has zero mean, and thus by construction the average carbon efficiency of car models supplied by the industry does not change over time. At the level of individual new cars, however, the average ϵ_{it} need not have the zero mean: it depends on the popularity of CO₂ efficient models. It is apparent from Figure 3 that the watershed in the development of the Carbon Efficiency component occurred in 2008 when Finland introduced the CO₂-based vehicle registration tax. Before 2008, Carbon Efficiency was slightly deteriorating with a small increasing effect on the average emissions, but after 2008, the Carbon Efficiency component has systematically lowered the emissions. While improved Carbon Efficiency helped to decrease CO₂ emissions, the total impact of this pathway proves rather marginal.

Introduction of the CO₂-based vehicle registration tax in 2008 had a more notable impact on the development

of Vehicle Attributes (the red line). Note that before 2008 Vehicle Attributes had a positive contribution to the CO₂ emissions as increasing demand for heavier and more powerful vehicles almost completely offset the benefits of technical progress. In 2008 when the CO₂ tax was introduced, many Finnish consumers switched to smaller and less powerful cars. While the demand for vehicle attributes has somewhat increased after 2008, the slope of the increasing trajectory for the Vehicle Attributes component was clearly flatter after 2008 than prior to the introduction of the CO₂-based tax. Of course, the global economic crisis may have also influenced demand for cars around 2008, but in our view, the notable change in the slope of the Vehicle Attributes component reveals the permanent impact of the policy change that cannot be explained by a temporary shock.

Finally, we note that the trajectory of the Fuel Mix component was almost flat during the study period, indicating that the change in fuel mix simply contributed to maintaining the fleet average emissions rather than playing a decisive role in reducing the average emissions. This finding is further explained in the next subsection.

5.3. Decomposition Results for the Gasoline and Diesel Cohorts

We next examine the gasoline and diesel cohorts separately to gain some further insights. Figure 4 presents the cumulative changes in the components of our proposed decomposition for the gasoline and diesel cohorts. While the average CO₂ emissions of the diesel cohort were lower than that of the gasoline cohort in 2002, the emissions of the gasoline cohort decreased more rapidly during the study period, as indicated by the top-left panel of Figure 4. The decrease in CO₂ emissions can be largely attributed to the improvement in Available Technology, where the downward trajectory has a somewhat steeper slope in the case of the gasoline cohort.

Interestingly, the developments in the gasoline and diesel cohorts differ most remarkably in terms of the Carbon Efficiency (bottom left panel) and Vehicle Attributes (bottom right panel of Figure 4). Carbon Efficiency component of the diesel cohorts shows a rather consistent downward trend (interpreted as efficiency improvement) throughout the study period, whereas Carbon Efficiency component of the gasoline cohorts deteriorated prior to 2008, but then sharply decreased in 2008 and 2009, returning to an increasing trajectory after 2010. Therefore, it seems that the introduction of the CO₂-based vehicle registration tax had a sharper impact on Carbon Efficiency of gasoline-powered cars. This finding is explained by the fact that the owners of a diesel car in Finland must pay an additional yearly diesel tax of 300–1,000 euros, which implies that the diesel car is an economical choice for those consumers who drive more than 15–18 thousand kilometers per year (depending on the model and the fuel prices). Since the diesel cars are also generally more fuel efficient than the gasoline cars, the impact of the CO₂-based vehicle registration tax on the total use cost of a diesel vehicle over its entire life cycle is lower than that of a gasoline car.

In contrast, the introduction of the CO₂-based vehicle tax had a more notable impact on the Vehicle Attributes component of diesel cars. Note that increasing mass and power of both gasoline and diesel cars contributed to the increase of CO₂ emissions during the study period. However, the sharp increasing trend of

Figure 4: Cumulative Contributions of Different Pathways to the Decarbonization of the Gasoline and Diesel Cohorts; 2002–2014.

the Vehicle Attributes component of diesel cars experienced a sharp downward shift in 2008, and then resumed to an upward trend until 2012. In the gasoline cohort, the increasing trajectory of the Vehicle Attributes component turned to a decreasing trend since 2008. During the study period, the increase in the Vehicle Attributes component contributed to a cumulative growth of 11.2 g/km in the diesel cohort-average emissions, but only 1.7 g/km in the gasoline cohort-average emissions. We note that increasing popularity of heavier and more powerful diesel cars offset the increased market share and carbon efficiency of new diesel cars, which explains the rather marginal effect of the Fuel Mix component in Figure 3.

5.4. Adjustment for Test Manipulation

It is well-known that the official CO₂ emissions data used in the above analysis were subject to systematic test manipulation as car manufacturers exploited the outdated, unrealistic type-approval test procedure. Therefore, in this section we adjust the empirical decomposition for the test manipulation (ΔTM) based on the aggregate-level statistics reported by Tietge et al. (2016).

According to Tietge et al. (2016), the difference between the type-approval CO₂ emissions of passenger cars and the real-world CO₂ emissions expanded, on average, by 1.85% per year from 2002 to 2014. Consequently, the impact of technical progress on the fleet average emissions was to a large extent offset by the test manipulation, as shown in Figure 5. The cumulative contribution of the Available Technology component in reducing the fleet average emissions over the study period decreased from 55.5 g/km to 24.3 g/km. In other words, more than half of the estimated technical progress was due to test manipulation. Still, it is worth to emphasize that

Figure 5: Adjustment to the Change in Available Technology at the Fleet Level by Discrepancy Change; 2002–2014.

the contribution of the Real Technical Change component remains the most important pathway for decreasing the average CO₂ emissions of passenger cars even after adjusting the Available Technology component for Test Manipulation.

5.5. Total CO₂ abatement

We conclude this section by briefly examining the magnitude of the key pathways identified in the previous sub-sections on the CO₂ abatement at the aggregate level of the new passenger car fleet, taking into account the yearly sales of new passenger cars and the average mileage per vehicle. On average, 126.8 thousand new passenger cars per year were registered in Finland during the study period, with the yearly sales fluctuating between 96 and 153 thousand. Statistics Finland collects mileage data of passenger cars based on the yearly technical inspections data. The average yearly mileage of all passenger cars was 14 thousand km in year 2017, and this statistic has been stable over time. The average mileage was 11.3 thousand km in the gasoline cohort and 20.8 thousand km in the diesel cohort, respectively.

Combining the information of yearly sales and average mileage with our decomposition of the average CO₂ emissions of new passenger cars, we can estimate that technical progress in terms of the Available Technology component contributed to CO₂ abatement approximately 8 thousand metric tons per year, on average. This figure is based on the type-approval CO₂ emissions of passenger cars. If we adjust this figure for the test manipulation as in Section 5.4, then the real technical change contributed only 3.5 thousand tons per year to CO₂ abatement. We believe these aggregate figures are helpful to demonstrate the importance of technical progress in passenger cars in reducing the greenhouse gas emissions, but also the magnitude of the distortion due to the test manipulation.

It is interesting to compare and contrast the above estimates of the abatement impact of technical change with the impacts of the carbon efficiency of consumer choices and the demand for vehicle attributes. We note that improved carbon efficiency contributed CO₂ abatement the average of 0.2 thousand tons per year, which was more than offset by the increased CO₂ emissions due to vehicle attributes, amounting to 0.8 thousand tons average increase per year. These figures are considerably lower than the impact of technical progress, even if we adjust for the test manipulation based on estimates published in the literature. However, the importance of consumer choices for CO₂ abatement becomes more evident if we compare the contributions of carbon efficiency and vehicle attributes before and after 2008 when the CO₂-based vehicle registration tax was introduced. Recall from Figure 3 that the increased demand for vehicle attributes and deteriorating carbon efficiency almost completely offset the CO₂ reduction due to technical progress prior to 2008, whereas after 2008 the growth trajectories in Vehicle Attributes and Carbon Efficiency components came to a halt. Prior to 2008, the deteriorating carbon efficiency increased CO₂ emissions on average by one thousand tons per year, and the increased demand for vehicle attributes further increased CO₂ emissions by 3.7 thousand tons per year. After 2008, carbon efficiency has improved, which contributed to the decrease of CO₂ emissions on average by one thousand tons per year, and the lower demand for vehicle attributes further decreased CO₂ emissions by 1.3 thousand tons per year. Summing these numbers together suggests that the total impact of improved carbon efficiency of consumer choices and lower demand for vehicle attributes comes close to that of technical change.

Thus, how large was the abatement impact of the CO₂-based vehicle registration tax introduced in 2008? As the counter-factual, suppose the demand for vehicle attributes and carbon efficiency would have continued along their linear trend that prevailed prior to 2008 in the absence of the tax reform. Regressing the combined yearly contributions of the Vehicle Attributes and Carbon Efficiency components on a linear time trend and a structural break due to the tax reform, and multiplying the estimated coefficient of structural break with the yearly sales and average mileage of cars, we obtain as the estimated yearly impact of the tax reform 13.4 thousand tons per year. The estimated impact of tax policy is staggeringly high compared to the observed impacts of carbon efficiency and vehicle attributes, far exceeding the estimated impact of technical progress. Of course, we may debate if the linear growth in vehicle attributes is an appropriate counterfactual, and we must admit that the stagnation of the Finnish economy that followed the global economic crisis has obviously influenced the demand for new cars.

We stress that the main purpose of the above counterfactual discussion is to illustrate how the proposed decomposition and its individual components can be used in combination with time series econometrics and other techniques of economic impact assessment in order to empirically estimate policy impacts of interest to provide evidence-based policy support for decision makers.

6. Conclusions and Policy Implications

In this paper we have developed a new decomposition method to shed light on the driving factors behind the decarbonization of new passenger cars. Our decomposition offers three major benefits compared to previous works reviewed in Section 2. First, it systematically breaks down the change in the average CO₂ emissions of new passenger cars to components representing changes in the available technology, carbon efficiency of consumer choices, vehicle attributes, fuel mix, and test manipulation. Second, it combines insights from the traditional index decomposition analysis with a frontier-based decomposition. Estimating the technology frontier by convex nonparametric least squares allows us to handle stochastic noise without a need to assume *a priori* any particular functional form for the emissions generating function. Third, the proposed decomposition satisfies the desirable properties of time reversal, factor reversal, and zero-value robustness.

In the empirical part of this paper the proposed decomposition was applied to a unique register data from Finland in years 2002–2014 to quantify the driving factors behind the decarbonization of new passenger car fleet. Our results demonstrate that technical change was the most important pathway of decreasing CO₂ emissions, and technical progress in new cars remains the strongest driver even when we adjust for test manipulation. Our decomposition also helps to understand the impact of the CO₂-based vehicle registration tax that was introduced in Finland in 2008. While the tax had a rather modest effect on carbon efficiency of consumer choices, at least, it helped to slow down the increasing demand for heavier and more powerful cars.

The critical role of technological progress demonstrated by the Available Technology component of our decomposition clearly highlights the importance of the technical standards at the EU level. Strict emissions standards in such major markets such as the EU or the USA will influence car manufacturers around the world. In contrast, as far as the car technology is concerned, the possibilities of a single EU member state such as Finland are very limited. However, an individual state can considerably influence the consumer choices by national policy instruments such as taxes and subsidies. While Finland met the EU target of decreasing CO₂ emissions in 2015, more ambitious policy measures are needed. Achieving further decrease in the CO₂ emissions will have to heavily rely on technical progress, but also employ effective policy instruments to incentivize consumers to choose carbon efficient models and counter the demand for heavier and more powerful cars. We believe the empirical decomposition of the decrease in the average CO₂ emissions of new passenger cars, adjusted for the empirical evidence concerning test manipulation, helps to put the relative contributions of better technology and the CO₂-based vehicle registration tax to appropriate perspective. Such empirical evidence is critically important going forward as Finnish policy makers are planning and designing future policy instruments.

Today electric vehicles and plug-in hybrids are becoming increasingly popular in many countries, including Finland. However, electric vehicles are not a panacea; it is important to take the CO₂ emissions from electricity generation into account. While our empirical analysis focused on gasoline and diesel cars, which were the dominant cohorts during the study period, our decomposition can readily accommodate other fuels and energy

sources. Indeed, it would be interesting to apply the proposed decomposition to investigate how the introduction of electric and other low emission vehicles contributes to decarbonization of the new passenger car fleet not only in Finland, but also in other countries for which comparable data are available.

Besides electric cars, there are many other interesting avenues for future research. The proposed method could be extended to model the dynamics of the entire fleet of vehicles, not only the new passenger cars. While new cars entering the fleet is an important pathway of decarbonization, also the exit of highly polluting vehicles from the fleet could be influenced by policy measures. And although passenger cars are the most important source of CO₂ emissions from road transportation, there is significant potential to reduce emissions from trucks, vans, and buses. Beyond road transportation, the proposed decomposition can also be adapted to other forms of transportation and/or other environmental variables.

Regarding the limitation of the present study, it is somewhat restrictive to study the average CO₂ emissions (g/km) of a cohort without taking into account the mileage. We acknowledge that a mileage-weighted average would be a better measure of a cohort, but as yet, our data collected from the Trafi database do not provide a reliable measurement of the mileage. This is a challenge for future research. Further, we suggest the use of CNLS, StoNED, or CQR in the frontier-based decomposition analysis and the Malmquist index as a fascinating avenue for future research.

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Appendix A. Proofs of Proposition 2 and Corollary 1

Proposition 2. *The decomposition of the average CO₂ emissions of a cohort stated in Proposition 1 satisfies the properties of factor-reversal, time-reversal, and zero-value robustness.*

PROOF. Recall that the decomposition of the average CO₂ emissions of a cohort stated in Proposition 1 is

$$\frac{\bar{x}_{t+1}}{\bar{x}_t} = \Delta AT \times \Delta CE \times \Delta VA$$

Consider first the factor-reversal property. If the change of an aggregate indicator Z from year t to $t+1$ can be decomposed into multiplicative components ΔC_j ($j = 1, \dots, k$), then the factor-reversal property is formally

stated as

$$\frac{Z_{t+1}}{Z_t} = \prod_{j=1}^k \Delta C_j \quad (\text{A.1})$$

This property ensures that the decomposition is exhaustive and does not leave any residual term that cannot be properly explained; in other words, the components ΔC_j together completely explains the change Z_{t+1}/Z_t . It follows from Proposition 1 that the proposed decomposition satisfies the factor-reversal property.

Consider next the time-reversal property. Note that each component ΔC_j is defined as the change from year t to $t + 1$. Suppose now that we reverse the direction of change and calculate the components as changes from year $t + 1$ to t , denoted by ΔC_j^R ($j = 1, \dots, k$). Then the time-reversal property is formally defined as

$$\Delta C_j = \frac{1}{\Delta C_j^R} \quad \forall j \quad (\text{A.2})$$

By reversing the direction of change in each component of our proposed decomposition, it is easy to verify that the decomposition stated in Proposition 1 satisfies the time-reversal property.

Finally, we consider the zero-value robustness property. This property is important here because it ensures the possibility to extend our proposed decomposition to incorporate carbon-free vehicles such as electric cars powered by renewable energy. In this sense, the zero-value robustness property is formally defined as the following:

Definition 1. If the CO₂ emissions (x) of a cohort are zero and replaced by a small positive number (ζ) to avoid division by zero, then the decomposition still yields meaningful results.

If the CO₂ emissions of a cohort are zero and replaced by the number ζ , the technology frontier of the carbon-free cohort would be a plane that approaches the plane made up of the axes of total mass and engine power. Consequently, the contributions of components Available Technology, Carbon Efficiency, and Vehicle Attributes are simply unity, indicating these components make no change to the cohort average emissions as the decarbonization of the cohort has been achieved. $\square$

Corollary 1. *The decomposition of the average CO₂ emissions of the fleet stated in Equation (13) satisfies the properties of factor-reversal, time-reversal, and zero-value robustness.*

PROOF. The LMDI-II decomposition of the fleet average emissions stated in Equations (9–12) is summarized as follows:

$$\begin{aligned} \frac{\bar{X}_{t+1}}{\bar{X}_t} &= \Delta CC \times \Delta FM \\ &= \prod_h \left(\frac{\bar{x}_{t+1}^h}{\bar{x}_t^h} \right)^{\omega_{t,t+1}^h} \times \prod_h \left(\frac{S_{t+1}^h}{S_t^h} \right)^{\omega_{t,t+1}^h} \end{aligned} \quad (\text{A.3})$$

According to Ang & Choi (1997) and Ang & Zhang (2000), the above decomposition possesses the three desirable properties. Inserting Proposition 1 into the expression of ΔCC in Equation A.3 yields

$$\Delta CC = \prod_h \left(\Delta AT^h \right)^{\omega_{t,t+1}^h} \times \prod_h \left(\Delta CE^h \right)^{\omega_{t,t+1}^h} \times \prod_h \left(\Delta VA^h \right)^{\omega_{t,t+1}^h} \quad (\text{A.4})$$

Taking the properties of the LMDI-II method and Proposition 2 together, it is obvious that the decomposition of ΔCC satisfies the three desirable properties.

Since the decomposition of the average CO₂ emissions of the fleet stated in Equation (13) synthesizes Equations (A.3–A.4), Corollary 1 is a consequence of Proposition 2 and the properties of the LMDI-II method. $\square$

Appendix B. Description of Data Preparation

The original Trafi data contain detailed information on a total of 5,103,966 registered vehicles in Finland as of October 2015. The model-specific data used in the empirical analysis has been pre-processed as follows:

1. From all passenger cars (types M1 and M1G) based on Trafi’s vehicle classification, we formed yearly cohorts of new cars taken in use during the period 2002–2014 (i.e., the new car fleet from year 2002 to 2014).
2. 1.7% of passenger cars had missing values for at least one of the three variables of interest (CO₂ emissions, total mass, and engine power). These vehicles were excluded from further analysis.
3. The yearly fleets of new cars were divided into the gasoline and diesel cohorts according to the fuel type. Note that hybrid electric cars in which gasoline or diesel is the primary fuel and the electricity is generated on board (rather than plug-in) were considered here as gasoline or diesel cars, respectively.
4. Individual vehicles were sorted to the corresponding car models using the Pivot Table function of Microsoft Excel, which also allowed us to count the frequency of each model.
5. A number of cases were identified where two or more models with a different name had exactly identical values for the three variables of interest. To avoid redundancy, we merged such car models as a single model if they belonged to the same brand or automobile group (e.g., Skoda and Volkswagen, Citroen and Peugeot), of course, keeping track of their relative frequency.

Table B.1 reports the numbers of new cars and models within the Finnish new car fleet during the period 2002–2014. It is evident from the table that there was a remarkable rise in the number of cars per model (i.e., average frequency of models) between 2002 and 2014, particularly for the diesel cohort. This rise was mainly due to the fact that, many of the same models were considered different in the earlier years simply because they had very slight differences in names or technical parameters, but such cases were greatly reduced with an improvement in the quality of Trafi’s vehicle data entry.

Table B.1: Numbers of New Cars and Models in the Finnish New Car Fleet; 2002–2014.

Year	New Car Fleet			Gasoline Cohort			Diesel Cohort		
	Cars	Models	Cars/Model	Cars	Models	Cars/Model	Cars	Models	Cars/Model
2002	115,337	4,020	29	95,327	2,648	36	20,010	1,372	15
2003	147,295	4,489	33	121,255	2,840	43	26,040	1,649	16
2004	146,219	4,519	32	118,845	2,725	44	27,374	1,794	15
2005	152,808	4,885	31	122,665	2,890	42	30,143	1,995	15
2006	153,235	4,812	32	116,835	2,688	43	36,400	2,124	17
2007	134,996	4,898	28	91,321	2,588	35	43,675	2,310	19
2008	145,978	4,262	34	71,921	2,313	31	74,057	1,949	38
2009	96,004	2,869	33	50,412	1,485	34	45,592	1,384	33
2010	114,931	2,625	44	65,420	1,322	49	49,511	1,303	38
2011	127,269	2,317	55	72,204	1,156	62	55,065	1,161	47
2012	109,140	2,106	52	66,293	1,060	63	42,847	1,046	41
2013	101,600	1,944	52	64,066	985	65	37,534	959	39
2014	103,668	1,758	59	63,465	915	69	40,203	843	48
Total	1,648,480	45,504	–	1,120,029	25,615	–	528,451	19,889	–
Mean	126,806	3,500	36	86,156	1,970	44	40,650	1,530	27

It is worth noting that the number of inequalities in problem (16) rises as a quadratic function of the number of observations, and as such the computation of problem (16) using standard quadratic programming algorithms and solvers will become a serious issue when the data size reaches beyond 300 (Kuosmanen et al., 2015). This is more so for the present study since the number of observations (i.e., car models) ranges from 843 to 2,890 across different cohorts and years (see Table B.1).

To address this issue, we resorted to a penalized method for the computation of CNLS estimators proposed by Keshvari (2017). This algorithm is capable of handling several thousands of observations; the largest sample tested in Keshvari (2017) consists of 2,500 observations. Note that the algorithm entails the use of optimization solvers like Mosek or Cplex. By using the Mosek solver in the MATLAB environment on a laptop running Windows 7 (CPU: Intel Core i5, 1.6 GHz; RAM: 8 GB), we solved the quadratic programming problem (16) for each cohort in each year and obtained the CNLS estimate of the emissions generating function f . The execution time of the estimation process is reported in Table B.2.

Table B.2: Execution Time in Seconds of the Estimation Process

Cohort	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Gasoline	103,238	136,663	122,671	153,259	109,485	104,452	62,189	11,062	1,574	763	703	604	485
Diesel	1,915	16,612	21,931	33,418	43,843	99,004	52,793	1,544	1,640	1,170	766	550	431

Appendix C. Additional Tables and Results

Table C.1: Decomposition Results for the Gasoline and Diesel Cohorts; 2002–2014.

Period	$\bar{x}_{t+1}^g/\bar{x}_t^g$	ΔAT^g	ΔCE^g	ΔVA^g	$\bar{x}_{t+1}^d/\bar{x}_t^d$	ΔAT^d	ΔCE^d	ΔVA^d
2002–03	0.9911	0.9870	0.9990	1.0052	1.0062	0.9917	0.9956	1.0191
2003–04	1.0051	0.9841	1.0104	1.0108	1.0054	0.9881	1.0065	1.0109
2004–05	0.9935	0.9852	0.9997	1.0088	1.0047	0.9919	0.9982	1.0148
2005–06	0.9945	0.9854	1.0017	1.0075	1.0123	0.9919	0.9952	1.0254
2006–07	0.9926	0.9695	1.0087	1.0150	0.9737	0.9805	0.9996	0.9934
2007–08	0.9320	0.9740	0.9805	0.9759	0.9131	0.9771	0.9872	0.9466
2008–09	0.9435	0.9650	0.9727	1.0051	0.9825	0.9671	1.0003	1.0155
2009–10	0.9488	0.9568	1.0062	0.9855	0.9506	0.9602	0.9796	1.0106
2010–11	0.9613	0.9466	1.0110	1.0045	0.9665	0.9318	1.0119	1.0250
2011–12	0.9640	0.9572	1.0053	1.0017	0.9696	0.9490	1.0071	1.0145
2012–13	0.9460	0.9533	0.9917	1.0006	0.9543	0.9621	1.0013	0.9907
2013–14	0.9677	0.9800	0.9978	0.9897	0.9674	0.9688	1.0006	0.9979
<i>g</i> -mean								
2002–07	0.9953	0.9822	1.0039	1.0095	1.0004	0.9888	0.9990	1.0127
2007–14	0.9518	0.9618	0.9949	0.9946	0.9575	0.9594	0.9982	0.9998
2002–14	0.9697	0.9703	0.9987	1.0008	0.9751	0.9715	0.9986	1.0051

Table C.2: Decomposition Results for the Finnish New Car Fleet; 2002–2014.

Period	$\bar{X}_{t+1}/\bar{X}_t$	ΔAAT	ΔACE	ΔAVA	ΔFM
2002–03	0.9935	0.9878	0.9984	1.0075	0.9999
2003–04	1.0048	0.9848	1.0097	1.0109	0.9997
2004–05	0.9954	0.9865	0.9994	1.0099	0.9998
2005–06	0.9979	0.9868	1.0003	1.0114	0.9996
2006–07	0.9864	0.9725	1.0062	1.0090	0.9991
2007–08	0.9191	0.9753	0.9832	0.9639	0.9944
2008–09	0.9628	0.9660	0.9861	1.0101	1.0007
2009–10	0.9496	0.9583	0.9941	0.9968	1.0000
2010–11	0.9635	0.9402	1.0114	1.0133	1.0000
2011–12	0.9659	0.9538	1.0061	1.0070	0.9996
2012–13	0.9488	0.9567	0.9954	0.9967	0.9996
2013–14	0.9679	0.9757	0.9988	0.9928	1.0004
<i>g</i> -mean					
2002–07	0.9956	0.9837	1.0028	1.0097	0.9996
2007–14	0.9538	0.9608	0.9964	0.9971	0.9992
2002–14	0.9710	0.9703	0.9990	1.0023	0.9994

Table C.3: Adjusted Results for the Finnish New Car Fleet; 2002–2014.

Period	ΔTM	Adjusted ΔAAT	$\bar{X}_{t+1}^*/\bar{X}_t^*$
2002–03	1.0225	1.0100	1.0158
2003–04	1.0159	1.0005	1.0208
2004–05	1.0069	0.9933	1.0023
2005–06	0.9880	0.9750	0.9859
2006–07	1.0197	0.9917	1.0059
2007–08	1.0147	0.9896	0.9326
2008–09	1.0179	0.9833	0.9800
2009–10	1.0257	0.9829	0.9740
2010–11	1.0310	0.9693	0.9934
2011–12	1.0124	0.9656	0.9779
2012–13	1.0398	0.9947	0.9865
2013–14	1.0279	1.0030	0.9949
<i>g</i> -mean			
2002–07	1.0105	0.9940	1.0061
2007–14	1.0242	0.9840	0.9768
2002–14	1.0185	0.9882	0.9889

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