# Energy Efficiency in the Passenger Transport Sectors of Germany and the Netherlands

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# Energy Efficiency in the Passenger Transport Sectors of Germany and the Netherlands

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## Abstract

This thesis examines, quantifies, and ranks the influence of various factors of activity, structure, and intensity on passenger transport energy consumption to assess the progression of energy efficiency. For this purpose, four logarithmic mean Divisia index (LMDI) decomposition analyses are conducted employing continuous data from 2000 to 2016, one each for the land passenger transport sector and one for the LDV sector. In particular, the question of to what extent gross efficiency gains can be attributed to technical efficiency improvements versus behavioral factors is answered. The analyses on land passenger transport solely feature gross energy intensity, whereas the subsequent analyses on LDV energy consumption further decompose gross efficiency into fuel share, average occupancy, and technical energy intensity. Beyond that, population factors are introduced to obtain results normalized per capita. The results of the full decomposition analyses highlight that technical energy efficiency enhancements are always substantially offset by behavioral factors, such as passenger activity per capita or LDV average occupancy. What is more, modal split is of the least significance even though it holds an enormous energy savings potential. However, passenger transport energy consumption per capita decreases throughout all scenarios. Ultimately, a successful policy response must address behavioral and personal utility factors since measures exclusively focused on technical energy efficiency improvements are likely to induce rebound effects.

# Table of Contents

# I. List of Figures

# II. List of Tables

# III. List of Abbreviations

**EEI** Energy Efficiency Indicator

**GHG** Greenhouse Gas

**HEV** Hybrid Electric Vehicle

**HDV** Heavy Duty Vehicle

**IDA** Index Decomposition Analysis

**IEA** International Energy Agency

**LDV** Light Duty Vehicle

**LMDI** Logarithmic Mean Divisia Index

**PHEV** Plug-in Hybrid Electric Vehicle

**pkm** Person Kilometer

**PLF** Passenger Load Factor (pkm/vkm)

**PMF** Passenger Move Factor (vkm/pkm)

**SDA** Structural Decomposition Analysis

**TFC** Total Final (Energy) Consumption

***ViZ*** *Verkehr in Zahlen (traffic in numbers)*

**vkm** Vehicle Kilometer

# 1. Introduction

In the face of climate change, our societies are confronted with the generational task of curbing GHG emissions in order to halt global warming. While the political debate is often dominated by decarbonization concerns (i.e., the switch to lower or no carbon fuels), energy efficiency often falls short in this discussion. And yet, the IEA (International Energy Agency) views energy efficiency as the first fuel of all energy transitions. (IEA, 2019) The benefits of energy efficiency are numerous. Improved energy efficiency not only lowers consumer spending, which may lead to a redirection of consumer spending to other (potentially more value-creating) economic sectors, but also reduces import dependency of resource-poor countries, thereby increasing energy security. (IEA, 2013, 2018, 2019) After all, non-consumed energy due to energy efficiency is carbon-free by default, and associated externalities with energy use and production decline accordingly. (IEA, 2018) However, the overall rate at which technologies and processes become less energy intensive is slowing, and structural and behavioral factors are further limiting gross efficiency gains. When technologies become less energy intensive, this often leads to rebound effects, i.e., purchased devices or machines become larger or more powerful or are simply used more, thus offsetting technical efficiency gains. Therefore, barriers to energy efficiency play a decisive role in translating technical efficiency gains into ultimately less energy consumed. (Craglia and Cullen, 2019; IEA, 2013, 2019) According to the IEA, of all energy sectors, the transport sector comprises the biggest potential for cost-efficient energy intensity improvements, accounting for around 27 % of global final energy consumption in 2010. (Craglia and Cullen, 2019; IEA, 2013, 2018)

This thesis decomposes drivers and impediments to energy consumption of passenger transportation in Germany and the Netherlands from 2000 to 2016. This happens by decomposing energy consumption into factors of activity, structure, and energy intensity by using a Logarithmic Mean Divisia Index (LMDI) approach. In doing so, an additional population factor is introduced to exclude fluctuations in population. The countries and time periods to be studied are selected primarily for reasons of data quality and availability. Four index decomposition analyses (IDA) are performed. Two per country, including one focusing on the land passenger transport sector and one on the LDV (light duty vehicle) sector itself. Behavioral patterns are of utmost importance for energy efficiency outcomes, especially in the passenger transport sector, which is deeply embedded in our everyday lives and strongly shaped by our everyday decisions. Generally, there are few studies on decomposing energy demand in the passenger transport or LDV sector, and none do both. Jiang et al. decompose GHG emissions of the US passenger and freight transport sectors (Jiang et al., 2022), and Jennings et al. decompose energy consumption and related emissions of the Irish passenger transport sector (Jennings et al., 2013). For the LDV sector, there are more examples, such as Dennehy and Ó Gallachóir, who decompose energy and emissions of the Irish LDV sector (Dennehy and Ó Gallachóir, 2018), Craglia and Cullen decomposing LDV energy consumption in the UK (Craglia and Cullen, 2019) and (Papagiannaki and Diakoulaki, 2009) decomposing LDV emissions of Greece and Denmark (with it the only example of a two-country study). This IDA study is unique in the sense that two similarly developed neighboring countries are analyzed, allowing us to draw conclusions based on a related benchmark. Moreover, in contrast to the mentioned studies, this thesis decomposes energy consumption of the passenger transport sector and the (therein included) LDV sector with respect to the base year but also interjacent years to account for interim fluctuations. Besides that, all energy units are in J to facilitate inter-fuel comparisons, and data on vehicle fuel economy most commonly stems from type approval ratings which must be corrected for real-world consumption (Craglia and Cullen, 2019; Dennehy and Ó Gallachóir, 2018), whereas this study employs associated data in a top-down approach.

The primary aim of this thesis is to investigate the evolution of energy efficiency in the land passenger transport sector and determine the relative contributions of the underlying factors by the example of Germany and the Netherlands. After outlining the background and scope, the first objective is to develop a comprehensive understanding of the concept of energy efficiency and its implications in the context of passenger transport. This includes exploring the various dimensions but also drivers and barriers of energy efficiency and examining its relevance to sustainable development goals and environmental considerations. Additionally, it involves delving into the concept and expressiveness of energy efficiency indicators and

developing an understanding of how the underlying data is collected and ultimately validated. This theoretical review is consummated by the theory of decomposition analysis, also involving a review of variant decomposition approaches. After deducing the applied methodology, underlying efficiency indicators, and addressing concerns of data quality and sources, the LMDI IDA is applied to discern the various factor contributions to land passenger transport energy consumption. Given the limitations in the available primary data for passenger land transport, a secondary analysis concerning the LDV sector (representing the majority share in passenger transport energy use) is conducted, aiming to further decompound gross energy intensity into technical and usage efficiency and to explore the implications of an altering fuel share. In the course of the analysis, historical trends of the underlying indicators are analyzed, aiming to identify patterns and interrelations.
The central question here is:

How did energy efficiency evolve in the land passenger transport sectors between 2000 and 2016, and, more importantly, to what extent can the energy efficiency gains be attributed to technical energy efficiency improvements versus behavioral factors?

This question seeks to ascertain the relative influence of technological advancements and changes in passenger behavior on energy efficiency to infer the possible existence of a rebound effect. Based on existing literature and prior research in the field, the hypothesis that there is a rebound effect, with technical efficiency gains offset first and foremost by increasing passenger activity, will be tested.
By achieving these objectives and addressing the central question, this thesis aims to contribute to the understanding of energy efficiency dynamics in the passenger transport sector and provide valuable insights for decision-making processes to promote sustainable and energy-efficient practices.

# 2. Theoretical Review

## 2.1. Relevance of the Transport Sector and Scope of the Thesis

The transport sector accounts for all energy consumed transporting people or goods. (IEA, 2018) Energy used in transport infrastructures – such as illumination in train stations or airports – should not be included and attributed to the tertiary sector. Therefore, the definition of the transport sector is quite different in energy consumption statistics from its definition in economic statistics. (ODYSSEE-MURE, 2020) In 2018, transport accounted for roughly one fifth of worldwide energy demand, with an especially high reliance on oil, which supplies 92 % of its energy needs and is equivalent to 56 % of global oil consumption. (IEA, 2018) Transport activities are usually classified by the infrastructure type, thereby road, rail, air, water, and pipeline and further by vehicle types. Moreover, there is a distinction between passenger and freight transportation. So-called active modes of transportation – such as walking and cycling – are not considered here since they do not consume any commercial energy source even though they may account for sizable amounts of transport activity. (ODYSSEE-MURE, 2020)

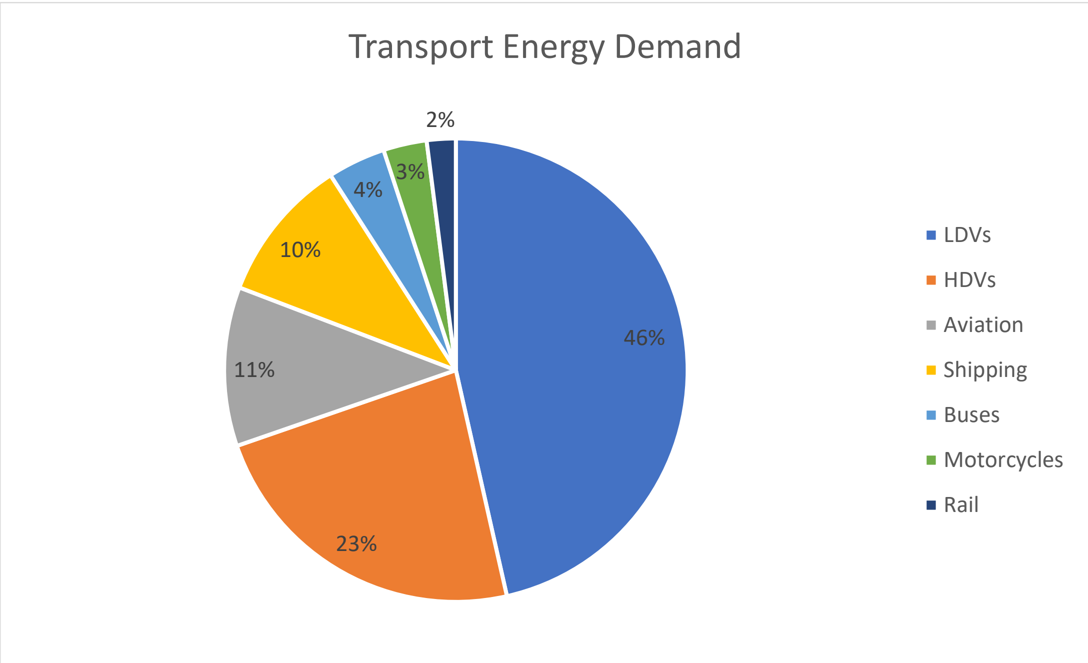


**Figure 1: Worldwide Transport Energy Demand across Modes, adaptation from (IEA, 2018)**

As it can be seen in **Figure 1**, the road transport sector – comprised of LDVs (light duty vehicles, such as cars, vans, or light-duty trucks), HDVs (heavy duty vehicles, which include medium- and large-sized trucks), buses and motorcycles (which include two- and three-wheelers) – is of predominant importance with an aggregated share of 76 % in worldwide transport energy demand.

The recent decades have been characterized by a steady increase in demand for transport activities, driven – amongst other things – by an increase in population sizes and disposable incomes, accompanied by relatively low fuel prices and technology advances. Between 2008 and 2018, the distance traveled by passenger light-duty-vehicles (PLDVs) increased by 3.1 % per year on average and the quantity of freight moved by road grew by 3.4 % annually (expressed in ton-kilometers). In contrast, the distance traveled by airplane passengers grew by 5.8 % per year.

Across scenarios developed by the IEA, demand for passenger and good mobility is expected to rise substantially – with a doubling of traveled distance of PLDVs until 2050. However, the transport sector offers a variety of energy-saving potentials, with its current high reliance on low-efficiency internal combustion engines. This includes friction reduction, vehicle weight reduction, downsizing, propulsion electrification, or intermodal shift. (IEA, 2018)

When looking at passenger transport on a country level, international transport (such as cross-border traffic or international marine and aviation) is excluded. Therefore, domestic transport comprises all transport activities and associated energy consumption subject to the country's territory, performed by vehicles registered in and outside of the country while also accounting for fuel quantities purchased abroad (i.e., fuel tourism). (IEA, 2014a)

This thesis looks at the land passenger transport sectors of Germany and the Netherlands between 2000 and 2016. The selection was made largely owing to data quality and availability. Due to insufficient data quality, motorcycles are excluded from the analyses, which correspond to roughly 1.5 %  (of LDV energy consumption in both countries. (IEA, 2020a) Notwithstanding, domestic passenger transport (including motorcycles, navigation, and aviation) accounts for most of transport energy consumption compared to (domestic) freight transport. In Germany, it stands for around 72 % and in the Netherlands for around 66 % of total domestic transport energy consumption, with little variance over the years. Land passenger transport (excluding motorcycles), on the other hand, accounts for around 95 and 98 % of passenger transport energy demand in Germany and the Netherlands. (IEA, 2020a; ODYSSEE-MURE, 2023) Therefore, the land passenger transport sector is a significant driver in energy demand and, thus, a powerful lever to enhance economy-wide energy efficiency. For 2000, 2009, and 2016, the passenger land transport sector (i.e., LDVs, busses, and passenger trains) accounts for roughly a third, 39 % and 41 % of TFC of oil products[1] and around 16 % of total TFC in all periods in Germany. The entire domestic transport sector is responsible for around 24 % of Germany's TFC. In the Netherlands passenger land transport stands for 29, 28 and 27 % of TFC of oil products and around 10 % of overall TFC. Here, entire domestic transport is responsible for approximately 18 % of the country's TFC. (IEA, 2020c) Notably, passenger transport energy consumption per capita only decreased slightly in the observed periods, with a 3.3 % decrease in the Netherlands and 1.7 % in Germany. At the same time, passenger kilometers per capita decreased by 6 % in the Netherlands but increased by 11.9 % in Germany. (IEA, 2020a) In both countries, land passenger transport is clearly dominated by LDVs, representing approximately 95 % of energy consumption and respectively 84 % (Germany) and 83 % (Netherlands) of passenger kilometers. (IEA, 2020a) Whereas both are subject to a slightly positive trend in Germany, in the Netherlands, the share in energy increased whereas the share in passenger activity decreased.

At first glance, one notices that LDVs are dominant but comparably significantly less energy efficient than buses or trains, as LDVs are responsible for much more of the total energy consumption than passenger activity. Also, we can see that land passenger transport is overly reliant on crude oil products, and its energy consumption per capita reduced only slightly. These presented metrics provide us with a first understanding of the economic importance of passenger transport and underlying trends. However, to provide sound policy-relevant insights, we must first understand the term energy efficiency itself to identify key drivers of passenger energy consumption after that.

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[1] excluding Biofuels

## 2.2. Efficiency in the Passenger Transport Sector

### 2.2.1. The Role of Energy Efficiency

Energy efficiency is an intuitively understandable yet hard-to-clearly define term. (IEA, 2014b) To illustrate this, one may think of two passenger cars that cover the same arbitrary distance. Car A is carrying one person and has a specific fuel consumption of $5\ \mathrm{l/100\ km}$, and the other car B is carrying four persons with a specific fuel consumption of $10\ \mathrm{l/100\ km}$. If we look at car A, it obviously uses less energy to cover the same distance. Is car A thus more efficient than car B? If we take the technical or mechanistic perspective, car A is more efficient as it uses less fuel to cover the distance. However, if we see this from a service- or overall- perspective and look at the fuel the cars use to move one person, car A uses $5\ \mathrm{l/100}$ person kilometers ($\mathrm{pkm}$). Car B, however, as four passengers occupy it, only uses $2.5\ \mathrm{l/100}$ $\mathrm{pkm}$. In this case, a general statement regarding efficiency is hard to make, as car A could be more efficient in the latter terms if more passengers occupied it. In accordance with the efficiency indicators used by the $\mathrm{ODYSSEE\text{-}MURE}$ project, we can speak of technical efficiency in the first case, as it does not consider usage behavior, whereas we can speak of gross or overall efficiency in the second case, as it does take usage behavior into account. (ODYSSEE-MURE, 2020) Therefore, human behavior plays a decisive role in energy consumption. The human dimension can catalyze and amplify technology-based energy savings but can also cancel out technical energy savings. (IEA, 2014a)

Historically, the relevance of energy efficiency started to grow in the 1970s due to the prevailing oil crisis, with oil prices reaching all-time highs. Back then, the primary purpose was to reduce energy demand to import fewer energy carriers. Once the oil crisis fainted, so did global awareness of energy efficiency. Especially since 2010, alongside climate change awareness, the political and market perception of energy efficiency has experienced a revival. (Chlechowitz et al., 2022)

For the energy supply of an economy to be overall sustainable, the three dimensions of the so-called energy policy triangle must be fulfilled. Namely, Security of Supply, Environmental Sustainability, and Energy Affordability. In real politics, this often becomes an energy trilemma, as rarely all three dimensions can be satisfied simultaneously. If we think of the rapid expansion of decentralized renewable electricity production, this indeed adds to improved energy security and environmental sustainability. However, due to often necessary electricity infrastructure expansions, this may lead to an increased cost of electricity, thus impairing the dimension of affordability. This holds true for many other energy policy interventions. Improved energy efficiency reduces energy consumption, while providing the same amount of energy service, and thus it is recognized as the cheapest and cleanest energy source. There is a growing recognition that energy efficiency improvements are of the cheapest, proven, and readily available means of achieving the goals of the energy policy triangle. (Chlechowitz et al., 2022; IEA, 2013, 2014a)

Energy efficiency as a market

As with other energy resources, energy efficiency activity happens as part of a market, with forces on the demand and supply side. In its most basic form, investments are made in energy efficiency, leading to avoided energy use. However, this market is more diffuse and localized, as it is not traded as a commodity in the same way as traditional fossil fuels, like oil or gas. Still, there are parallels, yet it is much more difficult to directly measure markets for energy efficiency, as otherwise available information, such as trade volumes, extraction rates, or exchange-traded prices, are unavailable. The market is as diffuse as consumption patterns themselves. Describing the energy efficiency market in terms of drivers of supply and demand helps reveal its key factors and shows how interactions lead to investments and outcomes. Here, the broader economic environment is particularly sensitive to energy prices, and government policy interventions play a predominant role.

A cost-effective supply of energy efficiency can be defined as investment opportunities where the sum of benefits (i.e., avoided energy consumption) outweigh the investment costs. Therefore, the saved energy can be described in terms of physical energy quantities not consumed. Hereby the used physical units are interchangeable and depend on the context. Those avoided units of energy can be equated or directly substituted with supply-side energy commodities. Therefore, energy efficiency improvements can be quantified as a resource that provides the same level of service while avoiding a portion of the energy otherwise consumed without the efficiency improvement. Hence, energy efficiency is a domestically produced energy resource with a mostly local market. However, it is important to account for transformation and transmission losses when comparing final consumption (demand side) with primary energy (supply side).

When assessing potential returns on investments, further complicating factors are the differences between annual and cumulated avoided energy demand and the respective current and expected future energy prices. An upfront investment in a car with improved fuel economy – for instance – will produce an annual quantity of avoided fuel use over the car's lifetime. Therefore, understanding the lifetimes of a technology is crucial for energy efficiency investments. This implies similar considerations as with an investment decision for an electricity powerplant. A number of investment opportunities may be arranged in cost curves, which may be more or less economically viable at today's energy prices. Expressing energy efficiency's supply this way can usefully present the potential for avoided energy use in an economy. At an aggregate level, this can be considered as reserves of avoided energy consumption, analog to the world's stated reserves of coal or oil. The economic reserves expand when the cost of producing a unit of saved energy use diminishes or the cost of another energy supply option increases.

However, the energy efficiency demand/supply relationship is characterized by various market and behavioral failures, widely recognized to deter demand and thus investment. Still, demand is driven by the four factors of price, policy, consumer preferences, and multiple benefits in particular. Energy prices can be identified as a clear driver. Nonetheless, the market response often lags behind price movements by a considerable amount. Government policies can stimulate demand for energy efficiency and are driven by various considerations, such as improving trade balances, meeting energy security objectives, or greenhouse gas emission reduction. As a driver of demand, policies are especially relevant when price signals are ineffective. Generally, these policies aim to adjust the relative cost of more efficient options and attract investment. This primarily takes place as direct regulation (e.g., minimum energy efficiency standards), economic incentives (i.e., taxes or subsidies), provision of information (e.g., through efficiency labels), and promoting R&D efforts. Next to price and policy, consumer preferences and multiple benefits are considered as main drivers of demand for energy efficiency. Energy consumers encompass a wide range of economic and societal backgrounds, and consumption decisions can be influenced by personal preferences or utility factors in addition. Consumers seeking more energy services from a limited level of energy supply or consumers subject to limited energy access are also of importance. (IEA, 2013)

Multiple Benefits of Energy Efficiency

Moreover, saving energy while maintaining the level of energy service is accompanied by a myriad of non-energy benefits that greatly exceed the value of the avoided energy itself. Those include benefits of economic, environmental, and socio-economic nature. Hence, the associated benefits can aid in meeting various policy objectives. Improved energy efficiency contributes to enhanced energy affordability, reduced environmental damage, improved well-being and health, stronger trade balances, improved national competitiveness, and enhanced energy security and resilience at last. Beyond that, it can support international public goods, such as climate change mitigation efforts, and generally reduce resource consumption. With that said, multiple benefits can act as key drivers of demand for energy efficiency itself by altering how the returns of energy efficiency investments are valued. To exemplify this, politicians may pay more attention to the fact that improved energy efficiency lowers public expenditure on health or GHG mitigation efforts rather than reducing consumer expenditure on energy.

Prevalently, energy professionals measure the outcome – or benefits – of energy efficiency interventions in purely energy terms, even though a monetary value can be applied to those non-energy benefits. Quantifiable non-energy benefits of reduced energy demand include, amongst others, the financial benefit of not expanding electricity generation and transmission infrastructure to meet the else additional demand or redirecting consumer spending to other economic sectors due to decreased expenditure on energy. However, including those various factors substantially increases the complexity of assessing the value of avoided energy consumption. (IEA, 2013)

Barriers to Energy Efficiency

Energy-smart behaviors, practices, and choices play a fundamental role in allowing for additional sources of energy savings while ensuring these savings' persistence into the future. As mentioned earlier, numerous behavioral and market failures discourage energy efficiency demand and investment. On that account, these human and market dimensions are mainly responsible for the well-known gap between potential and actual levels of energy efficiency. Conversely, energy savings achieved from technical energy performance improvements can be canceled out by negative behavioral factors, which is commonly referred to as rebound effect. If a car is more fuel efficient, the variable driving costs per km decrease accordingly, which may encourage consumers to drive more. Companies may also utilize the capital saved on energy to expand production, or households may use more energy services to improve their living standards. Thus, the rebound effect is not necessarily a net-negative effect, as it may have a net-positive impact if the resulting improvement in living standards, health, and productivity is considered in addition to decreased energy savings. Yet, a substantial share of potential energy savings may be achieved through low-cost or no-cost behavioral changes rather than requiring more complex investment decisions. (Chlechowitz et al., 2022; IEA, 2014a; Laitner, J.A., Ehrhardt-Martinez, K. and McKinney, 2009; Ugarte et al., 2016) The entirety of those barriers are, in principle, mechanisms that inhibit a decision or behavior which is energy efficient and economically efficient at the same time, and the subject matter of non-realized investments in energy efficiency with a positive net present value is commonly referred to as "energy efficiency gap". (Chlechowitz et al., 2022; Hausman, 1979; Sorrell et al., 2006) In the academic discussion on this matter, several schemes to categorize those barriers emerged. Mostly, taxonomy follows behavioral, organizational, and economic (or market) barriers. Other approaches distinguish between market and non-market barriers, which is particularly of interest for policymakers as the identification of market failures helps justify policy interventions to overcome such. (Brown, 2001; Chlechowitz et al., 2022; Hirst and Brown, 1990; Ordonez et al., 2017; Sorrell et al., 2006)

Market barriers

Market failures tend to extenuate price signals and can increase an energy-saving technology's perceived costs and risks. Behavioral preferences, such as avoiding a perceived inconvenience, can discourage the uptake of new technology even in cases where financial benefits are clear. Altogether, this is considerably hampering the full potential of cost-effective energy efficiency improvements. In the literature, four main market failures have been widely identified. (IEA, 2013; Ryan et al., 2011) These include imperfect information, asymmetric information, the principal/agent problem, and externalities. Since energy efficiency comprises a wide range of products and services, accurate and sufficient information on energy performance can be difficult to obtain easily and at low cost. Additionally, it can be hard for consumers to separate energy efficiency from other attributes of a product or service. Thus, optimal investment decisions are often impaired by information not produced or provided in a sufficient manner by the market. (IEA, 2013) It could be demonstrated in studies about the impact of efficiency labels that consumers quickly adopt the most efficient technology when properly informed about appliance efficiency. (IEA, 2014a)

Information failure also occurs when parties to a transaction have access to different levels of information on the subject of the transaction. Typically, the manufacturer may know more about the actual energy performance of his product, or energy suppliers may withhold information on future supply risks or costs unknown to consumers. A principal/agent problem comprises a market failure encompassing split incentives and asymmetric information at once. A good example is the relationship between the landlord (principal) and the tenant (agent), as they are subject to misaligned responsibility and authority regarding energy consumption and efficiency investments. This may also arise in firms due to organizational arrangements, such as different budgets for operational energy costs and capital investments in energy equipment. Further, energy consumption and generation impose a cost on society and decrease social welfare. When the causer does not bear the costs, and those are thus not involved in his private cost function, this results in higher energy consumption – and thus lower energy efficiency – than socially desirable. (IEA, 2013)

<u>Non-market barriers</u>

On the other hand, there are non-market failures, which help further understand the energy efficiency gap. Those can be of financial, organizational, or behavioral kind. Financial non-market barriers comprise financial access, hidden cost, heterogeneity, and risk and uncertainty. As investments in energy efficiency are typically characterized by high upfront costs, access to external capital is often of relevance. One impeding factor is potentially high interest rates, and similarly to the beforementioned market failures, the relationship between debtor and lender may be characterized by information asymmetries on the performance and thus credit risk of the investment. Within companies, such investments may be perceived as less attractive due to their relatively long payback period. Beyond potential hidden costs, such as costs for administration, finding information, seeking capital, and installing the new technology, but also opportunity costs – i.e., when the perceived energy services of the more economical technology are inferior, such as slower acceleration of a more fuel efficient car – may be hidden to the observer but not to the investor. (Chlechowitz et al., 2022; Gillingham and Palmer, 2013; Schleich, 2009) Moreover, consumers are heterogenous and thus have different preferences, capital costs, and expected use of the energy efficient good or service. Hence, a more energy efficient technology may be cost-efficient for most consumers, but not all. Therefore, it is essential to recognize this when designing policies, measures, and products. (Cagno et al., 2012; Chlechowitz et al., 2022; Gillingham and Palmer, 2013) Investment decisions are generally associated to some extent with risks and uncertainty. In the context of energy efficiency, those especially lie in the uncertainty about future energy prices, technological risk, and uncertainty about future regulation. If future energy prices lie below a certain threshold, the investment may prove unviable. Similarly, the more efficient technology may prove to be more unreliable or may incumbent higher maintenance costs. On top of that, uncertainty about future regulation may increase the option value, and thus the investment may not be materialized in anticipation of future grants or subsidies. (Chlechowitz et al., 2022; Schleich, 2009; Thollander et al., 2010)

Organizational barriers mainly lie within the distribution of power and the culture in an organization (such as a company). Here, divisions responsible for energy topics may lack power which in turn leads to deficiencies in the implementation of energy efficiency measures. This is also strongly influenced by the company's corporate culture.

Conversely to the basic premise of neoclassical economics, consumers – be they individuals or companies – are not always rational decision-makers that strictly choose, based on all information available, the optimal solution that maximizes their utility and, thus, profit. When a consumer is faced with a decision to procure a technology or service with enhanced energy performance, several behavioral backgrounds are involved. Behavioral and organizational economics suggest that the assumed rationality of an agent is impaired by inattentiveness and cognitive limits, which may lead to inadequate processing of information or biases. This phenomenon is referred to as bounded rationality and suggests that individuals would rather satisfy than optimize their decisions by relying on heuristics or rules-of-thumb to simplify decision-making processes. Hence, opportunities for increased energy efficiency may be neglected even with present access to perfect information and incentive structures. This may partly account for the betimes relatively low priority conceded to energy efficiency when facing a consumption or investment decision. For instance, consumers may overvalue the price or delivery time of a car while largely ignoring its life-cycle cost.

For the consumer, it too plays a role from where and in which form the information on the subject of the decision comes, as people tend to be selective about attending to and assimilating information. In doing so, the form and design of information plays a vital role in the receiver assimilating and remembering the information. Moreover, potential distrust and incredibility may arise depending on the provider of the information. Relevant factors here are the nature of the information provider, as well as past experiences and the mutual relationship. Generally, information is considered more trustworthy when it stems from contacts within the own social and professional network, which may hold a partial explanation for the often very influential role of consultants and sectoral organizations. (Chlechowitz et al., 2022; Sorrell et al., 2006; Thollander et al., 2010)

Beyond this, personal values play a role in decision-making as well. Values may not present an inherent barrier to energy efficiency; however, values play an underlying role in the context of energy conservation measures. Of particular relevance here are environmental concerns, moral commitments, and cooperativeness, which can serve as reliable predictors for the implementation of low-cost energy saving measures, but this relationship weakens with the cost of the measure increasing. Similarly, the personal values of higher-level decision-makers in a company may reflect in an increased sensitivity to energy efficiency opportunities and vice versa. (Chlechowitz et al., 2022; Sorrell et al., 2006; Stern and Aronson, 1984) Ultimately, individuals and companies often prove to be plainly reluctant to move from the status quo. A well-known example of this phenomenon is the studied consumer behavior in the electricity market. Even when there are lots of tariffs to choose from in the liberalized European end-user electricity market – with corresponding money-saving opportunities – many consumers are content staying with their supplier rather than switching to a new one. Consumer inertia tends to get enhanced with an increasing number of potential choices and increasing risk and uncertainty. In a study on the Swiss residential sector, it was demonstrated that increased uncertainty about future energy prices paradoxically increases the preference for the status quo compared to investments in improved energy efficiency. (Alberini et al., 2013; Chlechowitz et al., 2022; Hartman et al., 1991)

To conclude, policy and price are two of the most important drivers for creating market signals that influence demand for energy efficiency investments. Beyond that, energy prices are just one of the factors influencing the intensity of energy consumption, and its precise relationship with energy efficiency outcomes is not straightforward. Reasons are – amongst others – inertial effects in the economy, slow turnover of capital stock, and general delay between price effects and induced innovation. Policy interventions can address market failures and technical barriers, along with behavioral and organizational barriers that may reinforce existing market failures. Regulation, information provision, and economic instruments often must be combined to overcome particular barriers facing energy efficiency. (Birol and Keppler, 2000; IEA, 2013; Popp, 2002; Ryan et al., 2011)

### 2.2.2. Assessing Energy Efficiency

As established in the previous chapter, relatively higher energy efficiency can be defined as delivering the same level of energy services while using less energy. A common way to observe to what extent energy is efficiently used is the use of indicators or energy efficiency indicators (EEI). An indicator can be said to be any of various statistical values that provide an indication, be it an absolute value, a ratio, or other compounded values. (IEA, 2014a) Fundamentally, EEI help demonstrate that one thing is more energy efficient than another or that the degree of energy efficiency of something changed over time. Therefore, EEI can be expressed in absolute units, in ratio terms, or as percentages, whereas ratio terms are most commonly used. The usual composition of ratio terms is with energy consumption as numerator and activity data as denominator, analog to energy intensities. In other cases, the inverse is used, such as liters per 100 kilometers with cars. (IEA, 2014b)

EEI have multiple objectives. They organize information and analyze interactions among economic and human activity, energy consumption, and emissions. (IEA, 2014a) Therewith, they help understand trends and thus provide market insights. They can aid in benchmarking (e.g., for cross-country comparisons) and monitoring of targets and the impact of policy measures. In this way, EEI can help create policy roadmaps for the future, improve information dissemination, and help to measure the multiple benefits of energy efficiency. (ODYSSEE-MURE, 2020) In doing so, indicators have different levels of aggregation, such as the whole transport sectoral energy intensity (e.g., energy consumption per passenger kilometer over all traffic modes) or the average unit consumption per kilometer of gasoline cars as examples of high and low aggregation. (IEA, 2014b)

Information from energy balances is often readily and widely available and thus well-suited to develop aggregate indicators. Those reveal high-level developments in energy consumption in simple terms and therefore provide a general idea of trends in energy consumption. Their usefulness is limited, however, as they can generate misleading results when not sufficiently contextualized. Many other possible factors, such as activity and structural variables, can have significant influences on aggregate EEI. Hence, aggregate indicators are useful to describe trends but cannot explain the trends observed. For instance, if we look at the energy consumption of all buses in a country, it shows us that the overall efficiency of buses in that country is changing, but a decrease does not necessarily imply an improved energy efficiency from a technical viewpoint. It could just have been that there are now fewer buses operating, with nevertheless more energy consumed in relation to the individual bus; or that the average bus’s activity (i.e., kilometers traveled) was decreasing, but not the specific energy consumption. Therefore, more detailed data is required to grasp the key drivers of energy consumption and thus to better assess the progress in energy efficiency to provide policy-relevant analysis. In a generalized way, EEI consider three main external factors to describe the links between human and economic activities and energy consumption. Those are measures of activity (such as the volume of passenger transport), measures of structure (such as changing modal shares in transport), and measures of energy intensity (generally the energy consumption per one unit of activity). (IEA, 2014a, 2014b)
Indicators can be arranged into a hierarchy – or pyramid – with data requirement increasing alongside disaggregation level, as visualized in **Figure 2**.

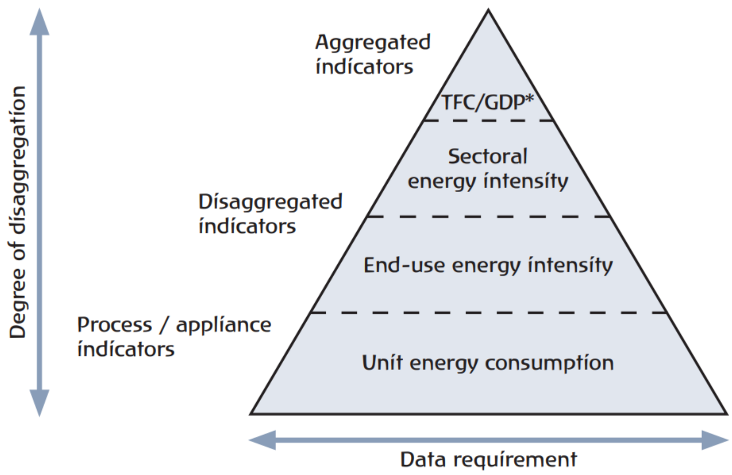


**Figure 2: Energy indicator pyramid, adaptation from (IEA, 2014b)**

This hierarchy shows how detailed changes at the lowest level (which may be the result of policy, technological progress, structural changes, or behavioral change) are linked to an indicator of higher order, showing how the former affects the latter. By this means, more aggregate changes in energy consumption can be better explained in terms of its components, and it thus aids in choosing the adequate level of depth of the performed analysis.

However, with more disaggregated EEI – next to increasing data requirement – the complexity of reaggregating the data to a higher-level increases as well. Having said this, descending the indicator hierarchy provides better measures of energy efficiency with regard to a specific sector/sub-sector, end-use, technology, or process. Associated with the respective energy intensities, there are activity and structural variables. The latter is necessary to weigh the respective intensities while forming the aggregate. When we conflate this information with economic and demographic data, we can already identify factors behind improving energy efficiency, but also factors that restrain it. Notwithstanding, it is also possible to develop $CO_2$ indicators where the same objectives and limitations apply as with indicators devoted to analyzing energy efficiency.

Each indicator has its purpose and limitations in what it can explain. Providing an accurate picture requires a set of several indicators that together deliver a strong basis for policymaking. Therefore, it is important to choose which indicators to give priority to. Indicator selection is based on the type and quality of data available, the resources available, and ultimately on the policy question sought to be answered.

Beyond that, selecting and developing indicators is only the first step in analyzing the context of energy use in a specific sector or country and in drawing initial conclusions on how to interpret the influence of past trends on future development.

Ultimately, understanding to what extent technical energy improvements have been (or have not been) responsible for the observed changes in final energy intensity in a sector or country is one of the most important issues from an energy policy perspective. This is mostly done using a decomposition approach, which separates and quantifies the impact of changes in activity, structure, and other exogenous factors. (IEA, 2014a) The theory and applications of decomposition analyses will be further elaborated in section **2.3.** of this thesis.

### 2.2.3. Energy Efficiency in the Passenger Transport Sector and Expressiveness of Data

How to get from energy balances to meaningful EEI

As already delineated in paragraph **2.1**., in the context of energy balances and EEI, the transport sector refers to the energy consumed solely for transporting people and goods, thus passenger and freight transport. Accordingly, energy consumed within transport infrastructure or fuels used for other reasons (such as off-road use, use in stationary engines, pipeline transport, or military purposes) is excluded and attributed to the respective economic sectors. Even so, the transport activity considered here is not linked to any specific economic activity or (sub)sector. Moreover, only transport activity using a commercial energy source is considered here. Consequently, so-called active modes of transportation – such as walking or cycling – are excluded, even though they may account for sizable amounts of transported passengers. For the analysis of individual countries, only transportation within national borders is considered, further excluding energy consumption from cross-border traffic and international aviation and marine bunkers. At the level of national energy balances, transport is generally disaggregated into four sub-sectors as per the type of infrastructure: road, rail, domestic aviation, and domestic navigation. For the sake of perspicuity, in this thesis, the term sub-sector is used for the higher level of aggregation (e.g., road or rail), and mode or vehicle type for the lower level of disaggregation (e.g., LGV or bus), as each sub-sector is characterized by a number of different modes and vehicle types. Further, the distinction between passenger and freight transport within each sub-sector is of utmost importance, as respective activity and energy consumption are driven by very different factors in those two segments. (IEA, 2014a, 2014b, 2020b)

In the collection of data and development of energy balances, it is inherently intricate to attribute energy consumption, as well as activity data to a single country. This holds especially true considering that international transport is a significant contributor to global transport energy consumption and emissions, against the background of the ubiquity of free cross-border flow of people and goods in the European Union across open borders. This gets further aggravated by the widespread phenomenon of fuel tourism, where motorists refuel in adjacent countries since fuel prices vary across borders, mainly owing to different levels of fuel excise duty. Due to considerable fuel price differentials, fuel tourism has visible effects, leading to national consumption statistics (based on fuel sales or taxation) not matching national activity data. The common practice applied by statisticians to enable cross-country comparability of energy balances is to include consumption of foreign vehicles on the country's territory and to exclude consumption of nationally registered vehicles abroad while simultaneously correcting the amount of consumed energy for fuel tourism. Common methods for this are cross-border traffic estimation practices, which typically rely on counting vehicles crossing the border and interviewing drivers at service stations. Estimating the extent of fuel tourism is additionally supported by collecting and comparing fuel price data across countries.
Despite all this, vehicle activity data –mainly gathered through odometer reading during regular vehicle safety inspections and national surveys – includes the activity of nationally registered vehicles abroad but excludes the activity of foreign vehicles on the territory. A common assumption lies in the two volumes compensating for each other. However, in reality, this is not necessarily correct. Possible explanatory factors for cross-border traffic are differentials in income, prices, industry production, and tourism between the countries. Therefore, to have a more accurate match between national activity and energy use data, kilometers traveled on the

national territory by foreign vehicles, and kilometers traveled abroad by domestic vehicles would have to be estimated with the aid of other data sources, such as statistics on tourism for passenger transport. However, such data does not always exist; if it does it may not have a harmonized methodology from one country to another. (IEA, 2014b)

Energy Efficiency in Passenger Transport

Coming from data acquisition and processing in the overall transport sector in composing EEI, we now talk about further disaggregation and sources of data in the context of passenger transport - according to the scope of this thesis defined in section 2.1. - and about which indicators to use to comprehensively examine the influence of the three established main external links between human and economic activity and energy consumption.

As established earlier, passenger transport includes the movement of people within the sub-sectors of road, rail, water, and air, while road and rail are of special interest here, standing for land passenger transport. Therefore, passenger transport by air or water is disregarded. Disaggregation in the road sub-sector usually happens by powered two- to four-wheelers (i.e., powered road vehicles not exceeding 400 kgs), passenger light-duty vehicles (LVDs, i.e., vehicles carrying up to eight persons, such as cars, minivans, SUVs, and private use pickup trucks, but also special purpose vehicles such as rental cars, motor homes or ambulances) and buses (ranging from minibuses, designed to carry more than eight persons, to coaches). Passenger trains may be further disaggregated by vehicle type (such as trams or high-speed trains) or scope of transport activity (i.e., urban, regional, or long-distance rail). A further disaggregation into fuel type can be performed for each vehicle type. With this, trains may run on electricity, diesel, or steam, and road passenger vehicles may run on gasoline, diesel, electricity, or others, such as CNG, LNG, or biofuels.

However, the level of disaggregation provided by national statistics depends on the structure of passenger transport in each country and, ultimately, on the availability of detailed data and resources available to develop indicators based thereon. Owing to its prominent role in passenger activity and energy consumption, data and indicators concerning the road sub-sector are typically more sophisticated than for other sub-sectors. The following analyses build on the disaggregation of the land passenger transport sector into passenger LDVs, buses, and trains, in line with the classifications stated above. Powered two- to four-wheelers are excluded. This is mainly due to poor data quality and a relatively low significance for activity and energy use in the countries considered. Therefore, when referring to the passenger transport sector, this aligns with the aforementioned delimitations. (IEA, 2014b)

Frequently used Indicators

When we now look at trends in passenger transport energy consumption, those are driven by a myriad of influencing factors. Among those are changes in the size and density of population, changes in land-use sprawl, transport infrastructure, travel patterns, disposable income, vehicle ownership and occupancy rates, as well as consumer preferences and average fuel economy. (IEA, 2014a) Depending on the availability of data, the structure of the looked-at (sub-)sector, and the question to be answered, one may build very disaggregated indicators (such as the energy consumption per passenger kilometer for each vehicle type) or stay at a level which may be too aggregated to entail meaningful information for energy efficiency analysis, despite providing information on the considered sector, such as the share of buses in total passenger transport consumption. Similar to other end-use sectors, EEI on passenger transport can be defined using a hierarchical or pyramidal approach. Here as well, the lower on the pyramid, the more disaggregated energy and activity data is required. In its guide on fundamentals on statistics for the development of EEI (IEA, 2014b), the IEA arranges indicators into three levels of aggregation. Indicators on level one encompass absolute values and percentage shares, whereas lower-level indicators consist of ratio terms.

At the most aggregated level – on top of the pyramid – indicators can provide first clues to the absolute and relative importance of passenger transport, and the relative reliance on various fuels. This can be expressed with respect to the overall economy, within passenger transport, or with regard to the overall transport sector. Even though those are not indicators of energy efficiency in the classical sense, they could be relevant to assess to what extent passenger transport may be relevant for potential energy savings and simply to gain a first grasp of the subject matter.

Level two indicators, by contrast, comprise energy intensities of yet superordinated nature. Three forms of intensity are here of relevance. We can look at energy consumption per passenger kilometer ($\mathrm{pkm}$), vehicle kilometer ($\mathrm{vkm}$), or per GDP/capita over the entirety of passenger transport. Having $\mathrm{pkm}$ or $\mathrm{vkm}$ as a denominator more closely relates to energy efficiency, representing ratios between energy consumption and activity data. Therefore, those are to be preferred. Yet, in the absence of better data, trends in GDP per capita are commonly used to estimate energy trends in passenger transport. Trends in energy intensity with regards to $\mathrm{pkm}$ are influenced by the technical energy efficiency of the respective transport modes, as well as by the share of those modes in a particular country (as different traffic modes are characterized by different passenger capacities). In other words, considering $\mathrm{pkm}$ takes usage efficiency into account. However, technical energy efficiency developments (also known as fuel economy) are not directly measurable as the relative importance of each mode is embedded into the indicator and, thus, hard to decompose without explanatory data. In contrast, expressing energy intensity per $\mathrm{vkm}$ provides insights into the technical efficiency but leaves out usage behavior. Combining energy intensities per $\mathrm{pkm}$ and $\mathrm{vkm}$, however, overcomes the core limitations of both and delivers a more wholesome picture, which allows for determining the passenger load factor or occupancy rate (i.e., the average number of passengers per vehicle, which can be calculated by dividing $\mathrm{pkm}$ by $\mathrm{vkm}$). Nonetheless, given the various influencing factors, no final conclusions can be drawn as to where efficiency improvements are achievable or more political focus is required. Similarly, results may be misleading when comparing different countries due to potentially hidden developments. Among those are the modal split, LDV ownership rate, but also population density, and public transport network. (IEA, 2014a, 2014b, 2020b)

Ideally, sound and informative EEI should be developed at the third level, featuring further disaggregation by sub-sector and preferentially by passenger mode/vehicle type. Once again, energy intensities involving pkm or vkm are most appropriate here. These could address subsectors (such as rail or road as a whole), make the distinction between individual and collective transport across sectors, extend to vehicle types, or even distinguish by the type of service provided (e.g., urban or inter-city service for collective transport or personal, public, or commercial ownership for LDVs) or a combination of type and category. In general, a higher level of disaggregation (by vehicle type) is recommended for the road sub-sector than for rail. Sub-sector intensities for rail are already helpful in assessing transportation policy options. Reasons therefore are the higher heterogeneity among road vehicles, as LDVs – for instance – generally have a much higher energy intensity per pkm than buses, owing to the much lower passenger capacity. Hence, the relative share of LDVs and buses may significantly impact road energy intensity. On that score, a differentiation between LDVs and buses is regarded as the minimum, which is generally performed by countries developing detailed indicators for road transport. Nonetheless, further disaggregation may be desirable or even required depending on the country's structure of road transport and, crucially, the availability of data and resources. One could include two- and three-wheelers (which are of higher importance in developing nations), distinguish between passenger cars and light trucks (which is particularly relevant in North America), or distinguish by fuel types (which may yield further insights against the background of increasing shares of diesel LDVs in European countries).

As a result, we can say that passenger transport energy consumption per pkm and vkm, decomposed by mode/passenger vehicle type are among the most expressive EEI to evaluate the energy efficiency within passenger transport. This allows us to compare different intensities across countries, indicating changes in driving conditions. Energy per pkm is helpful to assess the overall system efficiency (if specified at a detailed enough level), taking usage behavior into account, what also allows for – e.g. – evaluating programs that promote carpooling. However, important structural changes may still be hidden with limited disaggregation level, and there are still influential factors unrelated to energy efficiency, such as changing vehicle characteristics and features (e.g., increasing average vehicle tare weight or stronger motorization). On the other hand, looking at energy per vkm, assessing fuel economy on a vehicle level is more relevant to assess policies aiming at improving the technical energy efficiency of vehicles, as it is not influenced by vehicle occupancy. Notwithstanding, when deepening an indicator's detail resolution (i.e., disaggregation), more specified data is required for both the energy consumption and the respective activity, which in turn substantially increases the task's complexity.

Next to energy efficiency, there are numerous factors affecting passenger transport energy consumption that can provide vital information to better assess macroeconomic drivers of energy consumption. Among those are passenger travel activity, modal shares, car ownership, and annual vehicle mileage. Travel activity can provide insights into consumer trends in transport or provide a benchmark to understand the prospective evolution of travel. Furthermore, data on the modal split provide qualitative information on activity trends and on how a change in activity reflects in energy use. After all, modal shifts can also be thought of as measures of energy efficiency, given the substantial differences in energy intensity on a pkm basis across travel modes. Moreover, car ownership figures help explain the often observed increase in car travel and at the same time provide a sound basis for projecting future trends, whereas the combination with annual kilometers per vehicle allows assessing changes in travel patterns by providing useful qualitative information on activity trends. Combining both can even serve as a partial explanation for changing LDV occupancy factors. Overall travel patterns and kilometers per vehicle – and thus passenger load factors – are influenced by many diverse factors. Among them are the age profile of traffic participants, the number of vehicles per household and household size, disposable income, the flexibility of working and leisure activities, geographic characteristics, and local transport policies or the local availability of alternative modes of transport, respectively. For car ownership and travel activity, it is also worth examining the correlation between GDP and/or population size. Nevertheless, as with EEI, the actual informative value is ultimately related to the degree of disaggregation and, thus, the availability of detailed information. (IEA, 2014a, 2014b)

Data behind the indicators

After having understood the delineations, explanatory power, but also limitations of passenger transport energy and activity data – and thus indicators – at the national level, it is now time to clearly define utilized indicators and to discuss how the underlying data are collected, how we obtain them, and what steps need to be taken to ensure data are substantive enough to make a decent cross-country comparison. After all, the key to establishing sound transport indicators is to ensure that boundaries and definitions match between activity and energy data. A major challenge for cross-country comparisons lies within the often non-harmonized data collection methods for transportation activity data. Any the less, to adequately capture the three main drivers of passenger transportation energy demand (activity, structure, and energy intensity), we need energy and activity data (therewith $\mathrm{pkm}$ and $\mathrm{vkm}$) broken down by the total sector, by sub-sector, and ideally by vehicle type/transport mode. In addition, it is useful to have data on population size, GDP, and vehicle stock or annual mileage. (IEA, 2014b) For clarity, **Table 1** below summarizes all indicators used on a country level with the associated definitions. Further indicators are derived from these.

**Table 1: Definition of Utilized Indicators**

| Indicator | Definition |
|---|---|
| $TFE_{i,t}$ | Total final energy consumption [TJ] of traffic mode i in year t. |
| $pkm_{i,t}$ | One passenger kilometer ($\mathrm{pkm}$) represents the movement of one passenger over one kilometer. Therefore, $\mathrm{pkm}_{\mathrm{i,t}}$ is the total distance traveled by all passengers in the year t, summed up for all vehicles of type i. |
| $vkm_{i,t}$ | One vehicle kilometer (vkm) represents the movement of one vehicle over one kilometer. Therefore, $\mathrm{vkm}_{\mathrm{i,t}}$ is the total distance traveled by all vehicles of type i in year t. |
| $mileage_{i,t}$ | $\mathrm{mileage}_{\mathrm{i,t}}$ refers to the average distance performed of each vehicle of type i in year t. |
| $PLF_{i,t}$ | $\mathrm{PLF}_{\mathrm{i,t}}$ refers to the average number of passengers per vehicle of type i in year t. |
| $Stock_{i,t}$ | $\mathrm{Stock}_{\mathrm{i,t}}$ refers to all active (registered) vehicles of type i in year t. |
| $POP_t$ | $\mathrm{POP}_{\mathrm{t}}$ refers to the total population in year t. |
| $GDP_t$ | $\mathrm{GDP}_{\mathrm{t}}$ refers to the GDP in year t in constant 2015 USD. |

The relationships summarized in equations **E1** and **E2** must hold to ensure data consistency.

$$vkm_{i,t} = Stock_{i,t} \times mileage_{i,t} \quad \textbf{(E1)}$$

$$pkm_{i,t} = vkm_{i,t} \times PLF_{i,t} \quad \textbf{(E2)}$$

Therefore, pkm can increase either due to an increased length of the average trip or due to more passengers per vehicle on average.

Finding some kinds of data is undoubtedly easier than others when searching for data. This holds for both energy and activity data. As already outlined, the difficulty level in composing data increases alongside the degree of disaggregation. When compiling energy and activity data, there are generally four commonly applied methodologies: administrative sources, surveying, modeling, and measuring. All come with specific strengths and weaknesses. Beyond that, reporting countries often combine several methods to build proper sectoral indicators. Given the inherent complexity of the transport sector, applied practices do not homogeneously cover those four methodologies.

GDP and population are among the most readily available data, as they are usually reported by administrative sources, such as national statistics offices. Similarly, total transport energy consumption can be obtained by drawing on administrative sources, such as national energy balances and statistics. However, mobility surveys or modeling approaches usually must be resorted when it comes to energy data with resolution down to sub-sector, segment, or vehicle type. Data on vkm are usually published by national transport ministries or transport databases and collected by employing measurement approaches, such as odometer readings during periodic roadworthiness testing or traffic counts. Nevertheless, they may also imply mobility surveys, modeling approaches, and using administrative sources. It is worth noting that when traffic is counted on the road, this includes foreign vehicles operating on national territory and excludes activity of domestic vehicles abroad, while details on vehicle characteristics often are lacking. In contrast, traffic measurements based on odometer readings only consider nationally registered vehicles while including their activity abroad. Odometer readings – next to providing higher detail resolution on vehicle characteristics – have the additional advantage of directly measuring annual mileage. Data on $pkm$ are commonly conflated from administrative sources and mobility surveys and are mostly published by national transport ministries or transport databases. Vehicle stock data is usually obtainable from national statistics offices, national and international databases, or vehicle registers based on administrative sources and/or measurements. However, the quality of vehicle stock data varies across countries and is betimes overestimated, and this mainly depends on the quality of scrappage statistics and how the reporting bodies deal with temporarily deregistered vehicles. (IEA, 2014b; ODYSSEE-MURE, 2020)

Data validation

Since EEI are used to assess the status of energy efficiency in a country, enabling it to define policies and measure their success, a thorough validation of the data is of utmost importance. Needless to say, data validation is vital for any basic data collection. However, validation must be even more solid as basic data is further elaborated when forming EEI. Given the variety of employed methodologies among the number of different data sources, which generally must be consulted when collecting data on the transport sector, verifying the data's consistency is very important. Considering that lower-level EEI mainly comprise ratio terms of two variables, small uncertainties or errors in either can cause significant changes in the indicators' trends and thus reduce the overall conclusiveness of monitoring energy efficiency. On the other hand, having a compound term of distinct variables allows verifying whether the relationship turns out as expected and thus contributes to assessing basic data.

Therefore, a careful data validation process should include checking the data's coverage and definitions, internal and external consistency, and ultimately, plausibility. Especially when drawing data from more than one source, it is of utmost importance to ensure that applied coverage and definitions – such as for sub-sectors and mode/vehicle type – match across sources. This includes defined boundaries of a sector and how periods are defined (i.e., whether the data refers to a calendar or fiscal year and whether the datapoint refers to a year-round average or an effective date). When deriving figures from different sources, internal inconsistencies are likely to occur. Therefore, one should perform arithmetic checks whether totals equal the sum of sub-components (such as total distance traveled vs. sum of all distances traveled of all sub-sectors), whether basic relationships hold (e.g., the relationships in **E1** and **E2**), and check for the coherence of data in time. The latter is conducive to identifying discontinuities or breaks (such as changed definitions regarding coverage or classification of data or changed methodology or sources) within time series. Breaks can substantially complexify time series analysis by producing misleading results. Moreover, it is important to understand the reasons behind any historical data revision and to ascertain whether revisions were applied to the whole time series or not. With this, looking for potentially related variables is useful to verify whether a discovered divergence in trends is justifiable. After checking for internal consistency, it is advisable to examine whether the collected data are consistent with similar data produced by other sources and whether any significant discrepancies can be explained (e.g., by different methodologies, coverage, or boundary definitions). Even if all the former checks were performed, obtained results may still be implausible. The variability of data and indicators depends largely on the country's characteristics; therefore, adequate knowledge of the topic is required to assess the plausibility of EEI. In the end, it is hard to see whether a trend for a specific indicator is the expected outcome of a new policy, corresponds to technological progress, or if there are issues in the underlying data. However, values for energy consumption should not be negative and necessarily positive for some fuel end-uses (such as gasoline consumption of LDVs). If data is reported as zero, it should be examined whether this refers to actual zero values or unavailable information. Further, activity data and key indicators for various modes should fall within expected ranges and reflect country-specific characteristics (such as geography and wealth). Figures for average occupancy ($\mathrm{PLF}$) should be within the expected ranges. For a group of $20$ OECD countries in 2010, the average $\mathrm{PLF}$ for passenger LDVs was between $1.2$ and $1.9$, with a median of $1.6$. For buses, the average $\mathrm{PLF}$ was between $7$ and $38$, with $13$ as median. The same goes for average annual mileage by vehicle type. For the same group of countries, the average mileage was between $9{,}000$ and $18{,}000\ \mathrm{km}$ for LDVs and between $22{,}000$ and $143{,}000\ \mathrm{km}$ for buses. Beyond that, the average fuel economy of road vehicles (can be calculated as $\mathrm{MJ}$ per $\mathrm{vkm}$ or $\mathrm{pkm}$), which is calculated from activity and energy data, should lie within reasonable ranges. However, values determined by these means can deviate substantially from values published by vehicle manufacturers. For the same group of countries, reported values for the entire passenger transport sector ranged between 1 and 3 $\mathrm{MJ/pkm}$ with a mode of 2 $\mathrm{MJ/pkm}$. Besides, energy consumption per $\mathrm{pkm}$ and $\mathrm{vkm}$ should follow stable trends within reasonable ranges for each mode. (IEA, 2014b)

## 2.3. Decomposition Analysis

After establishing how to develop expressive energy efficiency indicators in the previous section, we now look at how to track – and ultimately decompose – energy efficiency progress in the passenger transport sector. While the presented EEI represent fundamental tools to explain changes in energy consumption, they cannot be used per se to describe the impact of underlying drivers wholesomely. For instance, if we think of a modal shift towards LDVs at the expense of collective transport (i.e., bus and train), accompanied by an enhanced technical energy efficiency across all modes and steady $\mathrm{PLF}$ per mode, the energy consumption on a pkm basis would still most likely increase. In other words, it is difficult to capture the broader context to a sufficient degree using EEI alone as they cannot predict variation in aggregate energy consumption. Therefore, the key goal of decomposing energy demand is to isolate and quantify the impacts of changes in a set of predefined factors on the aggregate. In its most basic form, those are aggregated activity (e.g., $\mathrm{pkm}$), structure (modal shares), and energy intensity by mode (as a proxy for energy efficiency) in the context of passenger transport. However, extending the decomposition to more than three factors is generally possible. For instance, activity can be divided into pkm per capita and population size to capture the effect of demographic variance separately. Moreover, the decomposition of energy consumption can be extended to address changes in $\mathrm{CO_2}$ emissions by introducing the dimensions of fuel mix and carbon intensity. Ultimately, the selection of metrics depends on the availability of data and the research questions sought to be answered.

By decomposition analysis, we can estimate to what extent each underlying driver is responsible for changes in gross sectoral energy demand and thus quantify the energy that would have otherwise been consumed if the respective underlying driver stayed constant. Besides decomposing energy demand by traffic mode, a more detailed decomposition can also be done by type of vehicle, given that the necessary data is obtainable.

At last, understanding how each of the underlying forces impacts energy demand is essential to localize where the largest energy savings potentials lie and, thus, the areas that should be targeted first by energy efficiency policies. (Goh and Ang, 2019; IEA, 2014a, 2014b) This chapter will give an overview of the fundamentals of decomposition analysis featuring a review of which attributes to consider when selecting the right decomposition method. It is worth noting that potential issues regarding data quality, level of sector disaggregation, data elicitation, and indicator choice are generally not method dependent despite significantly affecting the quality and validity of decomposition results. (Ang, 2004)

### 2.3.1. Theory of Decomposition Analysis

<u>SDA vs. IDA</u>

In the scientific literature on decomposition analysis, many methods can be found. Any decomposition analysis employs historical data and starts by identifying the time period and indicators of interest for which the driving forces are to be investigated. The choice of the base year is thereby extremely important. Usually, data from two periods are used (i.e., a fixed base year), but there is also the possibility to include the interjacent years (i.e., a chained base year). In the latter case, the previous year is used as the base year for every year, and thus continuous time series data is required. By doing so, results tend to be more accurate, and analyzing multiple time periods is facilitated. In any case, there are two fundamental techniques for decomposing indicator changes on the sectoral level, which have been developed quite independently from each other. Both methods have been extensively used in studies on economic, socio-economic, and environmental indicators. On the one hand, there is structural decomposition analysis (SDA), which draws on information from detailed input-output tables, and index decomposition analysis (IDA), which uses aggregate data on the (sub-)sector level, on the other hand. The different models being used constitute the main difference between both methodologies. As a result, SDA can decompose economic and technological effects in a more sophisticated way, including the capture of indirect demand effects (i.e., when a direct demand increase in one sector leads to an increase in the demand for inputs from another sector), whereas IDA can only capture direct effects. Beyond that, IDA is characterized by a greater variety of potential mathematical specifications and indicator forms. Given the necessity of having input-output tables for an SDA, conducting an IDA is characterized by a substantially lower data requirement, and hence more detailed time and country studies can be performed. In consequence, SDA studies are generally characterized by shorter and less continuous time periods. In contrast, IDA studies are usually highly detailed regarding considered time periods and thus commonly include annual time steps. A more sophisticated comparison of SDA and IDA can be found in Hoekstra et and van den Bergh 2003. As a result, having in mind the data requirements, SDA may be rather suitable for industry and service energy end-use sectors and less for analyzing passenger transport energy demand. (Ang, 2004; Dennehy and Ó Gallachóir, 2018; Goh and Ang, 2019; Hoekstra and van den Bergh, 2003; IEA, 2014a) Therefore, IDA is considered superior in this context and will thus be used in this thesis.

Index Decomposition Analysis

Index decomposition analysis was introduced in the late 1970s to study the impact of changing energy mix in the industry sector. Since then, IDA has been continuously extended and applied to several other areas of policymaking. Given the simplicity and flexibility of the methodology, IDA is relatively easy to adopt, especially when compared to SDA. By now, based on the number of scientific contributions, IDA is a widely accepted analytical tool for policymaking concerning national energy and environmental issues. Main application areas include energy demand and supply, energy-related GHG emissions, material flows, national energy efficiency trend monitoring, and cross-country comparisons. The decomposition of energy demand and supply can easily be extended to analyze demand patterns in the transport or residential sector but also in the whole economy. Given the common distinction into impacts of activity, structure, and energy intensity, the definitions of those impacts usually vary depending on the energy sector studied. For instance, structural change in the transport sector implies a change in modal share, whereas it addresses fuel mix changes in the case of electricity generation. Notably, the qualitative information associated with each factor (e.g., the environmental implications of a change in structure) is the same for all decomposition methods, whereas the quantitative information (i.e., the measured value of the relative contribution) is method dependent. This means that method selection affects the obtained numerical results, even though the meanings of those components are the same across methods. (Ang, 2004)

After defining the indicators of interest and the time period to be studied, the IDA begins by defining the governing function. This governing function – also called index decomposition identity – relates the aggregate to a number of pre-defined drivers of energy demand. Effectively, the governing function can contain any number of factors, each with arbitrary units. In order for the equation to add up to the aggregate energy consumption, all other elements of the equation (with their respective units) must cancel out so that the aggregate remains at the end. (Ang, 2004; Hoekstra and van den Bergh, 2003)In principle, this corresponds to the same basic mathematical idea of the so-called $\mathrm{I{=}PAT}$ equation in the field of resource economics, with energy consumption as the dependent variable (Chertow, 2000)

## 2.3.2. Choice of Decomposition Methodology

Steps to Method Selection and Desirable Attributes

Once having established the decomposition identity, various IDA methods can be formulated to quantify the impacts of the underlying drivers on the aggregate. The IEA, in its guide on essentials for policy marking from EEI (IEA, 2014a), and Ang (Ang, 2004), in his sophisticated review on IDA method selection, point out accordantly that there are at least four main issues to account for when choosing the right IDA methodology. The chosen method must be theoretically sound and adaptable to all (sub-)sectors so that sub-sector results can be interpreted in the same way and thus reaggregated. Further, the interpretation of the index must be straightforward (i.e., ease of understanding and result presentation), and the method should be easily applicable to a specific problem (i.e., adaptability). Since it is not self-evident to fulfill the abovementioned criteria, Ang states that a variety of methods have been adopted by researchers, but also by national and international agencies and organizations (Ang, 2004). Often, method selection has been made rather on an ad-hoc basis. However, from a theoretical foundation viewpoint, it is relatively easy to show that some methods are superior to others. Yet, from an application viewpoint – where ease of use and simplicity are important considerations – other methods may prove superior. (Ang, 2004; IEA, 2014a)

Method Properties

Hence, to adequately assess the eligibility of a decomposition method, we must look at the method's mathematical form, underlying index theory, and associated index properties.

Relevant index properties are – amongst others – zero value robustness, factor reversibility, and time reversibility. Factor reversibility (i.e., complete decomposition without a residual) is the most important criterion. Especially when underlying indicators change substantially, some methods may return a residual value bigger than determinant effects. A time-reversal test shows whether decomposition results are the same when the time periods of the determinants are reversed. Zero value robustness may pose an issue when there are zero- or negative values in the dataset or if an indicator does not differ from period $0$ to $\mathrm{T}$.

A decomposition analysis for $\mathrm{n}$ factors from year $0$ to year $\mathrm{T}$ can be performed multiplicatively or additively. In the multiplicative case, the ratio change $\mathrm{D_{tot}}$ of the aggregate $\mathrm{V}$ is decomposed into $\mathrm{n}$ determinant indicators $\mathrm{D_k}$. In the additive variant, the difference change $\Delta\mathrm{V_{tot}}$ of the aggregate is decomposed into $\mathrm{n}$ determinant indicators $\mathrm{V_k}$. These relationships are illustrated in **E3** and **E4**. In the case of perfect decomposition (i.e., when the method is factor-reversible), the residual is one in the multiplicative form and zero in the additive form. (Ang, 2004; Hoekstra and van den Bergh, 2003)

$$Multiplicative: D_{tot} = \frac{V_T}{V_0} = \prod\nolimits_k^n D_k \times Residual \tag{E3}$$

$$Additive: \Delta V_{tot} = V_T - V_0 = \sum\nolimits_x^n V_k + Residual \tag{E4}$$

From a theoretical foundation viewpoint, this choice is fairly arbitrary. It may be seen that the results of an additive decomposition are more easily interpretable by non-professionals. Yet, the existence of a direct relationship between multiplicative and additive decomposition would constitute a good property from a methodological viewpoint. (Ang, 2004)

Furthermore, since IDA methods are closely related to index numbers, their theoretical foundation is largely based on the underlying index theory. An index is a weight assigned to a determinant. Therefore, this decisively impacts the obtained numerical values for the determinants. The crucial issue here is how the indicators (or determinant effects) are weighted against the aggregate, given that the indicators are subject to changing values (and thus to differing weights) between year 0 and year T. Widespread IDA methods can be divided into two principal groups. There are methods linked to the Laspeyres index and methods linked to the Divisia index. Simply put, Laspeyres-related methods are based on the concept of percentage change relative to a particular point, whereas Divisia-related methods are based on the concept of logarithmic change employing a continuous function between two points. Their key difference is that logarithmic change is a symmetric and additive indicator of relative change, whereas ordinary percentages are non-additive and asymmetric. To illustrate this, let us assume that the energy consumption of a sub-sector increased from $10$ units in year $0$ to $20$ units in year $\mathrm{T}$. From year $0$ to $\mathrm{T}$, the percentage difference is $100\ \%$, whereas it is -$50\ \%$ with reversed periods. In the case of logarithmic change, the relative change only differs in sign and is thus symmetric ($\ln\ (20/10)\ =$ -$\ln\ (10/20)$). Although, several Laspeyres-linked approaches overcome this central limitation of asymmetry. Thus, most methods are time-reversal besides the conventional Laspeyres index. By implication, there are various sub-variants with divergent methodological properties among those two classes. Concerning the resulting index properties, Divisia methods are generally not robust to zero or negative values due to the inherent logarithm. (Ang, 2004; Dennehy and Ó Gallachóir, 2018; Hoekstra and van den Bergh, 2003)

<u>Choice of IDA Methodology</u>

Given the properties of various methodologies to consider, the Logarithmic Mean Divisia Index (LMDI) method emerges as the most appropriate method. LMDI decomposition passes the time-reversal test and factor-reversal test. Therefore, it provides complete decomposition without residual, and a determinant's absolute value is the same if time periods are reversed. (Ang, 2005) Moreover, the LDMI approach is consistent in aggregation, which implies the value of the index calculated in one step (i.e., on aggregate level) coincides with the summed-up effects of the sub-groups (i.e., in a multi-step procedure). However, this property only remains valid as long as the data used in the first step of the multi-step procedure are the same as those employed in the single-step procedure. Given this limitation, there is a situation where consistency in aggregation can be only partially satisfied. This is when there are factors on the right-hand side of the index decomposition identity (i.e., the governing function) whose definitions in a multi-step and one-step procedure differ. (Ang and Liu, 2001)

Beyond this, the choice between the multiplicative and additive layout is inconsequential, as the multiplicative LMDI also contains the additive form in the log form. Hence, both are linked by the simple relationship shown in **E5**. However, the primary problem is formulated as an additive LMDI, due to presentation considerations. (Ang, 2004)

$$\frac{\Delta V_{tot}}{\ln D_{tot}} = \frac{\Delta V_x}{\ln D_x} \qquad \textbf{(E5)}$$

After all, the LMDI formulation process is relatively easy and adaptable. The formulae for a multi-factor problem possess exactly the same form as a two-factor problem. However, LMDI is not applicable if the dataset contains negative values. In the case of zero values, it has been shown that the LMDI converges if small non-zero values replace the data. (Ang, 2004)

LMDI Formulation Process

For a decomposition with n factors contributing to an energy-related aggregate (such as total passenger transport energy consumption), the aggregate $V$ is decomposed into the general IDA identity stated in **E6**. Here, subscript $i$ constitutes the sub-category (i.e., sub-sector) of the aggregate for which the structural change is to be studied.

$$V = \sum_i V_i = \sum_i x_{1,i} \cdot x_{2,i} \cdots x_{n,i} \quad \textbf{(E6)}$$

The aggregate changes from $V^0$ in period 0 to $V^T$ in period $T$. Therefore, the change over time is decomposed according to **E7**, following from the additive form of the decomposition stated in **E4**. The subscript tot refers to the total change of the aggregate and the terms of the right-hand side give the effects of the associated factors from **E6**.

$$\Delta V_{tot} = V^T - V^0 = \Delta V_{x1} + \Delta V_{x2} + \cdots + \Delta V_{xn} \quad \textbf{(E7)}$$

The general formula for the effect of the k<sup>th</sup> factor on the right-hand side of **E7** is stated in **E8**. Here, $L(V_i^T, V_i^0)$ constitutes the logarithmic mean and can be calculated as stated in **E9**.

$$\Delta V_{xk} = \sum_i L(V_i^T, V_i^0) \cdot \ln\left(\frac{x_{k,i}^T}{x_{k,i}^0}\right) \quad \textbf{(E8)}$$

$$L(V_i^T, V_i^0) = \frac{V_i^T - V_i^0}{\ln(V_i^T) - \ln(V_i^0)} \quad \textbf{(E9)}$$

Starting from the IDA identity, all LMDI formulae can be readily derived and calculated by using – for instance – commercially available spreadsheet software. However, due to the inherent logarithmic terms, the variables must not contain negative or zero values. Potential zeroes of an indicator or a dataset value may be adjusted by small positive constants (e.g., between $10^{-10}$ and $10^{-20}$), as the LMDI has been shown to converge in this case. The same applies for an indicator not changing between period $0$ and $\mathrm{T}$, given the resulting division by zero in **E9**. (Ang, 2005, 2015; Dennehy and Ó Gallachóir, 2018)

# 3. Methodology

For the time period from 2000 to 2016, two consecutive index decomposition analyses are performed, respectively, for Germany and the Netherlands. The first IDA examines four drivers of energy demand in the land passenger transport sector (i.e., the sub-sectors of LDVs, buses, and trains). Given the great dominance of LDVs in terms of passenger traffic as well as energy use, the subsequent analysis further examines five drivers of energy demand within the LDV sub-sector. Against the background of the observed increasing dieselization of the LDV fleet in some countries in the European Union, the second IDA also takes the dimension of propulsion technology (gasoline, diesel, and others) into account.

This chapter begins by specifying the IDA model configurations used, including the respective underlying factors driving energy demand. Thereupon, utilized data sources are outlined, and issues regarding data quality and gaps are addressed.

## 3.1. Model configuration

Both analyses are performed as an additive LMDI approach, as specified in section 2.3.2. In order to allow for more flexibility in the follow-up result evaluation, all analyses are performed with fixed and chained base-year. This implies that the energy consumption of a particular year can be examined with regard to the energy consumption of 2000 and to the year prior.

### 3.1.1. Passenger Transport IDA

The analysis of land passenger transport energy demand ($E_{PT}$) takes effects of activity ($PI_i$ and $P_i$), structure ($MS_i$), and energy intensity ($EI_i$) into account. Thereby, the activity effect is split into passenger intensity per capita ($PI_i$) and population variation ($P_i$), to facilitate the comparison of obtained results for the two countries. Structure refers to the modal shift ($MS_i$) of the respective three traffic modes on a $pkm$ basis, and intensity ($EI_i$) is the energy used per $pkm$ of the respective modes. The subscript $i$ refers to the three traffic modes being examined (LDVs, busses, and trains). The index decomposition identity is given in **E10**.

$$E_{PT} = \sum_i \frac{pkm}{POP} \times \frac{pkm_i}{pkm} \times \frac{E_i}{pkm_i} \times POP = \sum_i PI \times MS_i \times EI_i \times P \qquad \textbf{(E10)}$$

In principle, the choice of units is arbitrary, however, pkm are measured in $10^9$ km, population size is given in $10^6$ inhabitants, and energy consumption is stated in PJ (1 PJ = $10^9$ MJ or roughly 23884.59 toe).

The changes in energy demand between year 0 and year T can therefore be decomposed into the four factors passenger intensity modal share, energy intensity, and population, using **E11-E15**. $L(E_i^T, E_i^0)$ is the logarithmic mean, as defined in E9.

$$\Delta E_{PT} = \Delta E_{PI} + \Delta E_{MS} + \Delta E_{EI} + \Delta E_P \qquad \textbf{(E11)}$$

$$\Delta E_{PI} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{pkm^T/POP^T}{pkm^0/POP^0} \qquad \textbf{(E12)}$$

$$\Delta E_{MS_i} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{pkm_i^T/pkm^T}{pkm_i^0/pkm^0} \qquad \textbf{(E13)}$$

$$\Delta E_{EI_i} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{E_i^T/pkm_i^T}{E_i^0/pkm_i^0} \qquad \textbf{(E14)}$$

$$\Delta E_P = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{POP^T}{POP^0} \qquad \textbf{(E15)}$$

### 3.1.2. LDV IDA

The analysis of energy demand within the sub-sector of passenger light-duty vehicles examines the influence of five factors driving energy demand ($E_{LDV}$). Thereby, activity effects are split into passenger intensity per capita (PI) and population variation (P), for the same motivation as in 3.1.1. However, in contrast to the passenger decomposition IDA, this analysis takes usage behavior separately into account to capture intensity effects. This implies that energy intensity ($EI_i$) is evaluated on a vkm basis – to capture technical energy efficiency – and that the analysis is extended to relate vkm to pkm with the passenger move factor (PMF; the inverse of PLF), with it including usage efficiency. The technology share factor ($TS_i$) accounts for structural effects regarding the share of propulsion technologies in overall LDV vkm. The subscript i refers to the three propulsion types studied (gasoline, diesel, and others). The resulting index decomposition identity is given in **E16**.

$$E_{LDV} = \sum_i \frac{pkm}{POP} \times \frac{vkm}{pkm} \times \frac{vkm_i}{vkm} \times \frac{E_i}{vkm_i} \times POP = \sum_i PI \times PMF \times TS_i \times EI_i \times P \quad \textbf{(E16)}$$

Person- and vehicle kilometers are measured in $10^9$ km, population size is given in $10^6$ inhabitants, and energy consumption is stated in PJ. The changes in energy demand between year 0 and year T can therefore be decomposed into the five factors passenger intensity, passenger move factor, technology share, energy intensity and population, using **E17-E22**. $L(E_i^T, E_i^0)$ is the logarithmic mean, as defined in E9.

$$\Delta E_{LDV} = \Delta E_{PI} + \Delta E_{PMF} + \Delta E_{TS} + \Delta E_{EI} + \Delta E_P \quad \textbf{(E17)}$$

$$\Delta E_{PI} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{pkm^T/POP^T}{pkm^0/POP^0} \quad \textbf{(E18)}$$

$$\Delta E_{PMF} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{vkm^T/pkm^T}{vkm^0/pkm^0} \quad \textbf{(E19)}$$

$$\Delta E_{TS_i} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{vkm_i^T/vkm^T}{vkm_i^0/vkm^0} \quad \textbf{(E20)}$$

$$\Delta E_{EI_i} = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{E_i^T/vkm_i^T}{E_i^0/vkm_i^0} \quad \textbf{(E21)}$$

$$\Delta E_P = \sum_i L(E_i^T, E_i^0) \cdot \ln \frac{POP^T}{POP^0} \quad \textbf{(E22)}$$

## 3.2. Data Sources and Quality

The two primary data sources used are for one the December 2020 edition of the database on energy efficiency indicators of the International Energy Agency (IEA, 2020a) and second, the January 2023 edition of the ODYSSEE-MURE database (ODYSSEE-MURE, 2023). Both aim at monitoring energy efficiency and provide data (i.e., energy and activity data) and indicators for the residential, services, industry, and transport sector. The data collection is decentralized and carried out by national teams. Data is primarily sourced from the respective national administrations (such as transport ministries or statistics offices) and centralized in the two common databases. Since analyzing demand-side energy efficiency trends requires highly disaggregated end-use data, data quality and coverage vary enormously across countries for both the IEA and ODYSSEE-MURE database. Therefore, the country's passenger transport sectors and time periods to be studied are selected based on data availability and coverage. (IEA, 2014b, 2020b; ODYSSEE-MURE, 2020)

After data collection, the data is validated according to the established criteria in paragraph **2.2.3**. Concerning coverage and definitions, no inconsistencies appear regarding vehicle- or (sub-)sector definitions between and within those two databases. However, concerning energy data, there are some major inconsistencies across sources. One major issue is that biofuels consumed as a blend with or as a substitute for liquid fossil fuels (i.e., bioethanol and biodiesel) are reported jointly in the respective fossil fuel category by the IEA while separately covered in the ODYSSEE-MURE database. Nonetheless, the sum of reported bio- and fossil fuel consumption largely corresponds to the reported values for the respective fossil fuels in the IEA database. Therefore, for the sake of coherency, when referring to gasoline or diesel consumption, this includes biofuels in the scope of this thesis. Nonetheless, biofuels may impact energy efficiency, particularly GHG emissions. However, in an extensive IDA study on the Irish LDV sector from 1995 to 2015 (Dennehy and Ó Gallachóir, 2018), biofuel substitutions ranked as the least significant factor affecting energy efficiency. Beyond that, the other primary reason for inconsistencies concerning energy data lies within differing detail resolutions regarding individual energy sources. This means that in some cases, for a (sub-sector) or mode, disaggregated energy data for some energy carrier is missing in one (or both) of the data sources, leading to differing values for total final consumption, despite values for other sources of energy being congruent. Beyond that, data is checked for internal consistency (i.e., that disaggregated data can be reaggregated and that **E1** and **E2** hold) and external consistency – apart from coverage – between the two sources. In case of implausibility or any validation criteria not fulfilled (e.g., due to a methodology break), data is compared – and possibly conflated – between the two databases or other external sources such as national administrations. Given the high intricacy in compiling energy and activity data for passenger transport, deviations across sources up to $2\ \%$ may be seen as consistent in the context of this thesis.

### 3.2.1. Passenger Transport IDA

The required data for $\mathrm{pkm}$ and energy consumption, disaggregated for the three traffic modes, as well as population data, can be readily derived from the $\mathrm{IEA}$ Database on EEI for the transport sector. After all, the decisive reason this analysis does not separately consider the technical and usage efficiency of the modes is that data on rail $\mathrm{vkm}$ or PLF – for Germany and the Netherlands – are not obtainable. Nonetheless, validation criteria are largely fulfilled for data concerning LDVs and trains, and the $\mathrm{IEA}$ data can be readily deployed. There were some minor issues with energy data quality for LDVs. On the one hand, the data quality is sufficient for this aggregated view of the LDV sector but not for the downstream analysis. Therefore, energy data from the subsequent LDV analysis is used to maintain the consistency of results.

For buses, however, there were some inconsistencies and implausibilities. Regarding energy data for Germany, values until 2012 for TFC are highly congruent (i.e., $< .5\ \%$ deviation across databases) and roughly follow the trend of bus $\mathrm{vkm}$. However, as of 2013, the $\mathrm{IEA}$'s values are decoupled from the $\mathrm{vkm}$ trend, whereas $\mathrm{ODYSSEE\text{-}MURE}$ data follow the trend. Another anomaly is that there is no consumption data for fuels other than diesel and gasoline in both data sources, even though their share in consumption is significant in the Netherlands (especially for gas). Looking into vehicle stock statistics of the German motor vehicle authority (KBA, 2009, 2010, 2016), the share of busses driven by alternative fuels comprised between 2 and 2.7 % of total busses in exemplary years between 2008 and 2015. Still, considerable amounts of fuel consumption are reported under other fuels, so it can be assumed that those represent alternative fuels. The observed decoupling from the vkm trend in IEA data can be explained by deviating or missing values reported under other energy sources as compared to ODYSSEE-MURE. Values for diesel and gasoline consumption largely correspond. However, owing to the relatively coarse value resolution and resulting rounding differences (with energy consumption data in PJ with two decimals in IEA and four decimals in ODYSSEE-MURE vs. a share in stock of below 3 %), few interferences can be drawn about the relationship between stock and energy data for alternatively fueled busses. Having said all this, energy consumption data from ODYSSEE-MURE is employed for the analysis.

Moreover, despite being congruent in both sources, data on bus pkm for the Netherlands seem implausible. The data suggest an average bus occupancy roughly half as big as in Germany, and pkm/cap (for busses) significantly less than half as large. In contrast, when we look at pkm per capita for the other modes, the biggest difference is less than 30 %. More extensive research shows a methodological change in 2015 regarding how bus pkm data are collected. Therefore, historical values found in the main sources have been retrofitted. This more recent approach estimates bus pkm based on a nationwide Dutch travel survey, where the share of bus transport is estimated over the aggregate bus, tram, and metro. Before the change in methodology, values provided in the statistical pocketbook of the European Commission on the transport sector more closely resemble trends in bus pkm per capita (and PLF) of Germany and other surrounding countries. (EC and Directorate-General for Mobility and Transport, 2018; KiM Netherlands Institute for Transport and Policy Analysis, 2018) Therefore, values before the methodology change were taken from the EU statistical pocketbook, and missing values have been imputed. Beyond that, energy consumption data between the two databases were not congruent, as values for CNG are missing in ODYSSEE-MURE. Yet, the TFC of buses fully matches once CNG consumption is added. Therefore, IEA energy data can be seen as valid.

A more exhaustive illustration of sources of data and how data was revised can be found in **Appendix A**.

### 3.2.2. LDV IDA

Since the second IDA looks at passenger light duty vehicles (LDVs) – disaggregated by three fuel types – within the road sub-sector of passenger transport, highly disaggregated energy and activity data (here: vkm) is needed. Data on population and pkm can simply be drawn from the previous analysis, as deduced in **Appendix A**. Disaggregated traffic performance and energy consumption data must be re-derived. Inherently, corresponding energy data can be found in both principal sources, whereas activity data is only available for overall LDVs in the IEA database. The ODYSSEE-MURE database provides mileage and stock data for gasoline, diesel, and overall LDVs. With relationship **E1** the corresponding vkm data for all disaggregation levels can be easily derived. Pkm data, however, are generally not collected broken down by fuel type. Yet, an allocation of pkm to the three fuel types would be principally possible as per vkm proportion but is not purposeful since LDVs of different fuel types are characterized by different ownership (regarding private and commercial), which in turn suggests differing average occupancies. In consequence, we can examine the technology share ($TS_i$) based on the share in total LDV vkm. However, we must assume an equal average occupancy across the three engine types, which does not necessarily correspond to reality. Another crucial issue is that coverage and definitions of activity and energy data match. In the case of this IDA, this is especially true for vkm since it constitutes the numerator in the IDA identity's central energy efficiency indicator (cf. **E16**). The discussion for this is provided in the following subparagraph.

Another prevailing issue in compiling energy data is partially missing or non-corresponding consumption values for certain energy carriers, especially for fuels other than gasoline and diesel. Therefore, energy data from the two sources are conflated to ensure sufficient coverage of non-conventional vehicles. Notwithstanding, the consumption of liquid biofuels is reported jointly under the respective fossil-fuel category in the IEA database, whereas it is separately reported in the ODYSSEE-MURE project. Even so, consumption data largely mutually correspond once reaggregated. As mentioned, when referring to gasoline or diesel consumption, it includes associated biofuels in this context.

With traffic performance data (i.e., vkm) data, there are two principal issues. For one, the calculated values based on average annual mileage and LDV stock data (from total, gasoline, and diesel) are not always valid. Secondly, the rise of bivalent LDVs (i.e., an engine running on more than one fuel) makes it hard to unequivocally assign activity data to one fuel category.

For Germany, the resulting vkm of other LDVs are partially negative, and there are discrepancies when obtained values are collated with further external sources. For instance, vehicle stock data are subject to an unmentioned revision up to 2008 due to a methodological break on the side of the national agency providing the statistics. Beyond that, until 2008, gasoline traffic performance contains gas vehicles, which holds as the primary explanation for the calculated traffic performance of others being invalid. In the absence of further explanatory data, energy, and activity data of gasoline LDVs entails natural gas vehicles until 2008, and further alternative fuels are neglected and therefore set to zero. For the Netherlands, calculated annual mileage values for other LDVs significantly deviate from figures published by the Dutch national statistics agency (CBS), which suggests data from ODYSSEE-MURE is erroneous or inconsistent respectively. Further, total LDV traffic performance in both principal sources substantially deviates from CBS data as well. Both are because LDV traffic performance calculations (in the IEA and ODYSSEE-MURE database) are subject to a wrong population (i.e., stock) of LDVs.

Further, bivalent LDVs exist as hybrids (this includes hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV)) and bivalent natural gas LDVs. HEVs are fueled solely with gasoline or diesel (thereof almost exclusively gasoline), with the battery charging while driving, whereas PHEVs can be additionally charged at a power outlet (CBS, 2016). In the scope of this thesis, gas LDVs are attributed to the other category, except until 2008 for Germany. However, the share of bivalent gas engines within gas LDVs is unfortunately not published for the periods under scrutiny and therefore the resulting data bias cannot be estimated. Furthermore, since we can assume that hybrids predominately run on gasoline (Fraunhofer ISI and Plötz, 2020; HandWiki, 2023), those are attributed to the gasoline category in terms of traffic performance. It is to be expected that both approaches have opposite effects on result accuracy and thus compensate for each other to a certain degree.

Ultimately, revised disaggregated energy consumption and traffic performance data are validated by plotting together the respective shares in the total together. An extensive outline of all data revisions, sources, and validation steps can be found in **Appendix B**.

Coverage and Definitions of energy and activity data

In order to form meaningful energy efficiency indicators (here: energy consumption per vehicle kilometer), the coverage and definitions of both must match. As delineated in Chapter **2.2.3**, one of the most intricate tasks – next to appropriate disaggregation of data into sub-sectors and vehicle types – is delimiting data to the national territory of the country under study. Given the open borders in the EU – with free movement of goods and people – this is of particular challenge. For energy data, this is generally easier, as this can be based on relatively easily available fuel sales volumes, additionally taking factors such as fuel tourism into account.

When it comes to capturing data on traffic performance, an often-adapted method is odometer readings. This comes with the advantage that data can be collected as part of periodic vehicle quality inspections without significant additional effort but with many observation points. Yet solely vehicles registered in the respective country can be captured by this means. This results in the so-called national traffic performance, i.e., distances covered domestically and abroad by vehicles registered in the respective country, but distances covered domestically by foreign-registered vehicles are excluded. Since utilized energy data are subject to the energy consumed within the respective national territory, the matching traffic performance measure is the domestic traffic performance since it includes all vehicle movement on the national territory by domestic- and foreign-registered vehicles but excludes distances abroad.

In the case of the Netherlands, the gathering of traffic performance is primarily based on odometer readings (yielding national traffic performance) and complemented by traffic counts, tourism statistics, and driver surveys to obtain domestic traffic performance. In practice, the domestic traffic performance is determined by a linear conversion factor by which the national traffic performance is multiplied. For this purpose, an equal distribution across all fuel types is assumed. (CBS, 2021c, 2022; Geilenkirchen et al., 2022; Molnár-in 't Veld, 2014) Moreover, the underlying population of vehicles is not the official LDV stock statistics (subject to the stock on Jan 1st) but the so-called “park in use,” which includes all vehicles on the road for at least part of the year.

In the case of Germany, the relevant LDV population is official stock statistics (subject to the stock on Jan 1st), whereas mileage data subject to traffic performance calculation are of arithmetical nature. The underlying basic idea is that the quantity of consumed fuels widely corresponds to the turned-over volumes of gas stations on the one hand and to the product of vehicle population, average fuel consumption, and average mileage on the other. Therefore, apart from the consideration of further influencing factors (e.g., fuel tourism and distances covered abroad), elements of the equation (thereof annual mileage in particular) are iteratively determined to reach equivalence. The resulting metric is the national traffic performance. (BMDV et al., 2016) A closer examination reveals that there are further national traffic performance studies that are based on primary data collection (Bäumer et al., 2017a) and process data (KBA, 2022). Resulting values are quite similar to each other (2014 values for national LDV vkm $599$, $611$, and $627$ $\text{billion km}$) (Bäumer et al., 2017a; BMDV et al., 2016). Furthermore, regular elicitations of domestic traffic performance are not conducted. In consequence, energy data (energy consumption on German territory) and activity data (traffic performance of German vehicles in and outside of Germany without kilometers of foreign vehicles in Germany) do not match in terms of coverage and definitions. In this respect, the common assumption is that both volumes cancel each other out (IEA, 2014b). However, a pair of traffic performance surveys identify the national and domestic traffic performance of several road vehicle types for 2014 (Bäumer et al., 2017a, 2017b). Results show that German LDVs covered $2.8\ \%$ of distances abroad, whereas $3.6\ \%$ of domestic $\mathrm{vkm}$ are driven by foreign vehicles. From this follows that approximately $5$ billion $\mathrm{vkm}$ more were driven by foreign vehicles in Germany than by German vehicles outside of Germany. Therefore, the domestic traffic performance of LDVs is roughly $1\ \%$ larger than the national traffic performance. However, this result cannot be judged with certainty, given the comparably bigger difference in overall LDV traffic performance from the three competing estimation methods (cf. **above**). On the other hand, given the methodological conformance within the two studies (Bäumer et al., 2017a, 2017b), we can assume that the resulting EEI slightly underestimate energy efficiency since the underlying $\mathrm{vkm}$ (i.e., national $\mathrm{vkm}$) are likely to be smaller than actual (i.e., than domestic $\mathrm{vkm}$).

In the Netherlands, there is the opposite situation, with domestic LDV $\mathrm{vkm}$ being $8.8\ \%$ smaller than the national traffic performance on average. In the period under scrutiny, the difference ranges from $6.4$ to $10.4\ \%$, with $9.4\ \%$ in 2014 (cf. **Table 17**). Given the geographical proximity to Germany, this suggests the extent or even direction of the in-/outflow balance is also subject to changes. Therefore, this adds to result uncertainty, and due to missing studies for the remaining periods, the extent cannot be reasonably assessed.

Final comments on data validity

Summarizing, the quality of energy data is generally higher for gasoline and diesel than for other fuels. German gasoline and diesel consumption data match across sources, whereas their values diverge by up to $2\ \%$ for the Netherlands. Consumption of other energy carriers varies significantly across databases in both cases. However, regarding respective registration counts, all seem plausible but Dutch electricity consumption (which is substantially underestimated).

The unclear allocation of bivalent LDVs to the energy categories further complicates result evaluation. This is especially true for the Netherlands since there are substantially more alternatively fueled LDVs than in Germany. In both cases, there are more (potentially bivalent) natural gas LDVs than HEVs roughly up to period 13 (i.e., 2012), with a growing tendency for HEVs thereafter. Since gas LDVs are attributed to the other category and HEVs to the gasoline category, these effects partially cancel each other out. However, the attribution of HEVs to the gasoline category implies that there are no diesel hybrids which may not be true. Nevertheless, the effect should be of subordinate significance. Moreover, disaggregated results from 2012 to 2014 for the Netherlands should be taken cautiously since these periods are subject to a linear imputation. Beyond that, for the reattribution of hybrid LDVs to the gasoline category in Germany as of 2009, the annual mileage of gasoline was assumed. Since the annual mileage of hybrids is likely higher than that of gasoline vehicles – due to comparably more commercial ownership – we can assume that not all of the hybrids' $vkm$ were reattributed.

All in all, given the high intricacy in compiling disaggregated data on the road passenger transport sector, there is considerable potential for upstream errors as well, which may be of higher magnitude than the aforementioned limitations. Therefore, results should always be interpreted with caution, also against the background that exact data collection of this diffuse sector is impossible.
Nevertheless, considering the plausible ratios of the share in total activity and energy of the individual disaggregation levels, a trend analysis seems quite possible.

# 4. Results

This chapter gives record of the results of the index composition analyses. The decomposed changes in transport energy consumption between 2000 and 2016 are presented in waterfall charts (cf. **Figures** 3, 6, 10, and 14), each supplemented by two stacked column diagrams with incremental year-on-year changes (one each in relation to 2000 (fixed base year; cf. **Figures** 4, 7, 11 and 15) and each one compared to the previous year (chained base year; cf. **Figures** 5, 8, 12 and 16) with the respective factor contributions and their total effect. In the latter two, the incremental change in energy consumption relates to the sum of negative and positive effects, symbolized by the line. The first chart with overall decomposition is well-suited for a first overview of the individual factor's significance over the entire period, whereas the latter two allow for deeper insights into the factor trends from year to year, relative to the base- and previous year. Underlying numerical results are provided in **Tables 24-31** in **Appendix C**.

## 4.1. Energy Consumption in the Land Passenger Transport Sector

### 4.1.1. Germany

From 2000 to 2016, aggregated land passenger transport energy consumption decreases by about $.5\ \%$, with a $5\ \%$ decline until 2009 and a subsequent rise. On a per-capita basis, total energy consumption decreases by $1.6\ \%$, decreasing by $4.7\ \%$ until 2008 and increasing subsequently. Overall, LDVs clearly dominate energy consumption, with the share even increasing from $95.5$ to $96.6\ \%$. The modal split stays quite constant - with around $84\ \%$ of $\mathrm{pkm}$ made by LDVs (subject to a $.4\ \%$ increase) and a slight increase in rail traffic, mainly at the expense of buses – explaining why the structural effect ($\mathrm{MS}$) is the least significant. Prominently, the effects of passenger intensity ($\mathrm{PI}$) and energy intensity ($\mathrm{EI}$) are of different signs yet similar amounts and, therefore, largely compensate for each other. Energy intensity – on a $\mathrm{pkm}$ basis – improves for all three traffic modes; therein, trains have the greatest relative improvement and buses the lowest. LDVs' contribution to the overall energy intensity effect is -182.33 PJ (89 %). Nonetheless, usage efficiency behavior (i.e., average occupancy) is embedded in the pkm-based energy intensity indicator and may distort results. Moreover, Germany's slight population increase of 1 % has an (expectedly) rather small effect when viewed over the entire period, although there are periodic trend reversals.

For the most part, aggregate energy consumption slightly decreases because energy efficiency gains have been greater than passenger activity increases.

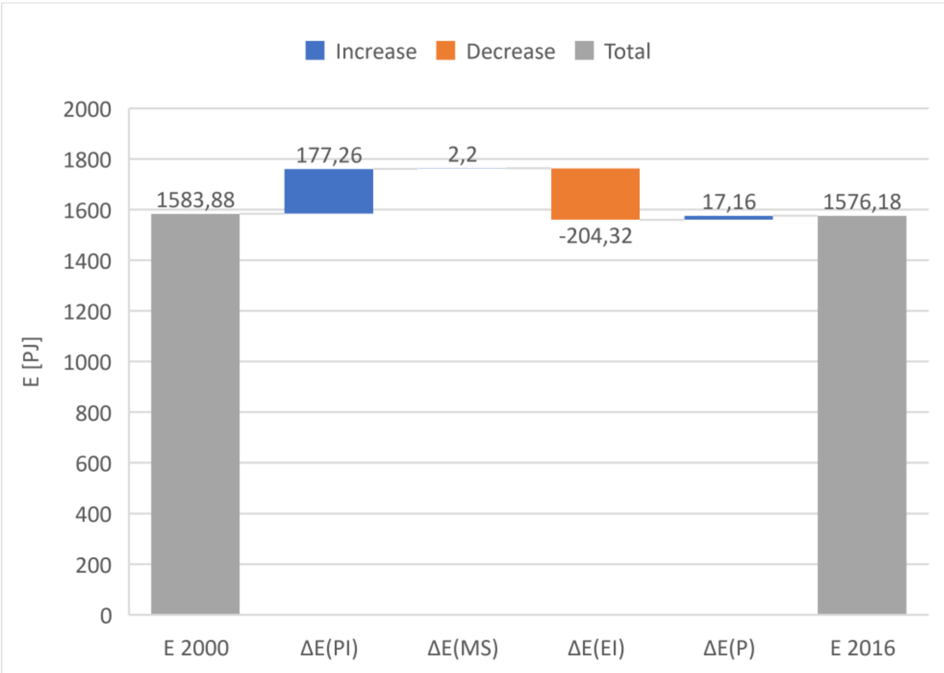


**Figure 3: German Passenger Transport IDA 2000 – 2016**

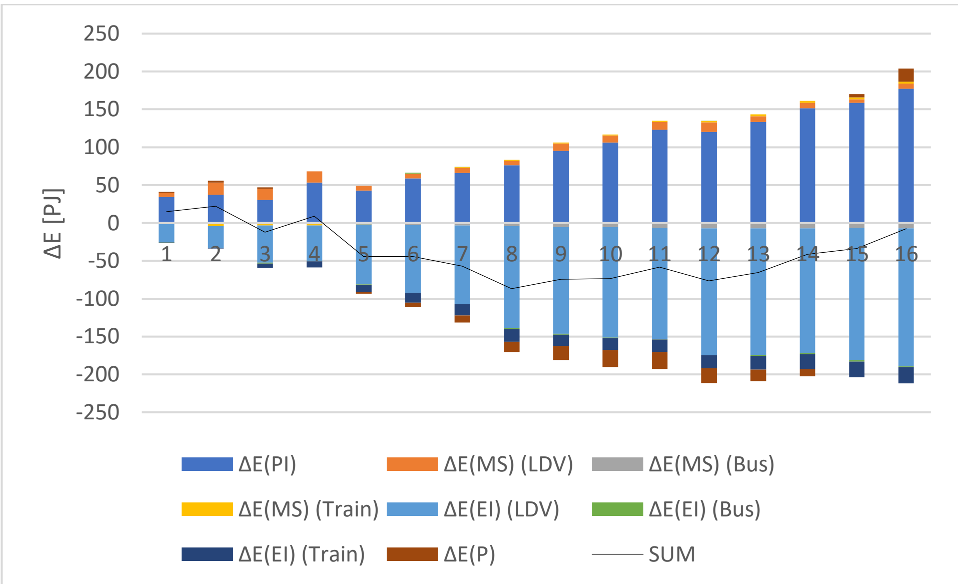


**Figure 4: German Passenger Transport IDA year-on-year vs. 2000**

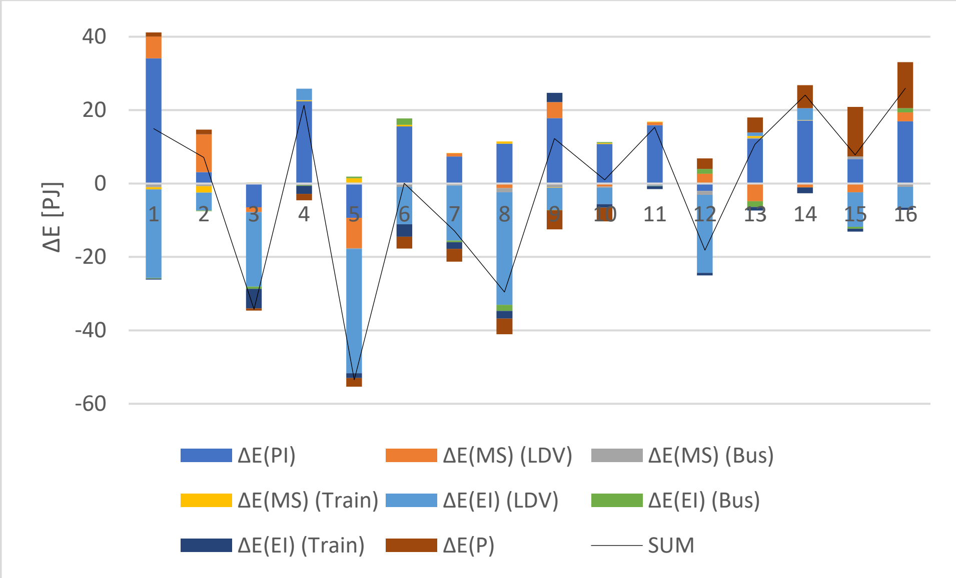


**Figure 5: German Passenger Transport IDA year-on-year vs. previous**

When looking at the year-on-year results, passenger activity – as the strongest overall driver of energy demand – is subject to a steady upward trend compared to 2000 but subject to three rather minor changes in direction compared to the previous year. During the entire period, $\mathrm{pkm}$ per capita increase by $11.9\ \%$. The opposite can be said for energy intensity, with LDVs – owing to the major share in aggregate energy consumption – dominating in terms of the effect's magnitude, which is subject to a steady downward trend (when compared to the base period) but also to three rather minor changes in direction when compared to the previous period. Altogether, LDV's energy intensity decreases from $1.78$ to $1.58\ \mathrm{MJ/pkm}$. In addition, LDVs' modal share effect has a consistently positive contribution to overall energy consumption compared to 2000 but is subject to several changes in direction when viewed with respect to the previous period. This is because LDVs' modal share was the lowest in 2000 and is following a "M-shaped" trend thereafter. In consequence, this effect's overall contribution is sensitive to the choice of the base period. Beyond that, trains' energy intensity is subject to a continuously decreasing trend (with meanwhile minor changes in direction) and, therefore, in total negatively affects total energy consumption. Effects other than that are of rather limited significance.

Ultimately, the aggregate change in energy demand is subject to a slight downward trend even though it was subject to an increase in five out of 17 periods. Therefore, if any period after 2004 were the base year, the aggregate change would be positive.

## 4.1.2. Netherlands

From 2000 to 2016, the aggregate energy consumption of passenger land transportation increases by $4\ \%$, whereas it decreases by $2.4\ \%$ on a per-capita basis. This can be seen in **Figure 6**, as aggregate energy consumption in 2016 is nominally higher than in 2000 but smaller when the (positive) population effect is subtracted. On a per capita basis, total energy consumption increases by $3.3\ \%$ until 2004 and follows a downward trend – except in the last period – thereafter. As in Germany, LDVs clearly dominate in terms of energy and passenger activity. LDVs' share in energy consumption rises by $.4\ \%$-points to $95\ \%$, whereas the share in passenger activity decreases by $.6\ \%$-points to $83\%$. The modal split stays quite constant, with LDVs' share decreasing mainly due to an increase in trains' modal share, which explains the structure ($\mathrm{MS}$) effect being the least significant but of the opposite sign when compared to Germany (where LDVs' activity share increases). Here the population effect is of greatest significance, but it is also the case that passenger intensity and energy intensity are of different signs yet similar amounts, whereby interestingly – opposing to Germany – the respective signs differ, and $\mathrm{PI}$'s negative effect predominates. This implies energy efficiency (on a $\mathrm{pkm}$ basis) deteriorating while traveled distance per capita decreases. In 2016, the average Dutch citizen traveled $6\ \%$ less than in 2000 but using $4\ \%$ more energy per kilometer traveled. Strikingly, LDVs' and buses' energy intensity increased by $5$ and $8\ \%$ (from $1.67$ to $1.76$ and from $.67$ to $.72\ \mathrm{MJ}/\ \mathrm{pkm}$), but trains' energy intensity decreased by $21\ \%$ to $.25\ \mathrm{MJ/pkm}$. The total contribution of increasing LDV energy intensity is $11.67\ \mathrm{PJ}$. Given that average occupancy is a masked but potentially significant influence, drawable conclusions from here are limited.

Therefore, aggregate energy consumption mainly increases due to the increase in population and gross energy intensity, attenuated by decreasing passenger intensity.

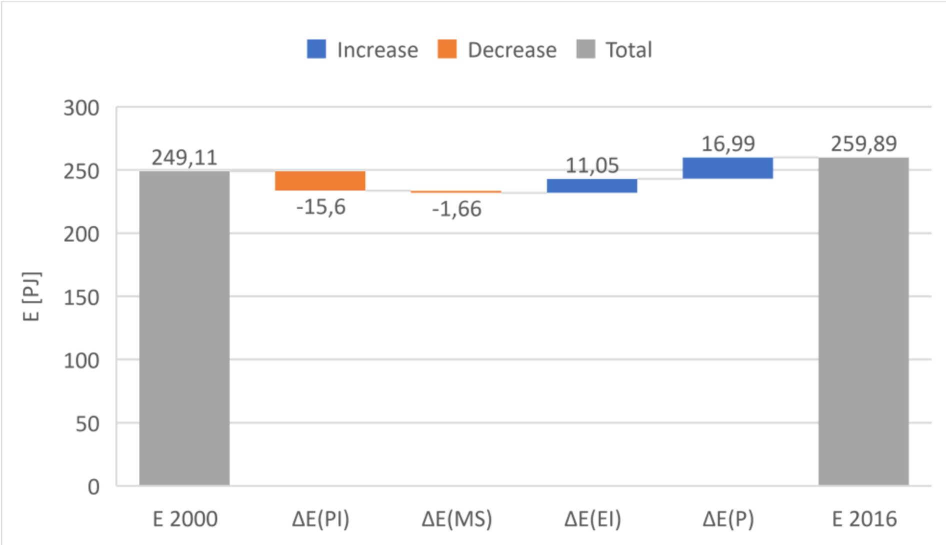


**Figure 6: Dutch Passenger Transport IDA 2000 - 2016**

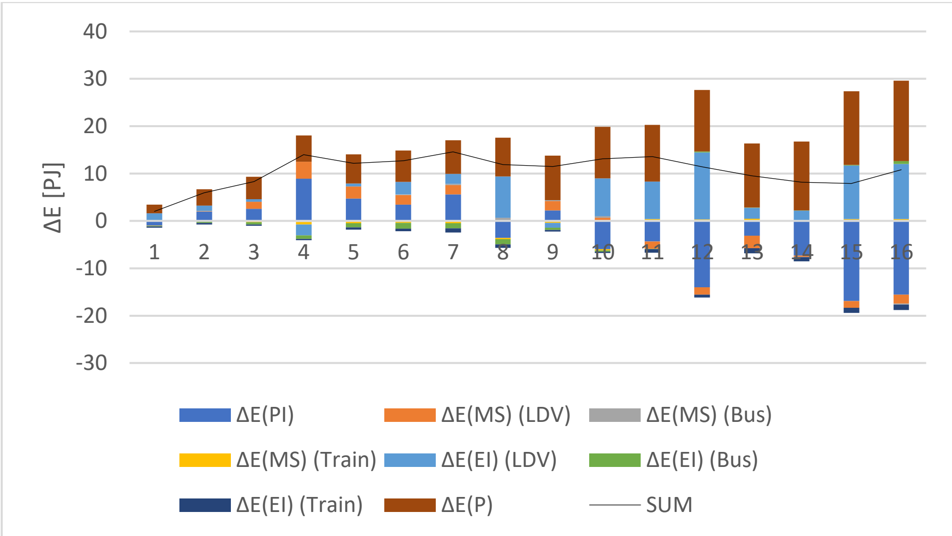


**Figure 7: Dutch Passenger Transport IDA year-on-year vs. 2000**

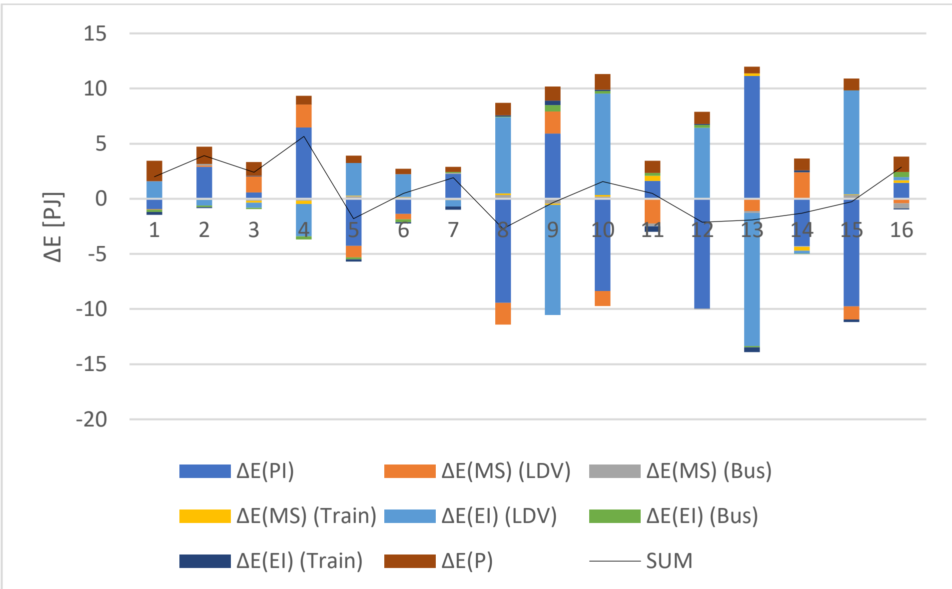


**Figure 8: Dutch Passenger Transport IDA year-on-year vs. previous**

The year-to-year results show that increasing LDV energy intensity and population are the most significant drivers of energy demand. Both consistently contribute to higher energy consumption compared with 2000, although LDV energy intensity is subject to several changes in direction compared with the previous year. The effect of LDVs' modal share is as well subject to several changes of direction, both when compared to the base and the previous year. This suggests that the choice of the base year greatly affects the magnitude and sign of the structural ($\mathrm{MS}$) effect. This is similar for passenger intensity ($\mathrm{pkm/cap}$) – which tendentially increases until 2007 and only decreases by tendency thereafter – but in contrast is subject to a negative trend overall. This is shown for perspective in **Figure 9**, where pkm per capita and LDV's modal share are indexed with respect to the values in 2000.

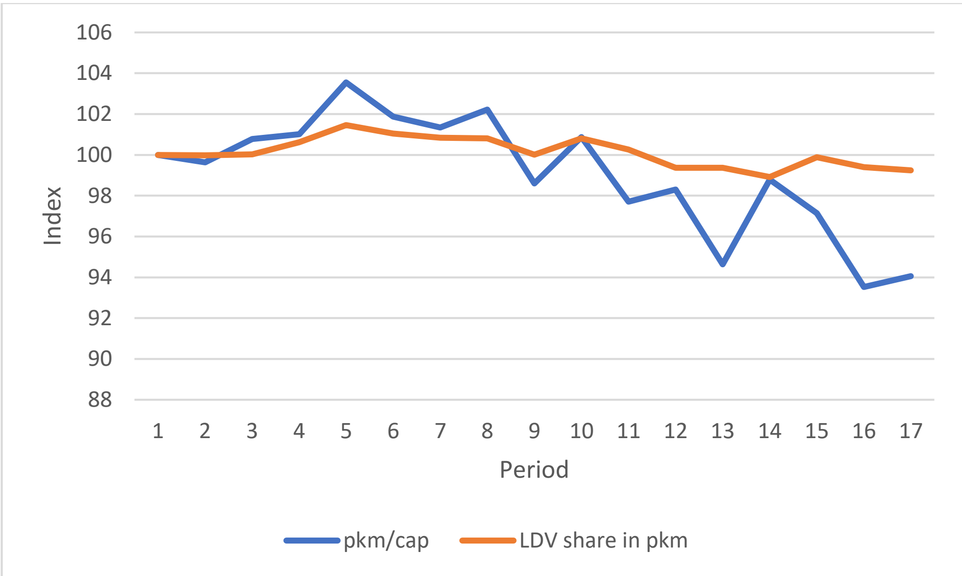


**Figure 9: Dutch LDV Modal Share and Overall Passenger Intensity indexed**

Beyond this, the other factors' contributions are of rather limited significance.

## 4.2. Energy consumption in the LDV sector

From decomposing energy consumption in the passenger land transport sector, we see that LDVs clearly dominate energy consumption and passenger activity and that the modal split is subject to minor changes. Furthermore, over the whole period overall and LDV energy intensity decrease in Germany but increase in the Netherlands. Apart from examining the effect of different fuel technologies, this IDA – looking at LDVs – seeks to decompose overall energy intensity on a $\mathrm{pkm}$ basis into technical energy intensity (i.e., on a $\mathrm{vkm}$ basis) and usage efficiency (i.e., passengers moved per $\mathrm{vkm}$).

### 4.2.1. Germany

Methodological remarks

Since traffic performance and energy consumption of other fuels are set to zero until 2008 (cf. paragraph **3.2.2**), present zero values must be replaced by very small positive values (following (Ang, 2004)) due to the mathematical limitations of the LMDI approach (including the inadmissibility of zeros in the denominator and logarithm). In principle, the form of the small positive values impacts the effects of $\mathrm{TS}$ and $\mathrm{EI}$ (cf. **3.1.2**), thereby potentially skewing results. Therefore, a sensitivity analysis is conducted for aggregate effects. With regards to the chained base-year case, the only impact is on the structure ($\mathrm{TS}$) and intensity ($\mathrm{EI}$) effect in period 10 (2009). In the fixed base-year case, the same applies to $\mathrm{TS}$ and $\mathrm{EI}$ effects for every year as of 2009. The values for vkm and energy consumption of other fuels are set in such a way that they are equivalent for one year and increase by a small amount each year. More precisely, the value in period $\mathrm{x}$ is $1+\mathrm{x}$ multiplied by $10^{-100}$. In period $0$, $\mathrm{x}$ is $0$, and in the following periods, $\mathrm{x}$ corresponds to the number of the period to the power of minus nine. From setting $\mathrm{vkm}$ and energy consumption equal in each period, it follows that the energy intensity is one. In an alternative approach, where $\mathrm{vkm}$ and energy consumption are set in such a way that the resulting energy intensity corresponds to the weighted average of gasoline's and diesel's energy intensity, the only significant difference lies in the $\mathrm{TS}$ effect in period 10. Additionally, the approach was tested with different exponents from -7 to -100, and the only significant differences occur in TS and EI effects for period 10. Moreover, it seems that effect sizes converge with increasing negative exponent. For the effects in 2016 compared to 2000, the difference in effect sizes for an exponent of -7 and -100 is less than 1.5 %. Therefore, the selected approach can be seen as valid for all effects and periods except for the TS and EI effect in period 10 in the chained base-year case.

Results

In contrast to land passenger transport, LDVs' total energy consumption increases by .8 % from 2000 to 2016 but stays almost constant on a per-capita basis (- 0.3 %). Positive impacts on energy consumption are increasing passenger activity per capita (PI), decreasing average occupancy (PMF) and to a small extent increasing population (P). Annual pkm per capita increase by 12.4 % to 11722 km, and the average PLF decreases from 1.52 to 1.49 pkm per vkm. Moreover, Germany's LDV fleet is subject to continuous dieselization, i.e., diesel LDVs – which are characterized by a comparably better fuel economy – continuously replace gasoline LDVs with a consequentially negative effect on total energy consumption. In addition, technical energy efficiency improvements (i.e., decreasing EI) contribute to the greatest extent to decreasing energy consumption.

Further, the observed increasing energy efficiency from the first IDA is composed of the increase in fuel-efficient diesel vehicles, a generally decreasing energy intensity (on a vkm basis), and a decreasing PLF (with the latter counteracting efficiency gains).

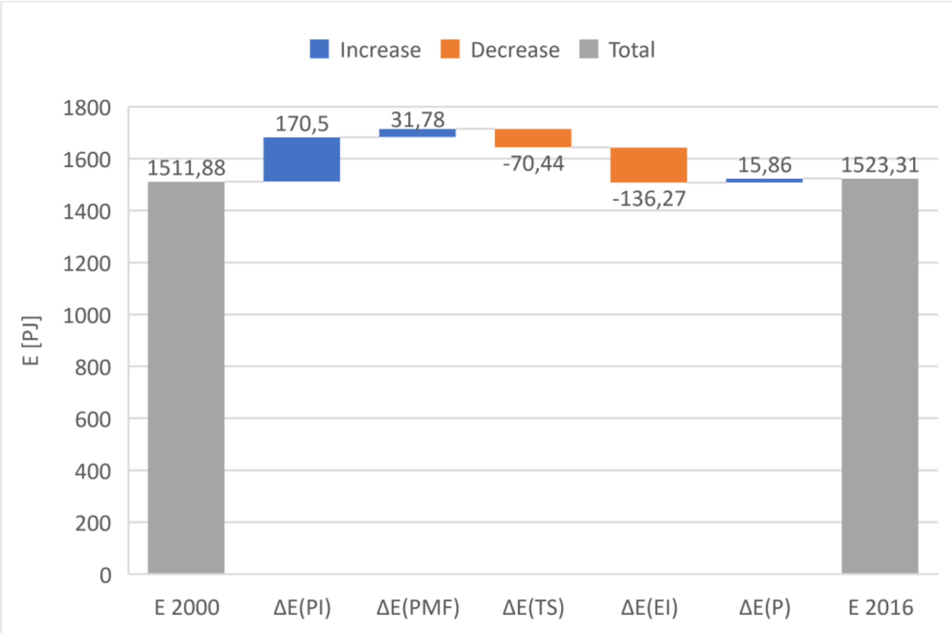


**Figure 10: German LDV IDA 2000 - 2016**

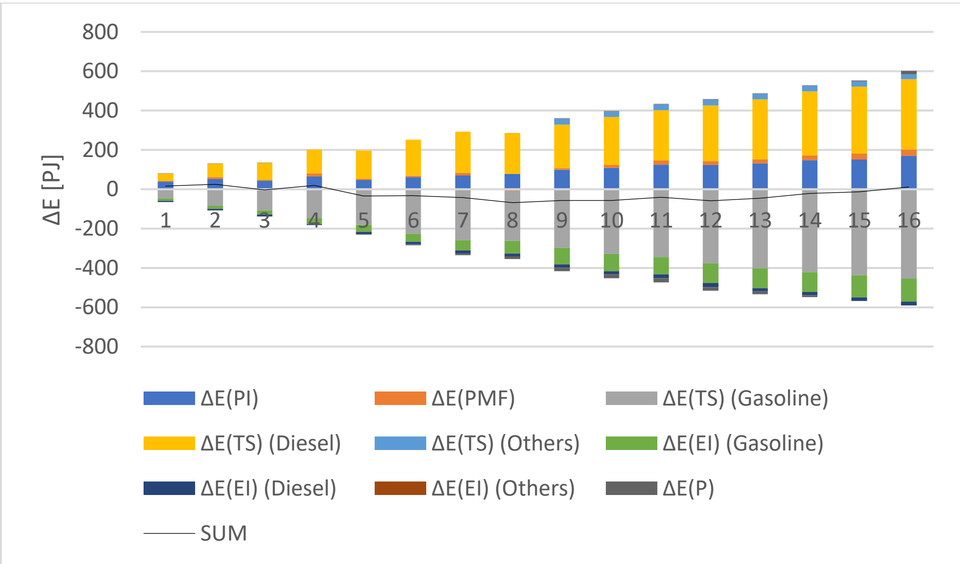


**Figure 11: German LDV IDA year-on-year vs. 2000**

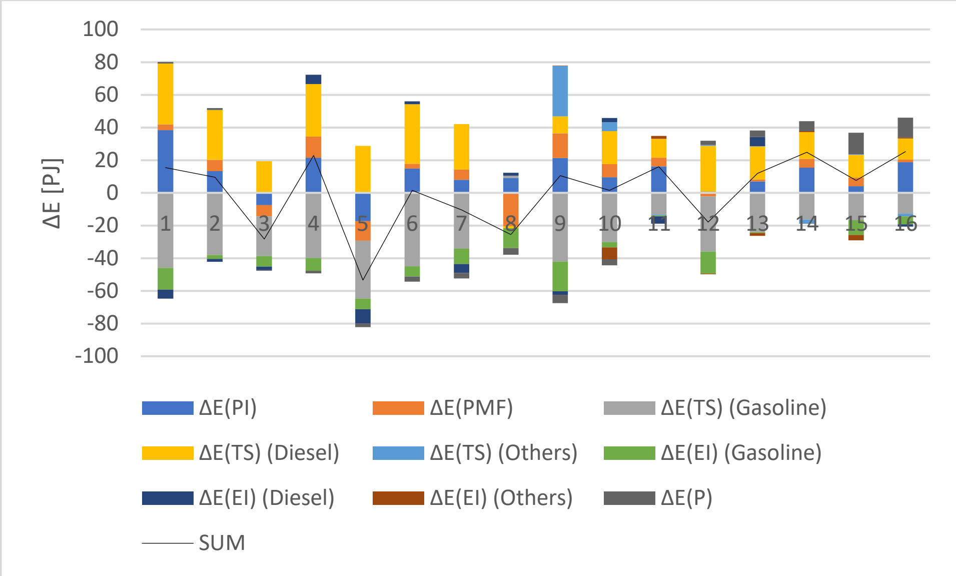


**Figure 12: German LDV IDA year-on-year vs. previous**

When looking at the year-to-year results, aggregate LDV energy consumption is lower in all years but 2004 and 2016 when compared to the base-year value. Therefore, the aggregate change is sensitive for base-year selection. However, as in the first analysis, increasing passenger activity has a mostly steady positive effect on energy consumption. The opposite – with isolated positive exceptions of diesel and fewer for others – can be said for energy intensity on a vkm basis. Compared to the base year, average occupancy (the inverse of PMF) is lower in every year but 2008, whereas when related to the previous period, the sign of the difference is alternating up to 2009. Hence, PMF is sensitive to the choice of the base year for periods under review up to 2009 but not for subsequent periods, as it is subject to an overall downward trend.

Beyond that, the changing technology share continuously has a negative effect. When the structure effect (TS) for a fuel type is positive, this implies that the share in overall traffic performance of this fuel type increased and that the structure effect of the fuel type subject to a decrease in vkm share is negative. The total structure effect is the sum of the respective disaggregated effects. Since, in our case, the share in traffic performance of comparably more energy-efficient diesel vehicles increases, the positive TS effect of diesels is of smaller size than the corresponding negative effect of gasoline LDVs, and therefore, the total TS effect is negative.

Beyond that, other effects are of comparably lower significance.

Advanced findings

It is worth noting that diesel LDVs are generally characterized by a higher annual mileage when compared to gasoline. Other LDVs lie in between. Therefore, gasoline-powered vehicles are overrepresented in the overall fleet compared to the overall traffic performance. Further, gasoline's average annual mileage decreases from $61$ % in 2000 to $54$ % in 2016 of diesel's average annual mileage. Moreover, registered LDVs per $1000$ inhabitants continuously increase from $487$ to $556$ in the period under study. As to be expected, the annual mileage of gasoline and diesel vehicles decrease accordingly. At the same time, however, the annual mileage of all LDVs remains fairly constant. This is due to the substitution of gasoline by diesel LDVs, thereby largely offsetting the effect of individually decreasing mileages. Ultimately, for a sophisticated overview, key activity metrics (including $\mathrm{vkm}$, $\mathrm{pkm}$, annual mileage per LDV and fleet) are presented standardized per capita and indexed to the base period in **Figure 13**. Notably, $\mathrm{pkm}$ and $\mathrm{vkm}$ roughly follow the same trend, which explains the small magnitude of the $\mathrm{PMF}$ factor. Since the LDV fleet is subject to a strong upward trend, but the annual mileage remains largely constant, this indicates that more vehicles overall drive more, but not the individual vehicle.

Therefore, in the aggregate view, we can infer that the additional demand for individual mobility is being met first and foremost by purchasing new vehicles since the active fleet is increasing while the annual mileage stays constant. However, against the background of decreasing fuel-type specific mileages being offset by the changing technology share, the conjecture arises that the LDVs' annual mileage increases in the wake of gasoline to diesel fuel technology substitution.

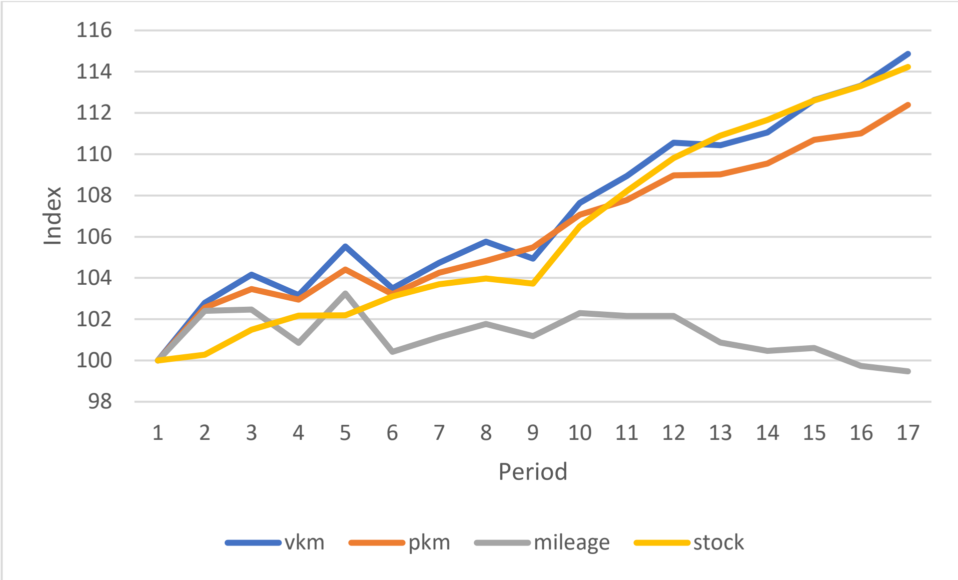


**Figure 13: Key German LDV Activity Metrics indexed to the Base Period (normalized per Capita)**

## 4.2.2. Netherlands

Similar to land passenger transport, aggregate energy consumption of LDVs increases by 5 % while it decreases by 2 % on a per-capita basis. Decreasing average occupancy has the biggest positive impact on energy demand, next to increasing population size. If the average $\mathrm{PLF}$ would stay equal – implying a decline in $\mathrm{vkm}$ corresponding to $\mathrm{pkm}$ – overall LDV energy consumption would decrease, especially since passenger activity decreases by 6.7 % to 8268 km per capita and year. In principle, declining average occupancy cancels out all technical efficiency gains ($\mathrm{EI}$) plus the negative structure effect ($\mathrm{TS}$) and thus largely explains the observed increasing energy intensity of the land passenger transport IDA.

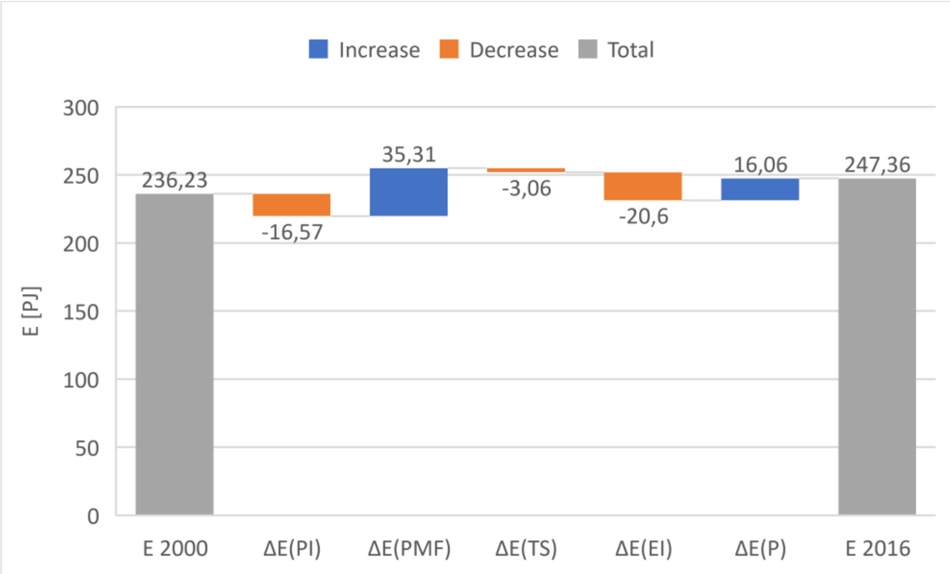


**Figure 14: Dutch LDV IDA 2000 - 2016**

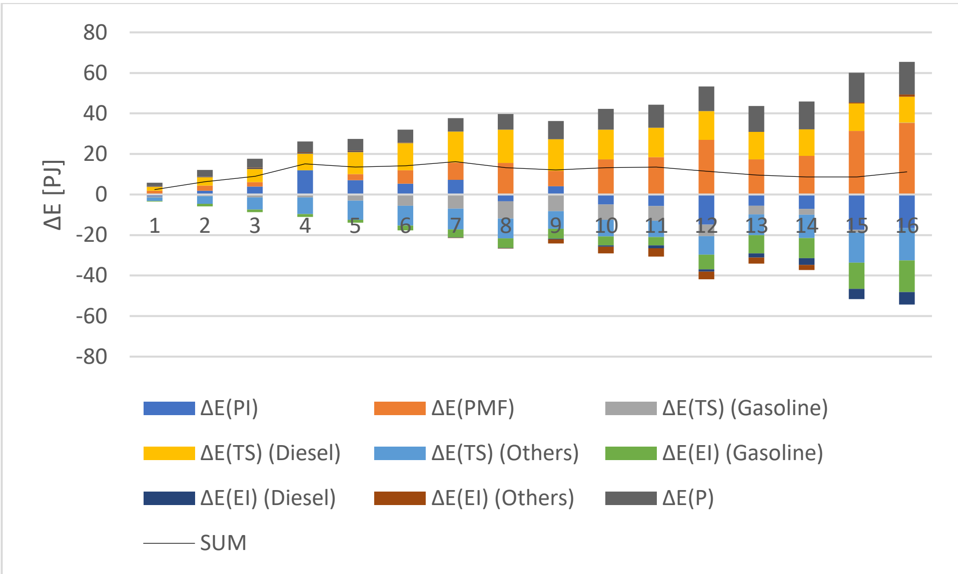


**Figure 15: Dutch LDV IDA year-on-year vs. 2000**

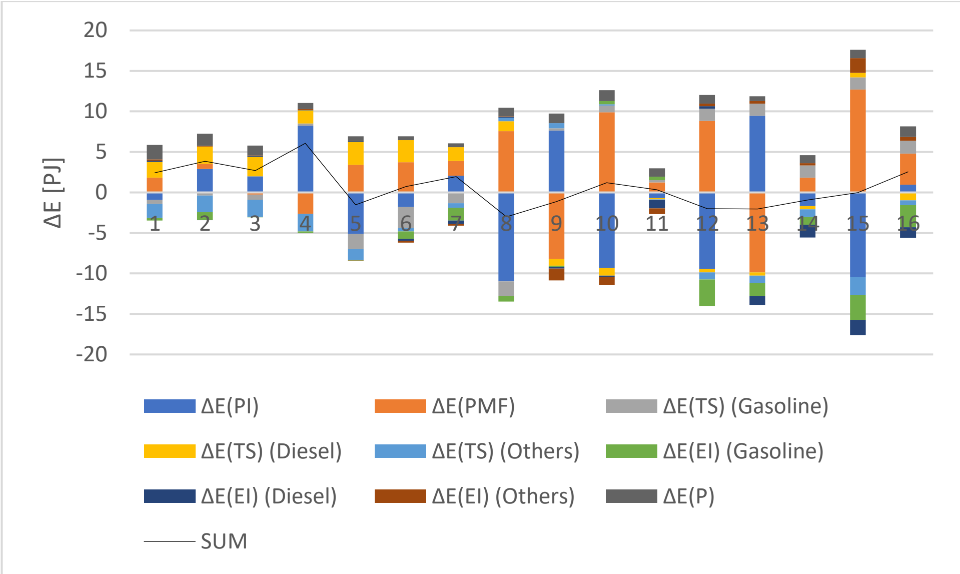


**Figure 16: Dutch LDV IDA year-on year vs. previous**

Total LDV energy consumption is higher in all years following 2000, peaking at 6.9 % more in 2008, but declines temporarily in six periods (relative to the previous). Therefore, the overall change in consumption is sensitive to base-year selection. Furthermore, in the cumulative view, changes in average occupancy, population, and diesel technology share have a throughout positive effect on energy consumption. With three exceptions, PLF is subject to a steady downward trend, decreasing from 1.51 to 1.31 pkm per vkm on average. On the other hand, pkm per capita peak in 2004 at 9305 km but follow a downward trend thereafter, reaching the minimum in 2015 with 8235 pkm per capita (-6.7 % compared to 8858 pkm/cap in 2000). Hence, the factor's magnitude is well dependent on the base period chosen but its direction to a lesser extent. Beyond that, energy intensity declines or stagnates in all periods (relative to the previous period) but declines relative to 2000 every year. However, energy data for other fuels do not meet validation criteria, and consequently, resulting indicators cannot be considered valid. Given the small significance in energy consumption and activity, the effect on the aggregate EI indicator is of small significance.

Also in the Netherlands, gasoline LDVs are characterized by a significantly higher energy intensity per vkm when compared to diesel vehicles (2.36 vs. 2.10 MJ/vkm in 2016). However, unlike in Germany, gasoline's share in traffic performance is decreasing from 66.9 % in 2000 to 63.4 % in 2009 and subsequently increasing to 67.0 % in 2016. On the other hand, the share of diesel is increasing from 24.7 % in

2000 to $32.0\ \%$ in 2008 but steadily decreasing thereafter down to $30.4\ \%$ in 2016. In contrast, the share of other fuels is continuously decreasing from $8.4\ \%$ in 2000 to $2.6\ \%$ in 2016. This is mainly due to the decreasing popularity of natural gas vehicles and since hybrid LDVs are attributed to the gasoline category, which in turn explains gasolines revival as pure-gasoline LDVs **stagnate** to around $63\ \%$ of traffic performance in 2016. As a result, the technology share effect is of a much smaller magnitude when compared to Germany.

Advanced findings

Also, registered LDVs per 1000 inhabitants in the Netherlands continuously increase from $453$ to $527$ over the review period. However, fleet statistics are not directly comparable to Germany since they follow a different methodology (cf. **Appendix B**). Therefore, Dutch registration numbers are overestimated against the background that it relates to the park in use, which is higher than registration numbers on the first day of the year. Moreover, the annual mileage of gasoline is only about $45\ \%$ of that of diesel, and the mileage of all fuel types is trending downwards. As a consequence, gasoline vehicles have a higher share in the LDV population than in LDV traffic performance, with the opposite being true for diesel. Annual mileage of other fuels lies in between. Given the comparably constant technology share, overall mileage follows accordingly. For a more sophisticated overview, key activity metrics (including $\mathrm{vkm}$, $\mathrm{pkm}$, annual mileage, and stock) of all Dutch LDVs is presented indexed to the base period and normalized per capita in **Figure 17**. The increasing widening of the gap between $\mathrm{pkm}$ and $\mathrm{vkm}$ illustrates the major effect of the $\mathrm{PMF}$ factor. Moreover, total $\mathrm{vkm}$ increase by a lesser extent than the LDV fleet, with annual mileage declining accordingly. This suggests that newly registered LDVs are substituting parts of itineraries of existing vehicles but also serve additional demand. On the whole, this additional demand does not consist in the demand for additional passenger transport per se but in the transport of fewer people spread over more vehicles, which in turn cover more kilometers in total.

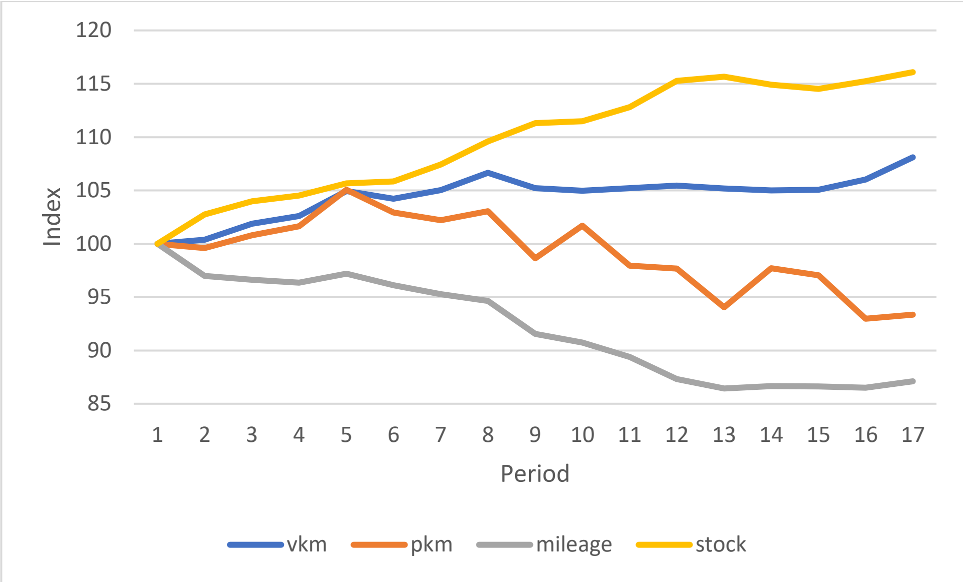


**Figure 17: Key Dutch LDV Activity Metrics indexed to the Base Period (normalized per Capita)**

## 4.3. Comparison

LDVs clearly dominate both countries' land passenger transport sectors in terms of energy consumption and passenger activity. Over the whole period in Germany, land passenger transport energy consumption slightly decreases while LDV energy consumption is subject to an increase. In the Netherlands, both measures increase. On a per capita basis, all measures decrease, with the smallest decrease observed in the German LDV sector, with only a .3 % decrease in per-capita energy consumption. However, over the whole period, German users of land passenger transport use around a quarter more energy per annum than their Dutch counterparts (decreasing to 17 % more in 2008 and subsequently increasing). This is while Germans travel 16.5 % more per capita in 2000 but 38.6 % more in 2016. Looking at the yearly values - as depicted in **Figure 18** below – both passenger land transport and LDV energy consumption per capita follow a parallel overall downward trend in both countries. This is reflected in the linear trend lines. However, in a few periods, energy consumption per capita is higher than in 2000. In the Netherlands, there is an upward trend until 2007 (period 8), which is followed by a strong downward trend until 2015, although the trend reverses from 2015 to 2016. In Germany, on the other hand, there is an overall downward trend until 2008 and a subsequent increase until 2016.

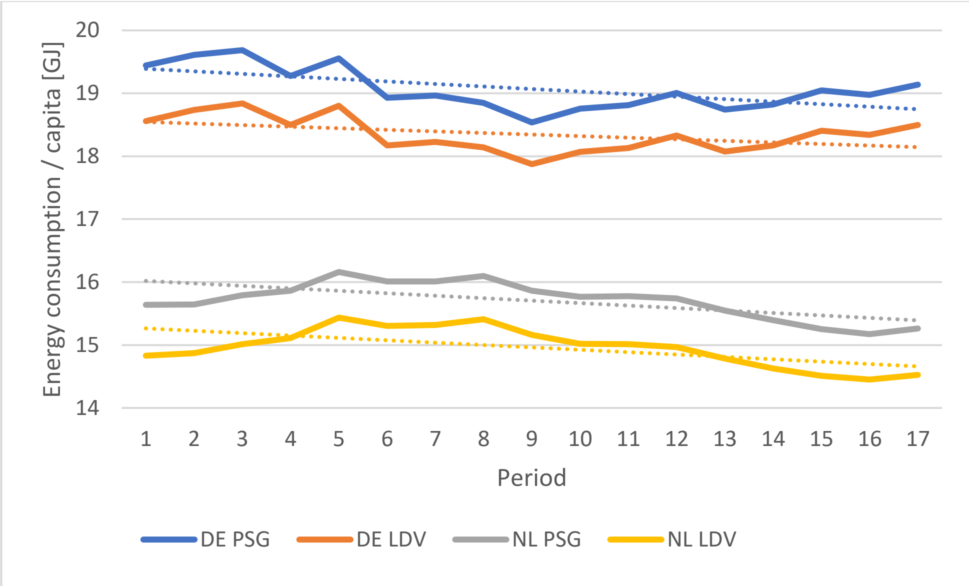


**Figure 18: Passenger Energy Consumption per Capita 2000 - 2016**

The most notable difference between the two countries is that passenger intensity ($\mathrm{pkm/cap}$) decreases in the Netherlands, whereas it substantially increases in Germany. Since passenger activity is often correlated with the country's GDP (IEA 14P), it is worth looking at. When indexing together passenger intensity ($\mathrm{pkm/cap}$) and GDP per capita (in constant 2015 USD; (World Bank and OECD, 2023); cf. **Figure 19**), we can see that both largely run the same path in Germany, whereas the two seem to be decoupled in the Netherlands. However, passenger intensity alone cannot be considered a predictor of transport energy consumption, as between 2000 and 2016, $\mathrm{pkm}$ per capita in the Netherlands decrease by 6 %, and passenger land transport energy consumption per capita decreases by $2.4\ \%$. However, in Germany, energy consumption per capita decreases by $1.6\ \%$ while passenger intensity per capita increases by $11.9\ \%$.

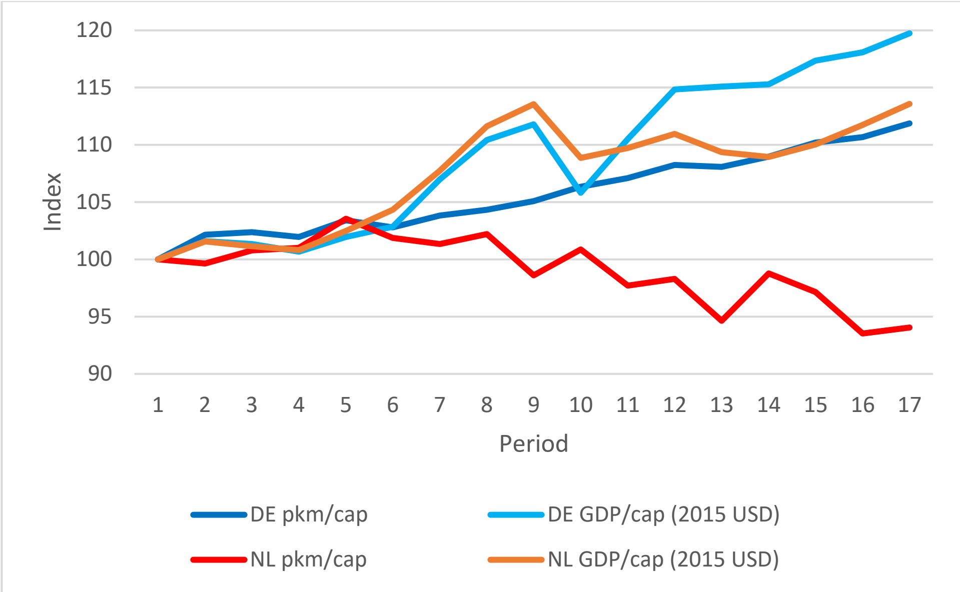


**Figure 19: Passenger Intensity and GDP per Capita Indexed**

Whereas the positive effect of increasing passenger intensity is canceled out by decreasing overall energy intensity (i.e., per pkm) in Germany, the negative effect of decreasing passenger intensity is canceled out by increasing overall energy intensity in the Netherlands. Thereby, average LDV occupancy only decreases slightly in Germany – limiting but still resulting in strong overall efficiency gains (i.e., on a pkm basis) – whereas the negative effect of decreasing technical energy intensity (i.e., on a vkm basis) in the Netherlands is completely canceled out by the drastically decreasing PLF. Beyond that, the substantial dieselization of the German LDV fleet results in a significant negative effect, whereas the comparably limited changes in fuel technology distribution have a smaller – yet still negative – effect in the Netherlands.

After all, LDVs' specific energy intensity is decreasing in both countries in a consistent downward trend. In line with the trend in aggregate LDV energy consumption, the trend in aggregate specific energy intensity runs concave in the Netherlands and convex in Germany. This is while the greatest relative improvement can be observed in Germany (-13.2 vs. -9.4 %).

# 5. Discussion

The results highlight the significant role of the human dimension in passenger transport energy efficiency, as behavioral factors substantially offset technical energy intensity improvements. After briefly reinstating the study's main results, results are interpreted in hindsight of the main objectives and research question. Furthermore, underlying causes and higher-level developments contributing to the obtained results are explored while examining their broader implications. The discussion is consummated by acknowledging and discussing the limitations inherent in this study. Moreover, the coverage of the chosen model is discussed, including contextualizing this work with other authors' approaches.

<u>Summary</u>

Passenger transport energy consumption per capita decreases in all four scenarios, although at a roughly double as high rate in the Netherlands. In Germany, aggregate energy consumption decreases until 2009 and increases thereafter, whereas energy consumption in the Netherlands increases until 2004 to decrease subsequently (except in the last period). Both countries' passenger transport sectors are clearly dominated by LDVs, both in terms of passenger activity and energy consumption. The fact that LDVs account for a significantly higher share in aggregate energy consumption than passenger activity already suggests LDVs are substantially less energy efficient. Yet, modal shift has a rather limited effect on energy consumption besides holding a huge theoretical potential. In line with the initial hypothesis, the analyses demonstrate that technical energy efficiency improvements are always counteracted by other effects, thus sizably curtailing overall energy efficiency improvements. However, against the initial assumption, passenger intensity in passenger transport is decreasing in the Netherlands while gross energy efficiency deteriorates. In Germany, on the other hand, passenger intensity is subject to a substantial increase while gross energy intensity decreases.

In Germany, decreasing gross energy intensity is the largest limiter of energy consumption and is mainly counteracted by increasing passenger activity (at it roughly following the trend in GDP per capita). Taking a deeper look at the LDV sector

– accounting for between $95.5$ and $95.6\ \%$ of passenger transport energy demand – the decline in gross energy intensity is supported by decreasing specific energy consumption per $\mathrm{vkm}$ and LDV fleet dieselization and slightly limited by decreasing LDV average occupancy.

In the Netherlands, however, overall passenger activity remains quite constant while $\mathrm{pkm}$ per capita decrease by $6\ \%$ over the whole period – counteracting the trend in GDP per capita. Therefore, population increase is the biggest contributor to increasing passenger transport energy consumption which would have decreased by about $2.5\ \%$ if the country's population had stayed constant (ceteris paribus). Notably, gross passenger energy intensity is increasing, counteracting the negative effect of decreasing passenger intensity. A closer examination of the LDV sector – representing between $94.8$ and $95.7\ \%$ of passenger energy consumption – shows that specific energy consumption per $\mathrm{vkm}$ decreases considerably, further but slightly supported by the altering technology share. However, the steadily decreasing $\mathrm{PLF}$ (from initially $1.51$ to $1.31$ in 2016) more than offsets the efficiency gains achieved otherwise. This observation is further supported by the fact that LDVs' share in energy consumption is increasing, whereas its share in overall $\mathrm{pkm}$ is decreasing.

Interpretation and Implications

In line with the scope and background of the energy efficiency concept developed at the outset of this thesis, obtained results strongly support the proposition that the human dimension is a decisive factor in energy efficiency. Technical energy efficiency improvements constitute one factor among many and can be offset or even canceled out by behavioral changes. Results for Germany support the initial hypothesis that we expect a decreasing gross energy intensity mainly counteracted by increasing passenger intensity. By contrast, passenger intensity in the Netherlands is subject to a decrease while gross energy intensity is increasing. Nonetheless, per capita energy consumption decreases in all cases. All in all, both results may be interpreted in favor of the existence of a rebound effect. The second IDA, decomposing LDV energy consumption (representing over $94\ \%$ of passenger transport energy consumption), further decomposes gross energy intensity into usage efficiency (i.e., $\mathrm{PMF}$), technology share, and technical energy intensity (i.e., per $\mathrm{vkm}$). While the decreasing technical energy intensity (plus technology share) in Germany is slightly offset by derogating usage efficiency and ultimately largely counterbalanced by increasing passenger intensity, the net effect remains negative. In the Netherlands, however, decreasing technical energy intensity is underpinned by decreasing passenger activity and technology share but is ultimately largely offset by the deteriorating average PLF. Therefore, we may interpret the deteriorating PLF in the Netherlands (accompanied by increasing vkm but decreasing pkm) as a rebound effect in the sense that even though aggregate pkm decline, the demand for individual mobility is still increasing in the way that passengers are transported spread over more vehicles while traveling more vkm but less pkm on aggregate. On the other, the rebound effect in Germany may be interpreted in a more straightforward way since reduced energy intensity (aided by the fuel share effect) is correlated with increased passenger intensity.

Beyond this, modal share effects are of rather limited significance for the passenger transport sector, given the relatively constant modal split. Bearing in mind the substantially differing energy consumption per passenger kilometer (for the energy an LDV uses to transport one passenger over one kilometer, between 2.4 and 3.3 and between 4.5 and 8.5 passengers are transported over the same distance in a bus or train, respectively), modal shift holds a large theoretical potential for energy savings. In 2016 LDVs' modal share in land passenger transport is 84.6 and 82.7 % in terms of pkm in Germany and the Netherlands, which is above the EU average of 81.3 %. Other than that – aside from concerns of transferability – LDVs' modal share in the Czech Republic and Hungary is merely 66.5 %. (EC and Directorate-General for Mobility and Transport, 2018)

Moreover, the decreasing Dutch overall passenger intensity correlates with an increase in passenger activity in active transport modes (i.e., walking and cycling). The Dutch MON/OViN travel survey – whose numbers are of limited statistical certainty due to limited sample sizes but are suited for trend analysis – suggests that pkm of cycling increased by approximately 10 % to 15.5 billion pkm between 2005 and 2015, thereby partially explaining the decline in passenger transport activity. In addition, consistent with this thesis, the study's results indicate a deteriorating average occupancy of LDVs, nonetheless to a lesser extent. (KiM Netherlands Institute for Transport and Policy Analysis, 2018) Another possible explanation for the deteriorating PLF could be an increase in the share of commercial LDV ownership. Nonetheless, the percentage share of LDVs registered on a commercial owner increased only marginally from 10.4 to 11.3 % in the period under study. (CBS, 2022)

What is more, on the grounds of the presented numerical results, the increasing technology share of diesel vehicles has a clear negative effect on energy consumption. It can therefore be regarded as clearly positive from a mechanistic energy efficiency viewpoint, simply owing to the fact that a diesel vehicle consumes on average less fuel per vkm (in absolute units) than a gasoline vehicle. This is especially true for Germany, where the magnitude of LDV fleet dieselization is substantially higher. For the sake of context, the (fleet) share of diesel LDVs in the EU increased significantly from a minor share in the 1980s to over 40 % in 2020, which is, in this form, unique in the world. Diesel fuels are taxed more leniently by most European countries because it is more energy efficient (than gasoline), and therefore, GHG emission reductions and energy savings were anticipated by policymakers. (Marrero and Rodríguez-López, J. González, R.M., 2020; Miravete et al., 2018) However, from an ecological viewpoint, externalities other than $CO_2$ of diesel LDVs are always higher when compared to gasoline. In addition, owing to the more intensive use of diesel vehicles and the higher mileage in contrast to gasoline, dieselization may be subject to a rebound effect, thus offsetting efficiency gains. Therefore, dieselization's actual impact on LDV energy efficiency is highly debated among transport economists. Marrero et al. conducted a dynamic general equilibrium model study regarding the choice of a diesel or gasoline LDV calibrated for main European countries. (Marrero and Rodríguez-López, J. González, R.M., 2020) In addition, the model was calibrated for a carbon-content-dependent Pigouvian fuel tax (therefore higher for diesel by assuming a carbon price of 25 € per ton of $CO_2$). The authors' findings suggest that the EU taxation favoring diesel caused an increase of 2.7 % in LDV traffic performance compared to the socially optimal carbon-content related fuel taxation. Consequentially, the authors point out that the relatively better fuel economy plus lower fuel price of diesel may imply an increase in traffic performance and thus significantly limit the associated energy savings potential. In a different dynamic panel data approach examining the dynamic relationship between LDV emissions and fleet dieselization in 13 EU countries from 1990 to 2015, the authors estimate that a .1-point increase in the relative gasoline/diesel fuel price leads to about a 1.4 % increase in aggregate LDV emissions. (González et al., 2019) However, fleet dieselization cannot be explained by the more lenient fuel taxation alone, as consumer preferences and productivity gains in the European automotive industry due to specialization and policy decisions also played a crucial role. (Marrero and Rodríguez-López, J. González, R.M., 2020) Barring LDV usage behavior, an analysis of new car purchasing trends in Germany from 1998 to 2008 shows that consumers switching to a diesel model did not always buy a matched pair but rather preferred a more powerful diesel car than what they might have bought otherwise with a consequential less steep decrease in LDV energy consumption. This is while gasoline sales shifted to lower-emitting models to a greater extent. (Zachariadis, 2013)

Conclusively, the induced effect on traffic performance caused by the lower fuel cost and higher energy efficiency of diesel LDVs may serve as a partial explanation for the overall steadiness of German LDVs' annual mileage against the background of individually declining mileages and increasing share in diesel vehicles, if we assume that new diesel car owners use their vehicle more in the course of the rebound effect than they would if they had kept their gasoline car. Notwithstanding, a change in LDV ownership distribution may serve as an alternative explanation for the observed progression of German LDV mileage since LDVs owned by a commercial owner are typically characterized by higher annual mileages. Nonetheless, throughout the period under study, commercial ownership rate remains at an almost constant 10 %, and thus this explanatory approach is not applicable. (BMDV et al., 2016)

Beyond the impact of improved fuel economy on LDV usage behavior, there is increasing evidence that technical energy efficiency enhancements may also change LDV purchase preferences itself. A three-factor IDA on the British LDV fleet from 2000 to 2018 – decomposing the sales-weighted average fuel economy of new vehicles into technical energy efficiency, technology shift, and vehicle attribute change – found that around $60\ \%$ of the potential energy savings achieved by technological progress have been offset by increasing size and engine power of the vehicles. (Craglia and Cullen, 2019) In a formal framework analysis on the impact of more efficient but larger new passenger cars on energy consumption in EU-15 countries from 1990 to 2010, the authors concluded that the technically achievable energy savings were compensated by $22\ \%$ due to more $\mathrm{vkm}$ and by $48\ \%$ due to larger (i.e., stronger and heavier) cars, thus constraining theoretical savings by $70\ \%$. (Ajanovic et al., 2012) However, involved feedback effects are complex, and many authors point out the significantly differing purchasing patterns of second-hand vehicles with accordingly different effects on the LDV fleet composition and energy demand. Moreover, effects identified in one or more European countries cannot be readily transferred to other countries. Nevertheless, we can assume a certain transferability. (Craglia and Cullen, 2019; Ó Gallachóir et al., 2009; Zachariadis, 2013)

At last, there is the widely recognized increasing gap between type-approval and real-world fuel economy of passenger cars, with the result that new LDV fuel economy standards set by the EU in 2008/09 had little effect on LDV energy efficiency. (Craglia and Cullen, 2019; Kok, 2015) In an ex-post energy consumption decomposition of Irish LDVs, on-road fuel consumption was, on average, $30$ and $40\ \%$ higher for gasoline and diesel vehicles, respectively. For one, this reemphasizes the importance of relying on multiple indicators in order to gain relevant insights into the state of energy efficiency (Dennehy and Ó Gallachóir, 2018) On the other side, this constitutes an information failure that makes it harder for consumers to make an energy-efficient vehicle purchase decision.

Limitations

Limitations in the data underlying the employed energy efficiency indicators are addressed in section **3.2**. However, in view of the incumbent complexity in collecting data from the passenger transport sector, all data can be considered valid for trend analysis except indicators involving alternatively fueled cars. Given the aggregate view with only one data point per year, it is difficult to ensure that the data points employed are all of the same definition with regarding the time period. This is especially true for indicators compounded by two non-contiguous data points, such as energy intensity indicators. Therefore, long-term trends are generally of higher significance than – e.g. – an observed year-on-year change. On top of that, some uncertainty remains, particularly with respect to Dutch bus activity data as well as with the conformance of coverage and definition of energy intensity indicators regarding German LDVs. For the latter, we can assume that the resulting energy intensity is slightly overestimated. By way of contrast, since gas LDVs are attributed to the other category while HEVs are assigned to the gasoline category, but both entail a partially significant share of bivalent engines, further uncertainty regarding gasoline intensity indicators emerges. However, both effects cancel each other out to some extent, and the share of these fuel types is generally minor. Additionally, given the methodological heterogeneity in data collection practices between the two countries, a direct country-to-country comparison or decomposition seems unrewarding yet potentially insightful. After all, this paper is less concerned with explaining the difference in transport activity and energy consumption between the two countries themselves but more about grasping the difference in the drivers underlying energy consumption.

Another inherent limitation lies within the breakdown of LDV gross energy intensity (energy per $\mathrm{pkm}$) into usage efficiency (i.e., $\mathrm{PMF}$) and technical energy efficiency (energy per $\mathrm{vkm}$ and $\mathrm{TS}$), which constitutes a central objective of this study. Since the LMDI methodology is generally consistent in aggregation, we might expect that the size of LDVs' $\mathrm{EI}$ effect in the passenger IDA (cf. **E14**) corresponds to the sum of the respective aggregate $\mathrm{PMF}$, $\mathrm{TS}$, and ($\mathrm{vkm}$-based) $\mathrm{EI}$ effects in the LDV IDA (cf. **E19**-**21**). This is also because when these three effects are multiplied out (cf. the IDA identity **E16**), the gross $\mathrm{EI}$ effect remains. However, since the definition of the factors differs in the single and multi-step procedure (namely the log mean of energy consumption), the sum of the three effects does not exactly match the size of the gross energy intensity of LDVs. The effect calculated in one step (i.e., LDVs' $\mathrm{EI}$ effect in the first IDA) involves the log mean of aggregate LDV energy consumption, whereas the sum of the disaggregated effects implies the log mean of the three subaggregates (i.e., LDV fuel types), which explains why the results do not necessarily coincide. Although this observation is in accordance with the limitations of the LMDI I approach mentioned in (Ang and Liu, 2001).

To illustrate this, LDVs' cumulative EI effect in 2007 for the Netherlands in the first IDA is $2.07$ PJ. The sum of the corresponding PMF ($8.4$ PJ), TS ($-1.88$ PJ), and EI ($-4.41$ PJ) effects in the second IDA is $2.11$ PJ, however. On average, this difference is $1.4$ % and $0.5$ % for German and Dutch results, respectively. The largest observed difference is $6.3$ % in 2005 and $4.22$ % in 2016 for the Netherlands and Germany, respectively.

Fundamentally, the preceding analyses aim to comprehend the influence of several factors of activity, structure, and intensity on passenger transport energy consumption. However, as here, it is infeasible for any study to capture the entirety of drivers underlying energy demand. As already addressed, this study fails to capture behavioral factors embedded in the gross energy intensity of passenger transport. The primary reason for this is missing data for passenger train vkm. While (Jennings et al., 2013) perform extensive refinements and estimations on Irish passenger transport data to obtain average occupancies for all traffic modes, this thesis aims to comprehend the phenomenon of usage efficiency by example of the LDV sector. Moreover, the reasons for the differing transport demand patterns (i.e., activity levels) between the two countries are not addressed. Those include, among others, differing geographic characteristics, such as population density and urbanization rate. (IEA, 2014a; Jennings et al., 2013) Other issues not addressed include the potentially significant impact of energy prices, the effect of policy changes (such as subsidies or emission limits and the impact on the level of dieselization), but also the effects of LDV ownership type and vehicle attributes. For instance, a study on transport behavior against the background of partial tax exemption for commercially registered cars in Germany concludes that company car benefits stimulate growth in the number of LDVs and an increase in car motorization and usage. (Metzler et al., 2019)

Beyond that, we could quantify the potential rebound effect in terms of an increase in passenger activity or changing PLF in parallel with declining energy intensity per

$\mathrm{vkm}$. Nevertheless, statements about the extent to which this occurred as a result of technical efficiency gains are not possible. On the other hand, a rebound effect in the course of inter-fuel substitution or in terms of changing vehicle attributes is not directly quantifiable in this setup. Nonetheless, given the myriad and possibly different nature of underpinning determinants, a top-down decomposition analysis does not seem the best way to address these questions.

What is more, given that volumetric energy intensities (such as liters per $100\ \mathrm{vkm}$ or miles per gallon) are still the most widely used units quoted either in public discussions about car energy efficiency or in the context of car efficiency labels, it would seem natural to employ such a metric in the context of this work. Moreover, volumetric energy indicators are employed in a number of scientific works on the topic. (Ajanovic et al., 2012; Craglia and Cullen, 2019; Dennehy and Ó Gallachóir, 2018; González et al., 2019; Marrero and Rodríguez-López, J. González, R.M., 2020) However, owing to the different volumetric carbon content of diesel and gasoline fuels, a volumetric energy intensity measure would substantially skew results, first and foremost, because the fuel share is not steady. Nonetheless, there is the possibility to employ volumetric energy intensity without distortions if the index of improvement for the individual fuels is calculated before aggregation or if a diesel intensity indicator – e.g. – is transformed into gasoline equivalents. Even so, such an indicator would be more difficult to interpret without further information on fuel composition and is further not suitable for comparing, for instance, the energy intensity of electric passenger trains with that of gasoline LDVs. Considering this, the use of an absolute indicator appears to be more elegant. Notwithstanding, the use of a single volumetric intensity indicator for all fuel types would still compound isolating and quantifying the impact of inter-fuel substitutions since this effect would be subsumed into the intensity effect. (Dennehy and Ó Gallachóir, 2018) Thus, introducing the $\mathrm{TS}$ effect remediates this issue. Any the less, in the $\mathrm{pkm}$-based intensity indicator employed in the first IDA, this concern still holds. However, since a $\mathrm{pkm}$-based intensity indicator also subsumes usage behavior (i.e., average occupancy), this is of secondary nature.

Beyond this, other authors based their technical LDV energy intensity metric on type-approval fuel economy and included an on-road factor to account for differences between laboratory testing values and real-world fuel consumption. (Craglia and Cullen, 2019; Dennehy and Ó Gallachóir, 2018) While this approach elucidates the often-stark differences between published and real-world fuel economy and quantifies it, this is less in line with the top-down approach applied here, which primarily aims to identify higher-level relationships in the overall passenger transport sector on the basis of its most important component.

Furthermore, the choice of metrics for activity, structure, and intensity metrics differs significantly among decomposition analysis studies. (Papagiannaki and Diakoulaki, 2009) employ registered LDVs per capita together with population change and annual mileage as activity metric and use a $\mathrm{vkm}$-based intensity metric. Passenger activity and, thus, average occupancy are disregarded. Similarly, (Dennehy and Ó Gallachóir, 2018) use the number of cars together with average mileage as activity metrics, also neglecting passenger activity while excluding population change in addition. Consequently, the fuel share in both approaches is weighted according to the stock ratio. While Dennehy and Ó Gallachóir acknowledge that a $\mathrm{vkm}$ ratio derived weighting is more accurate owing to the differing mileages (since LDV energy consumption ultimately depends on the mileage), the authors point out that this step was necessary to extend the analysis to further factors. If the analysis in this thesis had employed LDVs per capita together with mileage and population as activity metrics, the size of the former would be significantly larger than the utilized $\mathrm{pkm/cap}$ metric but would have been eventually mediated by the mileage factor. The population factor size would have stayed equal in any case. However, since this would necessitate a stock-weighted technology share, the effect's size would be substantially skewed in consequence of the differing annual mileages. To illustrate this, the stock-weighted technology share effect in the energy decomposition of the Irish LDV sector between 1995 and 2015 was substantially positive. This is against the background of profound dieselization (likewise to Germany) and corresponding negative contributions to technical energy intensity. The authors point out that this is primarily owing to the significantly greater mileage of diesel LDVs which is incorporated in the factor. (Dennehy and Ó Gallachóir, 2018) Nevertheless, population growth, which is not considered, additionally distorts the effect upward.

Furthermore, while we can observe the correlation between the increasing number of registered LDVs and decreasing average mileage only outside the IDA, a stock-based activity metric neglecting pkm would encompass this but – e.g. – curtain the substantial impact of the declining Dutch LDV car occupancy on the other hand. Without the use of secondary data, the conclusion that Dutch LDVs were driven more while transporting fewer passengers could not have been made. The offsetting effect to decreasing technical energy intensity would have been primarily attributed to the increasing number of vehicles and thus increased activity.

In conclusion, while the choice of factors is driven by the research objectives, it is essential to exercise caution when interpreting them. The size and sign of each factor are contingent upon their definitions and their interrelationships with other factors. It is crucial to view these factors not in isolation but rather as part of a complex functional interaction, recognizing that their interpretations are intrinsically linked to one another.

# 6. Conclusion

This research aims to ascertain and quantify the progress of energy efficiency of land passenger transport in Germany and the Netherlands. Based on an LMDI factor decomposition analysis, the aggregate energy consumption of land passenger transport and LDVs – in a separate analysis – are decomposed into various factors of activity, structure, and energy intensity. With this approach employing historical data from 17 years, it ought to be examined, particularly to what extent the energy efficiency pathway can be attributed to technical energy efficiency improvements and behavioral factors. Moreover, the hypothesis that there is a rebound effect in the form that technical energy efficiency improvements are primarily offset by an increase in passenger activity is tested. However, owing to non-obtainable data, the technical energy efficiency of passenger transport cannot be directly ascertained. Therefore, the second IDA – looking at LDVs which represent most passenger activity and energy consumption – examines both gross and technical energy intensity, serving in turn as a reasonable proxy for the passenger transport sector as a whole.

The numerical results suggest a rebound effect since technical efficiency improvements exist (for LDVs) yet are counteracted by behavioral factors. Thereby, gross passenger transport energy intensity improves in Germany but deteriorates in the Netherlands. While the case of Germany supports the initial hypothesis, the Netherlands is subject to declining per capita passenger activity (in $\mathrm{pkm}$/cap) with other behavioral factors thwarting the progress of technical energy intensity. In the Dutch case, the rebound effect lies within a deteriorating LDV average occupancy with the effect that fewer passenger kilometers are traveled spread over more vehicles which are driven more overall. Therefore, increasing passenger activity in a broader sense is a major counteracting effect to enhanced LDV energy intensity since vehicle kilometers per capita increase in all cases. Moreover, the German LDV fleet dieselization – which has a significant negative impact on the specific LDV energy consumption – may be additionally subject to a rebound effect against the background of individually decreasing annual mileages (i.e., per fuel type) but relatively constant annual mileages on aggregate in the course of fuel-technology substitutions. In the Netherlands, this observation cannot be made since the fuel

share stays more constant. Beyond that, further academic research on the subject indicates that technical energy efficiency enhancements may prompt a shift in vehicle purchase patterns towards heavier and stronger-motorized models, thus further limiting tangible reductions in energy consumed. (Ajanovic et al., 2012; Craglia and Cullen, 2019; Ó Gallachóir et al., 2009) However, this could not be quantified within the scope of this work.
After all, modal split has the most negligible impact on passenger transport energy consumption. This is surprising, given that modal shift offers some of the greatest saving potentials in view of the vast difference in energy consumption per passenger kilometer across modes.

In conclusion, this thesis has shed light on several important aspects of energy efficiency in passenger transport. Firstly, drivers and barriers to energy efficiency in general have been outlined and linked to passenger transport by delving into the concept of associated energy efficiency indicators and data collection practices. Moreover, an in-depth review of decomposition practices was conducted, building on the framework previously developed. In addition, numerous limitations in the data underlying utilized efficiency indicators have been addressed. This especially applies to adopted practices to delimit transport activity data to a national territory. Beyond that, some data documentation was found to be incomplete or unavailable, which particularly affected the validation of energy data. Secondly, the disaggregation of LDV fuel types against the background of an increasing prevalence of bivalent engines poses a considerable challenge. To achieve a more comprehensive understanding, there is a need for more detailed data on the actual fueling of such. In the present research, assumptions were relied upon for attribution, underscoring the importance of acquiring precise data to ensure sound analysis. Lastly, the expressiveness and generalizability of any IDA's results are intrinsically linked to the quality of underlying data. Addressing these limitations presents an auspicious opportunity to improve the streamlining of data collection methodologies to ensure the accuracy, reliability, but also comparability of energy efficiency indicators. By addressing these recommendations, researchers and policymakers can bolster their efforts in understanding energy efficiency trends and devising effective strategies to combat climate change and promote sustainable development.

Based on the main finding that the human dimension is an essential adversary to technical energy efficiency improvements, further research could address the context behind the differing levels of activity between the two countries. This may include the difference in passenger kilometers per capita but also as to why the Dutch LDV average occupancy decreases in such a manner. Ultimately, understanding the savings potential and monitoring the impact of technology and behavioral change on passenger transport energy consumption requires a holistic analysis, including a multifaceted set of employed indicators. Starting from the analyses' results, an impactful policy response should target, first and foremost, the reduction of LDV traffic share given the largely untapped potential of an altered modal split. Besides, policies targeting the deteriorating $\mathrm{PLF}$ observed for Dutch LDVs also hold a considerable energy saving potential in hindsight of the former more than offsetting technical efficiency gains achieved otherwise. Bearing in mind the minor share in energy consumption, measures targeting buses and trains in isolation are expected to have less impact on aggregate passenger transport energy consumption. Nonetheless, in view of the elusiveness of energy efficiency but also of passenger transport itself – with the myriad of involved stakeholders taking decisions that are deeply embedded in everyday life – transport policies solely targeting technical efficiency improvements are likely to fail considering associated rebound effects. Therefore, a successful policy to enhance passenger transport energy efficiency must address behavioral and personal utility factors.

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# 8. Appendix A: Data used in the Passenger Transport IDA

General Notes

This appendix gives record about sources and revisions of data instigated in chapter 3.2.1. To perform the IDA for the years 2000 through 2016, data series for pkm, energy consumption and population size is required, whereas disaggregation by traffic mode is required for pkm and energy consumption. With passenger transport sectors of two countries to be examined, this sums up to 14 data series. The finally employed data is given in **Tables** 6 and 7 at the bottom of this paragraph. As already discussed, LDV energy and all train data can be readily deployed from the IEA database on energy efficiency indicators for the transport sector. Revisions on energy data for light duty vehicles are approached in **Appendix B** in the respective sub-chapters. Nonetheless, German energy data, and Dutch energy and activity data on buses, are subject to some conspicuities which are dealt with in the following.

Revision of German bus energy data

Until 2012 bus energy consumption data are almost identical across databases. Missing values for energy carriers other than gasoline or diesel can be explained by values reported under other sources. However, in the periods after 2012, reported values for TFC vary substantially, where the IEA's values seem to have decoupled from the trend in vkm. When energy consumption data is indexed to a base period – together with vkm data – and mapped in a graph (cf. **Figure 20** with IEA energy data (IEA, 2020a) in blue, ODYSSEE-MURE (ODMU) (ODYSSEE-MURE, 2023) energy data in orange and IEA vkm data in grey), one easily finds, that the IEA's datapoints deviate from the trend of vkm as of 2012.

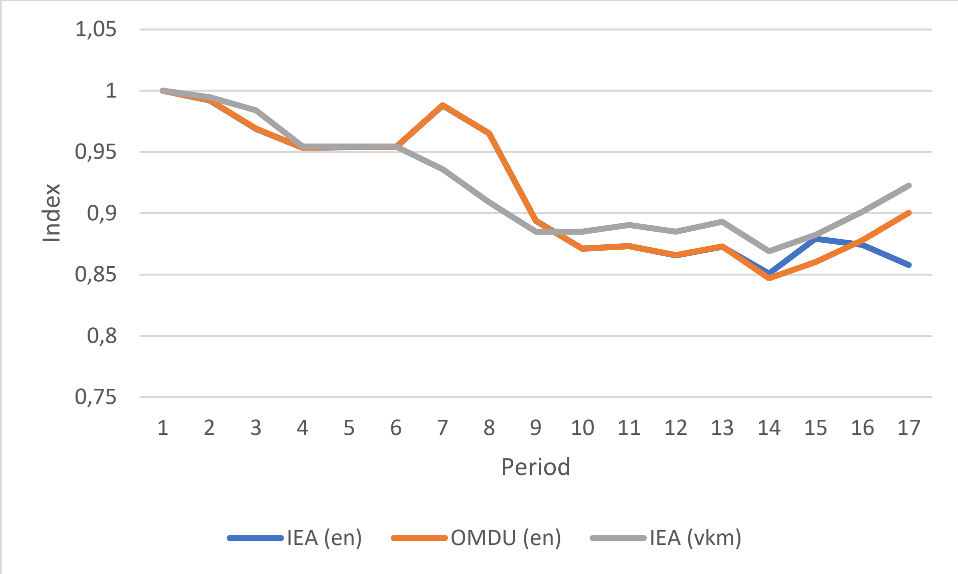


**Figure 20: Indexation of German Bus Energy Consumption and vkm Data**

As already deduced, the observed deviation can be explained by deviating values for other fuels in the IEA database. Therefore, energy consumption data from ODYSSEE-MURE is used. For the years from 2005 to 2008, energy consumption may be overestimated (in both data sources). In the absence of any trackable change in methodology, we must assume – with reservations – that the provided data are correct. Underlying data for **Figure 20** is provided in **Table 2**.

**Table 2: Bus TFC and vkm Values and Indexes for Germany**

| period (year) | TFC[a] [PJ] | TFC[b] [PJ] | vkm[a] [$10^9$ km] | TFC[a] indexed | TFC[b] indexed | vkm[a] indexed |
|---|---|---|---|---|---|---|
| 1 (2000) | 36,85 | 36,84 | 3,74 | 1 | 1 | 1 |
| 2 (2001) | 36,56 | 36,56 | 3,72 | 0,992 | 0,992 | 0,995 |
| 3 (2002) | 35,70 | 35,70 | 3,68 | 0,969 | 0,969 | 0,983 |
| 4 (2003) | 35,13 | 35,12 | 3,57 | 0,953 | 0,953 | 0,955 |
| 5 (2004) | 35,15 | 35,15 | 3,57 | 0,954 | 0,954 | 0,955 |
| 6 (2005) | 35,15 | 35,14 | 3,57 | 0,954 | 0,954 | 0,955 |
| 7 (2006) | 36,40 | 36,40 | 3,50 | 0,988 | 0,988 | 0,936 |
| 8 (2007) | 35,57 | 35,56 | 3,40 | 0,965 | 0,965 | 0,909 |
| 9 (2008) | 32,94 | 32,93 | 3,31 | 0,894 | 0,894 | 0,885 |
| 10 (2009) | 32,10 | 32,09 | 3,31 | 0,871 | 0,871 | 0,885 |
| 11 (2010) | 32,18 | 32,17 | 3,33 | 0,873 | 0,873 | 0,890 |
| 12 (2011) | 31,90 | 31,90 | 3,31 | 0,866 | 0,866 | 0,885 |
| 13 (2012) | 32,16 | 32,16 | 3,34 | 0,873 | 0,873 | 0,893 |
| 14 (2013) | 31,35 | 31,20 | 3,25 | 0,851 | 0,847 | 0,869 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 15 (2014) | 32,40 | 31,69 | 3,30 | 0,879 | 0,860 | 0,882 |
| 16 (2015) | 32,21 | 32,34 | 3,37 | 0,874 | 0,878 | 0,901 |
| 17 (2016) | 31,61 | 33,17 | 3,45 | 0,858 | 0,900 | 0,922 |

Superscripts: [a]: IEA Database; [b]: ODYSSEE-MURE Database

Notes on Dutch bus energy data

Contrary to IEA, in ODYSSEE-MURE, there are no reported values for CNG consumption of buses. Once those values are added from the IEA dataset, values for TFC correspond. In consequence, the IEA data may be regarded as externally consistent.

Revision on Dutch bus activity data Netherlands

Given that pkm per capita for trains are somewhat similar in Germany and the Netherlands, a value less than half for busses seems implausible. This holds especially true when looking at bus vkm, as this would imply busses in the Netherlands circulating with roughly half as many passengers on average. These relationships are depicted in **Figures 21** and **22**. Underlying data are presented in **Tables 3** and **4**.

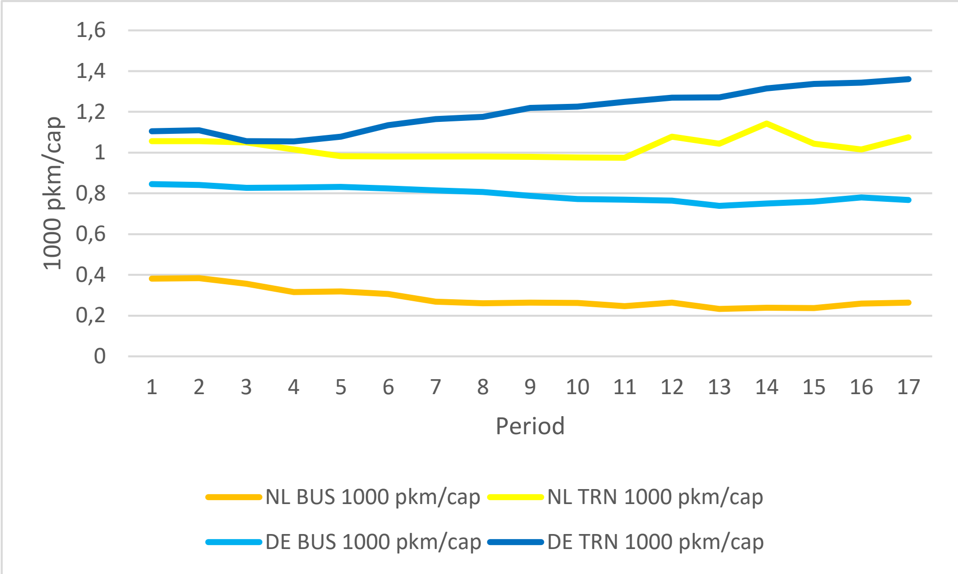


**Figure 21: Pkm per Capita for Public Transport Modes for Germany and Netherlands with IEA Data**

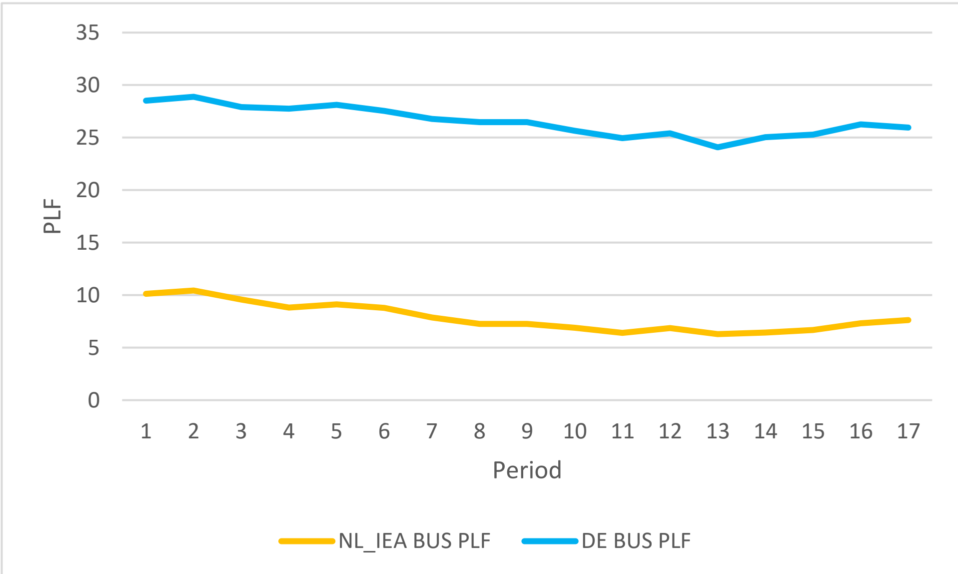


**Figure 22: Bus Passenger Load Factors for Germany and Netherlands with IEA Data**

Further investigation on the subject matter shows that provided Dutch bus pkm data are estimated based on a nationwide travel survey. Values before the methodological change can be found for the years 2000 and 2005-2014 in the book series "EU Transport in Figures" of the European Commission (EC and Directorate-General for Energy and Transport, 2008; EC and Directorate-General for Mobility and Transport, 2011, 2014, 2016). Resulting PLF and pkm per capita relate more to values found in Germany and other surrounding countries (cf. **Figure 23** and **Table 3**). Since values on bus $\mathrm{pkm}$ are missing for 2001 to 2004 and as of 2015, missing values must be imputed.

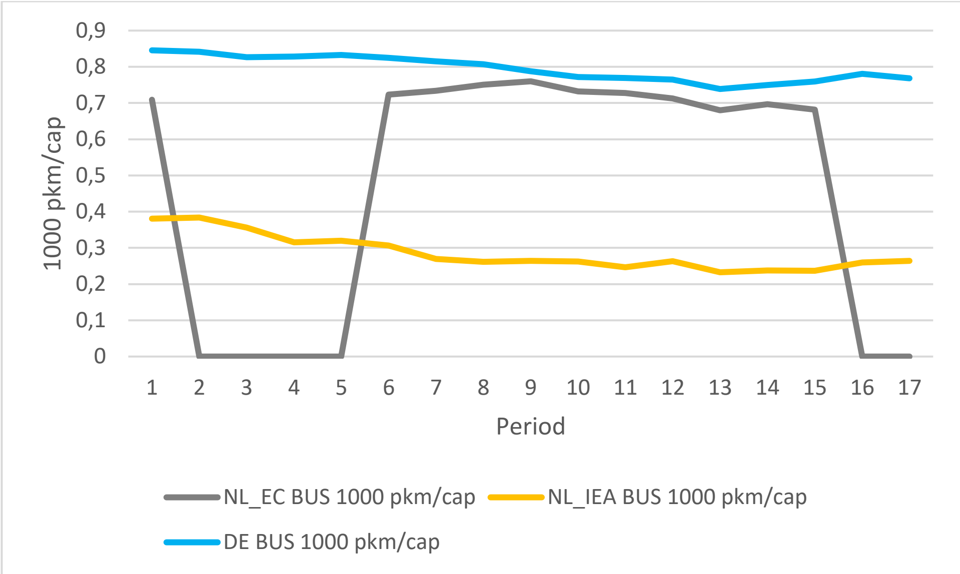


**Figure 23: Bus pkm per Capita for Germany and Netherlands of different Sources**

To impute the six missing values, we can look at adjacent growth trends. This includes $\mathrm{pkm}$ per capita and average occupancy ($\mathrm{PLF}$), both from $\mathrm{IEA}$ data and values from Germany. To easily find out whether growth trends resemble, we can index the values to the base year. Further scrutiny shows that $\mathrm{pkm}$ per capita is an unsuitable predictor since there are no observable correlations. The same is true when compared to data derived from the Dutch travel survey (i.e., $\mathrm{pkm}$ data drawn from $\mathrm{IEA}$ or $\mathrm{ODYSSEE\text{-}MURE}$ database). At last, when we index the $\mathrm{PLF}$ derived from $\mathrm{EC}$ $\mathrm{pkm}$ data and $\mathrm{IEA}$ $\mathrm{vkm}$ data together with $\mathrm{IEA}$ $\mathrm{pkm}$ data from Germany, we can see that as of 2009 (period 10), both functions behave in a very similar way (cf. **Figure 24** and **Table 5**). Notwithstanding, this cannot be said for values before 2009.

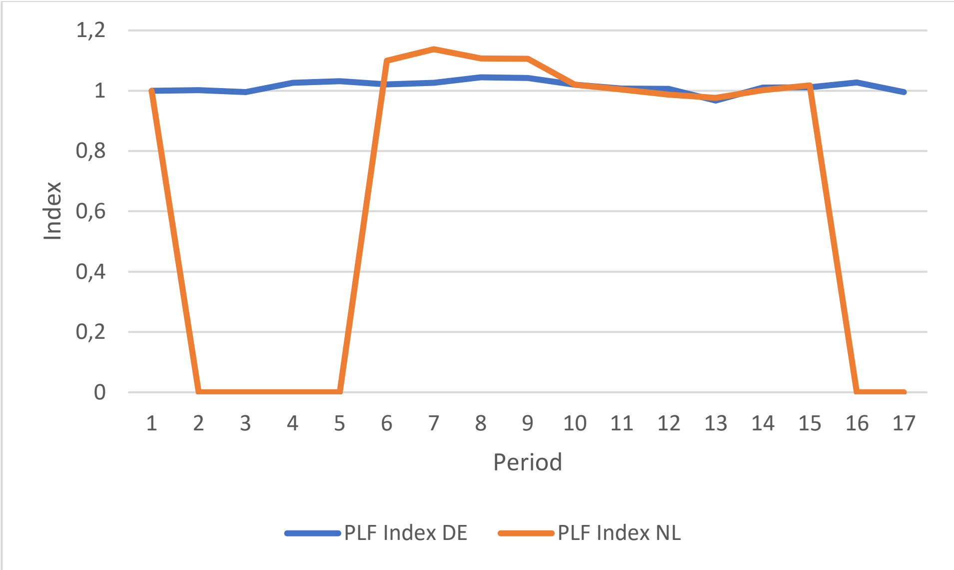


**Figure 24: PLF for Buses in the Netherlands (EC/IEA) and Germany (IEA) indexed together**

Given the geographic and economic proximity, we therefore may assume that the PLF for busses in the Netherlands behaved in the same way as in Germany for the years of 2016 and 2017 when compared to the base year value. Therefore, those two values are estimated via multiplying the index value of German bus PLF (from **Table 5**) to obtain the estimated PLF for the Netherlands. The value for $\mathrm{pkm}$ is obtained by the relationship established in E2. In the absence of any observable correlation, missing values for the years 2001-2004 are linearly interpolated (i.e., assuming a linear growth rate). The resulting finally deployed value for Dutch bus $\mathrm{pkm}$ – together with all other values relevant for the IDA – are given in Table 7 at the bottom of this chapter.

**Table 3: Data on 1000 pkm/cap used in Figures 21 and 23**

| Period (year) | 1000 pkm/cap (traffic mode, country) | | | | |
|---|---|---|---|---|---|
| | Bus, NL[c] | Bus, NL[a] | Bus, GE[a] | Train, NL[a] | Train, GE[a] |
| 1 (2000) | 0,709[c1,2,3,4] | 0,381 | 0,845 | 1,056 | 1,105 |
| 2 (2001) | n/a | 0,384 | 0,842 | 1,055 | 1,110 |
| 3 (2002) | n/a | 0,356 | 0,827 | 1,050 | 1,056 |
| 4 (2003) | n/a | 0,315 | 0,828 | 1,015 | 1,055 |
| 5 (2004) | n/a | 0,319 | 0,832 | 0,983 | 1,079 |
| 6 (2005) | 0,723[c1,2,3,4] | 0,306 | 0,824 | 0,982 | 1,135 |
| 7 (2006) | 0,734[c1] | 0,269 | 0,815 | 0,980 | 1,165 |
| 8 (2007) | 0,751[c2] | 0,261 | 0,807 | 0,981 | 1,176 |
| 9 (2008) | 0,760[c2] | 0,264 | 0,787 | 0,980 | 1,220 |

| | | | | | |
|---|---|---|---|---|---|
| 10 (2009) | 0,732[c2] | 0,263 | 0,772 | 0,976 | 1,226 |
| 11 (2010) | 0,728[c3,4] | 0,247 | 0,769 | 0,975 | 1,249 |
| 12 (2011) | 0,713[c3] | 0,264 | 0,764 | 1,078 | 1,269 |
| 13 (2012) | 0,680[c3] | 0,233 | 0,739 | 1,044 | 1,272 |
| 14 (2013) | 0,696[c4] | 0,238 | 0,750 | 1,143 | 1,315 |
| 15 (2014) | 0,682[c4] | 0,237 | 0,759 | 1,043 | 1,337 |
| 16 (2015) | n/a | 0,260 | 0,781 | 1,015 | 1,343 |
| 17 (2016) | n/a | 0,264 | 0,768 | 1,075 | 1,361 |

Superscripts: [a]: IEA Database, [c]: EC Pocketbooks (1: (EC and Directorate-General for Energy and Transport, 2008), 2: (EC and Directorate-General for Mobility and Transport, 2011), 3: (EC and Directorate-General for Mobility and Transport, 2014), 4: (EC and Directorate-General for Mobility and Transport, 2016))

**Table 4: Bus vkm and PLF**

| Period (year) | PLF bus (country) | | | vkm bus (country) | |
|---|---|---|---|---|---|
| | NL[a,c] [pkm/vkm] | NL[a] [pkm/vkm] | DE[a] [pkm/vkm] | NL[a] [$10^9$ km] | DE[a] [$10^9$ km] |
| 1 (2000) | 18,833 | 10,117 | 18,414 | 0,60 | 3,74 |
| 2 (2001) | n/a | 10,441 | 18,444 | 0,59 | 3,72 |
| 3 (2002) | n/a | 9,583 | 18,329 | 0,60 | 3,68 |
| 4 (2003) | n/a | 8,828 | 18,919 | 0,58 | 3,57 |
| 5 (2004) | n/a | 9,123 | 18,994 | 0,57 | 3,57 |
| 6 (2005) | 20,702 | 8,772 | 18,784 | 0,57 | 3,57 |
| 7 (2006) | 21,429 | 7,857 | 18,909 | 0,56 | 3,50 |
| 8 (2007) | 20,847 | 7,254 | 19,232 | 0,59 | 3,40 |
| 9 (2008) | 20,833 | 7,250 | 19,211 | 0,60 | 3,31 |
| 10 (2009) | 19,206 | 6,889 | 18,761 | 0,63 | 3,31 |
| 11 (2010) | 18,906 | 6,406 | 18,544 | 0,64 | 3,33 |
| 12 (2011) | 18,594 | 6,875 | 18,541 | 0,64 | 3,31 |
| 13 (2012) | 18,387 | 6,290 | 17,787 | 0,62 | 3,34 |
| 14 (2013) | 18,871 | 6,452 | 18,603 | 0,62 | 3,25 |
| 15 (2014) | 19,167 | 6,667 | 18,624 | 0,60 | 3,30 |
| 16 (2015) | n/a | 7,333 | 18,926 | 0,60 | 3,37 |
| 17 (2016) | n/a | 7,627 | 18,333 | 0,59 | 3,45 |

Superscripts: [a]: IEA Database, [a,c]: pkm from EC Pocketbooks (cf. table above) and vkm from IEA

**Table 5: Indexed Bus PLF for Germany and the Netherlands**

| Period (year) | PLF[a,c] (NL, indexed) | PLF[a] (DE, indexed) |
|---|---|---|
| 1 (2000) | 1,000 | 1,000 |
| 2 (2001) | n/a | 1,002 |
| 3 (2002) | n/a | 0,996 |
| 4 (2003) | n/a | 1,027 |
| 5 (2004) | n/a | 1,032 |
| 6 (2005) | 1,099 | 1,021 |
| 7 (2006) | 1,138 | 1,026 |
| 8 (2007) | 1,107 | 1,045 |
| 9 (2008) | 1,106 | 1,042 |
| 10 (2009) | 1,020 | 1,020 |
| 11 (2010) | 1,004 | 1,007 |
| 12 (2011) | 0,987 | 1,006 |
| 13 (2012) | 0,976 | 0,967 |
| 14 (2013) | 1,002 | 1,010 |
| 15 (2014) | 1,018 | 1,011 |
| 16 (2015) | n/a | 1,028 |
| 17 (2016) | n/a | 0,995 |

**Table 6: Final Data deployed for the German Passenger Transport IDA**

| Period (year) | Energy consumption (LDV)[a] [PJ] | Energy consumption (bus)[b] [PJ] | Energy consumption (train)[a] [PJ] | pkm (LDV)[a] [$10^9$ km] | pkm (bus)[a] [$10^9$ km] | pkm (train)[a] [$10^9$ km] | POP[a] [$10^6$] |
|---|---|---|---|---|---|---|---|
| 1 (2000) | 1511,88 | 36,84 | 35,16 | 849,60 | 68,87 | 90,00 | 81,46 |
| 2 (2001) | 1527,28 | 36,56 | 35,02 | 872,02 | 68,61 | 90,45 | 81,52 |
| 3 (2002) | 1536,9 | 35,70 | 33,39 | 880,28 | 67,45 | 86,11 | 81,58 |
| 4 (2003) | 1508,53 | 35,12 | 28,08 | 875,65 | 67,54 | 86,04 | 81,55 |
| 5 (2004) | 1531,43 | 35,15 | 26,43 | 887,10 | 67,81 | 87,89 | 81,46 |
| 6 (2005) | 1478,04 | 35,14 | 26,37 | 875,67 | 67,06 | 92,31 | 81,34 |
| 7 (2006) | 1479,56 | 36,40 | 23,63 | 882,65 | 66,18 | 94,56 | 81,17 |
| 8 (2007) | 1469,17 | 35,56 | 21,94 | 885,44 | 65,39 | 95,26 | 80,99 |
| 9 (2008) | 1443,56 | 32,93 | 20,59 | 888,53 | 63,59 | 98,53 | 80,76 |
| 10 (2009) | 1454,07 | 32,09 | 23,20 | 898,70 | 62,10 | 98,70 | 80,48 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 11 (2010) | 1455,55 | 32,17 | 22,68 | 902,40 | 61,75 | 100,30 | 80,28 |
| 12 (2011) | 1471,6 | 31,90 | 22,22 | 912,42 | 61,37 | 101,90 | 80,28 |
| 13 (2012) | 1453,76 | 32,16 | 21,64 | 914,56 | 59,41 | 102,30 | 80,43 |
| 14 (2013) | 1465,59 | 31,20 | 21,46 | 921,42 | 60,46 | 106,07 | 80,65 |
| 15 (2014) | 1490,39 | 31,69 | 20,30 | 934,96 | 61,46 | 108,31 | 80,98 |
| 16 (2015) | 1498,07 | 32,34 | 19,82 | 945,73 | 63,78 | 109,70 | 81,69 |
| 17 (2016) | 1523,31 | 33,17 | 19,70 | 965,30 | 63,25 | 112,04 | 82,35 |

Superscripts: [a]: IEA Database; [b]: ODYSSEE-MURE Database

**Table 7: Final Data deployed for the Dutch Passenger Transport IDA**

| Period (year) | Energy consumption (LDV)[a] [PJ] | Energy consumption (bus)[a] [PJ] | Energy consumption (train)[a] [PJ] | pkm (LDV)[a] [$10^9$ km] | pkm (bus)[a,c] [$10^9$ km] | pkm (train)[a] [$10^9$ km] | POP[a] [$10^6$] |
|---|---|---|---|---|---|---|---|
| 1 (2000) | 236,23 | 7,56 | 5,32 | 141,10 | 11,30 | 16,83 | 15,93 |
| 2 (2001) | 238,64 | 7,38 | 5,10 | 141,60 | 11,33 | 16,94 | 16,05 |
| 3 (2002) | 242,5 | 7,49 | 5,03 | 144,20 | 11,75 | 16,95 | 16,15 |
| 4 (2003) | 245,21 | 7,27 | 4,95 | 146,10 | 11,57 | 16,48 | 16,23 |
| 5 (2004) | 251,28 | 7,00 | 4,81 | 151,50 | 11,59 | 16,00 | 16,28 |
| 6 (2005) | 249,74 | 6,94 | 4,61 | 148,80 | 11,80 | 16,02 | 16,32 |
| 7 (2006) | 250,47 | 6,80 | 4,51 | 148,00 | 12,00 | 16,03 | 16,35 |
| 8 (2007) | 252,42 | 7,05 | 4,22 | 149,50 | 12,30 | 16,07 | 16,38 |
| 9 (2008) | 249,41 | 7,21 | 4,36 | 143,70 | 12,50 | 16,12 | 16,45 |
| 10 (2009) | 248,29 | 7,57 | 4,76 | 148,90 | 12,10 | 16,14 | 16,53 |
| 11 (2010) | 249,5 | 7,79 | 4,90 | 144,20 | 12,10 | 16,20 | 16,62 |
| 12 (2011) | 249,8 | 7,93 | 4,94 | 144,40 | 11,90 | 18,00 | 16,69 |
| 13 (2012) | 247,79 | 7,84 | 4,91 | 139,60 | 11,40 | 17,50 | 16,76 |
| 14 (2013) | 245,76 | 7,92 | 4,94 | 145,40 | 11,70 | 19,20 | 16,80 |
| 15 (2014) | 244,83 | 7,78 | 4,69 | 145,00 | 11,50 | 17,60 | 16,87 |
| 16 (2015) | 244,8 | 7,86 | 4,37 | 139,50 | 11,61 | 17,20 | 16,94 |
| 17 (2016) | 247,36 | 7,96 | 4,57 | 140,80 | 11,06 | 18,30 | 17,03 |

Superscripts: [a]: IEA Database; [a,c]: pkm from EC Pocketbooks, Value Imputation using IEA Database

# 9. Appendix B: Data used in the LDV IDA

General Notes

This appendix gives record about sources and revisions of data instigated in chapter 3.2.2. To perform the IDA for the years 2000 through 2016, data series for $\mathrm{pkm}$, $\mathrm{vkm}$, energy consumption and population size is required, whereas disaggregation by engine technology is required for $\mathrm{vkm}$ and energy consumption. With LDV sectors of two countries and three propulsion technologies to be examined, this sums up to 16 data series. The finally employed data is given in **Table** 22 and 23 at the bottom of this paragraph. As discussed at the outset, energy data for both countries must be conflated from the two primary sources, since it is dealt differently with biofuels and due to differing data availability for unconventional fuels. Activity data on $\mathrm{pkm}$ can be readily deployed and are externally consistent. $\mathrm{Vkm}$ disaggregated by engine type must be calculated based on available data for annual mileage and stock, which are available for gasoline, diesel, and overall LDVs.

Revision of German energy data

For Germany, the sum of gasoline, diesel, and biofuel consumption in the $\mathrm{ODYSSEE}$-$\mathrm{MURE}$ database equals the sum of gasoline and diesel consumption in the $\mathrm{IEA}$ database. Besides, data from both sources pass reaggregation tests and are thus internally consistent. However, the $\mathrm{ODYSSEE}$-$\mathrm{MURE}$ database is lacking values for other fuel consumption except LPG (whose values are substantially larger than in the counterpart). In contrast, the $\mathrm{IEA}$ provides consumption data on electricity, natural gas, and LPG. Strikingly, aggregated consumption of other fuels is remarkably similar with a mean difference of about $.3$ $\mathrm{PJ}$. This suggests that disaggregation of fuel consumption is erroneous in the ODYSSEE-MURE database. To enable data consistency, energy consumption data for diesel and gasoline are drawn from the $\mathrm{IEA}$ database and aggregated data for other fuels are averaged over both sources. This approach leads to an equivalence of consistently over 99.8 % when compared to reported TFC of both sources. It is worth noting that the share in energy consumption of other fuels lies between $.03$ and $2.14$ % within the examined period. Underlying data on TFC and consumption of other fuels are provided in **Table 8**. Here TFC values are as reported as TFC in the original source. Other fuel consumption from ODYSSEE-MURE solely constitutes LPG consumption and from IEA it is the aggregate of consumption of LPG, natural gas (CNG), and electricity. Since due to a methodological break (see sub-chapter to revision of German vkm data), the gasoline category in activity data contains gas driven LPGs from 2000 until 2008, energy consumption of the other category is allocated to the gasoline category for those years and consumption of other fuels is set to zero in those periods. Since the maximum LDV electricity consumption in this period is .06 PJ, this can be neglected. The revised – and therefore final – LDV energy consumption data is provided in **Table 16** in the sub-chapter validation of German energy and activity data.

**Table 8: Values for German LDV Energy Consumption**

| Period (year) | TFC[a] [PJ] | TFC[b] [PJ] | Others[a] [PJ] | Others[b] [PJ] |
|---|---|---|---|---|
| 1 (2000) | 1512,28 | 1511,17 | 0,92 | 0,09 |
| 2 (2001) | 1527,81 | 1526,47 | 1,14 | 0,10 |
| 3 (2002) | 1537,59 | 1535,93 | 1,98 | 0,61 |
| 4 (2003) | 1509,42 | 1507,36 | 2,47 | 0,69 |
| 5 (2004) | 1532,58 | 1530,00 | 4,18 | 1,89 |
| 6 (2005) | 1478,06 | 1477,74 | 5,53 | 5,48 |
| 7 (2006) | 1479,58 | 1479,26 | 9,10 | 9,05 |
| 8 (2007) | 1468,59 | 1469,46 | 13,64 | 14,78 |
| 9 (2008) | 1442,04 | 1444,81 | 19,75 | 22,79 |
| 10 (2009) | 1452,94 | 1454,92 | 30,02 | 32,28 |
| 11 (2010) | 1454,75 | 1456,06 | 29,01 | 30,59 |
| 12 (2011) | 1470,77 | 1472,18 | 30,69 | 32,38 |
| 13 (2012) | 1452,95 | 1454,31 | 30,76 | 32,39 |
| 14 (2013) | 1465,55 | 1464,86 | 30,37 | 30,46 |
| 15 (2014) | 1490,49 | 1490,01 | 29,12 | 28,93 |
| 16 (2015) | 1498,34 | 1497,53 | 26,90 | 26,37 |
| 17 (2016) | 1522,41 | 1523,92 | 25,13 | 26,93 |

Superscripts: [a]: IEA Database; [b]: ODYSSEE-MURE Database, [c]: Average of [a,b]

Revision of Dutch energy data

For the Netherlands, however, sums of gasoline and diesel consumption (and biofuels respectively) do not match, the percentage difference never exceeds 2 % though. This is unexpected since the IEA states the ODYSSEE database as key source for Dutch data (IEA, 2020b). Until 2006 the respective figures largely correspond, whereas from 2007 until 2014 the IEA's values are continuously larger, and smaller for the last two years. In absence of any traceable data revisions or breaks, the corresponding data for gasoline and diesel consumption (including bioethanol and biodiesel for the ODYSSEE-MURE counterpart respectively) are averaged. Moreover, consumption data for biofuels is missing until 2005 for bioethanol and until 2002 for biodiesel. Given the small values in the years onwards, we assume that consumption for the missing periods is zero. Underlying consumption data are provided in **Table 9**.

**Table 9: Gasoline, Diesel and Biofuel Consumption of Dutch LDVs**

| Period (year) | Gasoline[a] [PJ] | Gasoline[b] [PJ] | Bioethanol[b] [PJ] | Diesel[a] [PJ] | Diesel[b] [PJ] | Biodiesel[b] [PJ] |
|---|---|---|---|---|---|---|
| 1 (2000) | 161,97 | 161,29 | n/a | 53,63 | 53,62 | n/a |
| 2 (2001) | 162,83 | 162,58 | n/a | 56,38 | 56,29 | n/a |
| 3 (2002) | 164,45 | 165,16 | n/a | 59,69 | 59,63 | n/a |
| 4 (2003) | 166,04 | 166,25 | n/a | 62,96 | 62,81 | 0,027 |
| 5 (2004) | 170,47 | 170,66 | n/a | 66,26 | 66,14 | 0,028 |
| 6 (2005) | 167,73 | 167,99 | n/a | 68,87 | 68,78 | 0,021 |
| 7 (2006) | 166,07 | 165,02 | 0,77 | 72,04 | 71,70 | 0,208 |
| 8 (2007) | 166,90 | 161,38 | 3,48 | 75,11 | 71,86 | 2,050 |
| 9 (2008) | 162,99 | 156,56 | 4,17 | 75,69 | 72,83 | 1,647 |
| 10 (2009) | 163,87 | 155,64 | 5,30 | 74,87 | 71,32 | 2,279 |
| 11 (2010) | 166,40 | 158,11 | 5,24 | 74,03 | 72,52 | 0,910 |
| 12 (2011) | 168,29 | 159,17 | 5,78 | 73,58 | 70,90 | 1,621 |
| 13 (2012) | 166,59 | 158,62 | 5,04 | 73,72 | 70,37 | 2,039 |
| 14 (2013) | 166,58 | 158,50 | 5,18 | 72,23 | 69,00 | 1,987 |
| 15 (2014) | 167,95 | 159,54 | 5,42 | 70,61 | 66,73 | 2,628 |
| 16 (2015) | 166,98 | 161,13 | 6,05 | 69,41 | 67,80 | 1,911 |
| 17 (2016) | 168,50 | 166,59 | 5,14 | 68,58 | 67,96 | 1,467 |

Superscripts: [a]: IEA Database; [b]: ODYSSEE-MURE Database

Beyond that, as with German energy data, ODYSSEE-MURE only provides data for LPG, whereas the IEA database provides consumption data for LPG, natural gas, and electricity. By contrast, the aggregates of other fuels do not resemble. Since the differences in LPG consumption data are rather minor, we can assume that they correspond to actual LPG consumption and thus values for LPG are averaged and values for otherwise missing fuels are added from the IEA database. This approach leads to a deviation of consumption values calculated here to reported TFC values in both sources of max 1.1 %. Underlying consumption data of other fuels is provided in **Table 10**. The resulting finally deployed data for the three fuel categories and the total is presented in **Table 11**.

**Table 10: Consumption of other Fuels of Dutch LDVs**

| Period (year) | LPG[a] [PJ] | LPG[b] [PJ] | LPG[c] [PJ] | Electricity[a] [PJ] | Natural Gas[a] [PJ] |
|---|---|---|---|---|---|
| 1 (2000) | 20,85 | 21,05 | 20,949 | 0,02 | 0,00 |
| 2 (2001) | 19,51 | 19,65 | 19,580 | 0,02 | 0,00 |
| 3 (2002) | 17,92 | 18,10 | 18,008 | 0,02 | 0,01 |
| 4 (2003) | 16,07 | 16,20 | 16,137 | 0,02 | 0,01 |
| 5 (2004) | 14,40 | 14,54 | 14,472 | 0,02 | 0,01 |
| 6 (2005) | 12,95 | 13,08 | 13,016 | 0,02 | 0,01 |
| 7 (2006) | 12,48 | 12,58 | 12,529 | 0,02 | 0,02 |
| 8 (2007) | 11,94 | 12,02 | 11,982 | 0,02 | 0,03 |
| 9 (2008) | 12,88 | 11,92 | 12,400 | 0,03 | 0,04 |
| 10 (2009) | 11,48 | 11,60 | 11,540 | 0,03 | 0,08 |
| 11 (2010) | 10,68 | 10,79 | 10,735 | 0,04 | 0,12 |
| 12 (2011) | 9,83 | 9,92 | 9,876 | 0,05 | 0,21 |
| 13 (2012) | 9,18 | 9,30 | 9,238 | 0,07 | 0,29 |
| 14 (2013) | 8,55 | 8,65 | 8,602 | 0,12 | 0,30 |
| 15 (2014) | 7,76 | 7,82 | 7,789 | 0,25 | 0,35 |
| 16 (2015) | 6,92 | 7,22 | 7,068 | 0,67 | 0,42 |
| 17 (2016) | 6,44 | 6,57 | 6,505 | 1,25 | 0,49 |

Superscripts: [a]: IEA Database; [b]: ODYSSEE-MURE Database, [c]: Average of [a,b]

**Table 11: TFC of Dutch LDVs by Fuel Type**

| Period (year) | Total [PJ] | Gasoline [PJ] | Diesel [PJ] | Other [PJ] |
|---|---|---|---|---|
| 1 (2000) | 236,23 | 161,63 | 53,63 | 20,97 |
| 2 (2001) | 238,64 | 162,71 | 56,34 | 19,60 |
| 3 (2002) | 242,50 | 164,80 | 59,66 | 18,04 |
| 4 (2003) | 245,21 | 166,14 | 62,90 | 16,17 |
| 5 (2004) | 251,28 | 170,57 | 66,21 | 14,50 |
| 6 (2005) | 249,74 | 167,86 | 68,84 | 13,05 |
| 7 (2006) | 250,47 | 165,93 | 71,97 | 12,57 |

| | | | | |
|---|---|---|---|---|
| 8 (2007) | 252,42 | 165,88 | 74,51 | 12,03 |
| 9 (2008) | 249,41 | 161,86 | 75,08 | 12,47 |
| 10 (2009) | 248,29 | 162,41 | 74,23 | 11,65 |
| 11 (2010) | 249,50 | 164,87 | 73,73 | 10,89 |
| 12 (2011) | 249,80 | 166,62 | 73,05 | 10,14 |
| 13 (2012) | 247,79 | 165,13 | 73,06 | 9,60 |
| 14 (2013) | 245,76 | 165,13 | 71,61 | 9,02 |
| 15 (2014) | 244,83 | 166,45 | 69,98 | 8,39 |
| 16 (2015) | 244,80 | 167,08 | 69,56 | 8,16 |
| 17 (2016) | 247,36 | 170,12 | 69,00 | 8,24 |

Revision of vkm data

The IEA database solely provides figures for stock count and aggregate vkm, both not disaggregated for LDV propulsion technology. At the required disaggregation level, the ODYSSEE-MURE database provides annual mileage and stock data. These data are available arranged by total, gasoline, and diesel LDVs. Assuming that data are internally consistent one may derive the missing overall vkm values using relationship **E1**. Thereafter, stock and vkm of alternatively powered LDVs shall be the remainder once the figures of diesel and gasoline vehicles are subtracted from the respective total values. Consequently, the annual mileage for the other category corresponds to the quotient of the respective vkm and stock figures (cf. **E1**). To validate the results, values are checked for internal and external consistency and visualized in a graph to check whether the proportional share (of other LDVs) in overall energy consumption and vkm seems plausible. However, resulting values for Germany are not feasible since resulting vkm figures for other LDVs are in parts negative. Nonetheless, resulting overall vkm from this method greatly correspond to the respective values found in the IEA database. The following last two sections provide a detailed overview of how vkm data (and thus underlying stock and mileage data) were revised.

Revision of German vkm data

As mentioned above – when calculating the traffic performance of other LDVs based on average annual mileage and LDV population data for total, gasoline, and diesel –

the resulting annual total vkm of other LDVs are partially negative and seem to follow no trend. Moreover, when we multiply the average annual mileage of total LDVs with the respective population (based on data from ODYSSEE-MURE), obtained values only correspond to the stated traffic performance in the IEA database for the periods up to 2007. For subsequent periods, calculated values are consistently smaller. However, calculated stock values for other fuels (as remainder once gasoline and diesel are subtracted from the total) are plausible. In consequence, activity data cannot be readily deployed but must be revised.

Further scrutiny on German annual LDV stock data from administrative sources (all with respect to the 1st of January as reference date) reveals that there is a significant trend break as of 1st January 2008. Before that, fleet statistics included temporarily deregistered vehicles, whereas those are excluded from vehicle counts in the years onwards (BMDV et al., 2016; KBA, 2017; Statistisches Bundesamt, 2022). It is worth noting that reported numbers correspond across those three sources. According to the German Federal Statistics Office (Statistisches Bundesamt, 2022), temporarily deregistered vehicles amount to roughly 12 % of total stock.

German car stock data prior to 2008 therefore have been revised in the IEA and ODYSSEE-MURE databases to enable time-series comparability. However, this only becomes evident once cross-checked with German governmental sources, since there is no indication. Besides that, total traffic performance – as a product of vehicle stock and average annual mileage – after 2008 only corresponds to the IEA databases' values when multiplied with the car stock of Jan 1st of the subsequent year. Before the methodological change, the relationship holds when multiplied with stock count of the respective year.

Moreover, the annual publication "*Verkehr in Zahlen*" (ViZ) (traffic in numbers), published by the German Federal Motor Transport Authority (KBA) provides statistics on traffic performance of motor vehicles, calculated as national traffic performance (i.e., distances traveled by German vehicles in- and outside of Germany but without distances traveled by foreign cars in Germany). Those numbers are published as average annual mileage per vehicle and total traffic performance, broken down by eight vehicle types and the fuel types of gasoline and diesel (according to statement in ViZ, however, data broken down by fuel types is solely available via ODYSSEE-MURE). Gas-fueled vehicles are only separately considered as of 2009 and have been included in the gasoline category in antecedent years. Also here, the traffic performance of a vehicle type corresponds to the product of the respective traffic performance and vehicle count. However, in contrast to the Netherlands, annual mileage data is not based on odometer readings, but on a model calculation conducted by the German Institute for Economic Research (DIW Berlin). The underlying basic idea is that the quantity of consumed fuels in road transport widely corresponds to the turned over volumes of gas stations on the one hand, and to the product of vehicle population, average fuel consumption and average mileage on the other. To reach equivalence, elements of the calculation are iteratively determined, i.e., so that mileage-based consumption values correspond to total fuel consumption. Further determinants and influential factors that are considered comprise road fuels that are purchased abroad, distances covered abroad, and correction factors for real-world fuel consumption (since norm consumption values are used as input). (BMDV et al., 2016)

Starting from this it is unclear how journeys of foreign vehicles in Germany are dealt with. If mileage-based consumption values equate to the total fuel consumption, this would include fuels quantities consumed by foreign vehicle owners and therefore skew resulting domestic traffic performance values. According to the latest available methodological report from 2005, fuel quantities purchased by foreign motor vehicle owners are excluded from the computation base (Kalinowska et al., 2005).

Owing to the change in vehicle stock methodology, average annual mileages reported in ViZ are arithmetically larger in the years as of 2008 (due to a relatively smaller LDV population). Since mileage data from ODYSSEE-MURE for the years prior to 2008 are consistently smaller than in ViZ (after 2008 data correspond), those have been presumably revised accordingly. Beyond that, total traffic performance in ViZ corresponds to the reported values in the IEA database for all years.

On the grounds that in ODYSSEE-MURE and ViZ the DIW is the source of data regarding mileage and stock of all, gasoline, and diesel LDVs, and due to the general lack in legends regarding methodological changes or breaks in the ODYSSEE-MURE (but also IEA with respect thereto) database, we can assume that data for gasoline up to 2008 includes gas-powered LDVs. This is supported by the fact of the calculated traffic performance of others (in that period) being implausible. Hence, for activity data to match energy data in terms of coverage and definitions, LNG and CNG fuel consumption must be attributed to the gasoline category for those periods. In the absence of further explanatory data (such as revised fleet population and mileage data) for other LDVs, a data revision (i.e., reattributing gas LDVs' activity to the other category) is not possible in a substantiated manner. For what is more, the share of bivalent gas engines (i.e., the engine runs on more than one fuel type with mostly gasoline as second fuel) lies between 69 and 79 % between 2000 and 2005 among gas powered LDVs (KBA, 2010). Therefore, it is not possible to clearly assign this to a fuel-category in any case. Alas, there is no data on the share of bivalent gas LDVs available for the following years. For the sake of simplicity – and since alternatively powered cars other than CNG and LNG comprise less than 0,005 % of energy (IEA, 2020a) and vehicle stock in the years before 2008 (KBA, 2010) – activity and energy consumption of those car is disregarded and set to zero in those periods.

Despite, in the periods as of 2009, energy data of gas LDVs are reattributed to the other category since activity data is recorded separately as of then. Still, since gas LDVs also encompass bivalent engines – for the extent of which no data are available – this adds to result ambiguity and thus uncertainty. This is especially true for EEI for the other fuel category. On top of that there are hybrid vehicles. Before 2009, these play a negligible role in terms of LDV fleet (with the highest share in overall LDVs of .05 % in 2008 but grow in significance with .36 % of LDV stock in 2016 (thereof 12.7 % plug-in hybrids). (KBA, 2010) This may not be of great importance for gasoline or overall LDV EEI, but all the more for the other category as hybrids comprise from 5.7 up to 22.8 % of the fleet of other fuels in the years between 2009 and 2016 with a growing tendency. Since, hybrid vehicles – which form the majority against plug-ins – are solely fueled with fossil fuels (thereof almost exclusively gasoline) and since we can assume that plug-in hybrids predominantly run on gasoline as well (Fraunhofer ISI 2020), hybrids' activity shall rather be attributed to the gasoline category. This happens by adding the respective stock numbers (KBA, 2017) to the gasoline category and multiplying it with gasoline's average annual mileage in the absence of more fitting data. It is worth noting that we can assume, that hybrids have a higher annual mileage than gasoline LDVs, since hybrids are disproportionally owned by commercial parties with associated higher vehicle usage (e.g., 22.1 vs. 5.1 % of commercial owners in 2016 (KBA, 2017)). Given the relatively low share of hybrid LDVs, the associated effects should be of minor significance.

Having said all this, for all periods annual mileage data is used from ODYSSEE-MURE (which corresponds to ViZ data solely after 2007 owing to the change in LDV registration methodology). Until 2008 vehicle stock data for gasoline and diesel LDVs is employed from the ODYSSEE-MURE database, with stock of other LDVs set to be zero since gas LDVs are allocated to the gasoline category. For the periods after 2007, stock data for gasoline and diesel is employed from KBA (KBA, 2017)(data is the same as in ODYSSEE-MURE but with higher resolution). Until 2008, the traffic performance of gasoline and diesel is the product of the respective average annual mileage and vehicle stock (from the same year). Total traffic performance hence corresponds to the sum of the latter.
After 2008, traffic performance of total, gasoline, and diesel is the product of average annual mileage of the respective year and vehicle stock of the subsequent year. Thereby, the gasoline stock contains hybrids vehicles as well (cf. above). In consequence, traffic performance of others is the remainder once the respective vkm of gasoline (incl. hybrids) and diesel are subtracted from the total. Obtained values for total LDV traffic performance is benchmarked against provided values from the IEA database (which match ViZ). In 2007, provided mileages seem to be outliers, since the calculated total vkm are 11.8 % smaller, with the difference never exceeding .43 % in the other period. Therefore, the values are imputed with the mean of the values from 2006 and 2008, leading to a deviation of less than .2 % for that year.
In **Table 12** and **13**, the relevant stock values for traffic performance calculations are provided. Until 2009, the stock of others is assumed to be zero and therefore the total stock corresponds to the sums of gasoline (incl. gas) and diesel. The last column represents the unexplained LDV stock, that remains after gasoline (incl. gas) and diesel are subtracted from the stated total value. After 2008, the traffic performance

of hybrid LDVs included in the gasoline category and neglected in the prior periods due to missing data and relative insignificance. Gas LDVs' traffic performance is included in the other category as of 2009 – which is the remainder once the stock of gasoline and diesel LDVs are subtracted from the total. The respective average annual mileages for gasoline, diesel, and total are presented in **Table 14**.

**Table 12: Underlying German LDV Stock Data until 2008**

| Period (year) | Gasoline and gas | Diesel | Others | Unexplained |
|---|---|---|---|---|
| 1 (2000) | 34144400 | 5519800 | 0 | 5000 |
| 2 (2001) | 34023100 | 5781900 | 0 | 7500 |
| 3 (2002) | 33978900 | 6336000 | 0 | 3900 |
| 4 (2003) | 33658600 | 6913300 | 0 | 5200 |
| 5 (2004) | 32636500 | 7894200 | 0 | 13400 |
| 6 (2005) | 32258500 | 8578700 | 0 | 45700 |
| 7 (2006) | 31707500 | 9276300 | 0 | 99100 |
| 8 (2007) | 30955600 | 10046000 | 0 | 182400 |
| 9 (2008) | 30744500 | 10045600 | 0 | 393500 |

Source: ODYSSEE-MURE

**Table 13: Underlying German LDV Stock Data after 2008**

| Period (year) | Gasoline (incl. hybrids) | Diesel | Total |
|---|---|---|---|
| 10 (2009) | 30478479 | 10817769 | 41737627 |
| 11 (2010) | 30524834 | 11266644 | 42301563 |
| 12 (2011) | 30499661 | 11891375 | 42927647 |
| 13 (2012) | 30271467 | 12578950 | 43431124 |
| 14 (2013) | 30041871 | 13215190 | 43851230 |
| 15 (2014) | 29945368 | 13861404 | 44403124 |
| 16 (2015) | 29955588 | 14532426 | 45071209 |
| 17 (2016) | 30144040 | 15089392 | 45803560 |

Source: (KBA, 2017). Note: Stock figures for each period are from Jan 1st of the subsequent year (e.g., stock numbers of period 10 (2009) are from Jan 1st, 2010)

**Table 14: Average Annual Mileage of German LDVs for Gasoline, Diesel, and Total**

| Period (year) | Gasoline[a] [km] | Diesel [km] | Total [km] |
|---|---|---|---|
| 1 (2000) | 12970,05 | 21126,07 | 14104,13 |
| 2 (2001) | 12900,90 | 23627,22 | 14455,25 |

| | | | |
|---|---|---|---|
| 3 (2002) | 12691,60 | 24039,65 | 14474,62 |
| 4 (2003) | 12428,48 | 23074,74 | 14239,57 |
| 5 (2004) | 12649,03 | 22496,20 | 14562,14 |
| 6 (2005) | 12134,56 | 21765,66 | 14141,96 |
| 7 (2006) | 11943,71 | 22120,80 | 14212,71 |
| 8 (2007) | 11915,18[b] | 21842,73[b] | 14270,00 |
| 9 (2008) | 11886,66 | 21564,66 | 14147,44 |
| 10 (2009) | 11724,70 | 20914,39 | 14254,62 |
| 11 (2010) | 11439,49 | 21097,67 | 14200,00 |
| 12 (2011) | 11450,56 | 20736,06 | 14200,00 |
| 13 (2012) | 11112,73 | 20645,41 | 14046,61 |
| 14 (2013) | 10977,03 | 20517,54 | 14027,93 |
| 15 (2014) | 10998,48 | 20465,11 | 14106,67 |
| 16 (2015) | 10938,86 | 20253,72 | 14106,67 |
| 17 (2016) | 10936,57 | 20327,58 | 14183,15 |

Superscripts: [a]: Until 2008 including gas LDVs and excl. gas but incl. hybrid LDVs as of 2009; [b]: Imputed as mean from 2006 and 2008 values. Source: (ODYSSEE-MURE, 2023)

To obtain the traffic performance per fuel category, the two respective LDV populations are multiplied with the associated average annual mileage. In the periods up to 2008, vkm of others is assumed to be zero and therefore the total traffic performance of LDVs corresponds to the sum of gasoline and diesel vkm. It is worth noting that if total vkm are calculated by multiplying the total annual mileage (cf. **Table 14**) with total stock (refers to sum of all columns in **Table 12**), values deviate by less than .01 %.

After 2008, vkm of gasoline, diesel, and total are calculated again by multiplying the annual mileage with the respective population. Traffic performance of others is consequently the remainder once the vkm of gasoline and diesel are subtracted from the total. Results are presented together with the values from the IEA database in **Table 15**. Calculated values for total vkm deviate by max .4 % from the IEA's values.

**Table 15: Traffic Performance of German LDVs by Fuel Type**

| Period (year) | Gasoline[a] [$10^6$ km] | Diesel [$10^6$ km] | Others[b] [$10^6$ km] | Total[c] [$10^6$ km] | Total[d] [$10^6$ km] |
|---|---|---|---|---|---|
| 1 (2000) | 442854,74 | 116611,71 | 0,00 | 559466,44 | 559500,00 |
| 2 (2001) | 438928,62 | 136610,23 | 0,00 | 575538,85 | 575500,00 |
| 3 (2002) | 431246,54 | 152315,22 | 0,00 | 583561,76 | 583600,00 |

| | | | | | |
|---|---|---|---|---|---|
| 4 (2003) | 418325,21 | 159522,61 | 0,00 | 577847,82 | 577800,00 |
| 5 (2004) | 412820,01 | 177589,48 | 0,00 | 590409,49 | 590410,00 |
| 6 (2005) | 391442,74 | 186721,03 | 0,00 | 578163,77 | 578160,00 |
| 7 (2006) | 378705,07 | 205199,21 | 0,00 | 583904,29 | 583900,00 |
| 8 (2007) | 368841,70 | 219432,08 | 0,00 | 588273,77 | 587540,00 |
| 9 (2008) | 365449,52 | 216629,94 | 0,00 | 582079,45 | 584590,00 |
| 10 (2009) | 357351,029 | 226247,043 | 11355,895 | 594953,967 | 595040,00 |
| 11 (2010) | 349188,555 | 237699,918 | 13793,722 | 600682,195 | 599010,00 |
| 12 (2011) | 349238,046 | 246580,250 | 13754,292 | 609572,587 | 608770,00 |
| 13 (2012) | 336398,652 | 259697,590 | 13963,988 | 610060,230 | 610060,00 |
| 14 (2013) | 329770,519 | 271143,147 | 14228,327 | 615141,994 | 615140,00 |
| 15 (2014) | 329353,645 | 283675,147 | 13351,302 | 626380,093 | 627220,00 |
| 16 (2015) | 327679,843 | 294335,735 | 13788,968 | 635804,546 | 635800,00 |
| 17 (2016) | 329672,446 | 306730,814 | 13235,498 | 649638,757 | 649640,00 |

Superscripts: [a]: Until 2008 with gas LDVs and as of 2009 with hybrid LDVs; [b]: Set to zero until 2008 and after 2008 without hybrid LDVs; [c]: Calculated as sum of subcategories; [d]: Values from the IEA Database

Validation of German energy and activity data

To validate energy and activity data for the three fuel sub-categories, we plot together the respective share in total LDV energy consumption and traffic performance in **Figures 25-27**. For the years up to 2008, LPG and CNG consumption was attributed to the gasoline category and energy consumption of others was set to zero. Therefore, share in vkm refers to data in **Table 15** and share in energy to the revised energy consumption data **Table 16** below the graphs.

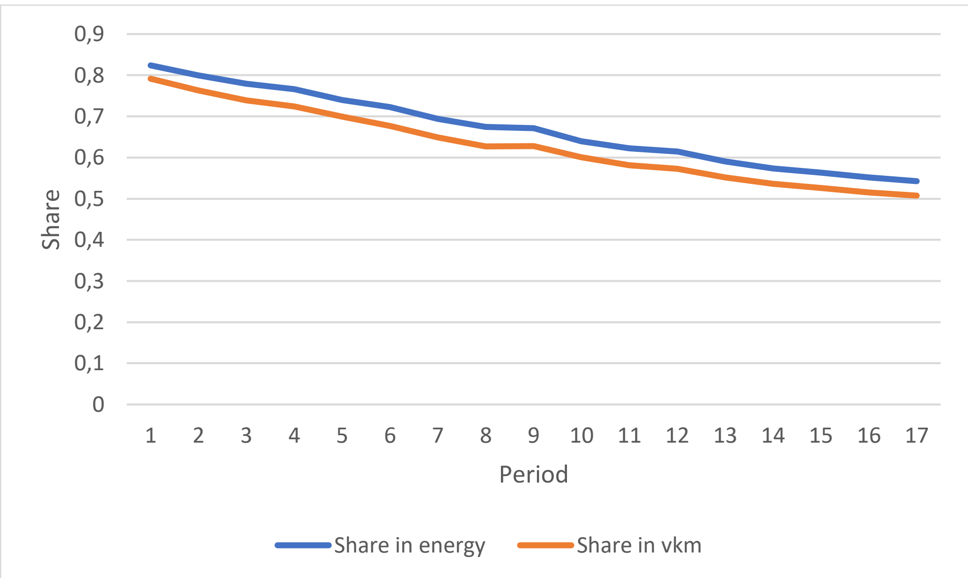


**Figure 25: Share in LDV Energy Consumption and Traffic Performance of Gasoline**

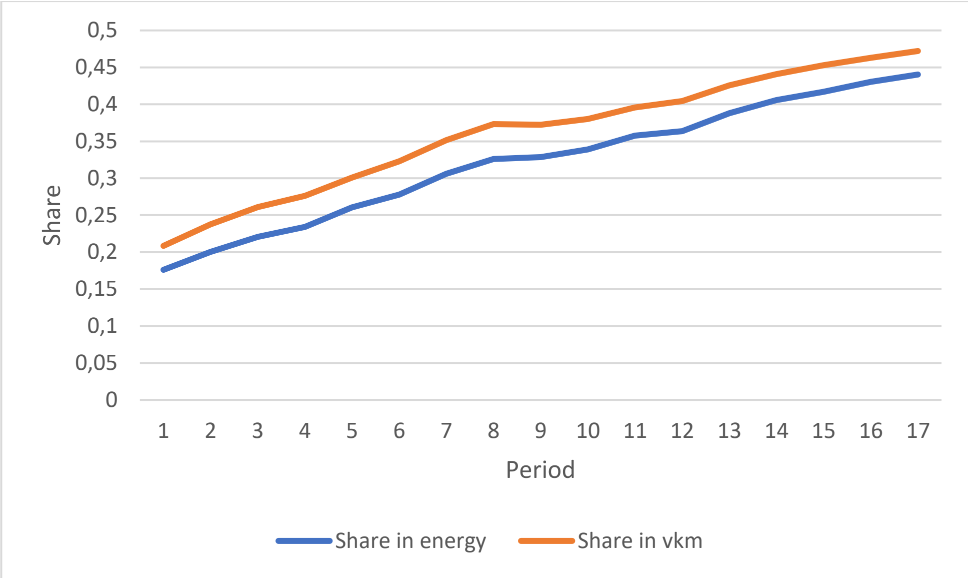


**Figure 26: Share in LDV Energy Consumption and Traffic Performance of Diesel**

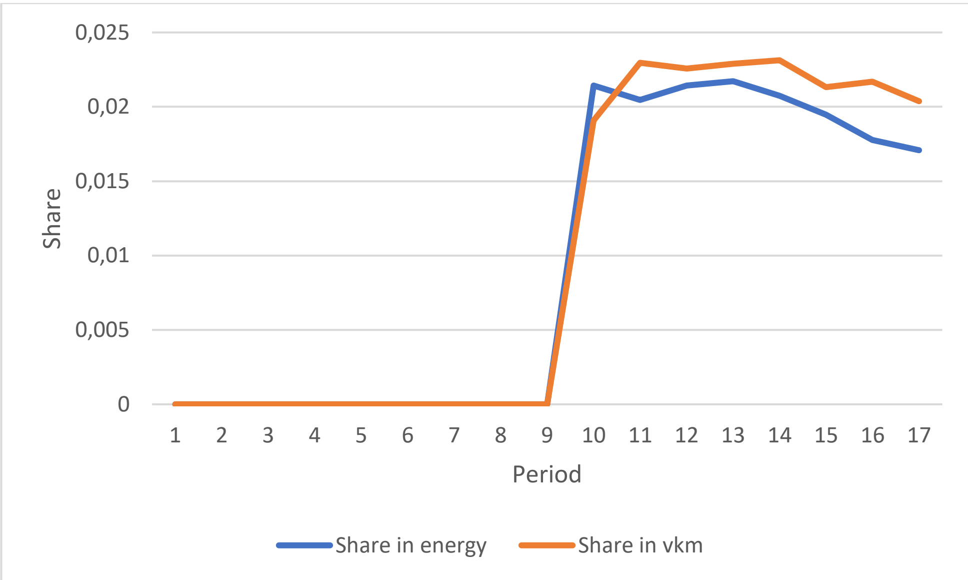


**Figure 27: Share in LDV Energy Consumption and Traffic Performance of other Fuels**

**Table 16: Final German LDV Energy Consumption by Fuel Type**

| Period (year) | Gasoline [PJ] | Diesel [PJ] | Others [PJ] | Total [PJ] |
|---|---|---|---|---|
| 1 (2000) | 1245,73 | 266,15 | 0,00 | 1511,88 |
| 2 (2001) | 1221,38 | 305,90 | 0,00 | 1527,28 |
| 3 (2002) | 1197,65 | 339,25 | 0,00 | 1536,90 |
| 4 (2003) | 1155,45 | 353,08 | 0,00 | 1508,53 |
| 5 (2004) | 1132,44 | 398,99 | 0,00 | 1531,43 |
| 6 (2005) | 1067,55 | 410,49 | 0,00 | 1478,04 |
| 7 (2006) | 1026,60 | 452,96 | 0,00 | 1479,56 |
| 8 (2007) | 990,56 | 478,61 | 0,00 | 1469,17 |

| | | | | |
|---|---|---|---|---|
| 9 (2008) | 969,37 | 474,19 | 0,00 | 1443,56 |
| 10 (2009) | 930,01 | 492,91 | 31,15 | 1454,07 |
| 11 (2010) | 905,41 | 520,34 | 29,80 | 1455,55 |
| 12 (2011) | 904,79 | 535,28 | 31,53 | 1471,60 |
| 13 (2012) | 858,35 | 563,83 | 31,58 | 1453,76 |
| 14 (2013) | 840,76 | 594,41 | 30,42 | 1465,59 |
| 15 (2014) | 839,71 | 621,65 | 29,03 | 1490,39 |
| 16 (2015) | 826,38 | 645,06 | 26,63 | 1498,07 |
| 17 (2016) | 826,54 | 670,74 | 26,03 | 1523,31 |

At first glance the obtained results seem valid and plausible since the graphs are highly consonant and since diesel vehicles are comparably more energy efficient than gasoline. Nonetheless, the other fuel category is subject to some degree of ambiguity since gas LDVs also encompass bivalent engines to an unknown extent and due to the possibly imprecise attribution of hybrid LDVs to the gasoline category since gasoline's annual mileage was assumed for it. Therefore, we can expect that a certain extent of gasoline consumption by bivalent gas LDVs is misattributed to gasoline LDVs and not accounted for with respect to the other category's activity data, whereas on the other hand a certain extent of electricity consumption from plug-in hybrid vehicles is not attributed for with respect to the gasoline's activity data. Since, between 2009 and 2016, there are between 3 and 15 times as many gas LDVs when compared to hybrids, we can expect the effect to be net negative for the other's energy efficiency (i.e., smaller energy consumption per activity assumed than actual) with a decreasing tendency – since hybrid LDVs increase in number over the years. Nonetheless, owing to the comparably much lower numbers, the effects to gasoline's EEI are of far smaller extent.

Besides, in the years prior to 2009, activity and energy consumption of the other category was set to zero due to missing data and since gas LDVs are included in the gasoline category. Since there exist some electricity and hybrid LDVs in those periods (with growing tendency, up to .97 % in stock in 2008, cf. Table 12) this also adds to result uncertainty with energy efficiency slightly underestimated owing to underestimated activity data in the numerator.

Against the background of the high intricacy in compiling energy and activity data for LDVs on side of national and energy agencies (such as attributing data to national territory or vehicle type), high-level data errors can neither be ruled out nor reconstructed. This holds especially true since the calculation of other's activity data is dependent on gasoline and diesel's activity data.

Ultimately, EEI regarding diesel and gasoline have all in all a clearly higher validity.

Beyond that, in contrast to Dutch energy data, there are no conspicuities regarding energy data of other LDVs. The respective relations between stock and energy consumption seem plausible. As well, pkm data can be readily deployed since overall LDV traffic performance is not altered when compared to the original sources.

Revision of Dutch vkm data

The ODYSSEE-MURE database provides stock figures and annual mileages for total, gasoline, and diesel LDVs. Stock numbers of other LDVs shall therefore be the remainder once the stock counts of gasoline and diesel LDVs are subtracted from the total. When we multiply the respective stock count with the associated annual mileage, we obtain the aggregate vkm of the respective sub-group. The aggregate vkm of other LDVs is therefore the remainder once vkm of diesel and gasoline LDVs are subtracted from the total. To obtain the annual mileage of others – following the rationale of **E1** – the mileage of others corresponds to the quotient of the respective stock count and aggregate vkm. The resulting total vkm values correspond to the ones provided in the IEA database and total LDV stock data also correspond with each other. Therefore, LDV activity data – besides different levels of disaggregation – mutually correspond among the IEA and ODYSSEE-MURE database and are internally consistent.

Nonetheless, further external validation with publicly available data by the Dutch central agency for statistics (CBS) reveals some major inconsistencies in the data. This is surprising, since the CBS is stated as single source for Dutch activity data in ODYSSEE-MURE. Stated average annual mileages for all, gasoline, and diesel LDVs match. (CBS, 2021e) The same is true for all LDV stock figures (CBS, 2022)(besides that CBS's stock numbers refer to the first day of the year, whereas the former are annual averages which simply correspond to the mean of the reference- and following year). However, reported annual mileages for LDVs other than gasoline or diesel are significantly lower than the calculated values, which suggests the data being inconsistent. Beyond that, overall $\mathrm{vkm}$ data do not correspond to the reported figures from the $\mathrm{CBS}$. The $\mathrm{CBS}$ publishes data on traffic performance (i.e., $\mathrm{vkm}$) grouped by kilometers traveled in the Netherlands (subdivided into kilometers by Dutch and foreign cars) and kilometers traveled by cars registered in the Netherlands (subdivided into kilometers traveled inside and outside of the Netherlands). (CBS, 2021d) Since Dutch annual mileage data is determined based on odometer readings, the product of annual mileage and vehicle stock shall correspond to the national traffic performance (i.e., kilometers performed by cars registered in the Netherlands in- and outside of the Netherlands). (Geilenkirchen et al., 2022; Molnár-in 't Veld, 2014) However, this is not the case since the values for overall $\mathrm{vkm}$ are consistently about $10\ \%$ larger than the values in the main sources.

Further scrutiny reveals that the average annual mileages are subject to a different population of registered LDVs and not to the values stated in official LDV stock statistics (CBS, 2022), or the $\mathrm{ODYSSEE}$-$\mathrm{MURE}$ and $\mathrm{IEA}$ databases. The relevant population of vehicles is subject to a wider scope and therefore values are higher. In consequence, given values for vkm in the principal databases are erroneous.

There exists a dataset where $\mathrm{LDV}$ traffic performance (grouped by territory as in (CBS, 2021d)(CBS, 2021c)(CBS, 2021c)) is provided together with average annual mileage and the associated LDV population, grouped by fuel type. (CBS, 2021e) However, time series data for mileage and stock are only available as of 2001. Data values are internally consistent, since **E1** is fulfilled and since values are consistent in aggregation. All values concerning mileage and $\mathrm{vkm}$ published by the $\mathrm{CBS}$ for the reference period are in line with this larger population of LDVs.

However, provided data from the $\mathrm{CBS}$ are not readily deployable since the data are disaggregated for the fuel types of diesels, LPG, and gasoline together with all other fuel types. This disaggregation is reflected in the different types of traffic performance, in annual mileages and stock in use (i.e., the here relevant population). Since the IDA requires disaggregation for gasoline, diesel, and others, we must attribute the values of other fuels – that are incorporated in the gasoline/other category – to the third LPG category. Here again, if we multiply the average annual mileage with the respective stock count, we obtain the national traffic performance (vkm by Dutch cars in- and outside of the Netherlands). (CBS, 2021e) Since energy data are subject to fuels consumed within the Netherlands (accounting for fuel tourism), the relevant activity data is the domestic traffic performance (i.e., vkm performed in the Netherlands by Dutch and foreign cars. Subsequent corrections of the national traffic performance to obtain the domestic traffic performance are based upon traffic censuses, travel surveys, and tourism statistics. (Geilenkirchen et al., 2022; Molnár-in 't Veld, 2014) It is worth noting that LDV traffic in the Netherlands is subject to an export surplus. This means that Dutch LDVs perform more kilometers abroad than foreign LDVs perform in the Netherlands. (CBS, 2021c) Therefore, the domestic traffic performance is smaller than the national traffic performance. In practice the CBS determines a linear correction factor to calculate the domestic traffic performance based on the national traffic performance (which is based on odometer readings). Thereby, a constant distribution across fuel types is assumed. Associated national and domestic traffic performances with correction factors are presented in **Table 17**. Further it is worth noting that data for 2000 is estimated and data prior to 2012 have been revised to enable sequential comparability since there are trend breaks as of 2001 and between 2012 and 2013 due to a change in methodology. (CBS, 2023)

**Table 17: National and Domestic Traffic Performance of LDVs in the Netherlands with Correction Factor**

| Period (year) | Traffic performance[a] [$10^9$ km] | | Correction factor[b] (national/domestic) |
|---|---|---|---|
| | National | Domestic | |
| 1 (2000) | 102,33 | 93,20 | 0,911 |
| 2 (2001) | 103,11 | 94,26 | 0,914 |
| 3 (2002) | 104,20 | 96,25 | 0,924 |
| 4 (2003) | 105,11 | 97,41 | 0,927 |
| 5 (2004) | 106,78 | 99,94 | 0,936 |
| 6 (2005) | 107,62 | 99,50 | 0,925 |
| 7 (2006) | 109,35 | 100,47 | 0,919 |
| 8 (2007) | 111,63 | 102,22 | 0,916 |
| 9 (2008) | 113,06 | 101,25 | 0,896 |

| | | | |
|---|---|---|---|
| 10 (2009) | 112,89 | 101,51 | 0,899 |
| 11 (2010) | 112,39 | 102,31 | 0,910 |
| 12 (2011) | 114,54 | 102,96 | 0,899 |
| 13 (2012) | 113,72 | 103,12 | 0,907 |
| 14 (2013) | 113,82 | 103,21 | 0,907 |
| 15 (2014) | 114,51 | 103,70 | 0,906 |
| 16 (2015) | 115,91 | 105,09 | 0,907 |
| 17 (2016) | 118,72 | 107,71 | 0,907 |

Superscripts: [a]: (CBS, 2021c, 2021d) [b]: own calculation

Summarizing, we can calculate the domestic traffic performance by multiplying the national traffic performance with the established correction factors. From this follows that foreign LDVs driving in the Netherlands – which account for between 4.3 and 5 % of traffic volume (CBS, 2021c) – are assumed to have the same fuel technology distribution as Dutch cars. Since this does not necessarily correspond to reality, this adds uncertainty to resulting energy efficiency indicators.

Now to attribute the vkm performed by LDVs other than gasoline, diesel, and LPG from the gasoline/other to the other category (together with LPG), we can calculate the share in stock of gasoline LDVs among the aggregate gasoline/others by using relationship E1 and by introducing the mileages of gasoline and other (incl. LPG) LDVs (CBS, 2021e). Mileages for the same fuel classification that are provided in several CBS datasets are matching, therefore we can assume that mileage data available in one dataset can be applicated to data of another dataset. Hence, following the rationale of E1, the share x of gasoline LDVs among the aggregate stock of gasoline and other (incl. LPG) LDVs can be defined according to **E23**. Here the subscript A refers to the aggregate gasoline/others (incl. LPG) which refers to the sum of gasoline/others and LPG from (CBS, 2021d). G refers to gasoline cars only and R refers to others (incl. LPG), both from (CBS, 2021e). Underlying data and results are provided in **Table 18**.

$$(x \times mileage_G + (1 - x) \times mileage_R) \times stock_A = vkm_A$$
$$x = \frac{vkm_A - mileage_R \times stock_R}{stock_R \times (mileage_G - mileage_R)} \quad \textbf{(E23)}$$

**Table 18: Data underlying E23**

| Period (year) | $mileage_G$ [km] | $mileage_R$ [km] | $Stock_A$ | $vkm_A$ [$10^6$ km] | x |
|---|---|---|---|---|---|
| 1 (2000) | n/a | n/a | n/a | 77033,0 | n/a |
| 2 (2001) | 11340 | 21363 | 6434912 | 76697,8 | 0,942 |
| 3 (2002) | 11227 | 20792 | 6519741 | 76509,8 | 0,947 |
| 4 (2003) | 11174 | 20261 | 6549399 | 76051,1 | 0,952 |
| 5 (2004) | 11241 | 19485 | 6595265 | 76523,8 | 0,956 |
| 6 (2005) | 11199 | 19100 | 6579102 | 75811,4 | 0,959 |
| 7 (2006) | 11075 | 18965 | 6649447 | 75761,3 | 0,960 |
| 8 (2007) | 11055 | 18596 | 6740244 | 76526,9 | 0,960 |
| 9 (2008) | 10924 | 18534 | 6846108 | 76931,3 | 0,959 |
| 10 (2009) | 10855 | 18769 | 6900220 | 77218,6 | 0,958 |
| 11 (2010) | 10679 | 18307 | 7023536 | 77316,8 | 0,957 |
| 12 (2011) | 10680 | 17636 | 7177538 | 78861,6 | 0,956 |
| 13 (2012) | 10471 | 16898 | 7228779 | 77865,6 | 0,953 |
| 14 (2013) | 10540 | 16641 | 7221063 | 78329,7 | 0,950 |
| 15 (2014) | 10578 | 18069 | 7239042 | 79380,4 | 0,948 |
| 16 (2015) | 10628 | 17346 | 7310919 | 80512,9 | 0,943 |
| 17 (2016) | 10673 | 18420 | 7451277 | 82935,0 | 0,941 |

Since some values for the year 2000 are missing, vkm values must be imputed later. Before that, we can apply our identified $x$ – which represents the share of gasoline LDVs among the aggregate of gasoline and others (incl. LPG) – and correct the stock data to get the values for gasoline and others (incl. LPG). Stock figures for gasoline with others (excl. LPG) and LPG (both provided in (t)), their aggregate, and the final stock of gasoline and others (incl. LPG) LDVs are provided in **Table 19**. To get the stock of gasoline cars, the aggregate is multiplied with $x$ (cf. **Table 18**) and to get the stock of others (incl. LPG), the aggregate is multiplied with $1\text{-}x$.

**Table 19: Revision of Dutch LDV Stock Figures**

| Period (year) | G/R excl. LPG | LPG | G/R incl. LPG | G | R incl. LPG |
|---|---|---|---|---|---|
| 1 (2000) | n/a | n/a | n/a | n/a | n/a |
| 2 (2001) | 6063456 | 371456 | 6434912 | 6063177 | 371735 |
| 3 (2002) | 6173924 | 345817 | 6519741 | 6173409 | 346332 |
| 4 (2003) | 6234679 | 314720 | 6549399 | 6233771 | 315628 |

| | | | | | |
|---|---|---|---|---|---|
| 5 (2004) | 6307264 | 288001 | 6595265 | 6305791 | 289474 |
| 6 (2005) | 6313734 | 265368 | 6579102 | 6309258 | 269844 |
| 7 (2006) | 6389145 | 260302 | 6649447 | 6380920 | 268527 |
| 8 (2007) | 6484759 | 255485 | 6740244 | 6473237 | 267007 |
| 9 (2008) | 6588598 | 257510 | 6846108 | 6564319 | 281789 |
| 10 (2009) | 6648389 | 251831 | 6900220 | 6607484 | 292736 |
| 11 (2010) | 6778817 | 244719 | 7023536 | 6720382 | 303154 |
| 12 (2011) | 6937471 | 240067 | 7177538 | 6860474 | 317064 |
| 13 (2012) | 6994707 | 234072 | 7228779 | 6890666 | 338113 |
| 14 (2013) | 7003742 | 217321 | 7221063 | 6857238 | 363825 |
| 15 (2014) | 7040434 | 198608 | 7239042 | 6864484 | 374558 |
| 16 (2015) | 7130208 | 180711 | 7310919 | 6892275 | 418644 |
| 17 (2016) | 7283851 | 167426 | 7451277 | 7011427 | 439850 |

The resulting figures for stock of gasoline and other cars seem probable, since in the official stock statistics (CBS, 2022)(which is not subject to traffic performance calculations) LDVs other than gasoline/diesel or LPG seem to continuously substitute LPG vehicles. Moreover, the average annual mileage for the gasoline/other (excl. LPG) category (provided in (CBS, 2021d)) increasingly diverge from those of solely gasoline, which further supports the obtained results. All this is reflected in the percentage of gasoline LDVs in the aggregate (of gasoline, others, and LPG) staying almost constant over the period under study.

Now, to obtain the domestic traffic performance broken down to gasoline, diesel, and other engine types, we multiply the adjusted stock figures (i.e., gasoline and others, cf. **Table 19**) with the respective mileages (cf. **Table 18**) to get the national traffic performance in a first step. Subsequently, we apply the correction factor established in **Table 17** to arrive at the domestic traffic performance. Since coverage and definitions match, traffic performance of diesel and total LDVs can simply be taken from (CBS, 2021d). Validation shows that results with calculated values for gasoline and others, and adopted values for total and diesel are consistent in aggregation.

As figures for 2000 are missing, those must be imputed. Since the share of LDVs other than gasoline, diesel, and LPG are negligible in 2001 – what is also reflected in domestic traffic performance for gasoline/others (excl. LPG) (CBS, 2021d) and gasoline (calculated) being the same in 2001 – we can simply adopt the value for 2000 from (CBS, 2021d). Traffic performance for others is thence the remainder. Resulting figures for the domestic traffic performance of passenger LDVs – disaggregated by gasoline, diesel and others – are presented in **Table 20**.

**Table 20: Preliminary Dutch Domestic Traffic Performance of LDVs by Fuel Type**

| Period (year) | Total [$10^6$ km] | Gasoline [$10^6$ km] | Diesel [$10^6$ km] | Others [$10^6$ km] |
|---|---|---|---|---|
| 1 (2000) | 93197,00 | 62325,93 | 23041,28 | 7829,79 |
| 2 (2001) | 94262,67 | 62858,52 | 24143,98 | 7260,16 |
| 3 (2002) | 96252,29 | 64025,41 | 25574,87 | 6652,01 |
| 4 (2003) | 97412,88 | 64555,19 | 26931,05 | 5926,64 |
| 5 (2004) | 99942,38 | 66345,41 | 28317,66 | 5279,31 |
| 6 (2005) | 99505,15 | 65331,23 | 29408,41 | 4765,51 |
| 7 (2006) | 100464,90 | 64928,99 | 30856,92 | 4678,99 |
| 8 (2007) | 102218,68 | 65528,30 | 32143,73 | 4546,65 |
| 9 (2008) | 101251,29 | 64216,20 | 32358,10 | 4676,99 |
| 10 (2009) | 101517,22 | 64497,32 | 32079,15 | 4940,75 |
| 11 (2010) | 102308,53 | 65330,66 | 31925,76 | 5052,11 |
| 12 (2011) | 102954,63 | 65860,16 | 32068,23 | 5026,25 |
| 13 (2012) | 103121,85 | 65426,71 | 32514,27 | 5180,88 |
| 14 (2013) | 103213,46 | 65539,24 | 32184,08 | 5490,14 |
| 15 (2014) | 103701,78 | 65758,30 | 31814,45 | 6129,04 |
| 16 (2015) | 105088,13 | 66410,08 | 32094,43 | 6583,62 |
| 17 (2016) | 107709,04 | 67889,53 | 32469,22 | 7350,29 |

Validation of Dutch activity and energy data

As mentioned at the outset of paragraph 3.2, in the scope of this thesis, energy consumption data for gasoline and diesel include biofuels. Liquid biofuels (i.e., bioethanol and biodiesel) for the road transport sector are exclusively sold as a blend with fossil fuels in the Netherlands. (CBS, 2020) Therefore, the approach of attributing biofuel consumption to the respective (liquid) fossil fuel categories seems appropriate. Beyond that, there are hybrid LDVs. Hybrid LDVs exist as hybrid electric vehicle (HEV) – which are solely fueled with gasoline or diesel and have a supporting electrical engine, with the battery charging while driving – and plug-in hybrids (PHEV) – which, on the other hand, can also be charged at a power outlet (CBS, 2016). Therefore, it is impossible to unequivocally assign activity data of PHEVs to one

category of energy data in forming EEI. However, the batteries of PHEVs are not always charged by the users and therefore it can be assumed that those disproportionately run on fossil fuels (HandWiki, 2023). Therefore, when looking at activity data, gasoline, and diesel LDVs should include HEVs and PHEVs.
However, for Dutch activity data this is not the case since gasoline and diesel LDVs encompass vehicles solely fueled by gasoline or diesel (i.e., hybrids are assigned to the other category, thence distorting EEI for gasoline and diesel LDVs). There is a dataset of the CBS providing traffic performance, annual mileage, and vehicle population data for the matching extended categories (i.e., gasoline/diesel including hybrids), but only from the year of 2015 onwards (CBS, 2021b). Comparing national traffic performance – which is transferrable to domestic traffic performance as this is subject to a linear conversion as previously delineated – shows that the traffic performance of diesel LDVs subject to the extended coverage is around 1 % higher for the years 2015 and 2016. For gasoline, vkm including biofuels/hybrids are 5 to 6 % higher in those years. Unfortunately, official stock statistics – besides not being subject to traffic performance calculations – (CBS, 2022; ODYSSEE-MURE, 2023) do not provide figures for hybrid LDVs but also do not explicitly include them in the fossil fuel categories. Therefore, it is not possible to draw conclusions about the extent of this phenomenon before 2015 based on official vehicle fleet statistics.

In our final step of data validation (and revision), we look whether energy and activity data match by plotting together the respective shares in overall vkm and energy consumption of each of the three fuel categories. Those are depicted in **Figures 28-30** and are based on activity data from **Table 20** and energy data from **Table 11**.

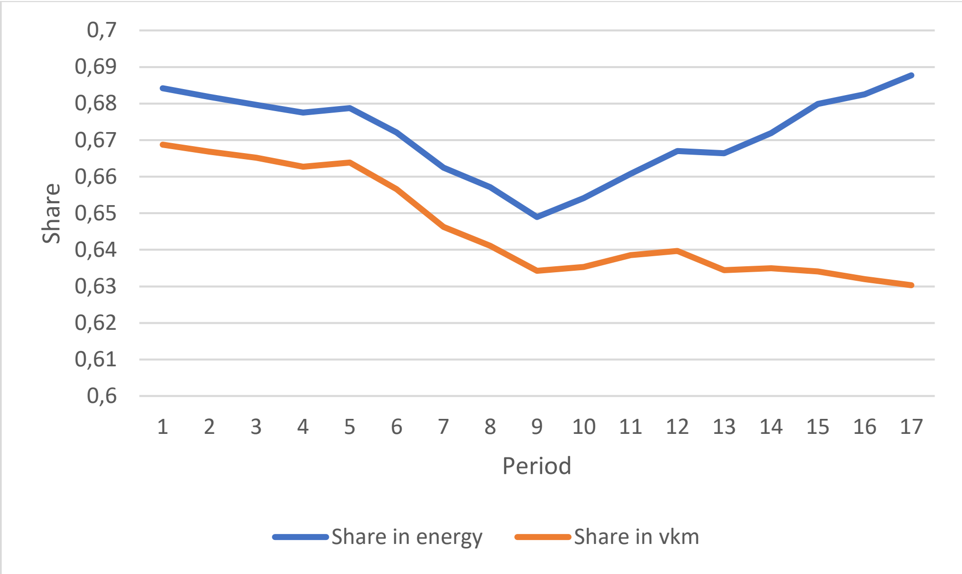


**Figure 28: Preliminary Share in LDV Energy Consumption and Traffic Performance of Gasoline**

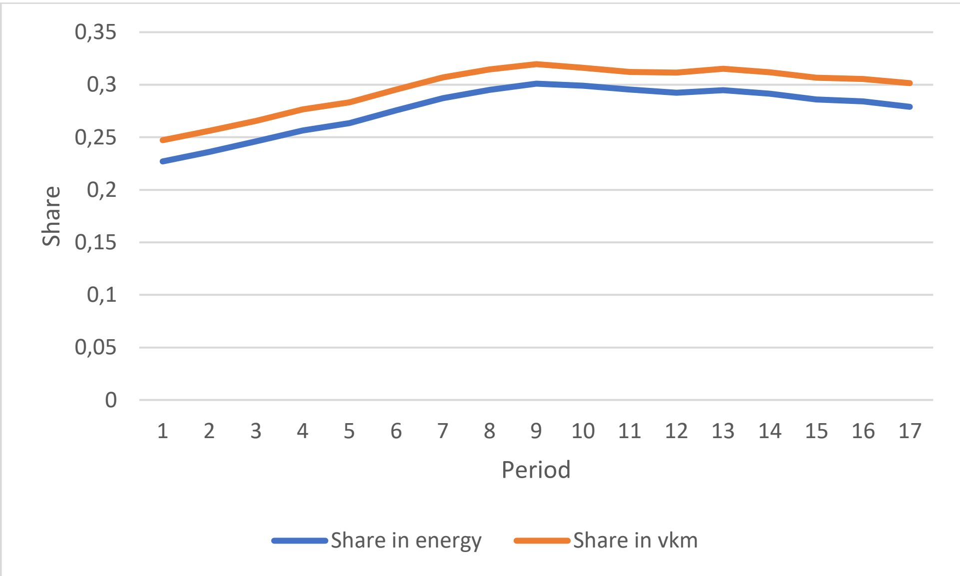


**Figure 29: Preliminary Share in LDV Energy Consumption and Traffic Performance of Diesel**

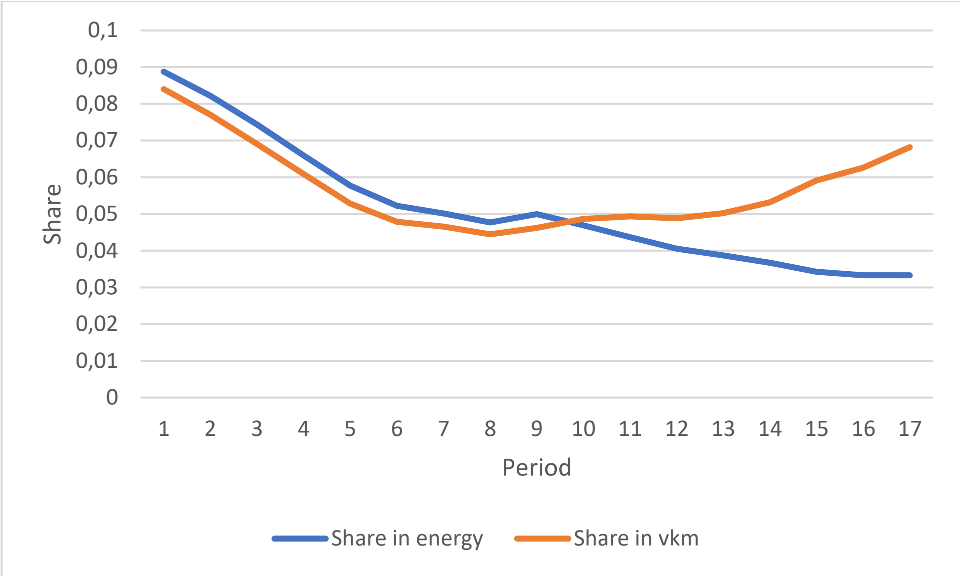


**Figure 30: Preliminary Share in LDV Energy Consumption and Traffic Performance of other Fuels**

Fundamentally, it is plausible that the share in energy is lower than the share in vkm for diesel and that the opposite is true for gasoline. Beyond, the findings for diesel seem overall plausible since the trends are consonant. However, there are peculiarities with gasoline and others. For gasoline as of period 13, and as of period 10 for others, there is an increasing gap in the data pairs. This suggests either coverage and definitions across energy and activity data not matching or underlying datapoints being erroneous. In consequence, the energy efficiency of gasoline LDVs is most likely underestimated and overestimated for other LDVs (i.e., values for energy consumption per vkm being too high and too low respectively).

As mentioned before, hybrid LDVs are more prevalent among gasoline vehicles than for diesel, resulting in particularly the traffic performance of gasoline-consuming vehicles being presumably underestimated. Moreover, since 2013 tax incentives for electric LDVs (including HEVs and PHEVs) have been expanded enormously in the Netherlands, resulting in a kick-off of sales and thus a significant increase in stock of hybrid and fully electric vehicles as of 2013 and little relevance before (CBS, 2016, 2021a; HandWiki, 2023; Wolbertus, 2020). This fits the observation in **Figure 28**, with the gap widening as of period 13 (i.e., 2012). Therefore, we can assume that missing vkm data of hybrid vehicles is at least in parts responsible for the break in data series. In order to revise activity data, we use the traffic performance data with extended fuel categories for 2015 and 2016 (period 16 and 17) from CBS (CBS, 2021b). Under the tenable assumption that the share of hybrid LDVs is negligible up to 2011, we then impute the traffic performance from 2012 to 2014 by assuming linear growth behavior.

This happens by taking the national traffic performance for the extended gasoline and diesel categories for 2015 and 2016 from (CBS, 2021b). Additionally, we add traffic performance of PEVs to the gasoline category. Subsequently the values get multiplied with the correction factor (cf. **Table 17**) to obtain the respective domestic traffic performance as a first step to replace the vkm values for gasoline and diesel given in **Table 20**. Subsequently, the traffic performance for others is the remainder once those two values are subtracted from the total. To impute the traffic performances for 2012-2014 (period 13-15), we assume that the share in overall LDV vkm of gasoline and diesel fueled LDVs grows in a linear manner. The obtained percentage values are then multiplied with the total vkm of the respective year to obtain corrected vkm values for gasoline and diesel. Traffic performance of others is once again the remainder once the previous are subtracted from the total. Thereby, total LDV traffic performance always stays equal. Resulting revised traffic performance is provided in **Table 21**.

**Table 21: Final Dutch Domestic LDV Traffic Performance by Fuel Type**

| Period (year) | Total [$10^6$ km] | Gasoline [$10^6$ km] | Diesel [$10^6$ km] | Others [$10^6$ km] |
|---|---|---|---|---|
| 1 (2000) | 93197,00 | 62325,93 | 23041,28 | 7829,79 |
| 2 (2001) | 94262,67 | 62858,52 | 24143,98 | 7260,16 |
| 3 (2002) | 96252,29 | 64025,41 | 25574,87 | 6652,01 |
| 4 (2003) | 97412,88 | 64555,19 | 26931,05 | 5926,64 |
| 5 (2004) | 99942,38 | 66345,41 | 28317,66 | 5279,31 |
| 6 (2005) | 99505,15 | 65331,23 | 29408,41 | 4765,51 |
| 7 (2006) | 100464,90 | 64928,99 | 30856,92 | 4678,99 |
| 8 (2007) | 102218,68 | 65528,30 | 32143,73 | 4546,65 |
| 9 (2008) | 101251,29 | 64216,20 | 32358,10 | 4676,99 |
| 10 (2009) | 101517,22 | 64497,32 | 32079,15 | 4940,75 |
| 11 (2010) | 102308,53 | 65330,66 | 31925,76 | 5052,11 |
| 12 (2011) | 102954,63 | 65860,16 | 32068,23 | 5026,25 |
| 13 (2012) | 103121,85 | 66575,27 | 31936,57 | 4610,01 |
| 14 (2013) | 103213,46 | 67243,09 | 31781,03 | 4189,34 |
| 15 (2014) | 103701,78 | 68172,79 | 31746,61 | 3782,38 |

| | | | | |
|---|---|---|---|---|
| 16 (2015) | 105087,83 | 69703,70 | 32432,48 | 2951,65 |
| 17 (2016) | 107709,39 | 72118,64 | 32781,56 | 2809,19 |

All this results in the updated validation graphs **31-33**.

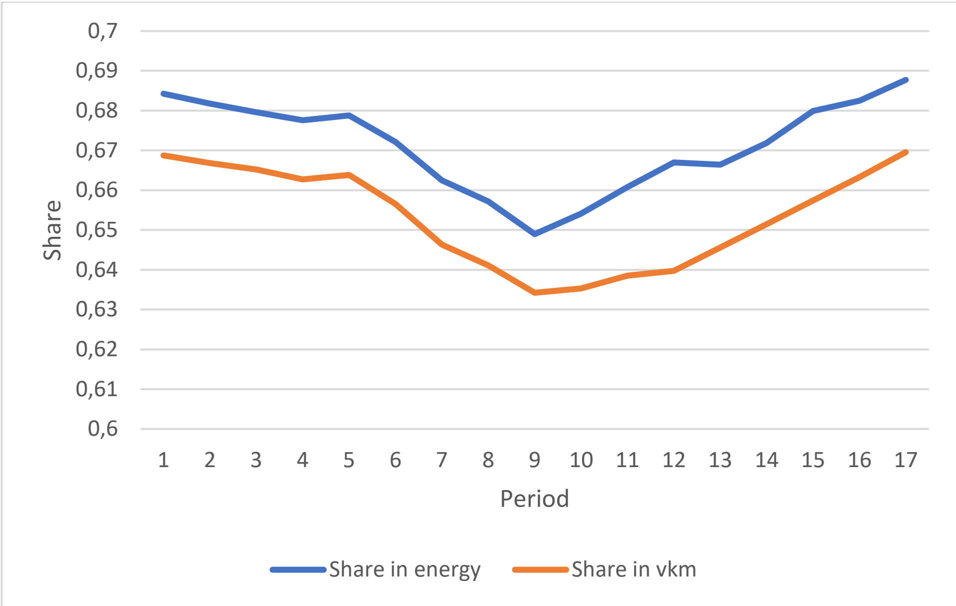


**Figure 31: Share in LDV Energy Consumption and Traffic Performance of Gasoline**

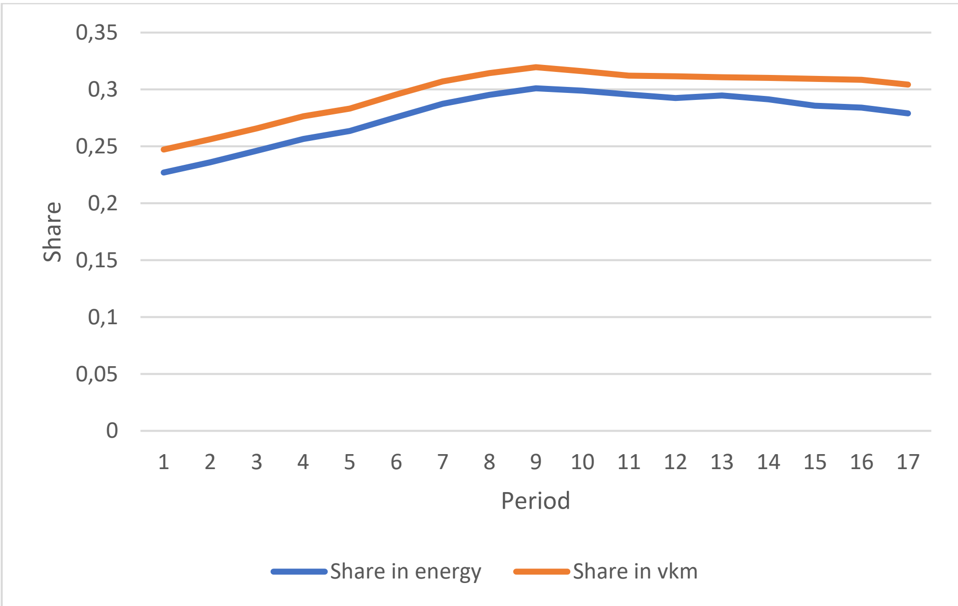


**Figure 32: Share in LDV Energy Consumption and Traffic Performance of Diesel**

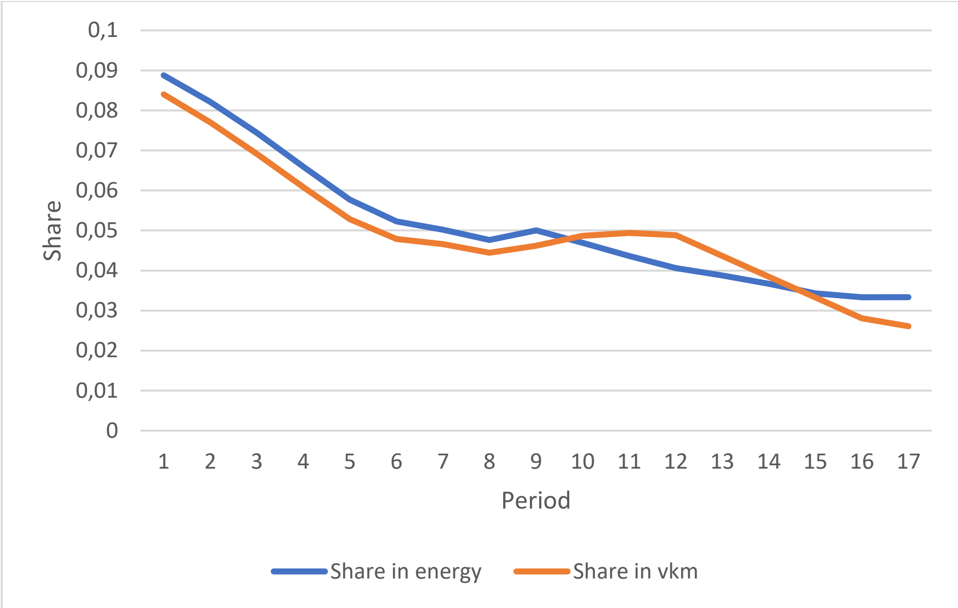


**Figure 33: Share in LDV Energy Consumption and Traffic Performance of other Fuels**

Compared to **Figures 28-30** there is no widening gap for gasoline fueled vehicles anymore. Still, the attribution of PEVs to the gasoline category is not neat altogether since PEVs consume electricity as well. However, with a share in overall LDV vkm of 1.2 and 1.9 % in 2015 and 2016 (CBS, 2021b) we cannot expect to have any observable effect of potentially misattributed electricity consumption.

Moreover, the curve shape from period 10 to 14 in **Figure 31** and **33** indicates the data yet being subject to some discrepancies. Besides a potentially invalid data imputation for periods 13 to 15, further scrutiny reveals some discrepancies in the underlying energy data for the other fuel category. Both, official Dutch vehicle stock statistics (CBS, 2022)(not subject to traffic performance calculations) and energy consumption data (cf. Table 10), provide data for electricity, LPG and CNG vehicles. In absence of better data sources, we can plot together the vehicle stock count with the associated energy consumption as a proxy for data plausibility. Examination shows that energy consumption of electricity fueled LDVs is drastically underestimated, with annual electricity consumption per car decreasing by more than one power of then during the period of investigation. It is worth noting that PEVs being attributed to the gasoline category is leading to an overestimated electricity consumption of pure EVs in principle. However, since official fleet statistics are inappropriate for activity data calculations the observation’s numeral value is of limited significance. In the absence of alternative data sources, it is therefore not possible to plausibly revise energy data.

Final comments on Dutch data validity

In conclusion, resulting energy efficiency indicators for other LDVs are of limited expressiveness due to erroneous electricity consumption data and due to a potential overallocation of traffic performance from period 9 to 15 (cf. **Figure 33**). Therefore, since it is not subject to any imputations and since electricity played a negligible role as a fuel, EEI on other LDVs are of higher meaningfulness for the periods up to 2009. EEI for gasoline and diesel LDVs are of higher expressiveness at large, given the more consonant curve characteristics in **Figure 31** and **32**. Moreover, data revision to separately account for gasoline vehicles (starting from the gasoline/other excl. LPG category) seems valid and plausible. However, especially after 2013 energy efficiency is potentially overestimated since the electricity consumption of PEVs is not accounted for. Yet, we can assume that this is of a rather limited extent. Still, owing to the linear imputation of values from 2012 to 2014, EEI for those periods shall be interpreted with caution while trend analyses can be reasonably rendered.
When looking at aggregate LDV EEI we can assume that overall energy efficiency is slightly overestimated since electricity consumption data is underestimated.

Ultimately it must be ruled out that Dutch pkm elicitations are connected to traffic performance elicitations. It may be that both are connected via the PLF. Since, data on person mobility in the Netherlands is based on travel surveys and studies (CBS, 2018) the extensive data revision on vkm data has no effects on the validity of pkm data.

Finally employed data

As mentioned at the outset, the LDV IDA requires time-series data for overall LDV pkm, population, and energy consumption and vkm disaggregated by the three fuel types. With two countries to be examined this adds up to 272 datapoints. Pkm and population data is applied from the passenger transport IDA (cf. **Table 6** and **7** in

Appendix A). For the sake of a clear overview, all the employed data are again summarized in **Tables 22** and **23** below.

**Table 22: Final Data deployed for the German LDV IDA**

| Period (year) | vkm G [$10^9$ km] | vkm D [$10^9$ km] | vkm R [$10^9$ km] | Energy consumption G [PJ] | Energy consumption D [PJ] | Energy consumption R [PJ] | pkm [$10^9$ km] | POP [$10^6$] |
|---|---|---|---|---|---|---|---|---|
| 1 (2000) | 442,85 | 116,61 | 0,00 | 1245,73 | 266,15 | 0,00 | 849,60 | 81,46 |
| 2 (2001) | 438,93 | 136,61 | 0,00 | 1221,38 | 305,90 | 0,00 | 872,02 | 81,52 |
| 3 (2002) | 431,25 | 152,32 | 0,00 | 1197,65 | 339,25 | 0,00 | 880,28 | 81,58 |
| 4 (2003) | 418,33 | 159,52 | 0,00 | 1155,45 | 353,08 | 0,00 | 875,65 | 81,55 |
| 5 (2004) | 412,82 | 177,59 | 0,00 | 1132,44 | 398,99 | 0,00 | 887,10 | 81,46 |
| 6 (2005) | 391,44 | 186,72 | 0,00 | 1067,55 | 410,49 | 0,00 | 875,67 | 81,34 |
| 7 (2006) | 378,71 | 205,20 | 0,00 | 1026,60 | 452,96 | 0,00 | 882,65 | 81,17 |
| 8 (2007) | 368,84 | 219,43 | 0,00 | 990,56 | 478,61 | 0,00 | 885,44 | 80,99 |
| 9 (2008) | 365,45 | 216,63 | 0,00 | 969,37 | 474,19 | 0,00 | 888,53 | 80,76 |
| 10 (2009) | 357,35 | 226,25 | 11,36 | 930,01 | 492,91 | 31,15 | 898,70 | 80,48 |
| 11 (2010) | 349,19 | 237,70 | 13,79 | 905,41 | 520,34 | 29,80 | 902,40 | 80,28 |
| 12 (2011) | 349,24 | 246,58 | 13,75 | 904,79 | 535,28 | 31,53 | 912,42 | 80,28 |
| 13 (2012) | 336,40 | 259,70 | 13,96 | 858,35 | 563,83 | 31,58 | 914,56 | 80,43 |
| 14 (2013) | 329,77 | 271,14 | 14,23 | 840,76 | 594,41 | 30,42 | 921,42 | 80,65 |
| 15 (2014) | 329,35 | 283,68 | 13,35 | 839,71 | 621,65 | 29,03 | 934,96 | 80,98 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 16 (2015) | 327,68 | 294,34 | 13,79 | 826,38 | 645,06 | 26,63 | 945,73 | 81,69 |
| 17 (2016) | 329,67 | 306,73 | 13,24 | 826,54 | 670,74 | 26,03 | 965,30 | 82,35 |

**Table 23: Final Data deployed for Dutch LDV IDA**

| Period (year) | vkm G [$10^9$ km] | vkm D [$10^9$ km] | vkm R [$10^9$ km] | Energy consumption G [PJ] | Energy consumption D [PJ] | Energy consumption R [PJ] | pkm [$10^9$ km] | POP [$10^6$] |
|---|---|---|---|---|---|---|---|---|
| 1 (2000) | 62,33 | 23,04 | 7,83 | 161,63 | 53,63 | 20,97 | 141,10 | 15,93 |
| 2 (2001) | 62,86 | 24,14 | 7,26 | 162,71 | 56,34 | 19,60 | 141,60 | 16,05 |
| 3 (2002) | 64,03 | 25,57 | 6,65 | 164,80 | 59,66 | 18,04 | 144,20 | 16,15 |
| 4 (2003) | 64,56 | 26,93 | 5,93 | 166,14 | 62,90 | 16,17 | 146,10 | 16,23 |
| 5 (2004) | 66,35 | 28,32 | 5,28 | 170,57 | 66,21 | 14,50 | 151,50 | 16,28 |
| 6 (2005) | 65,33 | 29,41 | 4,77 | 167,86 | 68,84 | 13,05 | 148,80 | 16,32 |
| 7 (2006) | 64,93 | 30,86 | 4,68 | 165,93 | 71,97 | 12,57 | 148,00 | 16,35 |
| 8 (2007) | 65,53 | 32,14 | 4,55 | 165,88 | 74,51 | 12,03 | 149,50 | 16,38 |
| 9 (2008) | 64,22 | 32,36 | 4,68 | 161,86 | 75,08 | 12,47 | 143,70 | 16,45 |
| 10 (2009) | 64,50 | 32,08 | 4,94 | 162,41 | 74,23 | 11,65 | 148,90 | 16,53 |
| 11 (2010) | 65,33 | 31,93 | 5,05 | 164,87 | 73,73 | 10,89 | 144,20 | 16,62 |
| 12 (2011) | 65,86 | 32,07 | 5,03 | 166,62 | 73,05 | 10,14 | 144,40 | 16,69 |
| 13 (2012) | 66,58 | 31,94 | 4,61 | 165,13 | 73,06 | 9,60 | 139,60 | 16,76 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 14 (2013) | 67,24 | 31,78 | 4,19 | 165,13 | 71,61 | 9,02 | 145,40 | 16,80 |
| 15 (2014) | 68,17 | 31,75 | 3,78 | 166,45 | 69,98 | 8,39 | 145,00 | 16,87 |
| 16 (2015) | 69,70 | 32,43 | 2,95 | 167,08 | 69,56 | 8,16 | 139,50 | 16,94 |
| 17 (2016) | 72,12 | 32,78 | 2,81 | 170,12 | 69,00 | 8,24 | 140,80 | 17,03 |

# 10. Appendix C: Numerical Results

Based on the input data from **Tables** 6, 7, 22 and 23 in accordance with the model configuration defined in chapter 3.1, this appendix provides the completive results (each IDA with fixed and chained base year). All energy units are in PJ and the sum of all effects (right column) corresponds to the difference in total energy consumption compared to the reference year (i.e., the year 2000 for fixed base year and the previous year for chained base year). Total effect always corresponds to the sum of the respective sub-effects, for instance the total effect of energy intensity ($EI_i$) corresponds to the sum of the energy intensity effects of LDVs, buses and trains in the passenger transport case. Moreover, the difference in energy consumption of a disaggregation level (e.g., gasoline LDVs in the LDV IDA) corresponds to the sum of factors for $i =$ Gasoline.

**Table 24: German Passenger Transport IDA Results with respect to 2000**

| Period (year) | ΔE(PI) | ΔE($MS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LDV | Bus | Train | Total | LDV | Bus | Train | Total | | |
| 2 (2001) | 34,11 | 5,89 | -0,95 | -0,60 | 4,33 | -24,18 | -0,14 | -0,32 | -24,64 | 1,17 | 14,98 |
| 3 (2002) | 37,28 | 16,20 | -1,66 | -2,37 | 12,18 | -29,06 | -0,38 | -0,26 | -29,70 | 2,35 | 22,11 |
| 4 (2003) | 30,41 | 14,84 | -1,43 | -2,06 | 11,34 | -48,96 | -1,02 | -5,66 | -55,64 | 1,74 | -12,15 |
| 5 (2004) | 53,17 | 14,79 | -1,76 | -1,75 | 11,27 | -46,17 | -1,13 | -8,00 | -55,31 | 0,00 | 9,13 |
| 6 (2005) | 42,91 | 6,31 | -1,89 | -0,02 | 4,39 | -79,02 | -0,74 | -9,56 | -89,33 | -2,30 | -44,33 |
| 7 (2006) | 58,72 | 6,17 | -2,71 | 0,45 | 3,91 | -89,40 | 1,02 | -12,96 | -101,34 | -5,57 | -44,29 |
| 8 (2007) | 65,94 | 7,00 | -3,20 | 0,57 | 4,36 | -104,29 | 0,60 | -14,81 | -118,51 | -9,00 | -57,21 |
| 9 (2008) | 76,37 | 5,66 | -4,21 | 1,35 | 2,80 | -134,51 | -1,13 | -17,04 | -152,68 | -13,29 | -86,80 |
| 10 (2009) | 95,02 | 10,11 | -5,26 | 1,23 | 6,09 | -141,12 | -1,19 | -14,61 | -156,92 | -18,71 | -74,52 |
| 11 (2010) | 106,11 | 9,30 | -5,62 | 1,55 | 5,22 | -145,78 | -0,91 | -15,56 | -162,25 | -22,57 | -73,48 |
| 12 (2011) | 122,96 | 10,15 | -6,17 | 1,68 | 5,67 | -146,69 | -0,98 | -16,44 | -164,11 | -22,68 | -58,16 |
| 13 (2012) | 120,18 | 12,77 | -7,33 | 1,76 | 7,19 | -167,36 | 0,41 | -17,09 | -184,03 | -19,66 | -76,32 |
| 14 (2013) | 133,10 | 7,87 | -7,00 | 2,45 | 3,33 | -167,09 | -1,22 | -18,26 | -186,57 | -15,49 | -65,63 |
| 15 (2014) | 151,67 | 6,86 | -7,01 | 2,54 | 2,39 | -165,20 | -1,26 | -19,87 | -186,33 | -9,23 | -41,50 |
| 16 (2015) | 158,77 | 4,52 | -6,25 | 2,51 | 0,78 | -175,13 | -1,85 | -20,64 | -197,61 | 4,42 | -33,65 |
| 17 (2016) | 177,26 | 6,92 | -7,28 | 2,56 | 2,20 | -182,33 | -0,69 | -21,31 | -204,32 | 17,16 | -7,70 |

**Table 25: German Passenger Transport IDA Results with chained base year**

| Period (year) | ΔE(PI) | ΔE($MS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LDV | Bus | Train | Total | LDV | Bus | Train | Total | | |
| 2 (2001) | 34,11 | 5,89 | -0,95 | -0,60 | 4,33 | -24,18 | -0,14 | -0,32 | -24,64 | 1,17 | 14,98 |
| 3 (2002) | 3,10 | 10,35 | -0,71 | -1,77 | 7,86 | -4,82 | -0,24 | 0,05 | -5,02 | 1,18 | 7,13 |
| 4 (2003) | -6,52 | -1,22 | 0,21 | 0,11 | -0,91 | -20,34 | -0,63 | -5,29 | -26,25 | -0,58 | -34,26 |
| 5 (2004) | 22,47 | -0,16 | -0,32 | 0,22 | -0,26 | 3,15 | -0,11 | -2,23 | 0,81 | -1,75 | 21,28 |
| 6 (2005) | -9,39 | -8,27 | -0,13 | 1,49 | -6,91 | -33,88 | 0,38 | -1,36 | -34,85 | -2,31 | -53,46 |
| 7 (2006) | 15,59 | -0,14 | -0,76 | 0,40 | -0,50 | -10,22 | 1,73 | -3,34 | -11,83 | -3,22 | 0,04 |
| 8 (2007) | 7,37 | 0,84 | -0,53 | 0,11 | 0,43 | -15,04 | -0,41 | -1,86 | -17,31 | -3,40 | -12,92 |
| 9 (2008) | 10,88 | -1,26 | -1,10 | 0,63 | -1,74 | -30,68 | -1,67 | -2,07 | -34,43 | -4,30 | -29,59 |
| 10 (2009) | 17,83 | 4,34 | -1,04 | -0,15 | 3,15 | -5,98 | -0,07 | 2,57 | -3,48 | -5,22 | 12,28 |
| 11 (2010) | 10,79 | -0,80 | -0,33 | 0,26 | -0,87 | -4,50 | 0,26 | -0,89 | -5,12 | -3,76 | 1,04 |
| 12 (2011) | 15,95 | 0,79 | -0,53 | 0,12 | 0,37 | -0,11 | -0,07 | -0,82 | -1,00 | 0,00 | 15,32 |
| 13 (2012) | -2,01 | 2,64 | -1,06 | 0,07 | 1,66 | -21,27 | 1,30 | -0,67 | -20,63 | 2,83 | -18,16 |
| 14 (2013) | 12,20 | -4,85 | 0,21 | 0,55 | -4,09 | 0,92 | -1,51 | -0,96 | -1,55 | 4,13 | 10,69 |
| 15 (2014) | 17,17 | -1,06 | 0,03 | 0,12 | -0,91 | 3,24 | -0,03 | -1,60 | 1,62 | 6,25 | 24,13 |
| 16 (2015) | 6,64 | -2,34 | 0,77 | -0,01 | -1,58 | -9,43 | -0,54 | -0,74 | -10,71 | 13,50 | 7,85 |
| 17 (2016) | 17,00 | 2,36 | -0,89 | 0,04 | 1,51 | -5,70 | 1,10 | -0,54 | -5,13 | 12,58 | 25,95 |

**Table 26: Dutch Passenger Transport IDA Results with respect to 2000**

| Period (year) | ΔE(PI) | ΔE($MS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LDV | Bus | Train | Total | LDV | Bus | Train | Total | | |
| 2 (2001) | -0,93 | -0,06 | -0,01 | 0,01 | -0,05 | 1,57 | -0,20 | -0,25 | 1,12 | 1,88 | 2,01 |
| 3 (2002) | 1,95 | 0,07 | 0,13 | -0,07 | 0,12 | 1,07 | -0,36 | -0,33 | 0,38 | 3,46 | 5,91 |
| 4 (2003) | 2,53 | 1,48 | -0,04 | -0,25 | 1,19 | 0,60 | -0,47 | -0,26 | -0,13 | 4,72 | 8,32 |
| 5 (2004) | 8,93 | 3,53 | -0,23 | -0,54 | 2,76 | -2,28 | -0,74 | -0,25 | -3,28 | 5,56 | 13,98 |
| 6 (2005) | 4,73 | 2,52 | 0,00 | -0,46 | 2,07 | 0,60 | -0,93 | -0,47 | -0,80 | 6,17 | 12,18 |
| 7 (2006) | 3,41 | 2,03 | 0,15 | -0,43 | 1,75 | 2,62 | -1,19 | -0,57 | 0,86 | 6,65 | 12,67 |
| 8 (2007) | 5,62 | 1,96 | 0,26 | -0,46 | 1,76 | 2,07 | -1,13 | -0,88 | 0,06 | 7,14 | 14,58 |
| 9 (2008) | -3,58 | 0,04 | 0,61 | -0,30 | 0,36 | 8,75 | -1,10 | -0,75 | 6,90 | 8,19 | 11,87 |
| 10 (2009) | 2,22 | 1,97 | 0,17 | -0,44 | 1,70 | -0,97 | -0,51 | -0,35 | -1,83 | 9,42 | 11,51 |
| 11 (2010) | -5,95 | 0,63 | 0,38 | -0,29 | 0,72 | 7,99 | -0,29 | -0,23 | 7,47 | 10,84 | 13,08 |
| 12 (2011) | -4,37 | -1,56 | 0,17 | 0,19 | -1,19 | 7,95 | -0,03 | -0,72 | 7,20 | 11,92 | 13,56 |
| 13 (2012) | -14,04 | -1,54 | 0,10 | 0,22 | -1,22 | 14,15 | 0,21 | -0,61 | 13,75 | 12,94 | 11,43 |
| 14 (2013) | -3,11 | -2,63 | -0,05 | 0,47 | -2,21 | 2,30 | 0,09 | -1,06 | 1,33 | 13,50 | 9,51 |
| 15 (2014) | -7,33 | -0,27 | -0,08 | 0,08 | -0,27 | 2,04 | 0,09 | -0,85 | 1,27 | 14,52 | 8,19 |
| 16 (2015) | -16,93 | -1,43 | 0,25 | 0,13 | -1,05 | 11,31 | 0,09 | -1,06 | 10,35 | 15,55 | 7,92 |
| 17 (2016) | -15,60 | -1,84 | -0,21 | 0,39 | -1,66 | 11,64 | 0,57 | -1,16 | 11,05 | 16,99 | 10,78 |

**Table 27: Dutch Passenger Transport IDA Results with chained base year**

| Period (year) | ΔE(PI) | ΔE($MS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | LDV | Bus | Train | Total | LDV | Bus | Train | Total | | |
| 2 (2001) | -0,93 | -0,06 | -0,01 | 0,01 | -0,05 | 1,57 | -0,20 | -0,25 | 1,12 | 1,88 | 2,01 |
| 3 (2002) | 2,90 | 0,12 | 0,14 | -0,09 | 0,18 | -0,52 | -0,16 | -0,07 | -0,75 | 1,57 | 3,90 |
| 4 (2003) | 0,58 | 1,44 | -0,17 | -0,18 | 1,09 | -0,48 | -0,11 | 0,06 | -0,53 | 1,27 | 2,41 |
| 5 (2004) | 6,48 | 2,07 | -0,19 | -0,28 | 1,60 | -2,94 | -0,28 | 0,00 | -3,22 | 0,80 | 5,66 |
| 6 (2005) | -4,28 | -1,03 | 0,22 | 0,07 | -0,73 | 2,96 | -0,19 | -0,21 | 2,57 | 0,64 | -1,80 |
| 7 (2006) | -1,36 | -0,51 | 0,14 | 0,02 | -0,35 | 2,08 | -0,26 | -0,10 | 1,72 | 0,48 | 0,49 |
| 8 (2007) | 2,25 | -0,08 | 0,10 | -0,03 | -0,01 | -0,59 | 0,08 | -0,30 | -0,81 | 0,48 | 1,91 |
| 9 (2008) | -9,43 | -1,97 | 0,34 | 0,15 | -1,48 | 6,92 | 0,05 | 0,13 | 7,09 | 1,12 | -2,71 |
| 10 (2009) | 5,93 | 1,98 | -0,44 | -0,12 | 1,42 | -9,97 | 0,60 | 0,39 | -8,97 | 1,27 | -0,36 |
| 11 (2010) | -8,36 | -1,38 | 0,20 | 0,15 | -1,03 | 9,19 | 0,22 | 0,12 | 9,54 | 1,42 | 1,57 |
| 12 (2011) | 1,62 | -2,25 | -0,21 | 0,47 | -1,99 | -0,05 | 0,27 | -0,48 | -0,25 | 1,10 | 0,48 |
| 13 (2012) | -9,95 | 0,01 | -0,07 | 0,03 | -0,03 | 6,40 | 0,25 | 0,11 | 6,76 | 1,09 | -2,13 |
| 14 (2013) | 11,13 | -1,12 | -0,15 | 0,23 | -1,04 | -12,08 | -0,12 | -0,43 | -12,63 | 0,62 | -1,92 |
| 15 (2014) | -4,31 | 2,40 | -0,04 | -0,36 | 2,01 | -0,25 | 0,00 | 0,17 | -0,09 | 1,07 | -1,32 |
| 16 (2015) | -9,76 | -1,19 | 0,34 | 0,05 | -0,80 | 9,44 | 0,01 | -0,22 | 9,23 | 1,06 | -0,27 |
| 17 (2016) | 1,46 | -0,41 | -0,47 | 0,23 | -0,65 | 0,28 | 0,48 | -0,08 | 0,68 | 1,37 | 2,86 |

**Table 28: German LDV IDA Results with respect to 2000**

| Period (year) | ΔE(PI) | ΔE(PMF) | ΔE($TS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gasoline | Diesel | Others | Total | Gasoline | Diesel | Others | Total | | |
| 2 (2001) | 38,45 | 3,48 | -45,92 | 37,11 | 0,00 | -8,81 | -13,38 | -5,45 | 0,00 | -18,84 | 1,12 | 15,40 |
| 3 (2002) | 51,78 | 10,23 | -83,96 | 67,76 | 0,00 | -16,20 | -15,66 | -7,37 | 0,00 | -23,03 | 2,24 | 25,02 |
| 4 (2003) | 43,87 | 3,23 | -107,17 | 86,42 | 0,00 | -20,74 | -21,93 | -9,44 | 0,00 | -31,37 | 1,66 | -3,35 |
| 5 (2004) | 65,49 | 16,15 | -147,41 | 120,35 | 0,00 | -27,07 | -29,86 | -5,17 | 0,00 | -35,03 | 0,00 | 19,55 |
| 6 (2005) | 47,15 | 3,95 | -180,40 | 145,87 | 0,00 | -34,52 | -35,73 | -12,49 | 0,00 | -48,22 | -2,19 | -33,84 |
| 7 (2006) | 61,92 | 6,84 | -225,66 | 183,52 | 0,00 | -42,14 | -41,92 | -11,74 | 0,00 | -53,65 | -5,29 | -32,32 |
| 8 (2007) | 69,50 | 13,12 | -259,48 | 210,71 | 0,00 | -48,78 | -51,59 | -16,43 | 0,00 | -68,01 | -8,54 | -42,71 |
| 9 (2008) | 78,12 | -7,55 | -255,32 | 208,82 | 0,00 | -46,50 | -64,71 | -15,06 | 0,00 | -79,77 | -12,62 | -68,32 |
| 10 (2009) | 98,90 | 7,73 | -298,17 | 221,25 | 31,01 | -45,92 | -84,00 | -17,12 | 0,13 | -100,99 | -17,53 | -57,81 |
| 11 (2010) | 108,27 | 15,61 | -329,25 | 243,07 | 29,69 | -56,49 | -86,90 | -15,83 | 0,10 | -102,63 | -21,10 | -56,33 |
| 12 (2011) | 124,72 | 20,97 | -344,65 | 255,39 | 31,41 | -57,85 | -87,75 | -19,31 | 0,11 | -106,94 | -21,18 | -40,28 |
| 13 (2012) | 124,14 | 18,54 | -375,99 | 283,17 | 31,46 | -61,36 | -101,44 | -19,83 | 0,11 | -121,16 | -18,28 | -58,12 |
| 14 (2013) | 131,13 | 19,75 | -401,41 | 305,96 | 30,31 | -65,14 | -101,29 | -16,46 | 0,10 | -117,65 | -14,38 | -46,29 |
| 15 (2014) | 147,25 | 24,98 | -421,13 | 325,21 | 28,92 | -67,00 | -101,20 | -17,05 | 0,10 | -118,16 | -8,56 | -21,49 |
| 16 (2015) | 151,33 | 30,07 | -438,46 | 341,54 | 26,54 | -70,38 | -111,60 | -17,38 | 0,08 | -128,91 | 4,09 | -13,81 |
| 17 (2016) | 170,50 | 31,78 | -454,30 | 357,91 | 25,94 | -70,44 | -117,60 | -18,74 | 0,08 | -136,27 | 15,86 | 11,43 |

**Table 29: German LDV IDA Results with chained base year**

| Period (year) | ΔE(PI) | ΔE(PMF) | ΔE($TS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gasoline | Diesel | Others | Total | Gasoline | Diesel | Others | Total | | |
| 2 (2001) | 38,45 | 3,48 | -45,92 | 37,11 | 0,00 | -8,81 | -13,38 | -5,45 | 0,00 | -18,84 | 1,12 | 15,40 |
| 3 (2002) | 13,31 | 6,78 | -38,11 | 30,62 | 0,00 | -7,49 | -2,38 | -1,73 | 0,00 | -4,11 | 1,13 | 9,62 |
| 4 (2003) | -7,47 | -6,97 | -24,20 | 19,40 | 0,00 | -4,80 | -6,42 | -2,16 | 0,00 | -8,57 | -0,56 | -28,37 |
| 5 (2004) | 21,42 | 12,93 | -39,76 | 32,23 | 0,00 | -7,54 | -7,84 | 5,61 | 0,00 | -2,23 | -1,68 | 22,90 |
| 6 (2005) | -17,29 | -12,03 | -35,42 | 28,77 | 0,00 | -6,65 | -6,41 | -8,79 | 0,00 | -15,20 | -2,22 | -53,39 |
| 7 (2006) | 14,83 | 2,89 | -44,97 | 36,44 | 0,00 | -8,53 | -6,34 | 1,76 | 0,00 | -4,58 | -3,09 | 1,52 |
| 8 (2007) | 7,92 | 6,31 | -34,13 | 27,76 | 0,00 | -6,38 | -9,41 | -5,57 | 0,00 | -14,98 | -3,27 | -10,39 |
| 9 (2008) | 9,22 | -20,48 | 1,32 | -1,08 | 0,00 | 0,24 | -12,14 | 1,70 | 0,00 | -10,44 | -4,14 | -25,61 |
| 10 (2009) | 21,29 | 15,06 | -42,07 | 10,43 | 31,01 | -0,63 | -18,08 | -2,29 | 0,13 | -20,23 | -4,98 | 10,51 |
| 11 (2010) | 9,60 | 7,94 | -29,98 | 20,16 | 5,61 | -4,20 | -3,40 | 2,42 | -7,26 | -8,23 | -3,62 | 1,48 |
| 12 (2011) | 16,16 | 5,34 | -13,17 | 11,60 | -0,54 | -2,10 | -0,75 | -4,42 | 1,82 | -3,35 | 0,00 | 16,05 |
| 13 (2012) | 0,70 | -2,25 | -33,72 | 28,04 | 0,45 | -5,23 | -13,43 | 0,07 | -0,43 | -13,79 | 2,73 | -17,84 |
| 14 (2013) | 6,92 | 1,20 | -23,95 | 20,16 | 0,34 | -3,46 | -0,68 | 5,62 | -1,75 | 3,19 | 3,99 | 11,83 |
| 15 (2014) | 15,52 | 5,20 | -16,29 | 16,48 | -2,44 | -2,24 | 0,02 | -0,25 | 0,51 | 0,28 | 6,03 | 24,80 |
| 16 (2015) | 4,07 | 5,21 | -16,68 | 13,90 | 0,49 | -2,30 | -9,10 | 0,05 | -3,30 | -12,35 | 13,04 | 7,68 |
| 17 (2016) | 18,78 | 1,57 | -12,78 | 12,97 | -1,64 | -1,45 | -4,84 | -1,44 | 0,47 | -5,82 | 12,16 | 25,24 |

**Table 30: Dutch LDV IDA Results with respect to 2000**

| Period (year) | ΔE(PI) | ΔE(PMF) | ΔE($TS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gasoline | Diesel | Others | Total | Gasoline | Diesel | Others | Total | | |
| 2 (2001) | -0,94 | 1,85 | -0,46 | 1,94 | -1,76 | -0,28 | -0,29 | 0,15 | 0,16 | 0,02 | 1,78 | 2,42 |
| 3 (2002) | 1,92 | 2,50 | -0,86 | 4,07 | -3,81 | -0,60 | -1,22 | 0,13 | 0,25 | -0,84 | 3,28 | 6,27 |
| 4 (2003) | 3,89 | 2,28 | -1,50 | 6,50 | -5,95 | -0,95 | -1,25 | 0,20 | 0,33 | -0,72 | 4,49 | 8,98 |
| 5 (2004) | 12,01 | -0,29 | -1,23 | 8,14 | -8,14 | -1,22 | -1,44 | 0,26 | 0,44 | -0,74 | 5,29 | 15,05 |
| 6 (2005) | 7,02 | 3,00 | -3,05 | 10,88 | -9,37 | -1,54 | -1,51 | 0,34 | 0,36 | -0,82 | 5,86 | 13,52 |
| 7 (2006) | 5,27 | 6,64 | -5,61 | 13,54 | -9,68 | -1,75 | -2,39 | 0,12 | 0,05 | -2,23 | 6,31 | 14,24 |
| 8 (2007) | 7,29 | 8,41 | -6,93 | 15,27 | -10,22 | -1,88 | -3,95 | -0,26 | -0,21 | -4,41 | 6,78 | 16,19 |
| 9 (2008) | -3,35 | 15,64 | -8,58 | 16,37 | -9,77 | -1,99 | -4,60 | -0,21 | -0,08 | -4,89 | 7,77 | 13,18 |
| 10 (2009) | 4,06 | 7,65 | -8,31 | 15,56 | -8,66 | -1,41 | -4,76 | -0,38 | -2,02 | -7,16 | 8,92 | 12,06 |
| 11 (2010) | -5,00 | 17,29 | -7,55 | 14,72 | -8,18 | -1,01 | -4,43 | -0,51 | -3,33 | -8,27 | 10,25 | 13,26 |
| 12 (2011) | -5,68 | 18,50 | -7,30 | 14,52 | -8,08 | -0,86 | -4,05 | -1,36 | -4,23 | -9,65 | 11,27 | 13,58 |
| 13 (2012) | -14,80 | 26,95 | -5,76 | 14,16 | -9,18 | -0,78 | -7,28 | -1,10 | -3,66 | -12,03 | 12,23 | 11,56 |
| 14 (2013) | -5,55 | 17,26 | -4,28 | 13,66 | -10,30 | -0,93 | -8,89 | -2,02 | -3,09 | -14,00 | 12,75 | 9,53 |
| 15 (2014) | -7,19 | 19,01 | -2,82 | 13,14 | -11,47 | -1,14 | -9,87 | -3,35 | -2,58 | -15,80 | 13,71 | 8,59 |
| 16 (2015) | -17,43 | 31,42 | -1,35 | 13,59 | -14,88 | -2,64 | -12,92 | -5,01 | 0,44 | -17,49 | 14,70 | 8,57 |
| 17 (2016) | -16,57 | 35,31 | 0,20 | 12,68 | -15,94 | -3,06 | -15,70 | -6,14 | 1,24 | -20,60 | 16,06 | 11,13 |

**Table 31: Dutch LDV IDA Results with chained base year**

| Period (year) | ΔE(PI) | ΔE(PMF) | ΔE($TS_i$) | | | | ΔE($EI_i$) | | | | ΔE(P) | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Gasoline | Diesel | Others | Total | Gasoline | Diesel | Others | Total | | |
| 2 (2001) | -0,94 | 1,85 | -0,46 | 1,94 | -1,76 | -0,28 | -0,29 | 0,15 | 0,16 | 0,02 | 1,78 | 2,42 |
| 3 (2002) | 2,88 | 0,65 | -0,40 | 2,13 | -2,04 | -0,32 | -0,93 | -0,02 | 0,09 | -0,86 | 1,49 | 3,85 |
| 4 (2003) | 1,99 | -0,25 | -0,64 | 2,43 | -2,16 | -0,37 | -0,02 | 0,07 | 0,09 | 0,13 | 1,20 | 2,71 |
| 5 (2004) | 8,24 | -2,64 | 0,29 | 1,59 | -2,17 | -0,29 | -0,17 | 0,06 | 0,11 | 0,00 | 0,76 | 6,07 |
| 6 (2005) | -5,12 | 3,40 | -1,87 | 2,85 | -1,34 | -0,36 | -0,09 | 0,08 | -0,05 | -0,06 | 0,61 | -1,53 |
| 7 (2006) | -1,81 | 3,75 | -2,63 | 2,71 | -0,37 | -0,28 | -0,91 | -0,26 | -0,24 | -1,40 | 0,46 | 0,72 |
| 8 (2007) | 2,07 | 1,81 | -1,34 | 1,71 | -0,56 | -0,19 | -1,58 | -0,44 | -0,19 | -2,21 | 0,46 | 1,95 |
| 9 (2008) | -11,00 | 7,56 | -1,76 | 1,22 | 0,46 | -0,09 | -0,71 | 0,06 | 0,09 | -0,56 | 1,07 | -3,01 |
| 10 (2009) | 7,64 | -8,21 | 0,29 | -0,84 | 0,62 | 0,07 | -0,16 | -0,20 | -1,47 | -1,83 | 1,21 | -1,12 |
| 11 (2010) | -9,33 | 9,91 | 0,82 | -0,92 | 0,16 | 0,06 | 0,37 | -0,15 | -1,01 | -0,79 | 1,35 | 1,20 |
| 12 (2011) | -0,70 | 1,24 | 0,29 | -0,14 | -0,11 | 0,04 | 0,41 | -1,00 | -0,71 | -1,30 | 1,05 | 0,32 |
| 13 (2012) | -9,45 | 8,82 | 1,53 | -0,42 | -0,88 | 0,24 | -3,29 | 0,31 | 0,32 | -2,67 | 1,04 | -2,02 |
| 14 (2013) | 9,46 | -9,85 | 1,50 | -0,42 | -0,90 | 0,19 | -1,63 | -1,09 | 0,31 | -2,41 | 0,59 | -2,03 |
| 15 (2014) | -1,70 | 1,84 | 1,49 | -0,40 | -0,94 | 0,15 | -0,96 | -1,56 | 0,27 | -2,25 | 1,02 | -0,94 |
| 16 (2015) | -10,48 | 12,70 | 1,50 | 0,56 | -2,16 | -0,11 | -3,07 | -1,90 | 1,82 | -3,15 | 1,01 | -0,02 |
| 17 (2016) | 0,98 | 3,80 | 1,59 | -0,97 | -0,60 | 0,02 | -2,71 | -1,30 | 0,48 | -3,54 | 1,30 | 2,56 |