



UHASSELT

KNOWLEDGE IN ACTION

School of Transportation Sciences

Master of Transportation Sciences

Master's thesis

Road Safety Evolution in European Nations (2001-2020): Trends and Policy Implications

Goytom Kebedew Welegerima

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization
Traffic Safety

SUPERVISOR :

Prof. dr. Elke HERMANS

CO-SUPERVISOR :

Prof. dr. Evelien POLDERS



UHASSELT

KNOWLEDGE IN ACTION

www.uhasselt.be

Universiteit Hasselt
Campus Hasselt:
Martelarenlaan 42 | 3500 Hasselt
Campus Diepenbeek:
Agoralaan Gebouw D | 3590 Diepenbeek

2023
2024



School of Transportation Sciences

Master of Transportation Sciences

Master's thesis

Road Safety Evolution in European Nations (2001-2020): Trends and Policy Implications

Goytom Kebedew Welegerima

Thesis presented in fulfillment of the requirements for the degree of Master of Transportation Sciences, specialization Traffic Safety

SUPERVISOR :

Prof. dr. Elke HERMANS

CO-SUPERVISOR :

Prof. dr. Evelien POLDERS

Road Safety Evolution in European Nations (2001-2020): Trends and Policy Implications

Goytom Kebedew Welegerima*, Elke Hermans^a, Evelien Polders^b

^aProf. Dr., Hasselt University, Hasselt, Belgium

^bProf. Dr., Hasselt University, Hasselt, Belgium

Abstract

Road safety remains a significant challenge, with 1.19 million fatalities worldwide in 2021. The EU, however has achieved remarkable progress but road traffic crashes remain a severe public health concern in Europe. This study examines the evolution of road safety in European countries from 2001 to 2020 using time series analysis techniques, including ARIMA, SARIMA, and XARIMA models, as well as piecewise linear regression. These methods were applied to aggregated and disaggregated road safety outcome and performance indicators across 18 EU member countries to identify trends, patterns, and influential factors affecting road safety outcomes. The analysis reveals a general decline in traffic fatalities and injuries across Europe despite an increase in traffic volume, implying enhanced safety measures, such as, speed limit, compulsory use of seatbelts, standards for vehicle safety, and safety requirements and investment on road infrastructure. The study identified key change points in road safety trends, notably in 2003, 2008, 2014, and 2017, reflecting the impact of policy interventions and socio-economic factors on road safety outcomes. Countries such as Belgium, Finland, Ireland, and the Netherlands exhibited consistent declines in fatalities. However, older adults and vulnerable groups, including pedestrians, bicyclists, and motorcyclists, face higher fatality risks. The study highlights significant variations in road safety outcomes across different transportation modes, genders, and age groups, underscoring the need for targeted safety strategies. The impact of road safety laws and measures has been substantial, particularly those implemented between 2003 and 2010. However, subsequent regulations showed limited effects, indicating a need for continuous policy evaluation and adaptation. Speeding remains a significant challenge, necessitating improved enforcement and public awareness. This study provides valuable insights for policymakers and practitioners, aiming to reduce traffic fatalities and enhance road safety.

Keywords: Time series analysis; Road safety outcome and performance indicators; ARIMA; SARIMA; XARIMA; Tipping points; Intervention analysis

* Student.

Goytom.welegerima@gmail.com/goytomkebedew.welegerima@student.uhasselt.be

1. Introduction

Despite the United Nations' Decade of Action for Road Safety, 1.19 million people died on roads worldwide in 2021 (World Health Organization, 2023). With just 2% of the estimated road fatalities worldwide, the EU has made tremendous progress in road safety. Its roads are among the safest in the world. The EU's emphasis on road network safety, vehicle safety, transportation of hazardous materials, and intelligent transport systems is responsible for this success (Davide & Debyser, 2023; European Commission, 2020).

Between 2001 and 2020, the EU significantly reduced the number of road deaths by 64% (Adminaité-Fodor et al., 2021; European Commission, 2020). However, this progress has slowed down recently, and the yearly toll of fatalities and severe injuries on European Union (EU) roads exceeded 25,000 and 135,000, respectively, in 2018 (Carson et al., 2023; European Commission, 2020). There are still many important issues to be resolved, such as the high death toll among young men and other vulnerable road users and the increased frequency of crashes on local roads (European Commission, 2018d).

Europe has implemented many best practices to increase traffic safety. These procedures include establishing a road safety vision like Sustainable Safety in the Netherlands and the Swedish Vision Zero that places the needs of people first, putting in place a car design rating system to incentivize safety enhancements, clearly enforcing traffic regulations, and taking action to lessen the increased dangers that inexperienced drivers face (European Commission, 2007, 2010, 2020).

Despite notable progress in recent decades, road traffic crashes remain a severe public health concern in Europe. Nonetheless, 18,840 fatalities and almost 164,437 major injuries occurred on EU roads in 2020 (Adminaité-Fodor et al., 2021). A recent study estimates the annual financial cost of traffic crashes in the EU to be approximately EURO 280 billion, or 2% of the GDP (European Commission, 2020). These figures underscore the need for effective mitigation strategies in the sector. To establish effective road safety strategies, a comprehensive understanding of safety trends and their underlying causes is essential (European Commission, 2004; Theodor D., 2020).

Road crashes arise from a complex interaction between road users, and technological and organizational factors in the traffic environment (European Commission, 2024). As a result of crash data's complexity and randomness nature, it necessitates rigorous analytical methods to understand its trends and patterns (Commandeur et al., 2013). While numerous studies have been conducted on road safety in Europe, (European Commission, 2015b, 2018b, 2019b; The Swedish Transport Administration, 2018; Tomašković & Završki, 2024)., relatively fewer studies have employed advanced econometric models, such as time series analysis, to deeply investigate these trends at both local and national levels (Lavrenz et al., 2017).

Time series analysis, incorporating various influencing factors, provides a robust framework for understanding the complexities of traffic safety trends (Box et al., 2016; Chatfield & Xing, 2019; Mikkonen et al., 1997). Moreover, complementing the analysis of outcome indicators with safety performance indicators (SPIs) offers a better understanding of road safety trends (European Commission, 2018c). SPIs can provide a more comprehensive perspective of the safety performance of a transport system by identifying the factors contributing to crash occurrences (ITF, 2023). When applied to both outcome indicators and SPIs, time series analysis can provide a strong foundation for identifying historical trends, assessing the effects of influential factors (*exogenous factors*), evaluating interventions, and informing evidence-based policies (European Commission, 2022; ITF, 2023; Theodor D., 2020). However, inconsistencies in data collection, lack of data, and methodological challenges related to time series modeling present obstacles to its implementation (Bergel-Hayat & Zukowska, 2015; Lavrenz et al., 2017). Despite these challenges, time-series modeling and road safety indicators are practical techniques for enhancing road safety (European Commission, 2022).

Antoniou et al., 2014, emphasize that time series analysis plays a crucial role in developing efficient traffic safety models that evaluate interventions, identify accident-related factors, and assess trends. Time series models, including the autoregressive integrated and moving average (ARIMA), and its extensions (*SARIMA and XARIMA*), effectively capture temporal patterns, allowing for the identification of influential factors and the evaluation of interventions (Bergel-Hayat & Zukowska, 2015; Hermans et al., 2006, 2007; Van den Bossche et al., 2004). Non-parametric methods like Sen's slope estimator further aid in detecting gradual shifts in safety indicators over time (Sen, 1968). The application of these models in time series analysis performed from 2000 to 2012 is given in Ruth & Joanna (2015). In those studies, these models showed changes in road safety indicators over a long period and assessed risk factors

and safety policies. However, existing studies examining the evolution of road safety in Europe using time series analysis to identify trends and external factors have primarily focused on data from before 2010 (Bergel-Hayat & Zukowska, 2015). Subsequent research has either predicted future outcomes (Antonioni et al., 2014; Bergel-Hayat & Zukowska, 2015) or employed standard statistical methods (Tomašković & Završki, 2024).

This study seeks to address these gaps by utilizing time series analysis of road safety data covering 2001–2020 in order to derive insights from history concerning the most effective road safety policies, strategies and initiatives across 18 European countries. This research will identify trends and patterns as well influential factors presenting valuable insights into the development of road safety in Europe. Moreover, evaluation of road safety-related policies and measures implemented during the study period (*the first and second decade of action for road safety in Europe*) will provide evidence to support targeted strategies aiming at improved traffic safety levels throughout Europe as well as other countries.

The study period from 2001 to 2020 is chosen to align with pivotal advancements in EU road safety policies and the evolution of road safety research. This era shifted towards a systems-based approach, such as Sweden's Vision Zero and the Dutch Sustainable Safety concept, reflecting a more holistic understanding of road safety (Hagenzieker et al., 2014; Hakkert & Gitelman, 2014). These years are also marked by significant EU milestones aimed at reducing road (Adminaité-Fodor et al., 2021; European Commission, 2015b), the introduction of the concept of safety performance indicators (European Transport Safety Council, 2001; Wegman, 2016), alongside improvements in data quality essential for robust analysis (CARE Team, 2023; Council of the European Union, 1993; European Court of Auditors, 2024). The period captures the integration of advanced technologies and the development of evidence-based interventions, making it ideal for assessing both historical progress and informing future road safety strategies (European Commission, 2007, 2015b). To achieve the study's objective, questions are set to complete the quantitative analysis.

- How did road safety evolve in European nations from 2001 to 2020, and what common patterns and trends were observed in road safety outcomes and performance indicators during this period?
- How do road safety outcomes (traffic fatalities) vary across different modes of transportation, genders, age groups, road types, and persons involved in Europe during the study period?
- How have road safety outcomes (traffic fatalities and injuries) in European countries from 2001 to 2020 been influenced by socio-economic factors, weather conditions, and laws and measures? Which of these exogenous variables have significantly influenced road safety outcomes, and which have not shown notable improvements?
- What policies and best practices from European road safety measures should be recommended to policymakers and practitioners, and under what conditions can these practices be effectively adapted and transferred to developing nations?

The rest of this paper is structured as follows: Section 2 provides a brief literature review of studies regarding road safety goals and trends in Europe, the actions taken by the EU in the area of road safety, time series analysis methods and their application, and application of SPIs in road safety. Then, in section 3, the indicators used and the data collected for this study are briefly introduced. Section 4 provides a description of the methodological approach, including the theoretical background of time series analysis. Section 5 provides the results of the analysis method performed in the framework of the current study. Lastly, a discussion on the road safety trends observed, and the impact of exogenous factors on road fatalities and injuries is highlighted in Section 6. The last section reveals conclusions on the study's originality, innovation, contribution to practice, and knowledge.

2. Literature Review

2.1. Road Safety Goals and Trends in Europe

Road safety has been a critical area of focus for European policymakers since the early 2000s (European Commission, 2015b). The European Union (EU) has set ambitious road safety goals over the past two decades (2001 to 2020), aiming to reduce the number of road fatalities and injuries. The primary goal has been to halve the number of road deaths within each decade, with the ultimate vision of achieving zero fatalities on European roads, as illustrated

by initiatives like Vision Zero and Sustainable Safety (European Commission, 2015b, 2019a; Safarpour et al., 2020; Tomašković & Završki, 2024).

In 2001, the EU launched its first road safety target to reduce road fatalities by 50% by 2010. This program began a systematic and coordinated approach to road safety across member states (European Commission, 2015b). Building on this progress, the EU introduced the "Safe System" approach in the 2011-2020 European Road Safety Action Plan. This target seeks to design a road transport system that accommodates road user error and mitigates the consequences of accidents. The goal for this period was again to halve the number of road deaths by 2020 (European Commission, 2011, 2015b).

From 2000 to 2010, the EU achieved a 43% reduction in road fatalities, falling slightly short of its 50% target. However, this period demonstrated the effectiveness of coordinated European efforts, including stricter vehicle safety standards, improved road infrastructure, and more effective enforcement of traffic laws (European Commission, 2019a). The period from 2011 to 2020 saw further advancements, albeit with a slower rate of decline in fatalities. By 2020, the EU had reduced road fatalities by an additional 37% compared to 2010. Despite not meeting the target of a 50% reduction, all countries made improvements and saved lives (Adminaité-Fodor et al., 2021). However, the progress was uneven across member states, with some countries achieving better outcomes than others do. Spain, Lithuania, and Latvia have made the most remarkable strides since 2001, resulting in an astounding 75% decrease in traffic fatalities by 2020. Nevertheless, with only 25% and 33% reductions, Malta and Romania have had difficulty achieving this aim (Adminaité-Fodor et al., 2021).

In 2018, the EU established its first goal of halving the rate of traffic injuries by 2030. However, road injury rates decreased by a relatively small 14% between 2010 and 2020 due to the lack of comprehensive policies and plans specifically focused on injury reduction from 2001 to 2020. There are many reasons for this deficiency, including variations in how road injuries are defined and perceived among EU member states (Adminaité-Fodor et al., 2021; Carson et al., 2023).

The past two decades have seen significant advancements in road safety across Europe, driven by ambitious goals and coordinated policy efforts. While substantial progress has been made in reducing road fatalities, the improvement has slowed, highlighting the need for continued innovation and a more targeted approach to meet future goals.

2.2. *EU Action in the Area of Road Safety*

Between 2001 and 2020, the EU implemented different strategies to reduce road fatalities across its member states. It has established the European Road Safety Observatory (ERSO) to coordinate data collection and analysis to achieve this.

The EU's focused efforts on road safety began with the launch of the first EU Road Safety Action Programme in 2001 (European Commission, 2001). The program identified several priority areas, including improving the quality of road infrastructure and strengthening enforcement. In addition, it includes soft measures such as information campaigns, data analysis, and legislative action (European Commission, 2015b). Building on the achievements of the previous decade, the EU introduced the 2011-2020 Road Safety Action Programme (European Commission, 2011). During this period, the EU set actions focusing on the education and training of road users, enforcement of road traffic rules, safer road infrastructure, safer vehicles, better use of modern safety technologies, serious injuries and emergency services, and safety of vulnerable road users. This program was characterized by a shift towards the "Safe System" approach (European Commission, 2015b, 2018a, 2019a, 2020).

Throughout the 2001-2020 period, the EU enacted several legislation and policy initiatives, listed in Davide & Debyser (2023) and European Commission, (2015b), that supported road safety efforts. These legislative actions reinforced the EU's commitment to road safety and provided a legal framework to support the implementation of road safety measures across member states (European Commission, 2001, 2011).

2.3. *Road Safety Performance Indicators*

To gain a deeper understanding of the underlying trends in road safety and assess the effectiveness of countermeasures, it is recommended to complement the existing crash and injury data ("final outcomes") with a set of SPIs (European Commission, 2018c). Unlike outcome indicators, SPIs focus on the underlying factors influencing

road safety outcomes. These indicators help identify a transport system's strengths and weaknesses and provide insights into areas requiring improvement. SPIs can help track progress toward implementing the Safe System (ITF, 2023). In addition, due to irregular and untrustworthy data, road safety outcome indicators are not always accurate. Therefore, more indicators must be found to evaluate the issue's scope more precisely (European Commission, 2022; Hermans et al., 2009; Jameel & Evdorides, 2023).

During the early 2000s, the European Union introduced the idea of SPIs. These are "Intermediate Outcome Indicators" or "any measurement causally linked to crashes or injuries to assess safety performance or comprehend the process that leads to crashes." Selection of appropriate SPIs for particular risk domains, such as alcohol and drugs, speed, protective systems, distraction, vehicle safety, and infrastructure is important in providing policymakers with valuable road safety performance information (Hermans et al., 2009; ITF, 2023; Silverans & Vanhone, 2023). The relevance, measurability, comprehensiveness, simplicity, comparability, sensitivity, independence, reaching the goal, validity, and data availability are some of the most important factors to consider when choosing SPIs. The availability of reliable and comparable data has a major influence on the indicator selection (Hermans et al., 2009; ITF, 2023; Jameel & Evdorides, 2023).

However, the most common challenge when deploying SPIs is insufficient data availability to measure the desired indicators (ITF, 2023). Similarly, there is a lack of uniformity in the collection and application of SPIs among EU member states (European Commission, 2018b). As a result, this study selects available historical SPI data from EU countries. These data are categorized by risk factors like speeding, alcohol use, and mobile phone use to analyze the performance of the transport system and their impact on road safety trends.

2.4. Time Series Analysis Methods

A key feature of a time series is the dependence between adjacent observations. Time series analysis focuses on techniques to examine this dependence. This involves developing mathematical models for time series data. (Bergel-Hayat & Zukowska, 2015; Box et al., 2016). Mathematical time series models that precisely predict the future value are deterministic. Unfortunately, because of the many unknown factors affecting the observation, it might not be possible to determine exact future values in many real problems, including road crashes. However, a model that can determine the likelihood that a future value would fall within two given limits might be derived. A probability model, often known as a stochastic model, is one such model. (Box et al., 2016; Cryer & Chan, 2008). A stochastic process is a mathematical framework that describes the probabilistic nature of a sequence of observations over time (Chatfield & Xing, 2019). These models can be either descriptive models where time is the only variable or explanatory models with extra explanatory, exogenous, and intervention variables throughout time (Bergel-Hayat & Zukowska, 2015).

Stationarity is crucial in time series models. A time series is stationary if its mean and variance remain constant over time and periodic fluctuations are removed. Mathematically, the joint distribution of $X(t_1), \dots, X(t_k)$ remains unchanged when shifted by τ . However, time series data often fail to be stationary. Therefore, one must ensure the data is stationary for meaningful statistical analysis. If not, it must be stabilized before analysis (Box et al., 2016; Chatfield & Xing, 2019; Cryer & Chan, 2008).

Road safety modeling should take into consideration variables that reflect risk exposure (population, vehicles, traffic, or fuel consumption), background indicators (socio-economic), climatic factors, and intervention effects (regulations, events) (Antoniou et al., 2014; Jameel & Evdorides, 2023; Qiong et al., 2022). In this context, two primary univariate dynamic models are commonly used: the ARIMA model, studied by Box and Jenkins, and the structural models developed by Harvey (1994) (Bergel-Hayat & Zukowska, 2015; Dupont & Martensen, 2007; European Commission, 2004; Karlis & Hermans, 2012).

Dupont & Martensen (2007), referring to Harvey (1989) and Durbin & Koopman (2001) claimed that state space models and ARIMA models have a lot in common and that using both models in an analysis can produce results that are nearly the same. Hermans et al. (2006) used state space-time series models to examine crash frequency and severity patterns in Belgium between 1974 and 1999. They mentioned that the state space method's outcomes resembled a regression model with ARIMA errors. In addition to their shared characteristics, state space, and ARIMA models differ significantly. However, ARIMA models are easier to understand and require less computing power than state space models (Institute for Road Safety Research, 2013).

Overstating the effectiveness of road safety measures is common, particularly in before-and-after studies without control groups. Time-series analysis can help identify underlying trends that may influence the evaluation of these measures, even in the absence of control groups (European Commission, 2004). For example, Harvey & Durbin (1986) studied the effect of seat belt legislation on road casualty rates through structural time series modeling. Michalaki et al. (2016) analyze the trends of hard-shoulder and motorway collisions by incorporating various exogenous variables, utilizing vector autoregressive time series models from 1993 to 2011. Utilizing ARIMA error models, Van den Bossche et al. (2004) investigate the impact of weather, laws and regulations, and economic conditions on the frequency and severity of accidents in Belgium from 1986 to 2000. Hermans et al. (2007) studied the impact of meteorological, socioeconomic, and legislative on traffic fatalities in Belgium from 1974 to 1999 utilizing state space and the ARIMA models.

3. Indicator Selection and Data Collection

Effective road safety strategies and impactful studies center on the availability of high-quality data to identify problems, design interventions, and monitor progress (Wegman, 2016). To gain a more comprehensive understanding of road safety trends and the effectiveness of interventions, a broader range of SPIs is needed (European Commission, 2018c, 2022; Hermans et al., 2009; Jameel & Evdorides, 2023). Setting out SPIs and collecting sufficient quality data are required to guide safety policy (Gitelman et al., 2014; ITF, 2023).

3.1. Data Sources

A thorough investigation was conducted using multiple sources to gather the necessary data on traffic safety performance indicators and related exogenous factors. These included Eurostat, the European Road Safety Observatory (ERSO), the European Transport Safety Council (ETSC), the Community Database on Accidents on the Roads in Europe (CARE) database, the Social Attitudes to Road Traffic Risk in Europe (SARTRE) project, the Baseline Project, the E-Survey of Road users' Attitudes (ESRA) project, the Organization for Economic Cooperation and Development (OECD), the Climate Change Knowledge Portal (CCKP) of the World Bank, and various national databases. It is important to note that not all sources provided the specific data needed, which required a strategic and selective approach to data collection.

When data is sourced from two distinct sources, a thorough cross-check is performed to identify inconsistencies, ensuring data accuracy and reliability. Data extraction from reports is collected chronologically, from the most recent to older reports. This approach guarantees that the most updated and relevant data are accurately incorporated into the study. When data for indicators and factors mentioned above are missing for some countries in particular years of the study period, these gaps are filled using statistical methods for estimating missing data.

3.2. Data Type

In this study, three types of road safety-related data are considered. Two are road safety indicators, and the other consists of exogenous factors. Among the road safety indicators, one is outcome indicators (fatality and injury), and the other is intermediate safety performance indicators, which reflect those operational conditions of the road traffic system that influence the system's safety performance (Gitelman et al., 2014). Both types of indicators are used in assessing the road safety trends, while the exogenous factors are used in analyzing their effect on road safety evolution.

To better understand the underlying trends in road safety and assess the effectiveness of countermeasures, it is recommended to complement the existing crash and injury data with a set of SPIs (European Commission, 2018c). Accordingly, 23 final outcome indicators are chosen based on data availability and reliability. These indicators focused on annual road fatalities disaggregated by gender, age, person involved, road type, and vehicle type. Gender and age-specific fatalities are measured per inhabitant, while other categories are counted in absolute numbers. Additionally, monthly counts of total fatalities and injuries are included. To better analyze traffic safety trends, an additional one indicator of traffic fatalities per billion vehicle kilometers is adjusted to annual traffic volume exposure in billion vehicle kilometers. This additional modified indicator allows for a more accurate assessment of how risk exposure has evolved over time and its impact on fatality rates.

The safety performance indicators can show the state of risk factors and their trends in more detail, as well as the potential to reduce these types of crashes (Qiong et al., 2022). Ideally, SPIs should encompass the most important risk areas related to road users, vehicles, and roads. Based on data availability, six SPIs are selected, representing five risk domains, as shown in Table 1.

Table 1: Selected safety performance indicators (ETSC)

Risk domain	Selected SPIs	Measuring unit
Alcohol	Share of fatalities involving alcohol-impaired drivers	percentage
Distraction	Annual total tickets issued for mobile phone use while driving	tickets per 1000 population
Protective system	Annual total tickets issued for seatbelt violations	tickets per 1000 population
Speeding	Annual total tickets issued for speeding violations	tickets per 1000 population
Road	Annual share of motorways in the total road network	ratio
	Annual road infrastructure investment	USD per inhabitant

The time and countries covered by the data can be found in Appendix A.

The selected external factors influencing road safety are categorized under socio-economy, weather conditions, and road safety intervention. Socio-economic factors are measured annually and include the share of household expenditure for transport in total household expenditure, the share of household expenditure for purchasing vehicles within the total transport expenditure, the employment share of the total population, gross domestic product (GDP) per capita in euros, and the average net income of households in millions of euros.

Table 2: Selected socio-economic factors (OECD)

Indicators	Unit	Abbreviation
Share of household expenditure for purchasing vehicles within the total transport expenditure	Percent	Veh_purchase
Employment share of the total population	Percent	Emp_share
Average net income of households	Million Euro	Ave_net_inc.
Gross domestic product (GDP) per capita in euros	Euro	GDP
Share of household expenditure for transport in total household expenditure	Percent	HH_exp_trans

The time and countries covered by the data can be found in Appendix A.

Weather conditions data is monthly, including the average temperature in degrees centigrade and the total precipitation in millimeters. Under road safety interventions, the study considers all directives and regulations implemented during the time scope of the study (*fifteen, to the author's knowledge*), assessing their impact on road safety (Davide & Debyser, 2023; European Commission, 2015b).

Table 3: Selected interventions (Davide & Debyser, 2023; European Commission, 2015b)

Categories	Directives
Type-Approval and Vehicle Standards	D_2002/24/EC (May 2003): Type-approval for two or three-wheel motor vehicles. D_2007/46/EC (May 2009): Framework for the approval of motor vehicles, trailers, and systems.
Safety Features and Requirements	D_2003/97/EC (Nov 2003): Additional blind spot mirrors for heavy goods vehicles.
	D_2004/54/EC (Apr 2004): Safety requirements for tunnels in the trans-European road network.
	D_2005/39/EC (Sep 2005): Standards for motor vehicle seats, anchorages, and head restraints.
	D_2003/20/EC (May 2006): Compulsory use of safety belts and child-restraint systems in vehicles <3.5t.
	D_2002/85/EC (Jan 2007): Compulsory speed limitation devices in motor vehicles.
Pedestrian and User Protection	R_78/2009 (Nov 2009): Type-approval to protect pedestrians and vulnerable road users.
Road Infrastructure and Management	D_2008/96/EC (Dec 2010): Road infrastructure safety management practices.
Technological Advancements	D_2010/40/EU (Feb 2012): Framework for Intelligent Transport Systems (ITS) in road transport.
	R_2015/758 (Apr 2018): E-call technology in all new cars for automatic emergency contact

Categories	Directives
Legal and Regulatory Measures	D_1999/37/EC (Jun 2004): Standardized vehicle registration documents.
	D_2010/48/EU (Dec 2011): Regular roadworthiness tests for vehicles and trailers.
	D_2006/126/EC (Jan 2013): Updated driving license regulations.
	D_2015/413 (Mar 2015): Cross-border exchange of information on road-safety-related traffic offenses.

The date in brackets following the directive number indicates the start date of application for the directive.

4. Methodology

4.1. Research Design

This thesis uses a quantitative approach, Apuke (2017), with ARIMA, SARIMA, XARIMA, piecewise linear regression models, and Sen's nonparametric trend slope estimator in R software to analyze road safety performance indicators evolution across Europe from 2001 to 2020. These advanced models manage non-stationary data, seasonality, and external factors (*such as socio-economic, interventions, and weather data*), providing a clear and comprehensive assessment of road safety indicators.

The focus is on 18 of the 27 EU member countries. These are *Austria (AT), Belgium (BE), Czechia (CZ), Denmark (DK), , Finland (FI), France (FR), Germany (DE), Greece (EL), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Spain (ES), and Sweden (SE)*. This focus is due to data availability and reliability for the selected indicators. Despite being among the safest globally, European roads still require strategic changes, as highlighted by the EU road safety progress report (Adminaité-Fodor et al., 2021; European Commission, 2015b, 2018c, 2020).

4.2. Data Sampling

Data sampling is conducted via a systematic process to ensure the reliability and accuracy of the analysis. First, all relevant indicators are reviewed, and any that do not align with the available data are reformulated to better fit the context. If data for a particular indicator is unavailable or insufficient, that indicator is removed from consideration. The selection of data sources involves comparing multiple datasets to identify the most reliable and comprehensive options. See Appendix A for a comprehensive description of the sampling process, including requirements for source selection and indicator reformulation.

4.3. Data Analysis Technique

A time series is a set of observations (*continuous or discrete*) generated sequentially over time. When observations are recorded continuously, the time series is continuous; otherwise, it is discrete (Box et al., 2016; R. J. Hyndman & Athanasopoulos, 2021; Mills, 2019). This study considers only discrete time series with monthly and annual observations.

Including road safety, various important areas apply time series analysis in their studies and applications (Box et al., 2016). Broadly, its objectives are twofold: first, to understand or model the stochastic process generating an observed series (*observation and explanation*), and second, to forecast future values based on the historical data of the series and potentially other correlated factors (*forecast and control*) (Box et al., 2016; Chatfield & Xing, 2019; Cryer & Chan, 2008). This study aims to understand the trends and patterns of road safety, which represents the first objective of time series analysis, in 18 EU countries by developing univariate dynamic models. These models are created both with and without explanatory variables and interventions

4.3.1. Time Series Patterns

Time series patterns capture the underlying structures and fluctuations observed in data over sequential time (R. J. Hyndman & Athanasopoulos, 2021). These patterns can be broken down into four key components: Trends represent the 'long-term' directionality of data, whether increasing, decreasing, or stable over extended periods, whereas 'long-

term' depends on the application (Chandler & Scott, 2011). Seasonality manifests as regular cycles or patterns that repeat at fixed intervals, often influenced by seasonal changes. Cyclic patterns denote irregular fluctuations that recur over longer spans, reflecting systemic influences (R. J. Hyndman & Athanasopoulos, 2021). Irregular components introduce random variability into the data, stemming from unpredictable events or noise (Chatfield & Xing, 2019; R. J. Hyndman & Athanasopoulos, 2021). Researchers and analysts utilize techniques such as time plots, autocorrelation functions (ACF) plots (correlogram), and box plots to explore relationships and identify influential patterns or relationships within the data (Box et al., 2016; Chandler & Scott, 2011; Chatfield & Xing, 2019; R. J. Hyndman & Athanasopoulos, 2021).

Time plots are essential for identifying the four key components. Decomposition methods like seasonal decomposition of time series (STL) can separate the data into trend, seasonal, and residual components, aiding in understanding the underlying patterns (Chatfield & Xing, 2019; R. J. Hyndman & Athanasopoulos, 2021). This study conducts a time series plot for all road safety indicators. Additionally, the study decomposes the components of the monthly aggregated fatalities and total injuries using the STL method to understand the patterns for subsequent analysis.

ACFs measure the correlation between a time series and its lagged values. In trended time series data, ACFs for small lags are typically large and positive because nearby observations in time are similar in magnitude. As the lags increase, these positive values gradually decrease. In seasonal data, autocorrelations are higher at seasonal lags than at other lags. When data exhibit trend and seasonality, you observe a combination of these effects in the autocorrelation function as shown in figure 1. (R. J. Hyndman & Athanasopoulos, 2021; Shumway & Stoffer, 2017). To capture the patterns in the time series data of the road safety outcome indicators, the study includes plotting the ACF correlogram in addition to the time series decomposition plot.

In time series analysis, box plots provide a robust way to visualize and understand data distributions across time. They help identify patterns by comparing the central tendency and data spread over these intervals (Dailys M.A. et al., 2022). The study uses this plots on the monthly aggregated fatalities and monthly aggregated total injury to observe the seasonality and variabilities of these data using a cyclic (*monthly*) and yearly box plot.

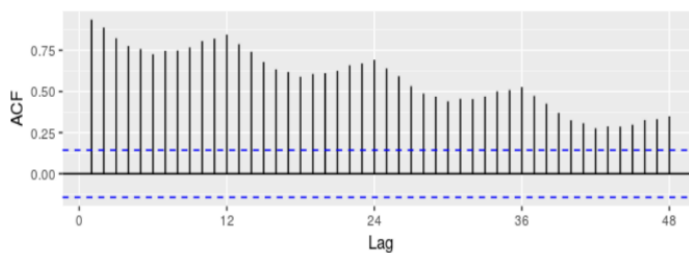


Figure 1: ACF correlogram of time series having both trend and season effect (Hyndman & Athanasopoulos, 2021)

4.3.2. Time Series Models

Trend detection techniques can be linear or nonlinear. Nonlinear methods use many parameters and numerical optimization, offering flexibility in modeling complex patterns. However, they can become too complex, making it hard to get simple trend and uncertainty values (Chatfield & Xing, 2019; George et al., 2016; Hyndman & Athanasopoulos, 2021). Without a clear understanding of the underlying processes, nonlinear models risk overfitting. Instead, these trends can be visualized and summarized qualitatively (Chang et al., 2023). To address apparent changes in the trend magnitude, often motivating the use of non-linear methods, piecewise linear trend analysis combined with change point detection is typically effective (Chang et al., 2023; Chatfield & Xing, 2019). Detecting structural breaks in data highlights abrupt shifts or changes in underlying factors, which can signify significant events or transitions affecting the data's behavior (Achim et al., 2022).

Therefore, ARIMA, SARIMA, ARIMAX models, piecewise regression for change point detection, and Sen's slope estimator for estimating the median of the trend slope are used in the analysis in R software.

4.3.2.1. Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA (p, d, q) model proposed by (Box et al., 2016) combines autoregressive(AR) and moving average(MA) models and explicitly includes differencing (*d, trend term*) in the formulation of the model suitable for univariate time series analysis. The AR model describes a time series in which the current observation depends on its preceding values, whereas the MA model describes past forecast errors' impact. The general form of the ARIMA (p, d, q) model is given as:

$$y'_t = c + \sum_{i=1}^p \varphi_i y'_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (1)$$

Where y'_t is the differenced series, p is the order of the autoregressive part, φ_i are parameters of the autoregressive part, d is the degree of first differencing involved, q is the order of the moving average part, θ_j are parameters of the moving average part, and ε_t the errors. The constant, c , has an important effect on the long-term (*trend*) forecasts obtained from these models. If $c = 0$ and $d = 0$, the trend converges to zero, and with $d = 1$, the trend stabilizes at a constant, and with $d = 2$, it forms a linear trend. When $c \neq 0$ and $d = 0$, the trend converges to the mean, and with $d = 1$, it forms a linear trend, and with $d = 2$, it follows a quadratic trend. (R. J. Hyndman & Athanasopoulos, 2021)

A statistically significant and adequate ARIMA (p, d, q) model for time series modeling and forecasting is formulated following the Box and Jenkins methodology (Box et al., 2016; Chatfield, 2003; R. J. Hyndman & Athanasopoulos, 2021). George et al. (2016) proposed a three-step iterative process of model identification, parameter estimation, and diagnostic checking to determine the best model.

a) Model identification

The first step in developing an ARIMA model involves determining whether the time series is stationary. In Box-Jenkins ARIMA modeling, *differencing* an observed time series until it becomes stationary is the approach to stationarity (Chatfield & Xing, 2019). However, *over-differencing* introduces extra serial correlation and increases model complexity (Box et al., 2016). Various tests assess different null and alternative hypotheses for testing stationarity. For instance, the Augmented Dickey-Fuller (ADF) test posits a null hypothesis of a unit root, indicating non-stationarity (Said E. & David A., 1984; Walter, 1995; Wayne A., 1996). Conversely, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit-root test assumes a null hypothesis of no unit root, indicating stationarity (R. J. Hyndman & Khandakar, 2008; Kwiatkowski et al., 1992). The ADF test checks for non-stationarity, with a low p-value ($p < \alpha$, typically 0.05, indicating a 95% confidence level) indicating stationarity. While the KPSS test examines stationarity, where a high p-value ($p > \alpha$) supports stationarity.

R. J. Hyndman & Khandakar (2008) suggested using unit-root tests for stationarity, noting that the ADF test biases results towards more *differences*, and recommended the KPSS unit-root test instead. Once stationarity is achieved and d is determined, the next step involves selecting the orders of the AR and MA parameters. The stationarity of the data is checked using ACF correlograms, and the KPSS test.

b) Model parameter estimation

A common challenge with ARIMA models is the subjective and difficult order selection process for forecasting (R. J. Hyndman & Khandakar, 2008). Researchers have developed automated order selection, to solve the difficulty (R. J. Hyndman & Athanasopoulos, 2021; R. J. Hyndman & Khandakar, 2008). The automated ARIMA parameter selection method developed by R. J. Hyndman & Khandakar (2008) using the `auto.arima` function in R from the package of 'forecast' is used in the study.

The method utilizes the maximum likelihood approach to estimate the parameters of the identified order of the model. Once the model order has been identified (i.e., the values p , d , and q), the parameters c , φ_1 , φ_2 , ..., φ_p and θ_1 , θ_2 , ..., θ_q shall be estimated. Akaike's Information Criterion (AIC), the corrected AICc for ARIMA models, and the Bayesian Information Criterion (BIC) help select optimal models by minimizing AIC, AICc, or BIC, as given in Equations (2 to 4). (R. J. Hyndman & Athanasopoulos, 2021; R. J. Hyndman & Khandakar, 2008). In this study, to ensure finding the minimum AICc model, `approximation=FALSE` and `stepwise=FALSE`, is set to search a larger

model set, as opposed to the default settings that use approximations and a stepwise selection (*faster*) (R. Hyndman et al., 2024; R. J. Hyndman & Athanasopoulos, 2021).

$$AIC = -2\log(L) + 2(p + q + k + 1) \quad (2)$$

$$AICc = AIC + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2} \quad (3)$$

$$BIC = AIC + [\log(T) - 2](p + q + k + 1) \quad (4)$$

Where L is the likelihood of the data, T is total time of the data, $k = 1$ if $c \neq 0$ and $k = 0$ if $c = 0$.

c) Model diagnostic checking

The adequacy of the model is assessed by examining the properties of the residuals using the ACF. Additionally, the `checkresiduals` function from the `forecast` package was employed, which generates a time plot of the residuals, the corresponding ACF, a histogram, and the results of a Ljung-Box test (R. Hyndman et al., 2024). A small p-value ($p < \alpha$, typically 0.05, indicating a 95% confidence level) from the Ljung-Box test indicates model inadequacy. Therefore, modify the model or consider a new one until identifying a satisfactory model.

4.3.2.2. Seasonal Autoregressive Integrated Moving Average Model (SARIMA Model)

In practice, many time series include a seasonal component that recurs every m (*monthly data, $m=12$, annual data, $f=1$*) observations (Box et al., 2016). Box and Jenkins extended the ARIMA model to address seasonality, defining the general multiplicative seasonal ARIMA (p,d,q)(P,D,Q)_m model as follows (Box et al., 2016):

$$y'_t = c + \sum_{i=1}^p \phi_i y'_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{l=1}^P \Phi_l y'_{t-ls} + \sum_{J=1}^Q \Theta_J y'_{t-Js} + \varepsilon_t \quad (5)$$

Where P is the order of the seasonal autoregressive part, Φ_l are parameters of the seasonal autoregressive part, D is order of seasonal differencing involved, Q is the order of the seasonal moving average part, Θ_J are parameters of the seasonal moving average part, and others are defined above. If $c \neq 0$, there is an implied polynomial of order $d + D$ in the forecast function (R. J. Hyndman & Khandakar, 2008).

Building an SARIMA model involves an iterative process similar to constructing a univariate Box-Jenkins ARIMA model, including model identification, parameter estimation, and diagnostic checking.

a) Model identification

The first step is to determine the stationarity of time series. The `auto.arima` function facilitates this by determining the non-seasonal differencing parameter, d , and the seasonal differencing parameter, D , necessary for stationarity. In the process, D is selected based on an estimate of seasonal strength (Wang et al., 2006). Following the determination of D , the parameter d is chosen by applying successive KPSS unit-root tests to either the seasonally differenced data or the original data, depending on whether $D=0$ (R. J. Hyndman & Khandakar, 2008). Stationarity of the data is further checked using the ACF correlogram and the ADF test.

b) Model parameter estimation

After selecting d (and possibly D), the `auto.arima` function using the maximum likelihood method to estimate the values of p , q , P , and Q by minimizing the AICc. Similar to the ARIMA model, to ensure finding the minimum AICc model, `approximation=FALSE` and `stepwise=FALSE` is set to search a larger model set. The AIC for selecting a SARIMA model is presented in equation 6 (R. J. Hyndman & Khandakar, 2008). Similar modifications apply to the AICc and BIC.

$$AIC = -2\log(L) + 2(p + q + P + Q + k + 1) \quad (6)$$

c) *Model diagnostic checking*

The adequacy of the model is assessed by examining the properties of the residuals using the ACF correlograms, and using the `checkresiduals` function in R.

4.3.2.3. *Autoregressive Integrated Moving Average Model with Explanatory Variables (ARIMAX model)*

The ARIMAX model, first discussed by Box & Tiao (1975), can identify the underlying patterns in time series data and to quantify the impact of environmental influences (Uyodhu Amekauma & Isaac Didi, 2016). ARIMAX model is also referred to as transfer function model (Box et al., 2016; Chukwutoo C. & Uchendu O., 2018). The environmental influences, X , transform ARIMA into a multiple regression model (Lin Ya et al., 2019). This transformation incorporates autocorrelation into the error of a regression model, with the error series following an ARIMA model (R. J. Hyndman & Athanasopoulos, 2021). ARIMAX model “*model in level*” is given as (Bierens, 1987):

$$y_t = c + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{k=0}^m \beta_k X_{t-k} + \varepsilon_t \quad (7)$$

Where X_t are exogenous variables (*socio-economic factor/ weather data/ intervention*) time series data at a time (t) , β are the regression coefficients, p, q, m are the optimal lag length variables, and others are defined above.

In analyzing the external effect case, it is aimed to describe an input time series (*observation of socio-economic factor and weather data*) and the corresponding output time series (*road safety outcome indicators*). However, interventions vary in both their onset (*abrupt or gradual*) and duration (*permanent or temporary*) of effects (Box et al., 2016). As a result, three types of input variables, X_t are considered for the intervention variable. Which are step function (*abrupt, permanent effect*) at time T , $X_t = \begin{cases} 0 & t \neq T \\ 1 & t \geq T \end{cases}$, puls function (*abrupt, temporary effect*) at time T ,

$X_t = \begin{cases} 0 & t \neq T \\ 1 & t = T \end{cases}$, and ramp function (*gradual, permanent effect*) at time T , $X_t = \begin{cases} 0 & t < T \\ t - T & t \geq T \end{cases}$.

The study employs these functions to create three monthly time series for each of the 15 interventions considered, spanning the study period. Each intervention, along with its three associated time series, is modeled independently against the monthly road safety outcome indicators (*single-input, single-output transfer function model*).

Building an ARIMAX model involves an iterative process similar to constructing a univariate Box-Jenkins ARIMA model, including model identification, parameter estimation, and diagnostic checking. In this study, ARIMAX is employed in two distinct ways: to analyze the impact of external factors (*socio-economic factor and weather data*) and to analyze interventions.

a) *Model identification*

The model in level includes two error terms: one from the regression model and one from the ARIMA model, where only the ARIMA errors are assumed to be white noise. Estimating the model parameters involves minimizing the sum of squared errors from the ARIMA component. Minimizing the regression's sum of squared errors can lead to several problems. Alternatively, using maximum likelihood estimation provides similar coefficient estimates. (R. J. Hyndman & Athanasopoulos, 2021). It is important that both \mathcal{Y} and the independent variables (X_t) be stationary. Hence, differencing the non-stationary variables of the model is required and the resulting model is “*model indifference*” given as (Hamilton (1994, as cited in Wandee & Bright Emmanuel, 2020); R. J. Hyndman & Athanasopoulos, 2021):

$$y'_t = \sum_{i=1}^p \varphi_i y'_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \sum_{k=0}^m \beta_k X'_{t-k} + \varepsilon_t \quad (8)$$

b) Model parameter estimation

The `auto.arima` function is used to automate selecting ARIMA model parameters. This function includes exogenous variables through the `Xreg` argument, allowing for integrating external predictors. Parameters and coefficients are estimated using maximum likelihood. The method selects the optimal model by minimizing the AIC, AICc, and BIC values.

c) Model diagnostic checking

The adequacy of the model is assessed using the `checkresiduals` function in R.

4.3.2.4. Linear Regression

Change point analysis is highly relevant to detecting trend change and attribution of intervention (Chang et al., 2023; Sharma et al., 2016). A change point does not have a unique meaning in the literature, it can be a break or turning point connecting two data series that are considered to have different averages (*a constant shift, variances, and/or trends*) (Beaulieu et al., 2012). Under circumstances where a change point is considered to represent both a mean shift and a trend change, it is appropriate to adopt a piecewise trend model with an offset at the change point. (Chang et al., 2023). Factors affecting the detection of trends (*e.g. seasonality*) are relevant to detecting change points, so deseasonalization and incorporation of necessary components in the regression model are suggested (Chang et al., 2023). Equation 9 represents a model characterized by shifts in both the intercept and trend, incorporating K change-points and thus resulting in $K+1$ segments for a single regressor (t). This model can account for continuous and discontinuous (with jump) regression lines.

$$y_t = \begin{cases} \beta_0^{(1)} + \beta_1^{(1)}t_i + \varepsilon_{i1}, & \text{if } t_i \leq r_1, \\ \beta_0^{(2)} + \beta_1^{(2)}t_i + \varepsilon_{i2}, & \text{if } r_1 \leq t_i \leq r_2, \\ \vdots & \vdots \\ \beta_0^{(k)} + \beta_1^{(k)}t_i + \varepsilon_{ik}, & \text{if } r_{k-1} \leq t_i \leq r_k, \\ \vdots & \vdots \\ \beta_0^{(k+1)} + \beta_1^{(k+1)}t_i + \varepsilon_{ik+1}, & \text{if } r_k \leq t_i. \end{cases} \quad (9)$$

Where $i = 1, \dots, N$ are observation numbers, N is the total sample size, $r_k, k = 1, \dots, K$, are change-point parameters for the regressor t , $\varepsilon_{i,k}$ are independent errors, possibly differing across segments. The change-point locations, given by r , are unknown parameters to be estimated (Beaulieu et al., 2012; Chen et al., 2011).

This study employs piecewise linear regression models to analyze road safety outcome indicators, where change points are not pre-defined. The model employs the piecewise trend approach with an offset at the change point, using the `breakpoints` function from the `strucchange` package by Zeileis et al. (2002) in R. Developing the models involves several key steps: data preparation, breakpoint identification, parameter estimation, and diagnostic checking.

a) Data preparation

To ensure accurate detection of change points, monthly traffic indicators are decomposed using Seasonal and Trend decomposition using Loess (STL), extracting the trend components for analysis.

b) Breakpoint identification

Change points are estimated using the `breakpoints` function. `Breakpoints` implement the algorithm described in Bai & Perron (2003), as cited in Zeileis et al. (2022), for simultaneous estimation of multiple breakpoints.

c) Parameter estimation

The piecewise linear regression model using the `breakpoints` function includes the following steps. Initially, the linear regression model is formulated. Breakpoints are estimated by minimizing the residual sum of squares (RSS),

which requires computing a triangular RSS matrix for all possible segments. The model is then fit to determine the optimal segmentation. Breakpoints and break dates are obtained for all segmentations up to the maximum number of breaks, along with their associated RSS and Bayesian Information Criterion (BIC) values. Optimal segments are selected for minimum RSS and BIC values. Finally, coefficients, covariance matrices, fitted values, and residuals are extracted, and the log-likelihood and information criteria are computed to select models with lower values.

d) Model diagnostic checking

The adequacy of the model is assessed by checking the residuals in R.

4.3.2.5. Sen's Slope Estimator

Sen's Slope Estimator, proposed by Sen (1968), is a non-parametric method for estimating the median slope of a univariate time series. It is resistant to outliers and does not assume a normal distribution of errors. This makes it particularly effective in analyzing environmental data where outliers can skew results significantly.

The estimator calculates the slope between all possible pairs of observations in the data set. If y_i and y_j are two observations at times i and j respectively, for all $i < j$, the slope b_k between these two points is given by:

$$b_k = \frac{y_j - y_i}{j - i} \quad (10)$$

This study employs Sen's slope estimator alongside ARIMA models to analyze road safety performance and outcome indicators trends. The differencing process in ARIMA models often removes the trend components from time series data. However, in some cases, the trend component persists and is represented by a constant, known as drift. By combining Sen's slope estimator with ARIMA models, one can effectively capture and analyze these trends, providing a comprehensive understanding of the underlying patterns in road safety data (Balasmeh et al., 2019; Gibrilla et al., 2017).

5. Results

5.1. Patterns in Road Safety Outcome Indicators

The ACF correlogram of the original annual fatality data for all countries demonstrates large positive values at small lags, which decrease linearly with increasing lag. In contrast, the ACF correlogram for the monthly aggregated fatality data and the monthly total aggregated injury data shows larger values at initial lags, accompanied by periodic spikes at seasonal intervals. An exception to this pattern is observed in the monthly aggregated fatality data for *Ireland, Netherlands, and Portugal*, where the ACF plot resembles that of the annual data, lacking the consistent periodic spikes typically indicative of seasonality. ACF correlogram are shown in Figure 2 for illustration.

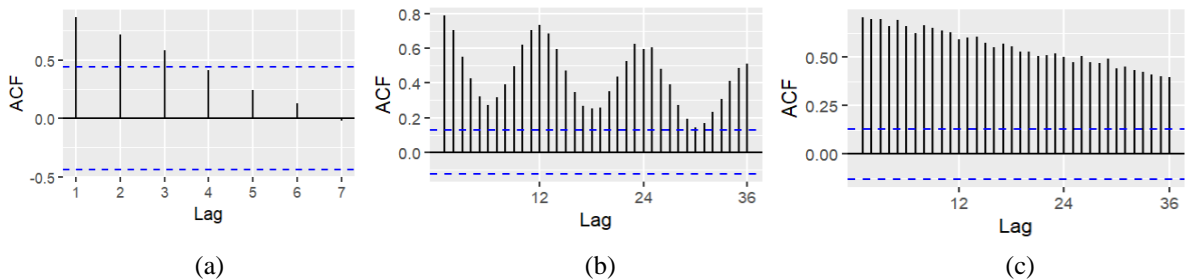


Figure 2: ACF plots for the (a) annual fatality data of Czech Republic, (b) monthly aggregated fatality data of Austria, and (c) monthly aggregated fatality data of Ireland

The time series decomposition of both monthly aggregated fatality and total injury data reveals the presence of both trend and seasonality components. The seasonal component displays periodic peaks and troughs, indicating higher fatalities and injuries during specific periods each year. However, for most countries, the seasonal pattern is not perfectly smooth within each cycle, suggesting the presence of minor short-term fluctuations. To illustrate these variations, Figure 3 shows time series decompositions for Austria and Italy, highlighting countries with relatively smooth and fluctuating seasonal patterns, respectively.

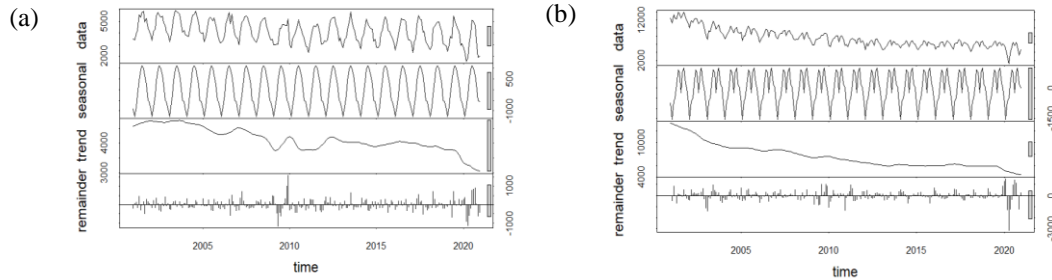


Figure 3: Time series decomposition plots for the monthly aggregated total injury data (a) Austria, and (b) France

The cyclic box plot of the monthly aggregated fatality and total injury data reveals a clear seasonal pattern, with fatalities and injuries peaking during the months of June to August and decreasing during the months of February and March. Furthermore, the yearly box plot of these monthly outcome indicators shows a decreasing trend over the study period, accompanied by high variability in observations during the initial years of the study. Box plots are shown in Figure 4 for illustration.

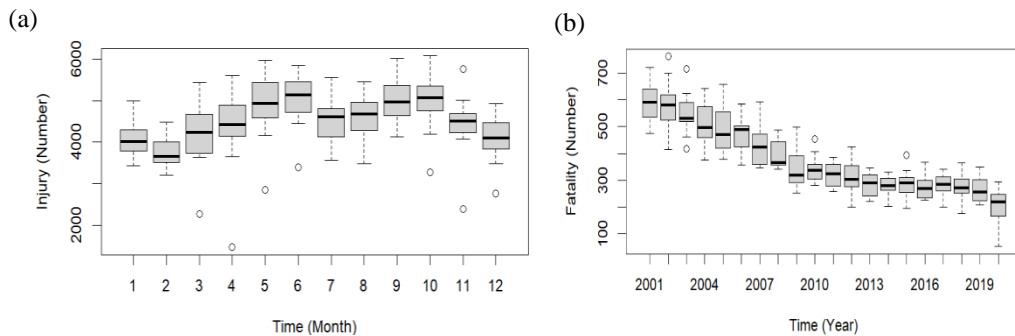


Figure 4: (a) Cyclic box plot for total monthly injury data of Austria, and (b) Yearly box plot for fatality data of Italy

5.2. Trend Analysis Results

For ARIMA models, applied to annually disaggregated fatality and performance indicators, when the drift or constant term is removed by differencing (*i.e.*, for moderate trended series), it is difficult to directly identify the direction of the trend. Therefore, the median trend slope value from Sen's slope estimator is used to interpret the direction of the trend. For SARIMA models without drift term, applied to monthly aggregated fatality and total injury data, the trend direction is explained using the slope from piecewise regression.

5.2.1. Road Safety Outcome Indicators

5.2.1.1. Aggregated Monthly Outcome Indicators

Analyzing road safety outcome indicators for all countries under study demonstrates systematic changes, indicating a trend and confirming the data's non-stationarity. To achieve stationarity, applying at least the first difference to the time series was necessary. Consequently, as shown in Tables 4 and 5, the best (S)ARIMA models incorporate either the first degree of non-seasonal differencing (d), seasonal differencing (D), or both. This approach was further validated by the ADF test results, which confirmed stationarity with p-values ($P < 0.01$) below the 95% confidence level threshold of 0.05.

The selected (S)ARIMA models effectively capture trends through non-seasonal and seasonal autoregressive (AR), moving average (MA), and differencing terms, along with a drift term, if present. To illustrate the SARIMA model, a model for the monthly fatalities in Greece (*ARIMA (2,0,1)(1,1,1)₁₂ with drift*) is used as shown in equation 11.

$$y_t = -0.4542 + 1.1749y_{t-1} - 0.1949y_{t-2} - 0.8707\epsilon_{t-1} - 0.2588y_{t-12} + 0.6993\epsilon_{t-12} + \epsilon_t, \quad \epsilon_t \sim N(0, 189) \quad (11)$$

The positive coefficients of AR(1) and SAR(1)₁₂ indicate that there is a positive relation between the observed aggregated monthly fatality and the seasonal and non-seasonal time-lagged observation. Whereas the negative coefficients of AR(2), MA(1), and SMA(1) show the negative relation between the observed aggregated monthly fatality and the non-seasonal time-lagged observation and the seasonal and non-seasonal lagged random shock. This implies that a unit increase in the positive parameters will raise fatalities, while a unit increase in the negative parameters will lower them, assuming other factors are held constant. Moreover, the negative drift term signifies a consistent decline in the level of the series over time, suggesting that approximately six ($\sim 0.4542 \times 12$) traffic fatalities have been prevented every month throughout the study period.

A diagnostic check of the residuals confirms the model's adequacy. The Ljung-Box p-value exceeds 0.05, as shown in Table 4. The residual plot, including the ACF correlogram, histogram, and residual time series, indicates that the residuals fluctuate randomly around zero, are approximately normally distributed, and exhibit no significant serial correlation.

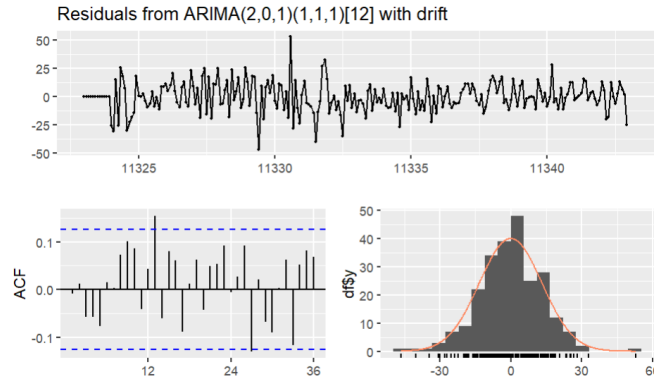


Figure 5: Residual plot for monthly aggregated fatalities from SARIMA model for Greece

Significant trends are identified by non-zero drift terms in the SARIMA models. Trends are classified as persistent when a non-zero drift term exists after differencing, moderate when fluctuations occur without a significant drift term, and non-existent when no evident trend exists. For series with moderate trends, where differencing removes the trend term, and no non-zero drift terms are present, the direction of the trend is not directly noticeable from the model. In such cases, piecewise regression slopes are employed to determine the trend direction.

a) Trend of aggregated fatality

(S)ARIMA analysis of the monthly aggregated fatality trends across European countries discloses different patterns, as shown in Table 4. Belgium, Finland, Ireland, the Netherlands, and Luxembourg exhibited consistent linear declines without seasonal fluctuations (*see d value in Table 4*). Austria, the Czech Republic, Italy, Poland, Romania, and Greece also demonstrated persistent linear declines, but with a noticeable seasonal trend (*see D value in Table 4*). Sweden, Denmark, Portugal, and Slovenia have trended moderately around an overall decreasing slope without seasonal effects. France, Germany, and Spain have also recorded moderate fluctuations around an overall decreasing slope, with the presence of both non-seasonal and seasonal factors. At a 95% confidence level, none of the countries confirmed stability; instead, all show distinct decreasing trends over the study period.

Piecewise linear regression analysis of aggregated monthly fatality data identified multiple change points across the countries (*the model results are not included here, but see Appendix B: country profiles for more information per country*). Most nations experienced at least three significant shifts in trend. Sixteen countries, excluding Sweden and Luxembourg, encountered four such points. Denmark, Portugal, the Netherlands, and Romania showed even greater breaks, with five identified change points. The initial breakpoints clustered between 2003 and 2006, with a concentration in 2003 (N=11). A second cluster emerged from 2006 to 2009, peaking in 2008 (N=9). Subsequent breaks occurred between 2009 and 2017, culminating in 2017 (N=14).

Before 2003, fatality numbers generally declined, except in the Czech Republic and Denmark. Ireland, Poland, and Romania have shown an increasing trend between the peaks of the first two clusters while the others have decreased. Within the third cluster, Denmark, France, Ireland, the Netherlands, Portugal, and Spain saw slight upward trends before a sharp overall post-2017 decline. The major breakpoints in 2003 and 2008 were generally associated with decreasing jumps, while a slight upward jump characterizes the 2017 breakpoints. Box plots are shown in Figure 6 for illustration.

b) Trends of total injury

In the SARIMA analysis of monthly total injury trends, as shown in Table 5, Austria, the Czech Republic, Finland, Greece, Italy, Poland, Portugal, and Slovenia demonstrated persistent linear declines but with noticeable seasonal variations. Germany, Ireland, and Spain have trended moderately around an overall decreasing slope without seasonal effects. Belgium, France, the Netherlands, and Sweden have recorded moderate fluctuations around an overall decreasing slope, with both non-seasonal and seasonal factors. In contrast, Luxembourg and Romania have trended moderately around an overall increasing slope without and with seasonal effects, respectively. However, at 95% confidence level, none of the countries exhibits a trend with zero value.

Piecewise linear regression analysis of aggregated monthly total injury data also identified multiple change points (*the model results are not included here, but see Appendix B: country profiles for more information per country*). Most nations experienced at least four significant shifts in trend. Austria, the Czech Republic, Denmark, Greece, Ireland, Luxembourg, and Sweden, showed even greater breaks, with five identified change points. The initial breakpoints clustered between 2003 and 2006, with a concentration in 2003 (N=8). A second cluster emerged from 2006 to 2009, peaking in 2008 (N=9). A third cluster was observed from 2009 to 2012, peaking in 2011 (N=8). Subsequent breaks occurred between 2012 and 2017, except 2016, culminating in 2017 (N=17).

Before 2003, total injury numbers generally declined, except in the Czech Republic, Finland, Slovenia, and Sweden. Between the peaks of the first two clusters, Belgium, Luxembourg, Romania, and Spain have shown an increasing trend while the others have decreased. From 2008 to 2012, Belgium, Finland, Germany, and Greece also exhibited an upward trend while others kept declining. Within the fourth cluster, Austria, the Czech Republic, France, Germany, the Netherlands, Portugal, Romania, and Spain saw upward trends before a sharp overall post-2017 decline. The major breakpoints in 2003, 2008 and 2011 were generally associated with decreasing jumps, whereas a slight upward jump majorly characterizes 2017 breakpoints. Tipping point analysis plots are shown in Figure 6 for illustration.

Table 4: Summary of best (S)ARIMA models for aggregated monthly traffic fatality across European countries

Country	Austria	Belgium	Czechia	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Poland	Portugal	Romania	Slovenia	Spain	Sweden
ARIMA Model	Order (p,d,q)	ARIMA (2,0,0)	ARIMA (1,1,2)	ARIMA (1,0,1)	ARIMA (3,1,1)	ARIMA (5,1,2)	ARIMA (0,1,1)	ARIMA (0,1,1)	ARIMA (2,0,1)	ARIMA (2,1,2)	ARIMA (2,1,2)	ARIMA (1,1,1)	ARIMA (1,0,2)	ARIMA (3,1,3)	ARIMA (1,0,1)	ARIMA (1,1,1)	ARIMA (1,1,1)	ARIMA (1,1,3)
	(P,D,Q) ₁₂	(2,1,1) ₁₂	(1,0,1) ₁₂	(0,1,1) ₁₂	(2,0,1) ₁₂	(3,0,2) ₁₂	(0,1,1) ₁₂	(2,1,2) ₁₂	(1,1,1) ₁₂	(0,1,1) ₁₂	(0,0,1) ₁₂	(2,0,0) ₁₂	(1,1,1) ₁₂	(2,0,1) ₁₂	(0,1,0) ₁₂	(1,1,1) ₁₂	(0,1,1) ₁₂	(1,0,1) ₁₂
	with drift	with drift	with drift		with drift				with drift	with drift	with drift	with drift	with drift	with drift	with drift			
P	Di	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
value	L	0.06108	0.2183	0.5639	0.1156	0.05506	0.9457	0.4563	0.1048	0.9559	0.8398	0.8256	0.4137	0.1224	0.2895	0.4336	0.4276	0.3258
Drift (std.. error)		-0.2287 (0.0251)	-0.3341 (0.155)	-0.3407 (0.0608)	-	-0.0767 (0.0383)*	-	-	-0.4542 (0.1155)	-0.1004 (0.0399)	-1.6619 (0.3724)	-0.0146 (0.0051)	-0.1657 (0.0987)	-1.2147 (0.346)	-	-0.3398 (0.1734)	-	-
significance		***	*	***					***	*	***	***	***	***		*		
Regress	R ²	0.9989	0.9991	0.9983	0.9968	0.9979	0.9988	0.9995	0.9994	0.998	0.9993	0.9922	0.9988	0.9986	0.9985	0.9991	0.998	0.9997
ssion	Slope	-0.2282	-0.2983	-0.3557	-0.113	-0.0776	-1.5544	-1.4925	-0.4913	-0.1148	-1.5984	-0.0128	-0.172	-1.368	-0.3899	-0.3405	-0.0818	-1.6003
		***	***	***	***	***	***	***	***	***	***	**	***	***	***	***	***	***

D is the Dickey-Fuller p-value for stationarity, and L is the Ljung-Box p-value for model adequacy.

Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 at 95% level of confidence

Table 5: Summary of best (S)ARIMA models for aggregated total monthly traffic injury across European countries

Country	Austria	Belgium	Czechia	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Poland	Portugal	Romania	Slovenia	Spain	Sweden
ARIMA Model	Order (p,d,q)	ARIMA (1,0,0)	ARIMA (1,1,2)	ARIMA (2,0,1)	ARIMA (5,1,3)	ARIMA (0,0,3)	ARIMA (2,1,2)	ARIMA (1,1,1)	ARIMA (3,0,0)	ARIMA (2,1,1)	ARIMA (1,1,1)	ARIMA (1,1,1)	ARIMA (1,0,1)	ARIMA (1,0,3)	ARIMA (1,1,1)	ARIMA (1,0,1)	ARIMA (2,1,1)	ARIMA (2,1,1)
	(P,D,Q) ₁₂	(2,1,1) ₁₂	(1,1,1) ₁₂	(0,1,1) ₁₂	(0,1,1) ₁₂	(0,1,1) ₁₂	(0,1,1) ₁₂	(1,0,3) ₁₂	(0,1,1) ₁₂	(2,0,0) ₁₂	(2,0,0) ₁₂	(0,1,1) ₁₂	(0,1,0) ₁₂	(0,1,1) ₁₂	(0,1,1) ₁₂	(0,1,1) ₁₂	(2,0,0) ₁₂	(0,1,1) ₁₂
	with drift	with drift	with drift		with drift				with drift				with drift	with drift		with drift		
P	Di	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
value	L	0.9315	0.5201	0.1199	0.3812	0.2254	0.3723	0.8129	0.5726	0.2276	0.2278	0.5846	0.8463	0.2971	0.7849	0.06672	0.201	0.7924
Drift (std.. error)		-5.0346 (0.7172)	-	-3.926 (1.598) *	-	-1.5749 (0.1553)	-	-	-4.7634 (0.49)	-	-64.0029 (5.7936)	-	-	-14.2181 (1.0083)	-7.4606 (3.564)	-	-3.5957 (1.2647)	-
significance		***		*		***			***		***			***	*		*	
Regress	R ²	0.9996	0.9994	0.9996	0.9993	0.9992	0.9996	0.9997	0.9992	0.9992	0.9993	0.9984	0.9986	0.9994	0.9991	0.9977	0.9983	0.9992
ssion	Slope	-4.9788	-5.6469	-3.5108	-2.3364	-1.5883	-27.1161	-39.3371	-4.5953	-0.6866	-62.6929	0.0478	-8.7009	-14.2139	-5.6591	11.1941	-4.0308	-7.9787
		***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***

Di is the Dickey-Fuller p-value for stationarity, and L is the Ljung-Box p-value for model adequacy.

Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 at 95% level of confidence

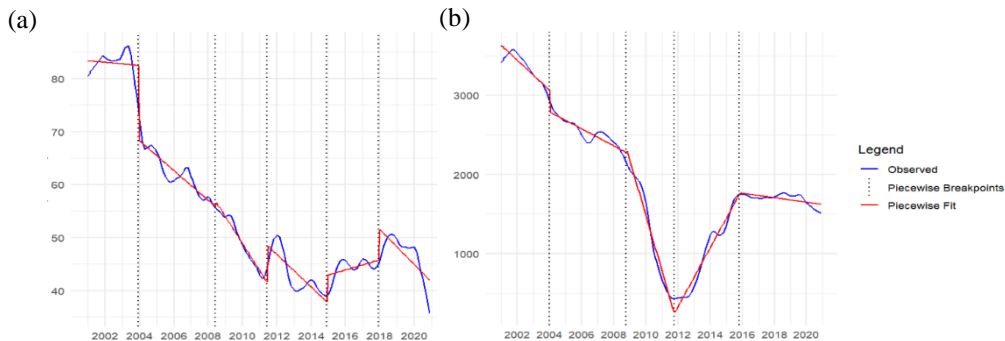


Figure 6: Tipping points for the Netherlands's monthly aggregated (a) fatality (b) total injury

5.2.1.2. Disaggregated Annual Outcome Indicators

As opposed to the ARIMA models of monthly outcome indicators that are aggregated, the disaggregated annual outcome indicator ARIMA model only includes the non-seasonal components. Like these models, though, the time series must attain stationarity. Thus, unless the indicator series was stationary in the first place, the optimal ARIMA models include a first degree of non-seasonal differencing. The KPSS test findings, which verified stationarity with p-values over the 95% confidence level threshold of 0.05, strengthened this strategy. Moreover, a diagnostic analysis of the residuals shows that the models are adequate, with a Ljung-Box p-value greater than 0.05. In order to ascertain the trend direction, the median slope of the series obtained by Sen's slope estimator is utilized, unless the optimal ARIMA model includes a drift following differencing. The model results are not included here, but see Appendix B: country profiles for more information per country.

a) Fatality by gender

The analysis of traffic fatalities by gender reveals that male drivers consistently exhibited higher fatality rates than females across all countries studied. With regard to the trend, countries exhibit either persistent linear decline or moderate oscillations around an overall falling linear and non-linear trend. This was observed in both genders of the countries under study, except for Romania, which has shown no evident trend in female traffic fatalities.

b) Fatality by age group

The study examined fatalities across different age groups. Children (<15) and adolescents (15 to 17) consistently demonstrated the lowest fatality rates. In contrast, younger adults (18-24 and 25-49) in eight countries experienced reductions in fatalities, moving from high-risk to lower-risk categories. However, the elderly population (50-64 and over 65) showed an increasing trend in fatality rates, with more countries ranking these groups as higher risks over time.

Traffic fatality trends varied by age group and country. Some countries demonstrated consistent linear declines across all age groups, while, some exhibited more fluctuating patterns with linear or non-linear tendencies. Remarkably, Romania (*ages 15-24 and over 65*) and Luxembourg (*over 50*) showed no clear trends in traffic fatalities by age group.

c) Fatality by road type

The analysis shows that rural roads generally accounted for the highest traffic fatalities across the studied countries, followed by urban areas, with motorways exhibiting the lowest rates. However, this pattern was not consistent. Romania presented a distinct profile with higher fatalities in urban areas than in rural and motorway roads.

Additionally, Greece and Portugal experienced a shift during the study period, with urban fatalities surpassing those on rural roads.

The trend analysis of traffic fatalities by road type across countries under study showed that some countries demonstrated consistent linear declines across all road types, while some exhibited more fluctuating patterns with linear or non-linear trends. However, Romania showed no clear trend in rural road fatalities, while Ireland and Luxembourg lacked clear trends on motorways. On the contrary, Portugal and Romania experienced a moderately increasing trend in motorway fatalities.

d) Fatality by the person involved

Drivers consistently represented the highest fatality rate across all countries. Passenger fatalities typically ranked second, followed by pedestrian fatalities. However, this pattern varied across countries. In Belgium, France, Slovenia, and Sweden, passengers consistently had the second-highest fatality rate. Conversely, in Poland and Finland, pedestrians consistently exhibited higher fatality rates than passengers did. In Austria, Czech Republic, Germany, Greece, Italy, the Netherlands, Portugal, and Spain, a shift occurred around mid-study, with pedestrian fatalities overtaking passenger fatalities. In contrast, Luxembourg, Ireland, and Denmark maintained interchangeable fatality ranks for both passengers and pedestrians throughout the study period.

The trend analysis of traffic fatalities by persons involved revealed that some countries demonstrated consistent linear declines across all road types, while some exhibited moderated fluctuating with decreasing linear or non-linear trends. However, Romania showed no clear trend for fatalities involving drivers.

e) Fatality by vehicle type

Analysis of vehicle-related fatalities proves different distribution across categories over the study period. Car occupants consistently occupied the highest fatality rank, with 16 countries consistently ranking it as the top fatality group highlighting a persistent safety challenge. The Bicycle category's fatality rankings shifted over time. Initially, seven countries ranked it as high-risk (rank 2), decreasing to six. However, the number of countries ranking it third highest increased from four to seven, suggesting a complex trend. The Motorcycle category experienced some movement, with nine countries initially placing it at rank 2, transitioning to ten countries at the same rank by the end. At the same time, Mopeds experienced a shift from mid-range to lower fatality rankings. In contrast, HGV and Lorry Occupants exhibited a more dispersed lower ranking pattern. HGV Occupants had a significant concentration of lower fatality, the sixth fatal group, with 11 countries initially, but two countries saw a shift to higher fatalities, fourth, towards the end. Similarly, Bus Occupants consistently ranked lowest (*rank 7*) across most countries, indicating fewer fatalities in this category throughout the study.

The trend of traffic fatalities exhibited substantial variation across vehicle types and countries. While car occupants consistently experienced declining fatality rates in all countries, trends for other vehicle categories were more diverse. For instance, bicycle fatalities decreased in most countries, except in Belgium, Finland, France, and Romania. Moped fatalities have no evident trend in Romania. Motorcycle fatalities declined in most countries except Denmark, Finland, Romania, Spain, and Sweden. HGV and lorry occupants' fatalities decreased in most countries, except for Belgium, the Czech Republic, Denmark, Finland, and Slovenia for HGV and Finland, France, and Sweden for Lorry. Bus occupant fatalities generally declined, although at no evident trend in Belgium, the Czech Republic, France, Germany, the Netherlands, Portugal, and Slovenia. Remarkably, Poland experienced an increased trend in moped and motorcycle fatalities.

5.2.2. Intermediate Road Safety Performance Indicators

5.2.2.1. Alcohol-Attributable Road Fatality Rate

The influence of alcohol on road traffic fatalities varies across countries. While Poland, Portugal, Spain, and Sweden experienced increasing trends in alcohol-related fatalities, the Czech Republic, Denmark, Germany, the Netherlands, and Slovenia experienced decreases. However, the remaining countries showed no clear pattern in alcohol-involved fatalities.

5.2.2.2. *Distraction-Related Indicator*

Analysis of mobile phone usage while driving reveals a general decline across most countries, suggesting increased enforcement and public awareness. However, Slovenia and the Netherlands present a contrasting trend with increased ticket issuance. Luxembourg and Poland did not show a clear trend in ticket numbers.

5.2.2.3. *Speed Related Indicator*

Analysis of speeding tickets reveals varying trends across countries. Austria, Belgium, Czech Republic, Denmark, France, Poland, and Spain reported speeding ticket increases, indicating speed control challenges. Conversely, Ireland, Italy, Portugal, Sweden, and the Netherlands showed decreases. However, Finland, Greece, and Slovenia exhibited no clear patterns in ticket issuance.

5.2.2.4. *Protective System Indicator*

In most of the sampled countries, seatbelt violation tickets declined, indicating improved seatbelt usage. Poland and Italy, however, still recorded an increase in these violations, suggesting potential challenges in enforcing proper seatbelt usage and raising awareness.

5.2.2.5. *Road Infrastructure Indicators*

a) *Share of motorways in the total road network*

The proportion of motorways within the road network has increased in most countries studied. While Belgium and Italy experienced a decline in motorway share, Austria and Sweden showed no significant change.

b) *Road infrastructure investment*

The investment in road infrastructure was quite different across countries: while Belgium, Sweden, and Finland increased spending on road infrastructure, investments in Austria, Ireland, Italy, Luxembourg, Slovenia, Spain, and France declined. On the other hand, in Denmark, Germany, Poland, the Czech Republic, and Greece, there is no trend in their expenditure on road infrastructure.

5.2.2.6. *Traffic Volume Exposure*

Analysis of vehicle kilometers traveled across 12 countries (*due to data availability*) discloses a predominantly linear upward trend. Belgium experienced a persistent increasing linear trend. Whereas Austria, the Czech Republic, Denmark, France, Ireland, Slovenia, and Sweden exhibit a moderate linear increasing trend. Conversely, Germany saw a decline, and Finland, Spain, and Luxembourg exhibited no clear pattern in vehicle kilometers traveled.

Despite varying trends in traffic volume, a positive correlation between vehicle kilometers and fatalities was observed in Belgium, Denmark, Germany, Spain, and Sweden, suggesting a negative impact on road safety in these countries. However, no significant correlation was found between these variables in the remaining seven countries.

5.2.3. *Exogenous Factors Analysis Result (XARIMA models)*

5.2.3.1. *Exogenous Effect Analysis Result*

Incorporating socio-economic and weather variables into the ARIMA model provided an understanding of how they influence road safety outcomes. Accordingly, average temperature positively correlated with fatalities and injuries across all countries, suggesting that warmer conditions may contribute to increased road activity and crashes. Conversely, the average monthly (amount) of precipitation did not significantly affect the models.

The socioeconomic factors exhibited a country-specific pattern of effects. Average household net income negatively correlated with fatalities, implying a positive effect on road safety. Conversely, GDP and employment rates positively influenced fatalities, suggesting an inverse relationship between economic achievements and road safety. Furthermore, the proportion of household expenditure allocated to vehicle purchasing and overall transportation positively influenced fatality rates in some countries.

5.2.3.2. Intervention Analysis Result

The results revealed a complicated relationship between road safety directives and outcome indicators. In addition, both positive and negative correlations in directives across countries were measured.

The initial directives from 2003 to 2010 positively impacted road fatalities in most countries. Specifically, directives D_2002/24/EC (May 2003), D_2003/97/EC (November 2003), D_1999/37/EC (June 2004), D_2005/39/EC (September 2005), D_2003/20/EC (May 2006), and D_2002/85/EC (January 2007) significantly influenced the reduction of road fatalities across 15 countries, predominantly showing a negative correlation with fatality rates. Other directives, including D_2004/54/EC (April 2004), D_2007/46/EC (May 2009), R_78/2009 (November 2009), and D_2008/96/EC (December 2010), also had a significant impact, negatively correlating with road fatalities in an average of 12 countries. However, for directives implemented in 2009, the number of countries showing positive and negative correlations between these measures and fatalities was balanced. The impact of these directives on road safety generally showed a gradual improvement (ramp effect), except for directive D_2008/96/EC (December 2010), which exhibited an immediate (impulse) impact.

Conversely, the remaining four directives had limited impact, most positively correlating with fatalities. Notably, directive D_2015/413 (March 2015) affected only two countries, Austria and the Czech Republic, which showed a positive correlation with fatalities.

On average, road fatalities in most countries responded to nine directives. Romania and Spain exhibited the least response, reacting to only five directives, four of which were issued between 2003 and 2010. Meanwhile, the Czech Republic showed the highest response, with 13 directives influencing its fatality rates. In Denmark, Luxembourg, Poland, Slovenia, and Sweden, all directives significantly correlated with fatalities, positively impacting road safety. Most significant directives positively impacted road safety in Belgium, Finland, Greece, and Ireland. On the other hand, in Austria, France, and Germany, most directives with significant correlations tended to correlate positively with fatalities. The remaining countries demonstrated an average response to these directives. Figure- 7 illustrates sample directives' impulse and ramp impact on road fatalities evolution. For detail information referee to Appendix B: countries profile.

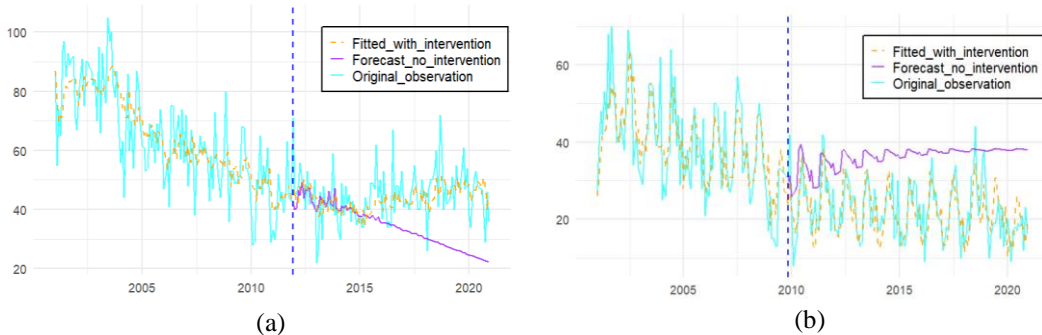


Figure 7: Effect of intervention (a) negative impulse impact of directive D_2010/48/EU (December 2011) on fatalities in the Netherlands, (b) positive ramp impact of directive R_78/2009 (Nov 2009) on fatalities in Sweden.

Unlike their impact on fatalities, the effect of these directives on road injuries was less pronounced, with most countries showing no significant correlation. Directive D_2015/413 (March 2015) reduced road injuries in eight countries, demonstrating a negative correlation with the total number of injuries. Other directives, such as D_2002/24/EC (May 2003), D_2003/97/EC (November 2003), D_2007/46/EC (May 2009), and D_2008/96/EC (December 2010), influenced road injuries in an average of nine countries, again mostly showing a negative correlation with total injuries. The remaining directives impacted an average of six countries, with most showing a negative correlation with injuries.

Austria, Belgium, the Czech Republic, Finland, and Sweden were the countries that responded most significantly to these directives concerning injuries, with an average of 11 directives influencing them. Finland had the highest response, with 14 directives affecting injury rates. In contrast, the remaining countries responded to an average of four directives, with Spain recording the lowest response, reacting to only one directive. In Sweden, all 11 significant directives negatively correlated with total injuries, positively influencing road safety. Similarly, in Austria and

Finland, almost all significant directives negatively correlated with total injuries. Whereas in Belgium and the Czech Republic majority of the significant directives positively correlated with total injuries. The response in the remaining countries was lower and showed varying correlations. Figure- 8 illustrates sample directives' step and ramp impact on road injuries and fatalities evolution. For detail information referee to Appendix B: countries profile.

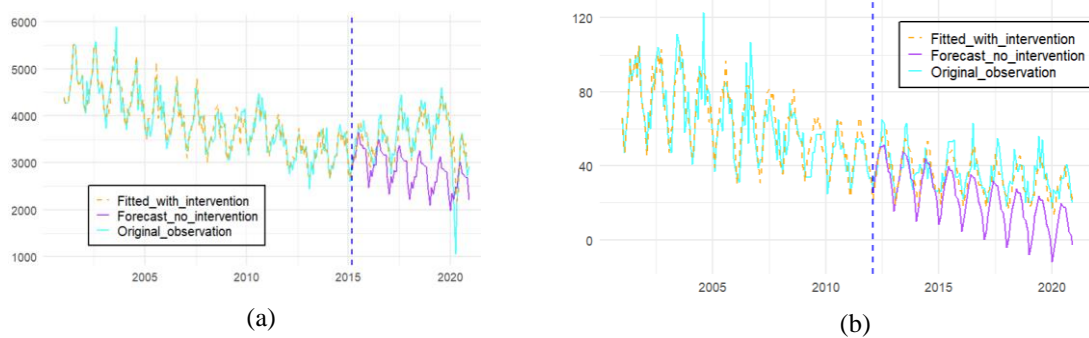


Figure 8: Effect of intervention (a) negative step impact of directive D_2015/413 (March 2015) on injuries negative in Portugal (b) negative ramp impact of D_2010/40/EU (Feb 2012) on fatalities in Austria

6. Discussion

This study contributes to the literature on European road safety by providing a comprehensive analysis of temporal trends, incorporating exogenous factors, and evaluating the impact of EU road safety directives. The findings align with previous reports and studies by the Adminaité-Fodor et al. (2021), Carson et al. (2023), the European Commission (2017), and several other reports of the European Commission where a general decline in road fatalities and injuries across European countries are reported. The presence of seasonal fluctuations in road safety outcomes is evident, highlighting the significance of temporal factors as discussed in Wiratama et al. (2021) and European Commission (2015b), where holidays and favoring seasons cause more casualties. The disaggregated analysis aligns with the findings of (European Commission, 2015b), highlighting an increased risk for vulnerable road users. This trend is consistent with the observations of Hakkert and Gitelman (2014), who attribute this to the shift towards sustainable transportation systems and the increase in the elderly population. These findings underscore the importance of targeted interventions to address specific risk factors and vulnerable road users.

The study identified that speeding remained a significant challenge to road safety in European countries, aligning with the findings from the European Commission (2024). In addition, alcohol consumption while driving devastated road safety; this aligns with the study result of the European Commission (2015b). Generally, significant improvements are observed in seatbelt use and driving while distracted, aligning with the study results of the European Commission (2015b, 2018b, 2019b). Besides, the increase in quality of road infrastructure and road investment has impacted road safety positively, aligning with the study results by Castillo-Manzano et al. (2014) and Tomašković & Završki (2024). Overall, traffic fatalities and injuries have shown a declining trend, though the exposure vehicle driven on European roads has increased over time. However, the exposure factor has shown a negative effect on road safety correlating positively with fatalities, which aligns with the study result by Castillo-Manzano et al. (2014). Common patterns suggested that improved road infrastructure, increased enforcement of traffic laws, and widespread public awareness (*behavioral changes*) have contributed to improved road safety outcomes collectively embodying the principles of a Safe System approach, have contributed to improved road safety outcomes. This holistic strategy, which prioritizes the prevention of crashes rather than solely addressing their consequences, has been instrumental in reducing fatalities and injuries on European roads.

As expected, weather is important in explaining road fatalities and injuries. The average temperature is found to cause more fatalities and injuries, whereas the amount of precipitation generally has no significant effect on road safety. A possible reason could be that the type of weather influences the choice of mode of transport, the higher exposure, and possibly less concentrated driving behavior in warm weather. Whereas, in rainy weather, more concentrated driving behavior may be observed when precipitation is expected; however, driving when the road is wet

can trigger a higher risk of exposure. These results align with the study findings by the European Commission (2015b), Hermans et al. (2007), Van den Bossche et al. (2004), and Wiklund et al. (2012).

A negative association was obtained between economic development and traffic safety. Decreases in GDP and employment rates were associated with lower fatality and injury rates, potentially due to reduced mobility during economic downturns, as evidenced by the significant drop in fatalities following the 2008 economic crisis. Conversely, while higher household income generally correlates with improved road safety due to increased access to safer vehicles, the observed relationship suggests a potential shift towards safer transportation modes among higher-income groups. The findings of these results align with the studies by the European Commission (2015b), Wiklund et al., (2012), and Yannis et al. (2014).

Road safety laws and measures have significantly influenced the evolution of road safety in Europe. Introducing road traffic directives, such as speed limits, seatbelt enforcement, standards for vehicle safety, and safety requirements for road infrastructure, has contributed to declining traffic fatalities and injuries. The implementation of road safety directives, particularly between 2003 and 2010, had a positive effect on road safety. However, subsequent directives showed limited impact on fatality reduction, suggesting a need for continued evaluation and adaptation of policies. In addition, the effect of these directives on injuries is less pronounced than on fatalities. Besides, the effect of these directives has variation among European countries. A possible reason could be that these directives have more control over fatalities than injuries, and may not be equally effective for injuries. In addition, the strengths of applying this directive in European countries differ. On the contrary, some interventions showed a positive correlation with both fatality and injury, implying a negative impact on road safety. Here it is practical to assume poor implementation or enforcement of the directives among the many reasons.

The implications of these findings are significant for both policy and practice in road safety. The study highlights the importance of tailoring road safety interventions to the specific conditions of each country, considering socio-economic and environmental factors. The success of early EU directives in reducing fatalities points to the effectiveness of coordinated, EU-wide policies, but the varied impact on injuries suggests that the same directive may not be sufficient for different road safety outcomes. Policymakers should consider developing more targeted strategies that address both fatalities and injuries, potentially through enhanced enforcement of safety measures, public awareness campaigns, and improvements in vehicle and infrastructure safety. Moreover, the study's use of advanced time-series models underscores the value of rigorous analytical methods in road safety research.

Despite the study's comprehensive approach, there are limitations that must be acknowledged. The analysis was constrained by the availability and quality of data, which may have affected the strength of the models. Additionally, the analysis of exogenous factors, SPIs, and total injury focused on aggregated data, potentially overlooking important variations in road user groups that could provide further insights into the effectiveness of road safety interventions.

Given these limitations, future research should address these gaps by incorporating more disaggregated road safety data, which could provide a clearer picture of the specific factors influencing road safety outcomes in different regions. Additionally, further studies could explore the interaction between different types of interventions, such as the combined effects of enforcement, infrastructure improvements, and public awareness campaigns. There is also a need for research that examines the long-term sustainability of the observed trends, particularly in light of emerging challenges such as the increasing prevalence of autonomous vehicles on road safety.

Moreover, the study's findings suggest that the success of European road safety strategies could offer valuable lessons for other regions, particularly in developing countries where road safety remains a critical issue. Adapting these strategies to local contexts could help improve road safety outcomes globally, but this requires a careful analysis of the conditions under which these practices can be successfully transferred.

7. Conclusion

This study set out to address the ongoing challenges in road safety across Europe, particularly in light of the progress observed between 2001 and 2020. Despite the European Union's determined efforts and notable advances, road traffic crashes remain a critical public health issue, as evidenced by deaths and injuries still registered in its member states. The problem statement highlighted the need to better understand the effectiveness of road safety directives and their impact on reducing traffic fatalities and injuries, given the complexity of the road traffic environment.

Key findings revealed that while most EU countries experienced a decline in road fatalities and injuries, the rate of improvement has slowed, particularly in the latter part of the study period. This slowdown suggests that earlier achievements may have been driven by initial, implemented measures, and economic activities, while further reductions may require more targeted interventions. Another major contribution of the research is the detailed study of trends observed in road safety indicators, both with and without exogenous variables, and the effects of applied EU road safety directives. This analysis revealed that many directives contributed positively to ensuring road safety. However, some had negative effects. This might be attributed to poor implementation or behavioral changes among road users. These findings underscore the importance of designing effective policies and ensuring their adaptability and enforcement across diverse contexts.

The study's key takeaway is that the review and adjustment of the road safety strategy are of continuous concern. The data show that mixed results may result from even the best-formulated policies without proper implementation and monitoring. These findings should be considered by policymakers, including when considering the transferability of European road safety practices to other regions or countries with varying patterns of road use, infrastructure, and cultural attitudes toward road safety.

Acknowledgments

I would like to express my sincere gratitude to Prof. Dr. Elke HERMANS and Prof. Dr. Evelien POLDERS for their invaluable guidance and support throughout this research process. Their expertise and encouragement were instrumental in the successful completion of this work.

I am deeply grateful to my wife, Saba Teklay Gebreselassie, for her firm support and encouragement throughout this challenging endeavor. Her belief in my abilities has been a constant source of motivation.

Furthermore, I would also like to thank the CARE database experts who generously shared data, making this research possible. Their contributions were essential to the study's success.

Finally, I would like to express my sincere gratitude for the opportunities this research has provided to develop my analytical and research skills, and broaden my knowledge in the safety.

Appendix A. Data Sampling

A.1. Outcome Indicators (OI)

The key sources for outcome indicators are the CARE database, Eurostat, ERSO, ETSC, OECD, and national road safety institutes.

Fatality data	Injury data
<ul style="list-style-type: none"> CARE database: Monthly total aggregated fatality data was obtained for the study, covering a complete data set across 17 countries. A 19-year data set (2001 to 2019) was also obtained for Ireland. Eurostat: The dataset provides comprehensive annual fatality data, disaggregated by gender, age, person involved, vehicle type, and type of road. It covers the complete time scope of the study for 17 EU countries. An 18-year dataset from 2001 to 2018 was obtained for Ireland. ERSO: The dataset provides annual fatality data, disaggregated by gender, age, person involved, vehicle type, and type of road. It covers the complete time scope of the study for 17 EU countries. A 17-year dataset from 2001 to 2017 was obtained for Ireland. However, despite the extensive data coverage, there are still gaps in the categorized data for these countries. Data extraction from this source follows a chronological sequence, beginning with the most recent reports and moving to older ones. This approach ensures that the latest and most updated fatality data are accurately reflected in the study. ETSC and OECD: ETSC fatality data are extracted from the report following a chronological sequence, beginning with the most recent reports and moving to older ones, while OECD is a structured database. The indicator for road fatalities per one billion vehicle-km is accessed from the OECD. However, it should be noted that both data sources primarily provide annual aggregated fatality data for EU countries. 	<ul style="list-style-type: none"> CARE database: This source provided total monthly injury data, offering a complete dataset across 17 countries. Additionally, a 19-year dataset covering 2001 to 2019 was obtained for Ireland. The data from CARE underscored the inconsistency in reporting injury data according to severity across different EU nations. ERSO and ETSC: Annual aggregated serious injury data for 18 EU countries from 2010 to 2020 was accessed from ERSO. For earlier data from 2001 to 2009, the same data was obtained from ETSC. However, a significant discrepancy exists between the datasets from ERSO and ETSC for the Netherlands, Austria, and Sweden. When these datasets are compiled, there is a noticeable jump in the reported figures during the transition year between the two sources, indicating potential inconsistencies in data reporting or collection methodologies between these periods.
<p>Considering the resources available and their inherent limitations, the study will employ fatality data for 18 EU countries from the <i>CARE database</i> for <i>monthly fatality data</i>. Additionally, <i>annual disaggregated fatality data</i> by gender, age, person involved, vehicle type, and type of road is sourced from <i>Eurostat and ERSO</i> for these countries. Furthermore, the <i>road fatalities per one billion vehicle-km</i> indicator from the <i>OECD</i> is selectively employed, depending on its availability for the countries included in the study (12 out of the 18). This indicator is <i>adjusted to annual traffic volume</i> exposure, measured in billion vehicle kilometers, to provide a more precise analysis of traffic safety evolution.</p>	<p>Considering the limitations and inconsistencies in reporting injury data according to their severity, the study utilizes total monthly injury data from the <i>CARE database</i>, which provides <i>total monthly injury data</i> for 18 EU countries.</p>

A.2. Intermediate Road Safety Performance Indicators

Sources reviewed for these indicators include the ETSC, OECD, SARTRE, ESRA, and Baseline projects. Initially, the SARTRE project, which aims to understand European road users' attitudes and behaviors concerning road transport and safety, was considered. However, the timing of the SARTRE surveys, September 2002 to April 2003 for SARTRE 3 (SARTRE 3 consortium, 2004) and September 2010 to November 2010 for SARTRE 4 (Antov et al., 2012), did not align with the required timeframe of the study. Similarly, the ESRA project, designed to collect and analyze comparable data on road safety performance and behavior, covered periods from 2015 to 2021 (*ESRA1 from 2015-2018 and ESRA2 from 2018-2021* (Meesmann et al., 2022)), which also did not fit the study's timeline. Additionally, the Baseline project, which focused on estimating road safety Key Performance Indicators (KPIs) in EU Member States, only provided data post-2020 (Silverans & Vanhone, 2023), thus falling outside the study's scope. Due to the abovementioned temporal limitations, the SARTRE, ESRA, and Baseline sources were deemed irrelevant to the study's needs. Thus, the only relevant sources for intermediate road safety performance indicators that remain are ETSC and OECD, which provide annual data.

The *ETSC* dataset provides various road safety indicators across multiple countries. The *alcohol-related indicator* captures the *annual number of fatalities resulting from crashes involving at least one driver impaired by alcohol*, spanning *17 countries* throughout the study period. Notably, *Italy lacks data for this indicator*. To enhance the analysis, it is suggested to adjust the fatality rates from *alcohol impairment relative to the total traffic fatalities*. This adjustment helps accurately track trends by focusing on the proportion of alcohol-related fatalities within total fatalities, reflecting true changes in alcohol-related risks.

The dataset also includes *distraction-related indicators*, recording the *annual total of tickets issued for mobile phone use while driving from 2010 to 2020* for 15 countries. Data for distraction-related indicators for *Czechia, Germany, and Sweden is missing* despite these countries being included in the study. *Speed-related indicators*, also from ETSC, follow a similar format, with data on *speeding tickets* issued during the same period for *15 countries, except for Germany, Italy, and Romania*. It also provides data for the *protective systems indicator* on the *annual total of tickets issued for seatbelt violations from 2010 to 2020* across *17 countries*, with *Germany missing* data. Data extraction from the ETSC reports is meticulously carried out chronologically, starting with the most recent reports and proceeding to older ones to ensure that the most current and updated data are accurately reflected in the study. The *vehicle-related indicators* from the *OECD* database, which include data on the *number of passenger cars by age from 2013 to 2020*, are available only for some EU countries. More critically, this data does not cover the full study period of 2001 to 2020, leading to its *exclusion from the analysis due to the mismatch* between the data availability and the *study's time scope*.

Furthermore, the OECD database provides information on *road infrastructure*, detailing *the annual proportion of motorways in the total road network* for *17 countries*, except *Portugal*. It also includes *annual road infrastructure investment data in constant USD per inhabitant* for *15 countries* but *lacks data* for the *Netherlands, Portugal, and Romania* throughout the study period.

A.3. Exogenous Factors

Sources reviewed for exogenous factors include the OECD, Eurostat, ERSO, the CCKP of the World Bank, and the German climate database.







Social and economic factors selected for the study are sourced from the OECD and Eurostat. *Eurostat* provides data on *population and employment, main GDP aggregates per capita and at market prices, and average household income* for EU countries. From the *OECD*, data is available on *the share of household expenditure for the operation of personal transport equipment* and *the share of household expenditure for the purchase of vehicles*. This socioeconomic data is available within the geographic and temporal scope of the study.

Weather data for the study is obtained from the *CCKP of the World Bank*, which includes *monthly average temperature in degrees Celsius* and *monthly total precipitation in millimeters*. This data is available within the geographic and temporal scope of the study. To ensure accuracy, this data is cross-verified with weather data for *Germany* from the national weather database, available at https://opendata.dwd.de/climate_environment/. This cross-checking process confirms the reliability of the weather data used in the study.

The dataset from *ERSO* provides information on *directives and regulations* concerning road safety applicable across EU countries within the scope of the study.

Appendix B. Countries Profile (Trend Analysis Results)

To fully understand the country profiles, please refer to the complementary key for an explanation of the symbols and abbreviations used.

To illustrate the observed trends in the indicators, the following symbols have been used:	
	The data shows a persistent decline trend
	The data shows a persistent positive trend
	The data shows a moderate decline trend
	The data shows a moderate positive trend
	The data exhibits no clear pattern, indicating variable progress.
	When seasonal variations influence the trend, this symbol is used to highlight this pattern
Numbers	The numerical values represent the trend change rate per specified unit of time (monthly or yearly).

Disaggregated analysis result:

In the disaggregated fatality analysis results by category, groups are ranked based on fatality rates, with 1 assigned to the highest rate and subsequent numbers indicating lower rates. To detect changes in **rank** over the study period, symbols are used as follows:

▲	An increase in rank indicates a shift toward a higher-risk category
▼	A decrease in rank indicates a shift toward a lower-risk category
—	A particular group maintained a consistent rank throughout the study period
① to ②⑩	The years 2001 to 2020, respectively, indicate the specific year in which a particular group experienced a change in rank

Exogenous effects analysis result:

Statements describing the exogenous effects on road fatalities and injuries indicate the correlation between the variable and the outcome. An 'increasing effect' implies a positive correlation, while a 'decreasing effect' suggests a negative correlation. If 'no effect' is stated, the variable is considered insignificant to the outcome. The numerical values associated with these statements represent the change in the outcome indicator for a one-unit increase in the exogenous variable.

Tipping point analysis result:

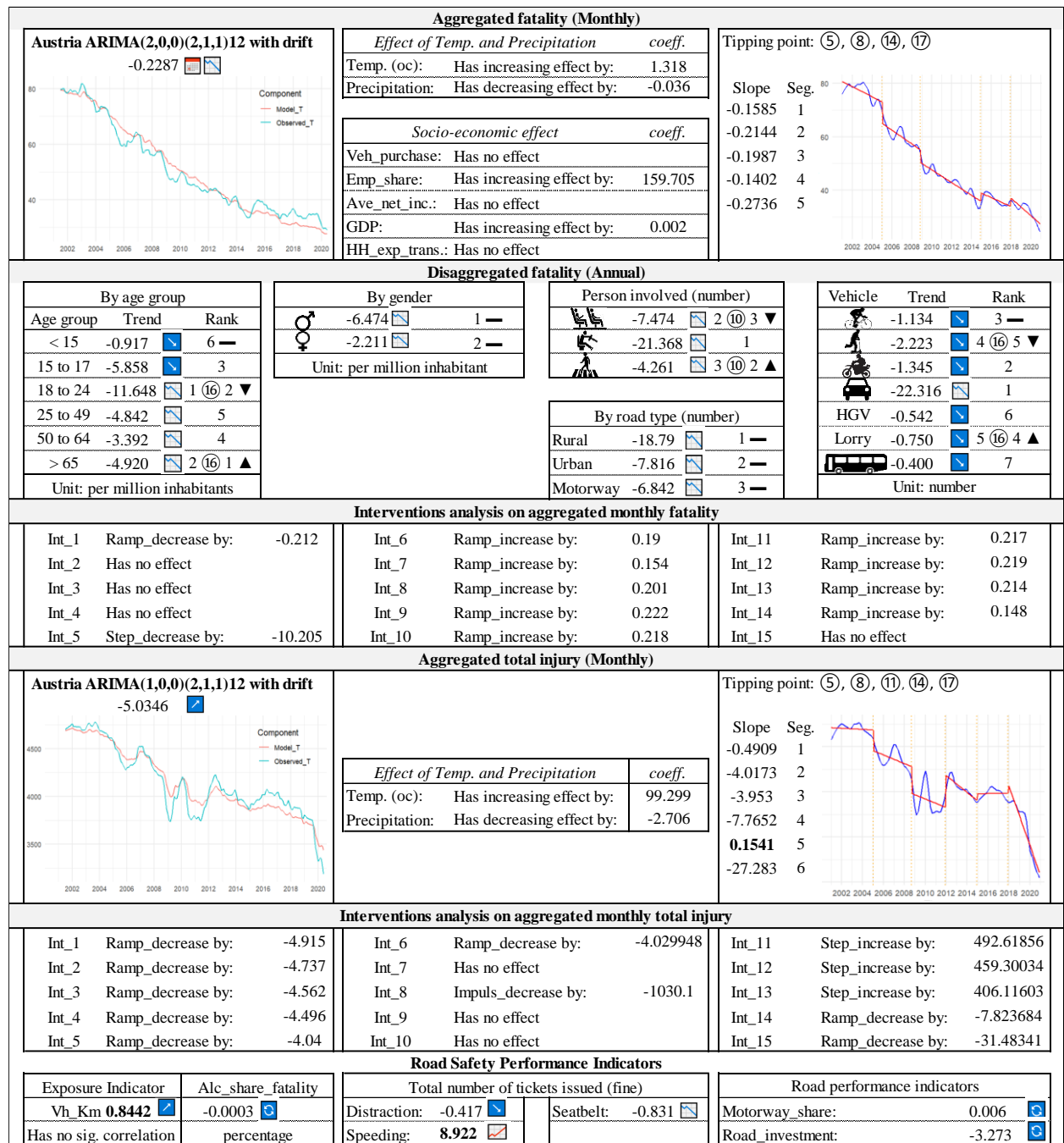
The term 'seg.' denotes segments within the data, while symbols ① to ②⑩ indicate the specific years in which tipping points occurred within the data from 2001 to 2020.

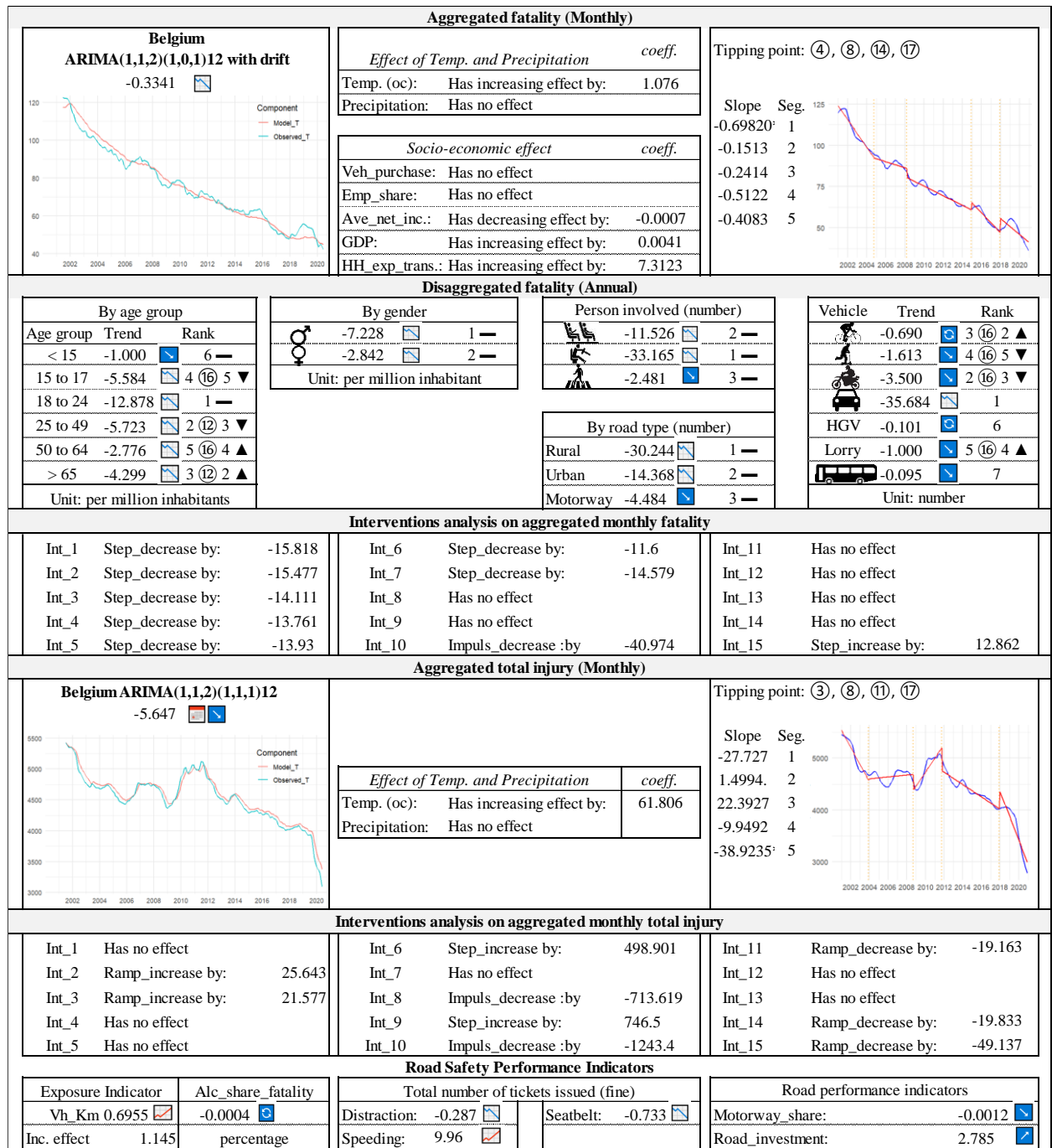
Interventions:

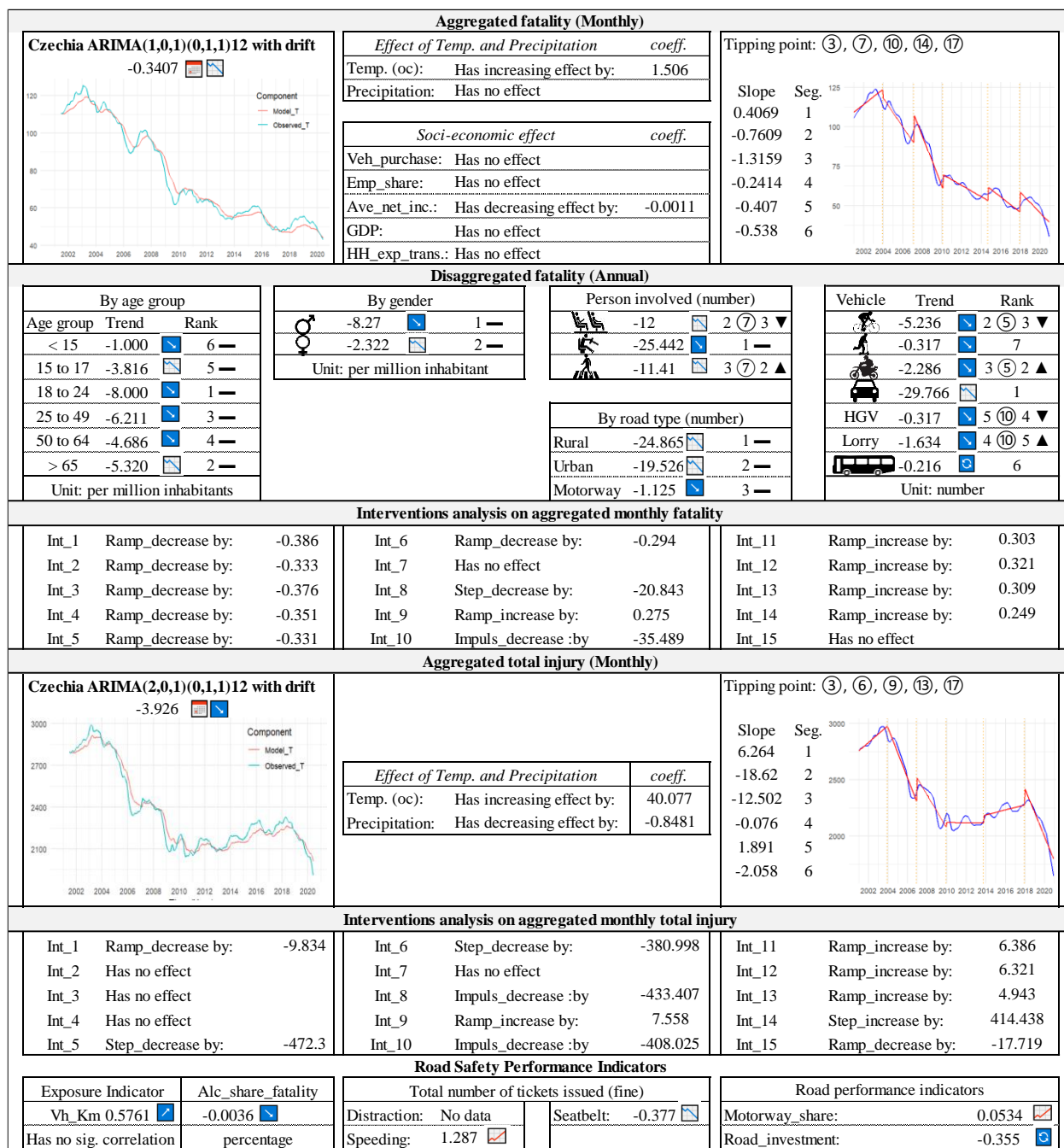
Abbreviation	Application date	Directives subject
Int_1	May-2003	Type-approval of two or three-wheel motor vehicles
Int_2	Nov-2003	Additional blind spot mirrors for heavy goods vehicles.
Int_3	Apr-2004	Safety requirements for tunnels in the trans-European road network
Int_4	Jun-2004	Standardized vehicle registration documents
Int_5	Sep-2005	Standards for motor vehicle seats, anchorages, and head restraints.
Int_6	May-2006	Compulsory use of safety belts and child-restraint systems in vehicles <3.5t.
Int_7	Jan-2007	Compulsory speed limitation devices in motor vehicles.
Int_8	May-2009	Framework for the approval of motor vehicles, trailers, and systems
Int_9	Nov-2009	Type approval to protect pedestrians and vulnerable road users
Int_10	Dec-2010	Road infrastructure safety management practices.
Int_11	Dec-2011	Regular roadworthiness tests for vehicles and trailers.
Int_12	Feb-2012	Framework for Intelligent Transport Systems (ITS) in road transport
Int_13	Jan-2013	Updated driving license regulations
Int_14	Mar-2015	Cross-border exchange of information on road safety-related traffic offenses.
Int_15	Apr-2018	E-call technology in all new cars for automatic emergency contact

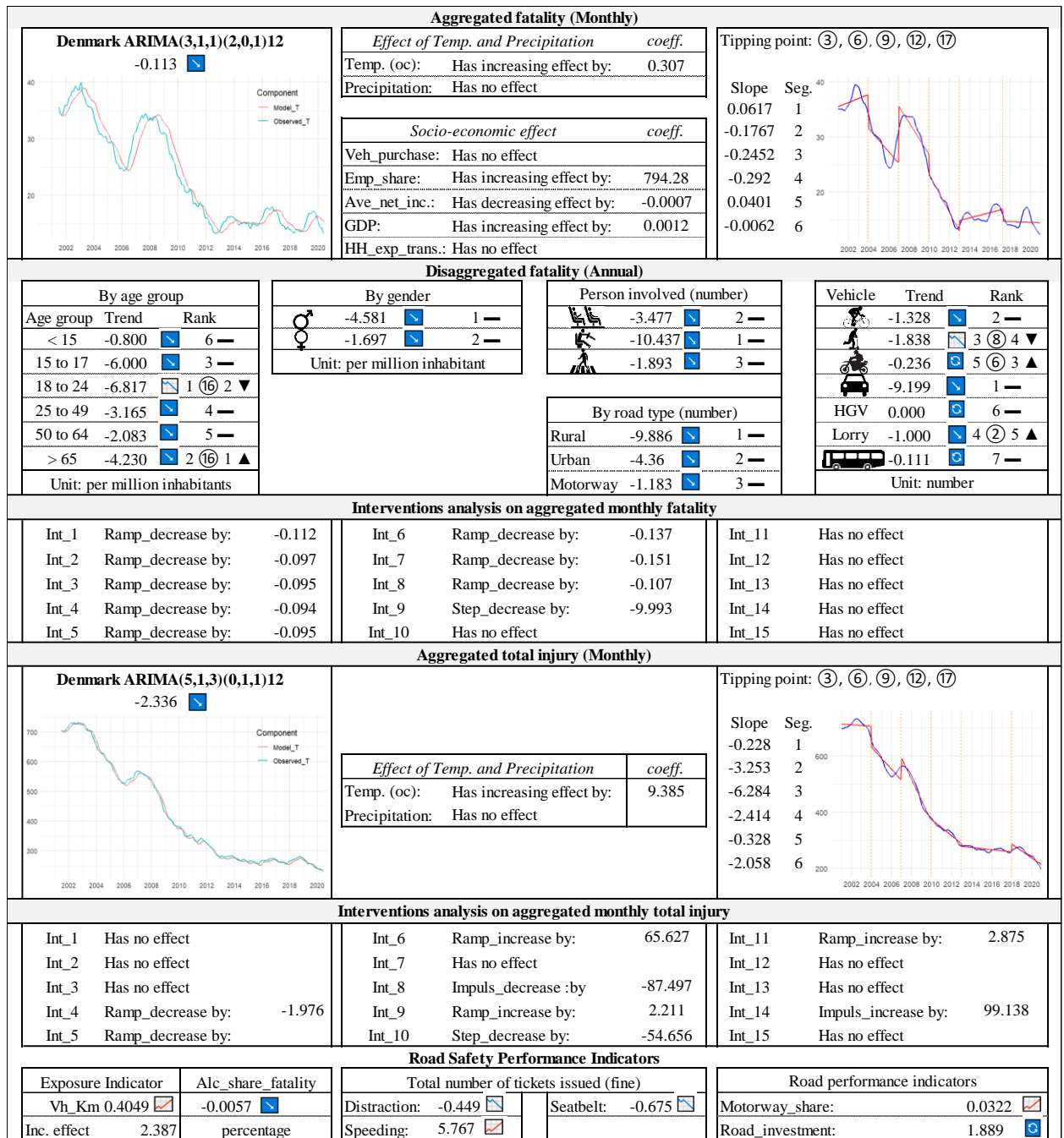
Exposure indicator (Vh_Km):

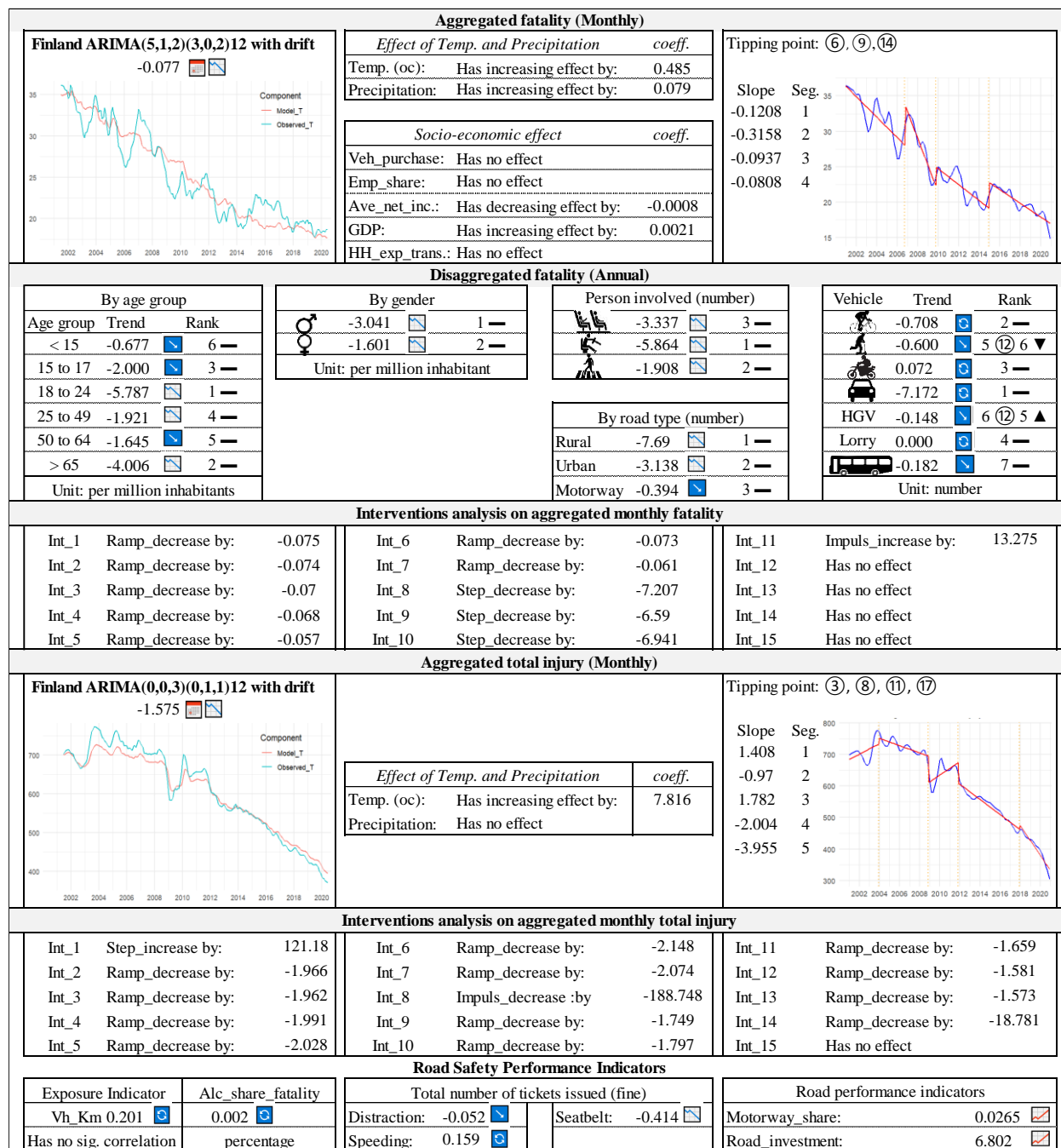
In the exposure indicator statements, 'Has no significant correlation' indicates no relationship between vehicle driving and road fatalities, while 'Inc. effect' implies a positive correlation. The numerical value following 'Inc. effect' represents the estimated increase in road fatalities for each

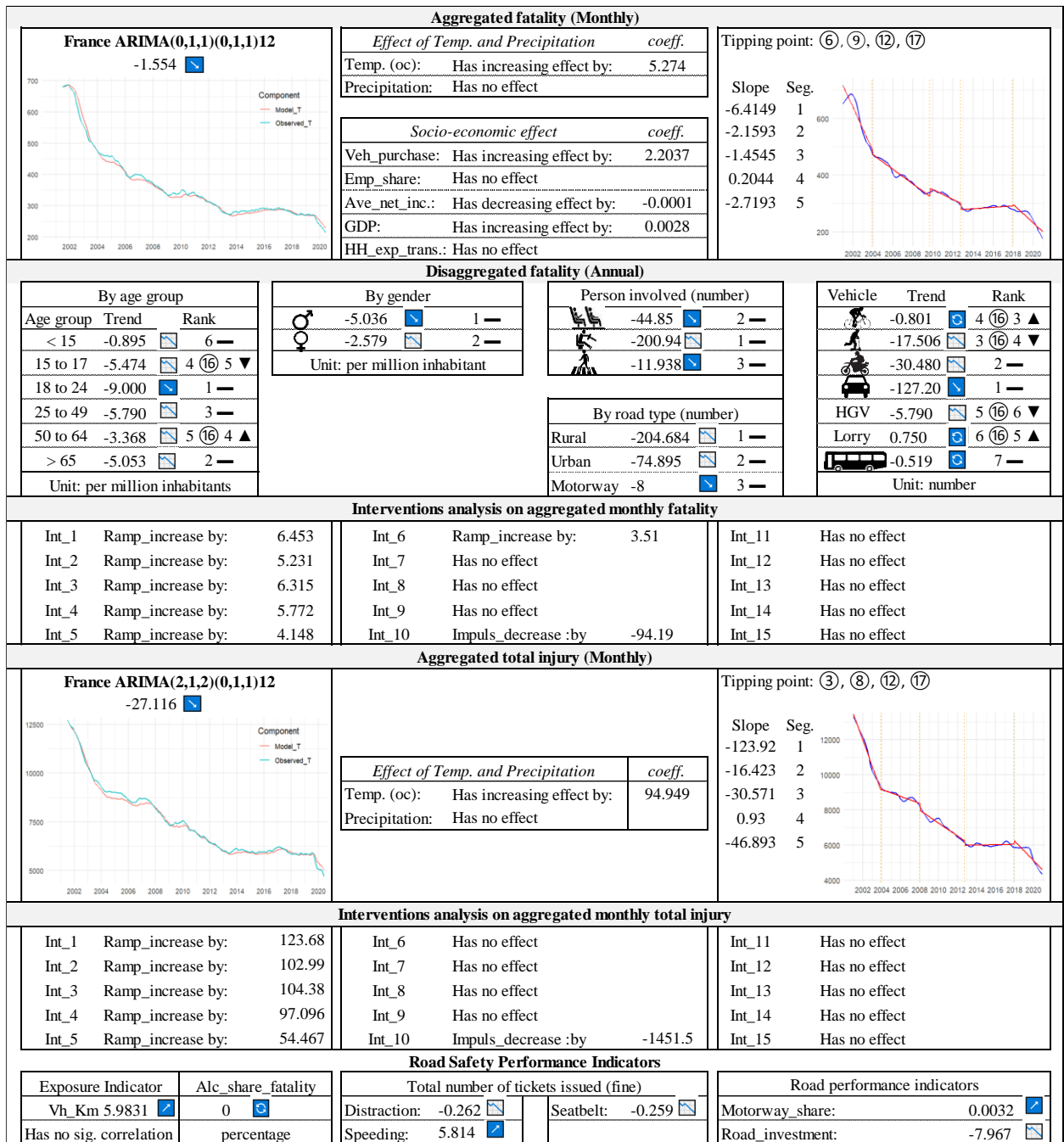


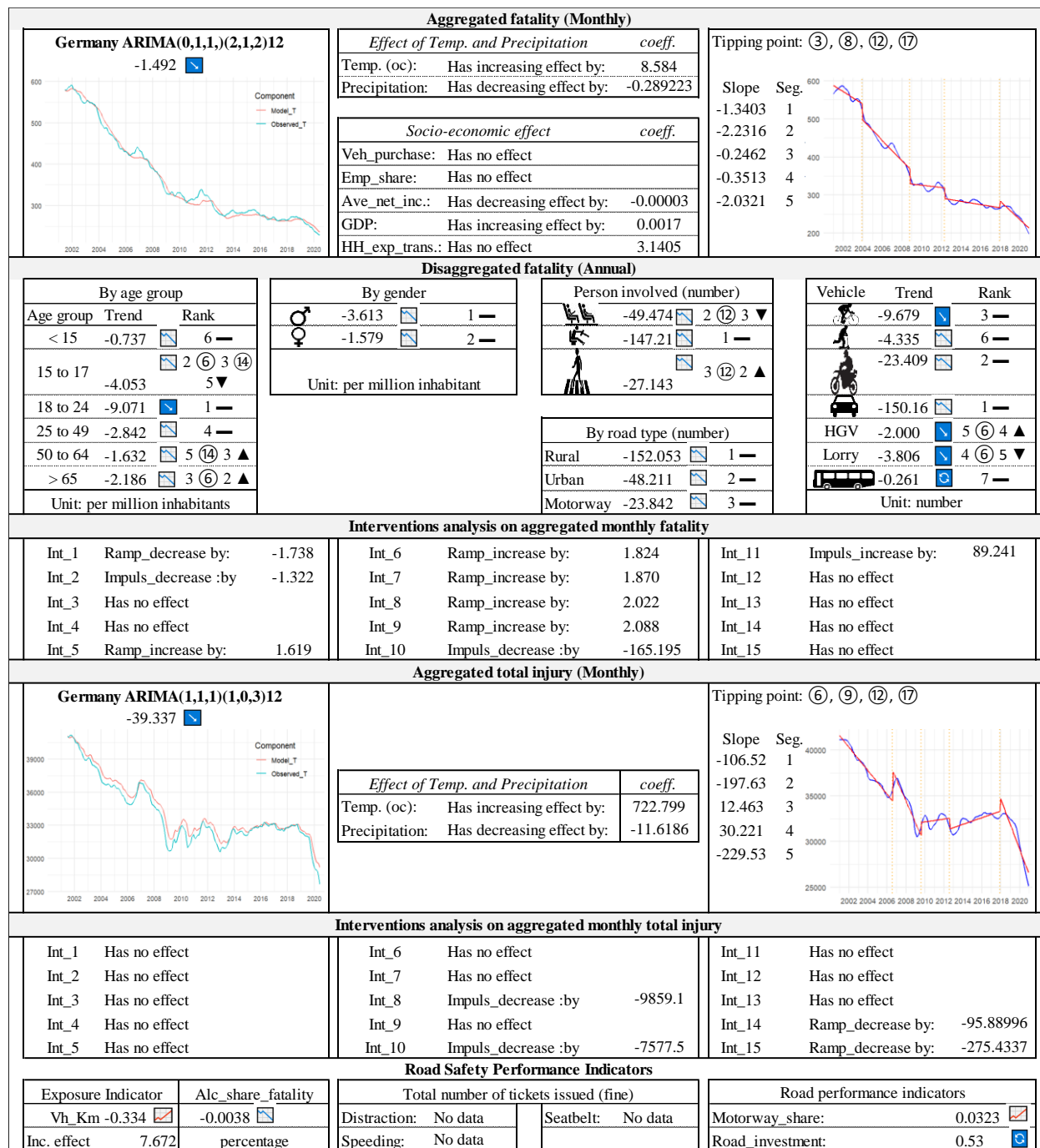


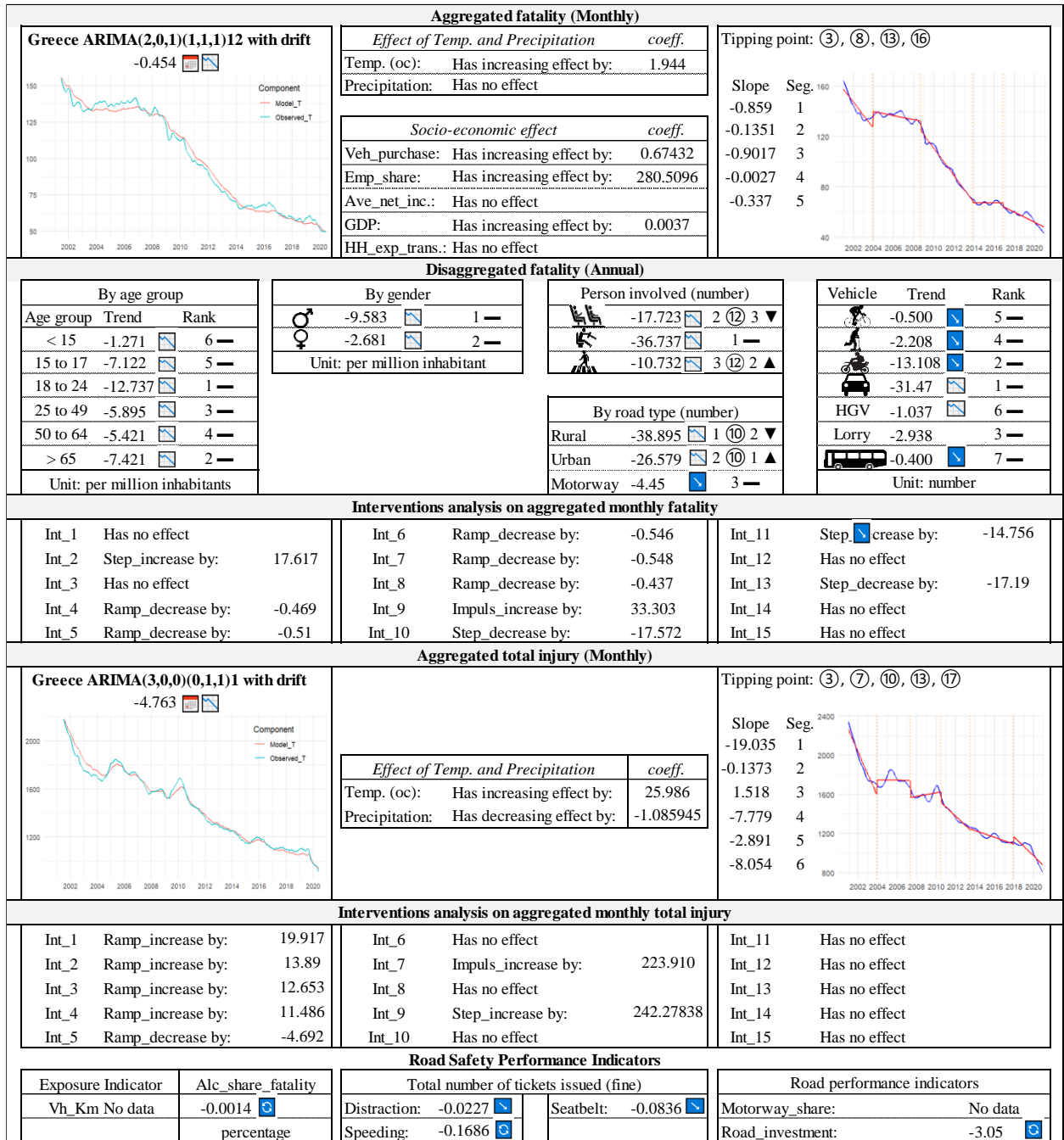


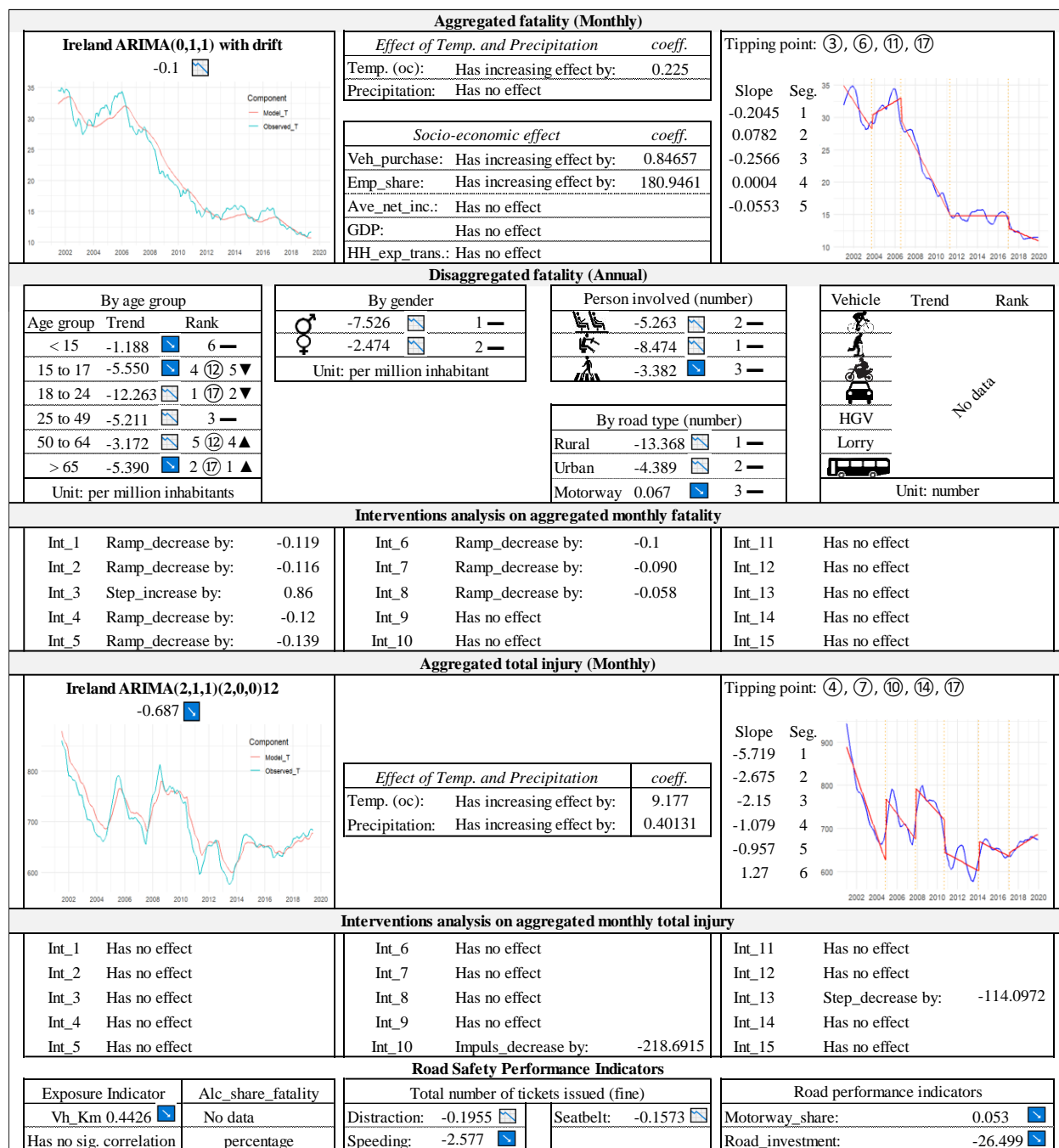


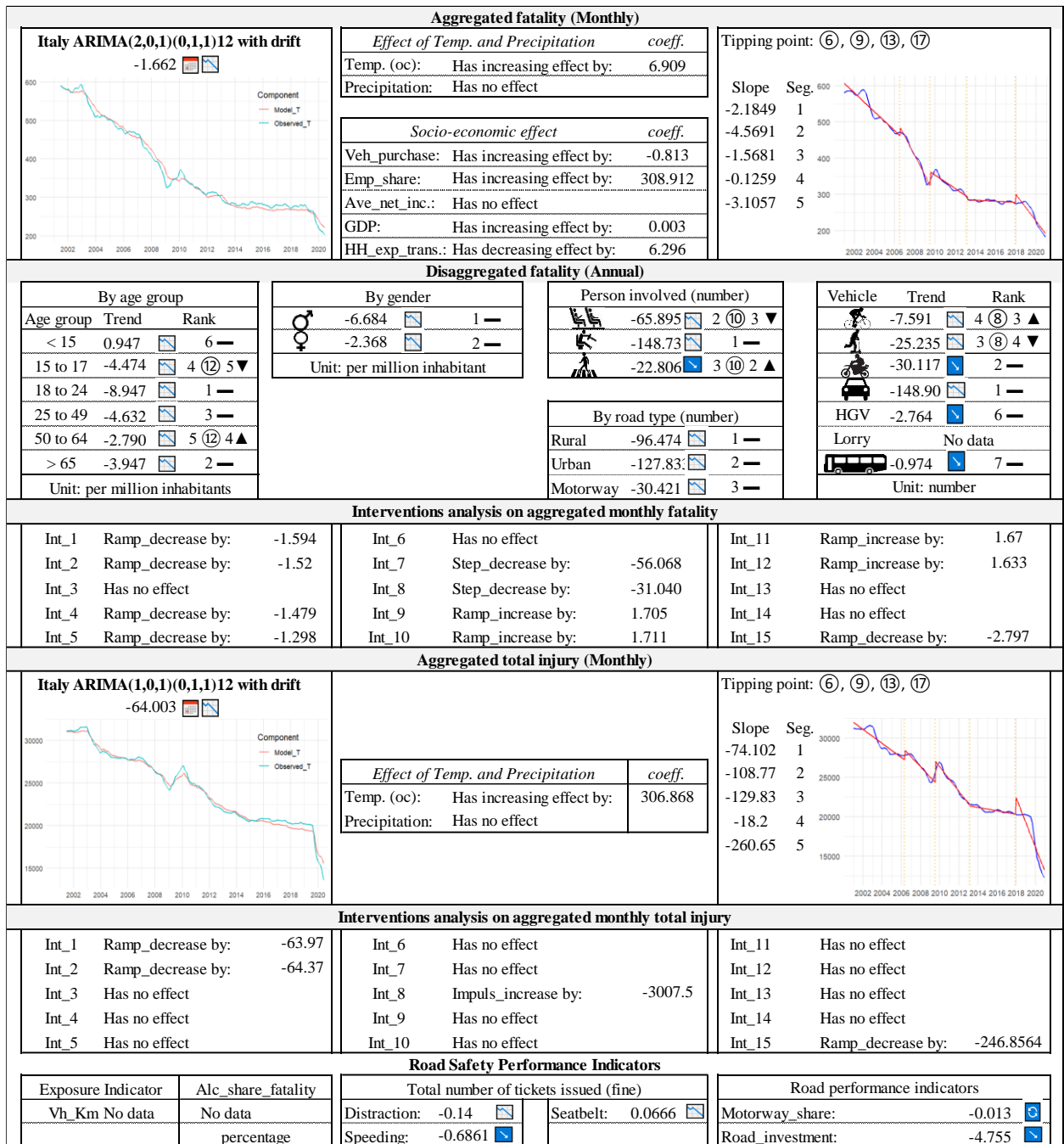


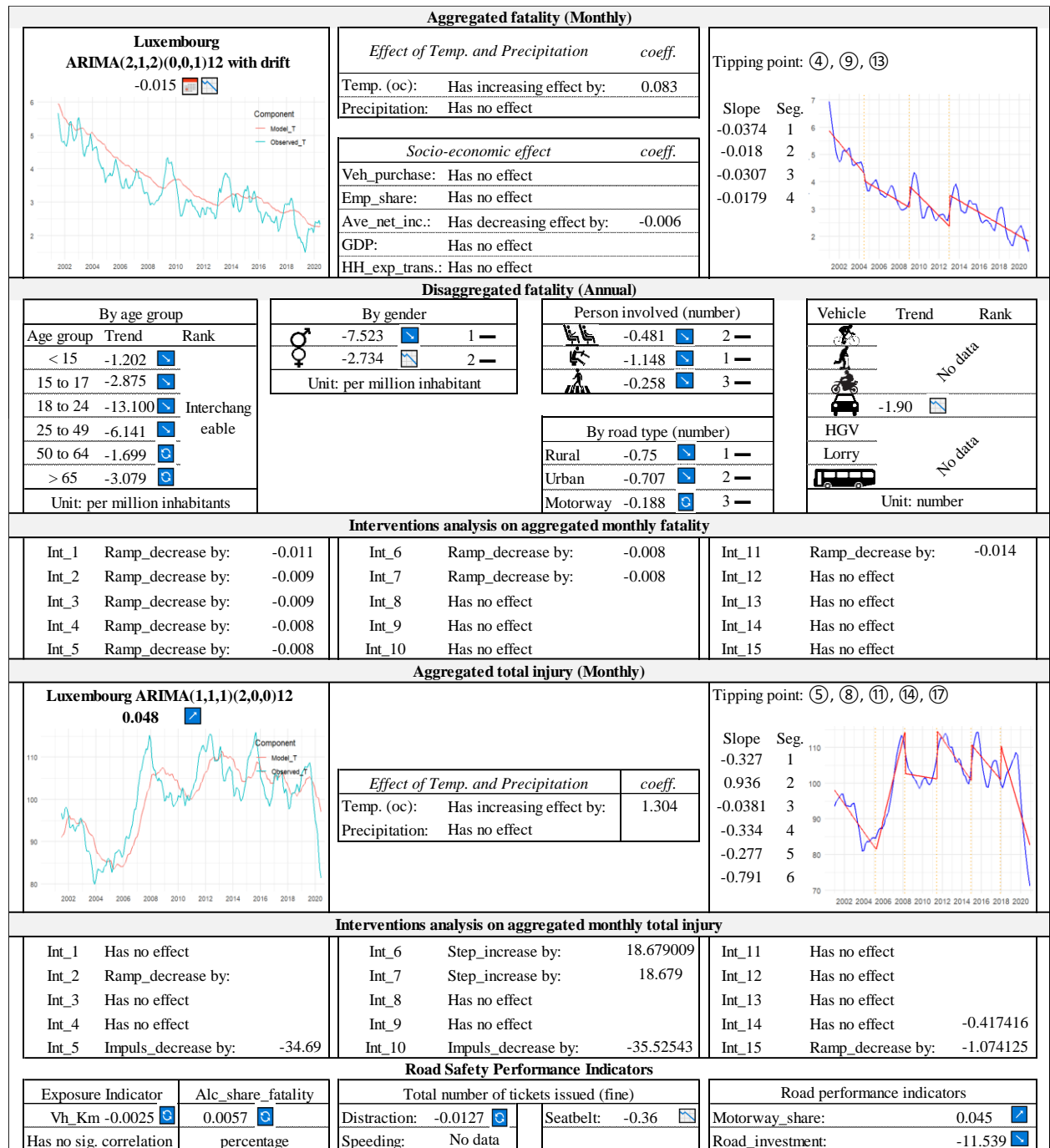


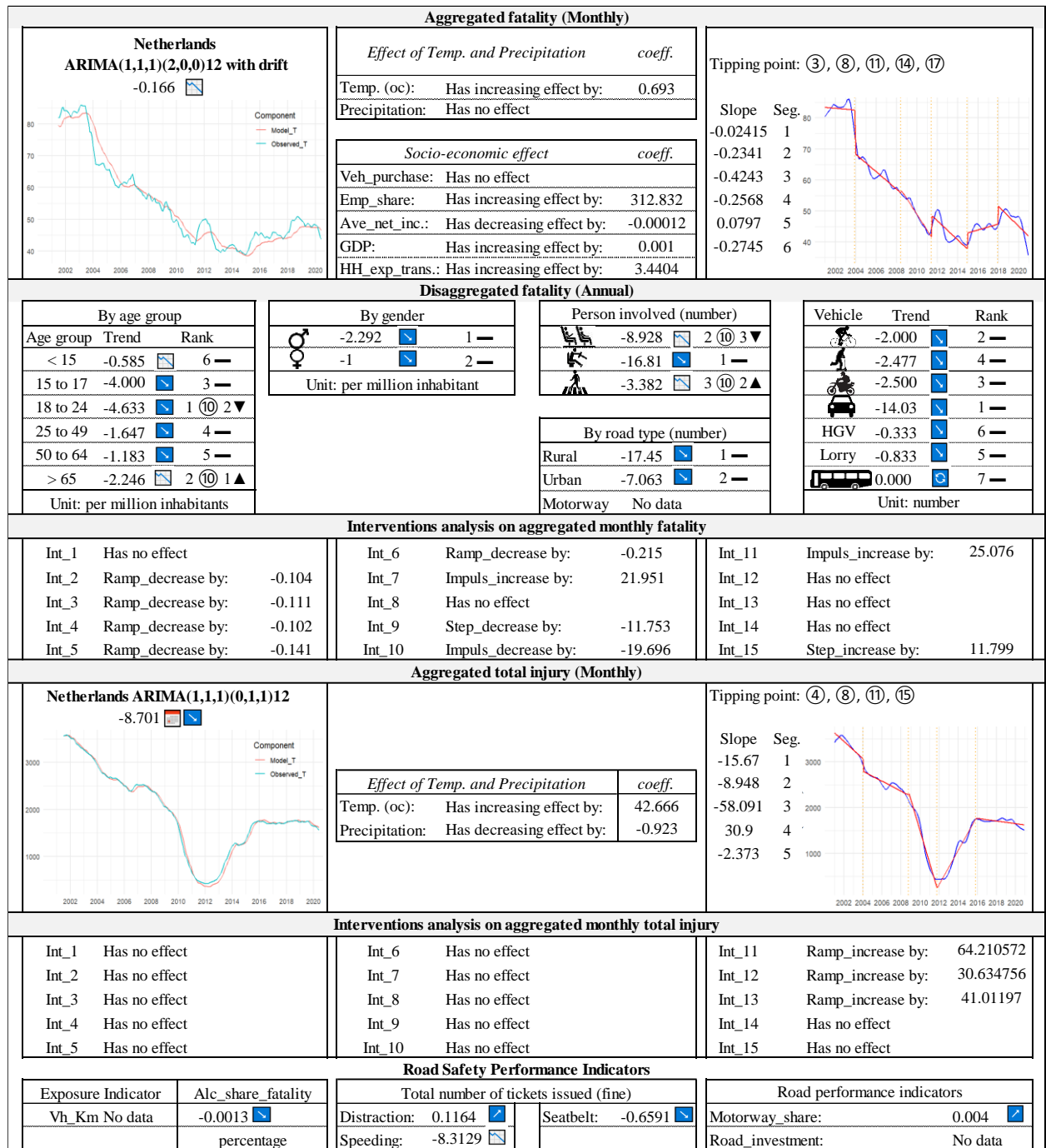


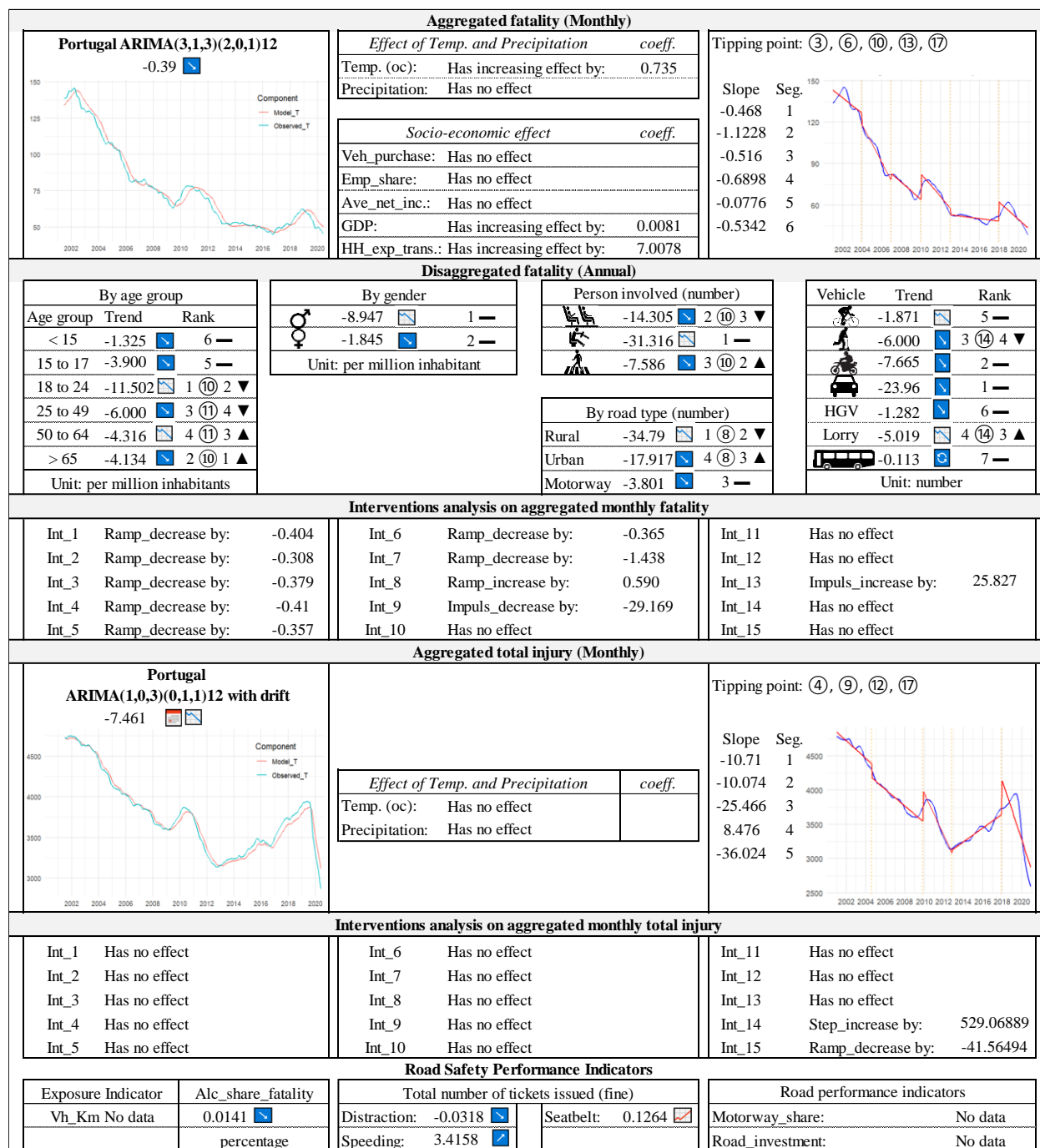


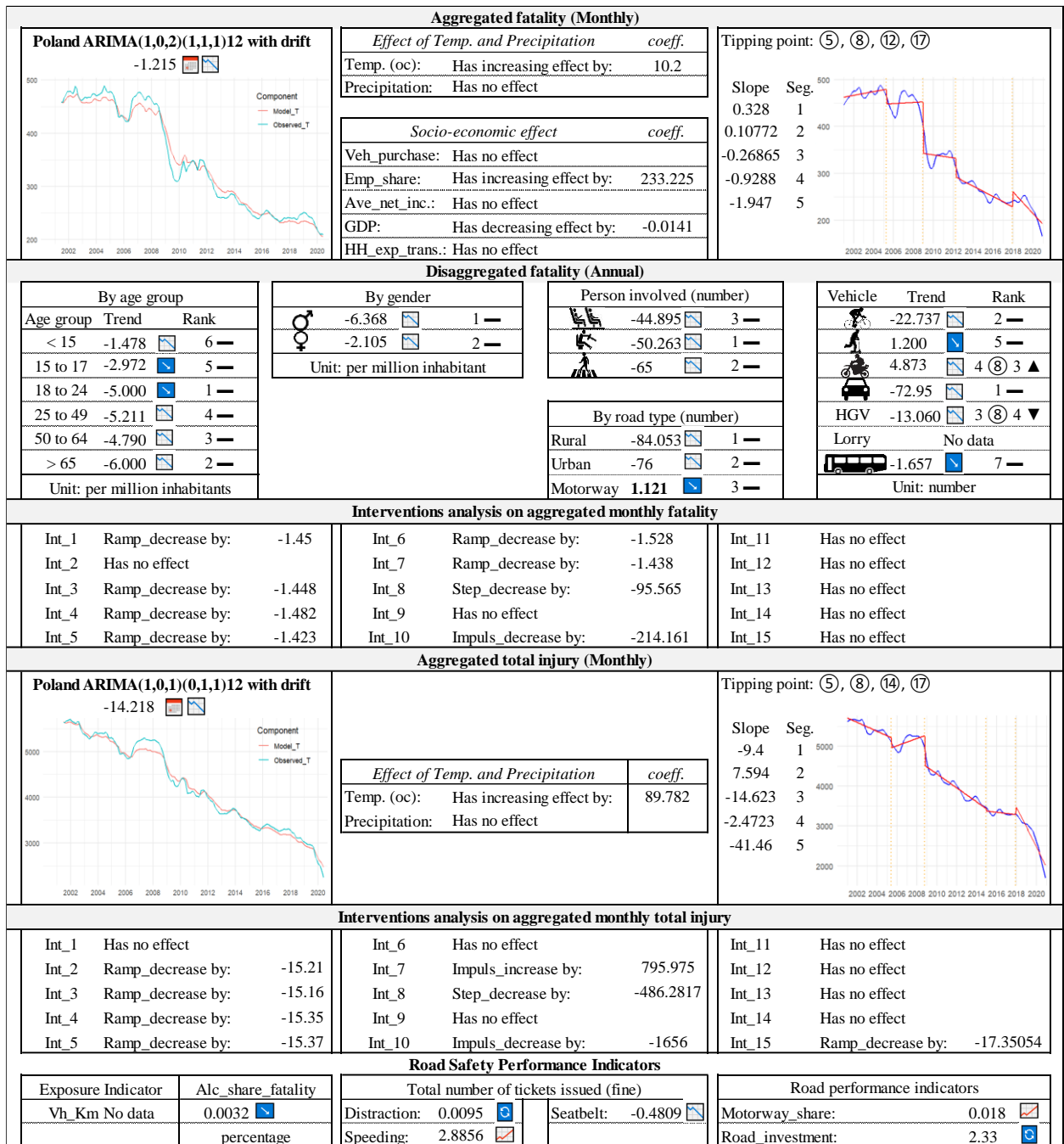


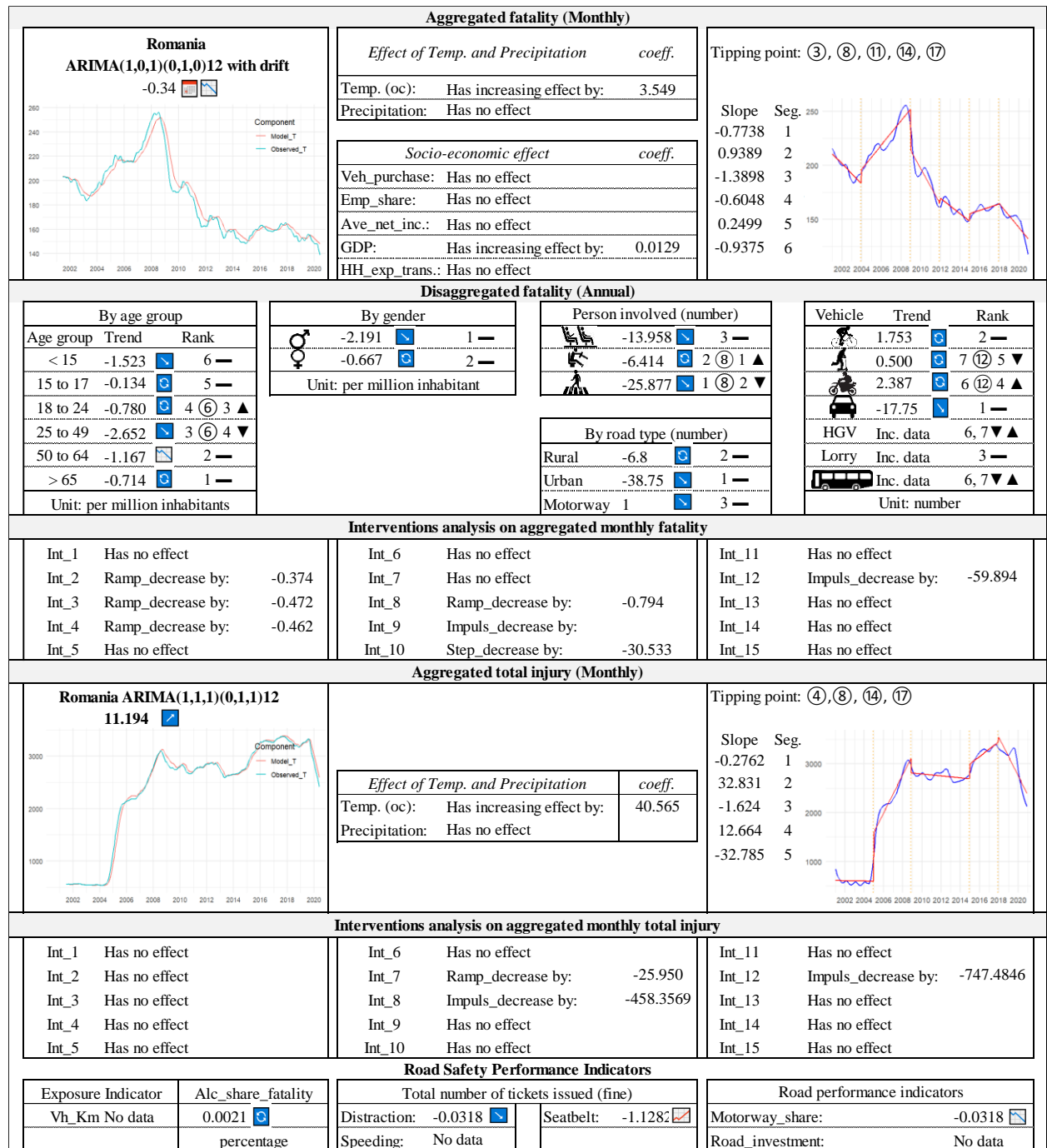


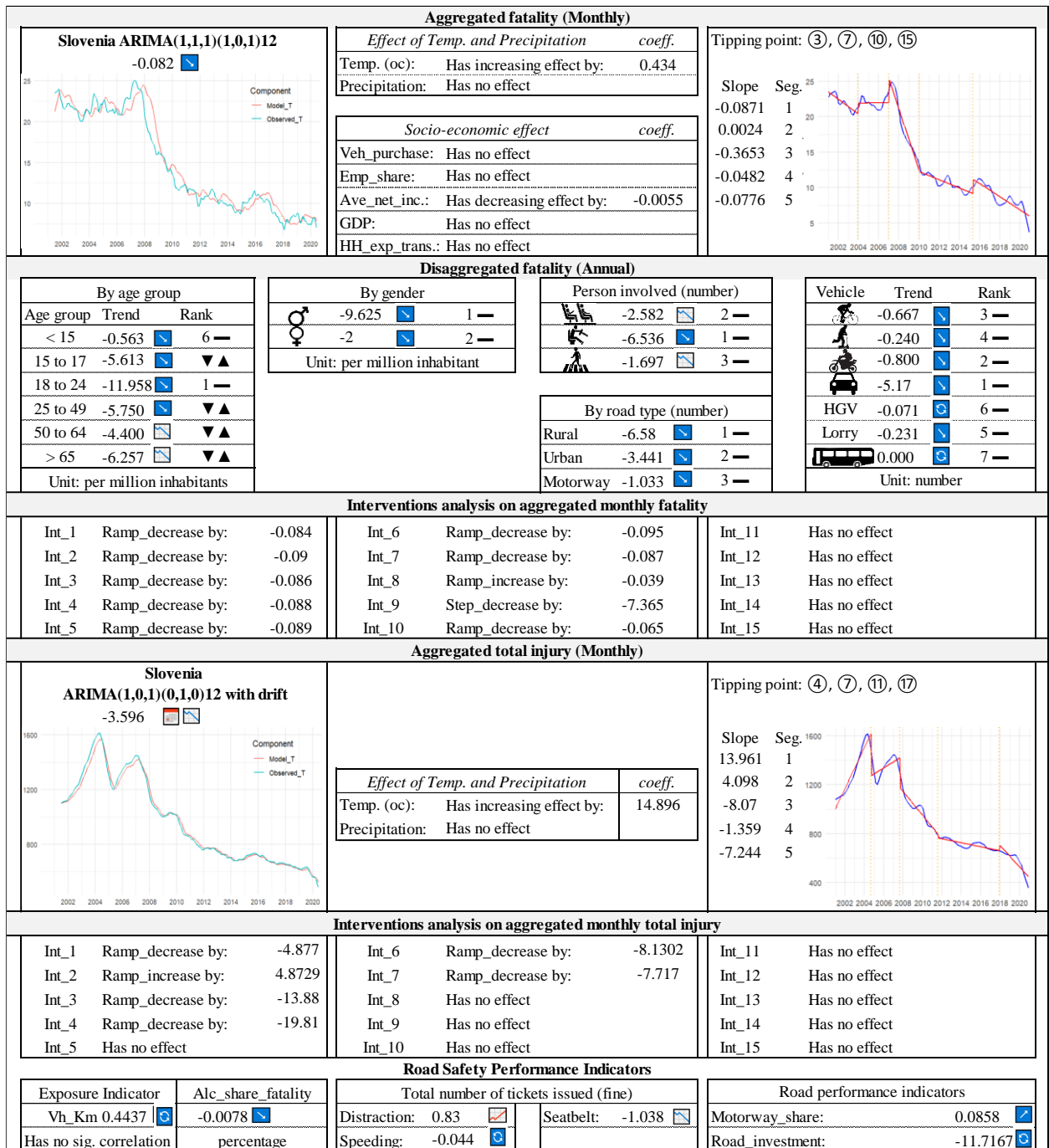


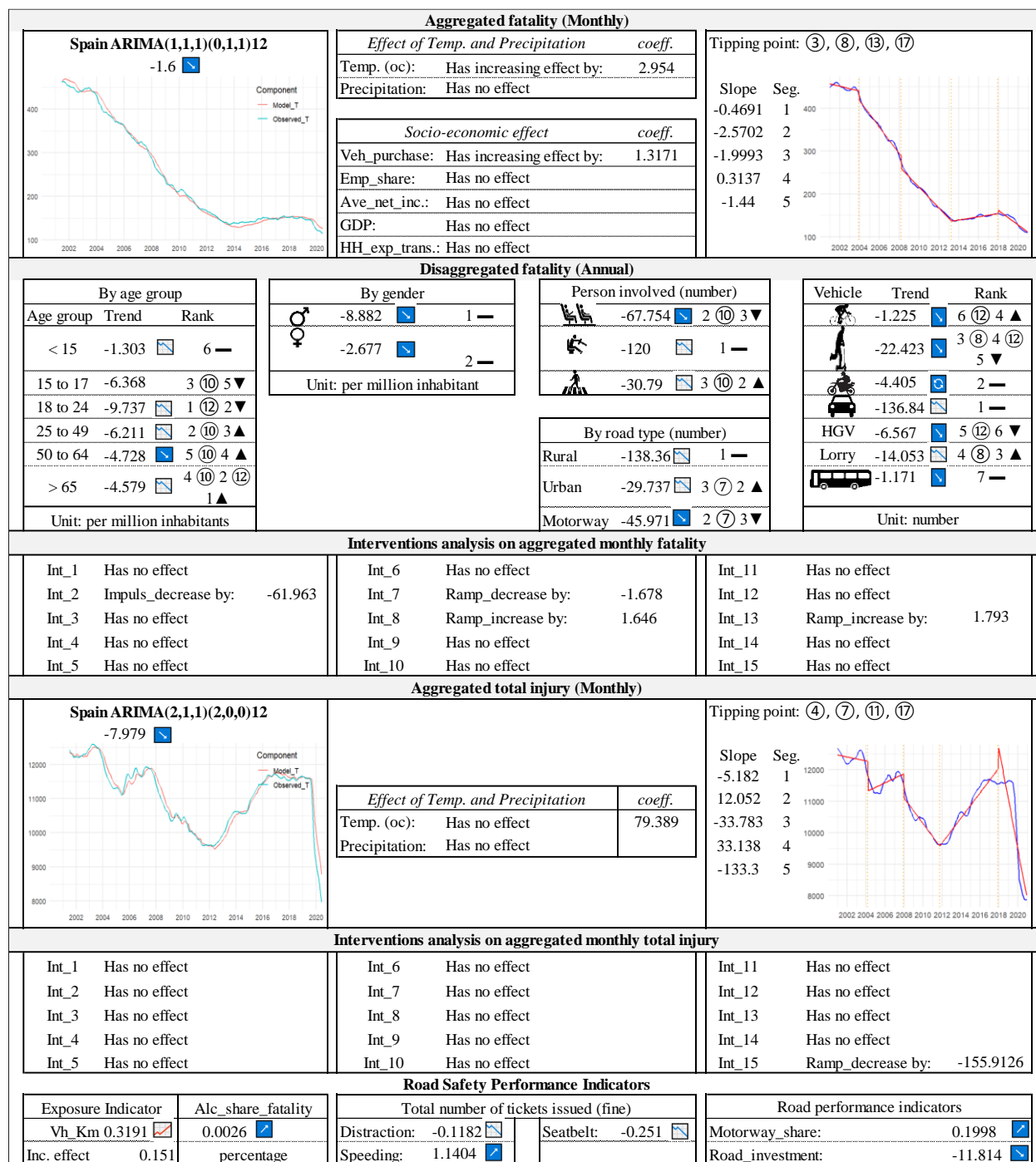


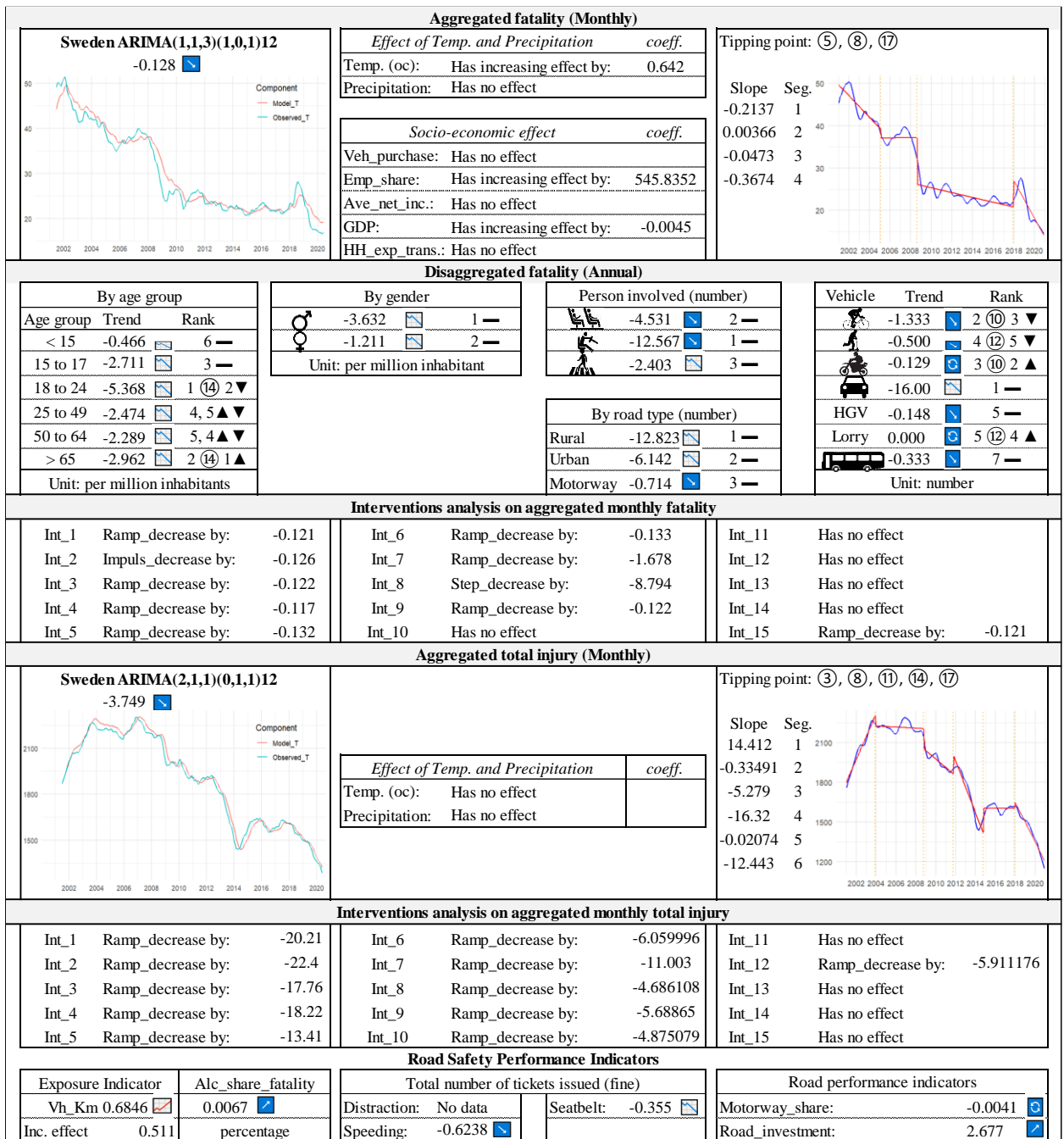












Appendix C. Code

C.1. Libraries Loaded

```
library(forecast)
library(tseries)
library(readxl)
library(trend)
library(openxlsx)
library(ggplot2)
library(dplyr)
library(reshape2)
library(strucchange)
library(lmtest)
```

C.2. R Code for Annual Road Safety Outcome and Performance Indicators:

```
#Load Necessary Libraries

# Load data
data <- read_xlsx(file.choose())
# Convert Date column to Date type
data$Date <- as.Date(data$ 'Date')
#Creat ts data type and check for stationarity
ts_data =ts(data $"Indicator", start = min(data $ 'Date'), frequency = 1)
sen's_slope = sens.slope(ts_data)
adf.test(ts_data)
acf(ts_data, main = 'Desired title')
pacf(ts_data, main = 'Desired title')

#Create base ts_Model using ARIMA and check for good fit
Base_model<- auto.arima(ts_data, approximation = FALSE, stepwise = FALSE)
kpss.test(Base_model$residuals)
acf(Base_model$residuals, main = 'Desired title')
pacf(Base_model$residuals, main = 'Desired title')
checkresiduals(Base_model)
coefstest(Base_model)
```

C.3. R Code for Monthly Road Safety Outcome Indicators:

```
#Load Necessary Libraries

# Load data
data <- read_xlsx(file.choose())
# Convert date column to date type
data$Date <- as.Date(data$ 'Date', format="%Y-%m-%d")
#Creat ts data type and check for stationarity
ts_data <- ts(data$ "Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
as.numeric(format(min(data$Date), "%m"))), frequency = 12)
adf.test(ts_data)
acf(ts_data, main = 'Desired title')
pacf(ts_data, main = 'Desired title')
# Decompose the ts
decomposed <- stl(ts_data, s.window = "periodic")
trend_component <- decomposed$time.series[, "trend"]
seasonal_component <- decomposed$time.series[, "seasonal"]
residual_component <- decomposed$time.series[, "remainder"]
# Plot the decomposed components
plot(decomposed)
```

```
# Box-plot
boxplot(ts_data ~ cycle(ts_data), main = 'Desired title' , xlab = 'Time (Month)', ylab= 'Indicator')
boxplot(ts_data ~ ts_data $Year, main = 'Desired title' , xlab = 'Time (Month)', ylab= 'Indicator')
#Create base ts_model using (S)ARIMA and check for good fit
Base_model<- auto.arima(ts_data, approximation = FALSE, stepwise = FALSE)
adf.test(Base_model$residuals)
acf(Base_model$residuals, main = 'Desired title')
pacf(Base_model$residuals, main = 'Desired title')
checkresiduals(Base_model)
coeftest(Base_model)
```

C.4. R Code for Exogenous Effect on Road Safety Outcome Indicators

```
#Load Necessary Libraries
```

```
# Load data, two type of data, one for the road safety outcome indicator and the other for the exogenous
variable
#Load road safety outcome indicator data
data <- read_xlsx(file.choose())
# Convert date column to date type
# For monthly data
data$Date <- as.Date(data$'Date', format="%Y-%m-%d")
#Creat ts data type and check for stationarity
ts_data <- ts(data$"Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
as.numeric(format(min(data$Date), "%m"))), frequency = 12)
#For annual data
data$Date <- as.Date(data$'Date', format="%Y-%m-%d")
#Creat ts data type and check for stationarity
ts_data <- ts(data$"Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
as.numeric(format(min(data$Date), "%m"))), frequency = 12)
#Load exogenous factor data
# Convert date column to date type
# For monthly data
Exo_data$Date <- as.Date(data$'Date', format="%Y-%m-%d")
#Creat exogenous ts data type
Exo_data_ts_data <- ts(Exo_data $"Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
as.numeric(format(min(data$Date), "%m"))), frequency = 12)
#For annual data
Exo_data $Date <- as.Date(data$'Date')
#Creat exogenous ts data type
Exo_data_ts_data <- ts(data$"Indicator", start = c(as.numeric(format(min(data$Date), "%Y"))))
#Creat Model with the exogenous factors and check for statinarity and good fit
Exogenous_Model = auto.arima(ts_data, xreg= Exo_data_ts_data, approximation= FALSE, stepwise = FALSE )
adf.test(Exogenous_Model $residuals)
coeftest(Exogenous_Model)
checkresiduals(Exogenous_Model)
```

C.5. R Code for Intervention Analysis

```
# Load necessary libraries

# Load data
data <- read_xlsx(file.choose())
# Convert Date column to Date type
data$Date <- as.Date(data$'Date', format="%Y-%m-%d")

# Create a time series object
ts_data <- ts(data$"Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
as.numeric(format(min(data$Date), "%m"))), frequency = 12)
# Fit the ARIMA base model to fit the time series data with intervention
```

```

Base_model<- auto.arima(ts_data, approximation = FALSE, stepwise = FALSE)
# Define intervention variables
Step <- as.numeric(as.yearmon(time(ts_data))) >= "Effective data")
Impuls = as.numeric(as.yearmon(time(ts_data)) == "Mar 2015")
Ramp = c(rep(0, Length_Before_Implementation), seq(1, Length_After_Implementation, 1))
Length_Before_Implementation = sum(step == 0)
Length_After_Implementation = length(ts_data) - Length_Before_Implementation
# Fit the model including the intervention
Model_with_Intervention=auto.arima(ts_data, xreg = cbind(step, impuls, ramp), approximation =
  FALSE,stepwise =FALSE)
# Fit the model without intervention for comparison
# Extract the ARIMA order, i.e., (p,d,q)(P,D,Q) from Model_with_Intervention and fit until the effective
  data
Model_with_Intervention_2= Arima(window(ts_data, end = c('Effective date')), order = c(p, d, q),seasonal
  = c(P, D, Q), include.drift = TRUE # if it exist in the model)
# Forecast without intervention
Model_Intervention_forecast = forecast(Model_with_Intervention_2, h = Length_After_Implementation)
# Convert forecasted data to time series object
Model_Intervention_forecast_ts = ts(as.numeric(Model_Intervention_forecast $mean), start = c('Effective
  date'), frequency = 12)
# Combine the time series for plotting
Models_ts = ts.union(ts_data, Model_Intervention_forecast_ts, fitted(Base_model))
colnames(ATfm_Total_ts_Int_14_2) <- c("Original_observation", "Forecast_no_intervention",
  "Fitted_with_intervention")

```

C.6. R Code for Tipping Points Analysis

```

# Load necessary packages

# Load data
data <- read_xlsx(file.choose())
# Convert Date column to Date type
data$Date <- as.Date(data$'Date', format="%Y-%m-%d")
# Create time series object
ts_data <- ts(data$"Indicator", start = c(as.numeric(format(min(data$Date), "%Y")),
  as.numeric(format(min(data$Date), "%m"))), frequency = 12)
# Decompose the time series
decomposed <- stl(ts_data, s.window = "periodic")
trend_component <- decomposed$time.series[, "trend"]
seasonal_component <- decomposed$time.series[, "seasonal"]
residual_component <- decomposed$time.series[, "remainder"]
# Prepare data for modeling
trend_data <- 1:length(trend_component)
data_frame <- data.frame(Time = trend_data, Trend = trend_component)
# Perform breakpoint analysis to identify initial breakpoints
bp <- breakpoints(trend_component ~ trend_data)
initial_breaks <- bp$breakpoints
# Perform piecewise regression with breakpoints
bp_model <- breakpoints(bp, breaks = length(bp$breakpoints))
fm1 <- lm(trend_component ~ breakfactor(bp_model) / (time(trend_component)) - 1)

```

References

- Achim, Z., Friedrich, L., Kurt, H., Christian, K., Bruce, H., Edgar C., M., & Nikolaus, U. (2022). *strucchange: Testing, Monitoring, and Dating Structural Changes*. <https://doi.org/10.32614/CRAN.package.strucchange>
- Adminaité-Fodor, D., Carson, J., & Jost, G. (2021). *Ranking EU Progress on Road Safety 15 th Road Safety Performance Index Report* (Issue June). www.etsc.eu/pin
- Antoniou, C., Papadimitriou, E., & Yannis, G. (2014). Road Safety Forecasts in Five European Countries Using Structural Time Series Models. *Traffic Injury Prevention*, 15(6), 598–605. <https://doi.org/10.1080/15389588.2013.854884>
- Antov, D., Banet, A., Barbier, C., Bellet, T., Bimpeh, Y., Boulanger, A., Brandstätter, C., Britschgi, V., Brosnan, M., Buttler, I., Cestac, J., De Craen, S., Delhomme, P., Dogan, E., Drápela, E., Forward, S., Freeman, R., Furian, G., Gábor, M., ... Zavrides, N. (2012). European road users' risk perception and mobility. The SARTRE 4 survey. *SARTRE 4 Report*, 1–496. https://www.ec.europa.eu/transport/road_safety/sites/roadsafety/files/ppdf/projects/sartre_4.pdf
- Apuke, O. D. (2017). Quantitative Research Methods : A Synopsis Approach. *Kuwait Chapter of Arabian Journal of Business and Management Review*, 6(11), 40–47. <https://doi.org/10.12816/0040336>
- Balasmeh, O. Al, Babbar, R., & Karmaker, T. (2019). *Trend analysis and ARIMA modeling for forecasting precipitation pattern in Wadi Shueib catchment area in Jordan*. *Trend analysis and ARIMA modeling for forecasting precipitation pattern in Wadi Shueib catchment area in Jordan*. January. <https://doi.org/10.1007/s12517-018-4205-z>
- Beaulieu, C., Chen, J., & Sarmiento, J. L. (2012). Change-point analysis as a tool to detect abrupt climate variations. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 370(1962), 1228–1249. <https://doi.org/10.1098/rsta.2011.0383>
- Bergel-Hayat, R., & Zukowska, J. (2015). Road Safety Trends at National Level in Europe: A Review of Time-series Analysis Performed during the Period 2000–12. *Transport Reviews*, 35(5), 650–671. <https://doi.org/10.1080/01441647.2015.1030005>
- Bierens, H. J. (1987). Armax model specification testing, with an application to unemployment in the Netherlands. *Journal of Econometrics*, 35(1), 161–190. [https://doi.org/10.1016/0304-4076\(87\)90086-8](https://doi.org/10.1016/0304-4076(87)90086-8)
- Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2016). *Time Series Analysis: Forecasting and Control* (5th ed.). John Wiley & Sons, Inc., Hoboken,.
- Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association*, 70(349), 70–79. <https://doi.org/10.1080/01621459.1975.10480264>
- CARE Team. (2023). *Directorate-General for Mobility and Transport CARE DATABASE*. September, 1–134.
- Carson, J., Jost, G., & Meirino, M. (2023). *Ranking EU Progress on Road Safety 17 th Road Safety Performance Index Report* (Issue June). https://etsc.eu/wp-content/uploads/16-PIN-annual-report_FINAL_WEB_1506_2.pdf
- Castillo-Manzano, J. I., Castro-Nuño, M., & Fageda, X. (2014). Could being in the European Union save lives? An econometric analysis of the Common Road Safety Policy for the EU-27. *Journal of European Public Policy*, 21(2), 211–229. <https://doi.org/10.1080/13501763.2013.829580>
- Chandler, R. E., & Scott, E. M. (2011). *Statistical Methods for Trend Detection and Analysis in the Environmental Sciences* (1st ed.). John Wiley & Sons, Ltd., <https://doi.org/10.1002/9781119991571>
- Chang, K., Schultz, M. G., Koren, G., & Selke, N. (2023). *Guidance note on best statistical practices for TOAR analyses*.
- Chatfield, C. (2003). The Analysis of Time Series. *The Analysis of Time Series*. <https://doi.org/10.4324/9780203491683>
- Chatfield, C., & Xing, H. (2019). *The Analysis of Time Series: an Introduction with R* (Seventh). Chapman & Hall/CRC. <https://doi.org/10.1201/9781351259446>
- Chen, C. W. S., Jennifer, S.K., C., Gerlach, R., & Hsieh, W. Y. L. (2011). A comparison of estimators for regression models with change points. In *Statistics and Computing* (Vol. 21, Issue 3). <https://doi.org/10.1007/s11222-010-9177-0>
- Chukwutoo C., I., & Uchendu O., O. (2018). Road traffic accidents prediction modelling: An analysis of Anambra State, Nigeria. *Accident Analysis and Prevention*, 112, 21–29. <https://doi.org/10.1016/j.aap.2017.12.016>
- Commandeur, J. J. F., Bijleveld, F. D., Bergel-Hayat, R., Antoniou, C., Yannis, G., & Papadimitriou, E. (2013). On statistical inference in time series analysis of the evolution of road safety. *Accident Analysis and Prevention*, 60, 424–434. <https://doi.org/10.1016/j.aap.2012.11.006>
- Council of the European Union. (1993). Council decision on the creation of a community database on road accidents (93/704/EC). *Official Journal of the European Communities*, L, 1991–1993. <https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:31993D0704&from=IT>
- Cryer, J. D., & Chan, K.-S. (2008). *Time series analysis: with applications in R* (G. Casella, S. Fienberg, & I. Olkin (eds.); 2nd ed.). Springer.
- Dailys M.A., R., Renata M.C.R., de S., & Adriano L.I., de O. (2022). A three-stage approach for modeling multiple time series applied to symbolic quartile data. *Expert Systems with Applications*, 187(June 2020). <https://doi.org/10.1016/j.eswa.2021.115884>
- Davide, P., & Debyser, A. (2023). Road traffic and safety Provisions. In *Fact Sheets on the European Union*. www.europarl.europa.eu/factsheets/en
- Dupont, E., & Martensen, H. (2007). Multilevel modelling and time series analysis in traffic safety research – Methodology. Deliverable D7.4 of the EU FP6 project SafetyNet. In *Transport*.
- European Commission. (2001). *European transport policy for 2010: time to decide* (Issue 2001). [https://doi.org/COM\(2001\)](https://doi.org/COM(2001))
- European Commission. (2004). *COST Action 329: Models for traffic and safety development and interventions Final report*.

- European Commission. (2007). *Best Practices in Road Safety: Handbook for Measures at the European Level*.
- European Commission. (2010). Best Practices: Handbook for measures at the country level. In *Business and Luxembourg: Publications Office of the European Union* (Vol. 67, Issue 1). <https://doi.org/10.2832/16225>
- European Commission. (2011). *White Paper, Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system*. [https://doi.org/COM\(2011\) 144 final](https://doi.org/COM(2011) 144 final)
- European Commission. (2015a). *Interim evaluation of the Policy orientations on road safety 2011-2020*.
- European Commission. (2015b). *Road safety study for the interim evaluation of Policy Orientations on Road Safety 2011-2020* (Issue February 2015). https://ec.europa.eu/transport/road_safety/sites/%0Aroadsafety/files/pdf/interim_eval_2011_2020/interim_eval.pdf
- European Commission. (2017). Annual Accident Report 2017. In *European Road Safety Observation*. https://ec.europa.eu/transport/road_safety/sites/roadsafety/files/pdf/statistics/dacota/asr2018.pdf
- European Commission. (2018a). *Advanced driver assistance systems*.
- European Commission. (2018b). *Monitoring Road Safety in the EU: towards a comprehensive set of Safety Performance Indicators*.
- European Commission. (2018c). *Monitoring Road Safety in the EU: towards a comprehensive set of Safety Performance Indicators*. In *European Road Safety Observation*.
- European Commission. (2018d). *Road Safety in the European Union: Trends, statistics and main challenges* (Vol. 29, Issue 3). <https://doi.org/10.2832/169706>
- European Commission. (2019a). EU Road Safety Policy Framework 2021-2030. Commission Staff Working Paper. SWD(2019) 283 Final COMMISSION, 2019, 1–17. https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/
- European Commission. (2019b). *Road safety : Data show improvements in 2018 but further concrete and swift. April 2019, 2017–2019*. http://europa.eu/rapid/press-release_IP-19-%0A1951_en.htm
- European Commission. (2020). *EU Road Safety Policy Framework 2021-2030: Next steps towards 'Vision Zero . '* <https://doi.org/10.2832/261629>
- European Commission. (2022). *European Road Safety Thematic Report - Road Safety Performance Indicators (RSPIs)*.
- European Commission. (2024). *Road safety thematic report – Main factors causing fatal crashes*.
- European Court of Auditors. (2024). *Reaching EU road safety objectives*.
- European Transport Safety Council. (2001). *Transport Safety Performance Indicators*. http://etsc.eu/wp-content/uploads/2003_transport_safety_stats_eu_overview.pdf
- Gibrilla, A., Anornu, G., & Adomako, D. (2017). Trend analysis and ARIMA modelling of recent groundwater levels in the White Volta River basin. *Groundwater for Sustainable Development*. <https://doi.org/10.1016/j.gsd.2017.12.006>
- Gitelman, V., Vis, M., Weijermars, W., & Hakkert, S. (2014). Development of Road Safety Performance Indicators for the European Countries. *Advances in Social Sciences Research Journal*, 1(4), 138–158. <https://doi.org/10.14738/assrj.14.302>
- Hagenzieker, M. P., Commandeur, J. J. F., & Bijleveld, F. D. (2014). The history of road safety research: A quantitative approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25(PART B), 150–162. <https://doi.org/10.1016/j.trf.2013.10.004>
- Hakkert, A. S., & Gitelman, V. (2014). Thinking about the history of road safety research: Past achievements and future challenges. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25(PART B), 137–149. <https://doi.org/10.1016/j.trf.2014.02.005>
- Harvey, A. C., & Durbin, J. (1986). The Effects of Seat Belt Legislation on British Road Casualties : A Case Study in Structural Time Series Modelling. *Journal of the Royal Statistical Society*, 149(3), 187–227.
- Hermans, E., Brijis, T., Wets, G., & Vanhoof, K. (2009). Benchmarking road safety: Lessons to learn from a data envelopment analysis. *Accident Analysis and Prevention*, 41(1), 174–182. <https://doi.org/10.1016/j.aap.2008.10.010>
- Hermans, E., Wets, G., & Van den Bossche, F. (2006). Describing the evolution in the number of highway deaths by decomposition in exposure, accident risk, and fatality risk. *Transportation Research Record*, 1950, 1–8. <https://doi.org/10.3141/1950-01>
- Hermans, E., Wets, G., & Van den Bossche, F. (2007). The frequency and severity of road traffic accidents investigated on the basis of state space methods. *Journal of Transport Statistics*, 9(1), 63–76. <http://www.mendeley.com/research/association-european-transport-contributors-2009-1/>
- Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., Kuroptev, K., & O'Hara-Wild, M. (2024). *Package 'forecast . '* <https://pkg.robjhyndman.com/forecast/>, <https://github.com/robjhyndman/forecast%0AVignetteBuilder>
- Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: principles and practice* (3rd ed.). OTexts. <https://otexts.com/fpp3/>
- Hyndman, R. J., & Khandakar, Y. (2008). Automatic Time Series Forecasting: The forecast Package for R. *Journal of Statistical Software*, 27(3), 22. <https://doi.org/10.18637/jss.v027.i03>
- Institute for Road Safety Research. (2013). SWOV Fact sheet Time series analysis. In *Institute for Road Safety Research* (Issue August).
- ITF. (2023). Using Safety Performance Indicators to Improve Road Safety: The Case of Korea. In *International Transport Forum Policy Papers* (Vol. 126). <https://doi.org/https://doi.org/10.1787/d35f8e67-en>
- Jameel, A. K., & Evdorides, H. T. (2023). Review of Modifying the Indicators of Road Safety System. *Journal of Engineering and Sustainable Development*, 27(2), 149–170. <https://doi.org/10.31272/jeasd.27.2.1>
- Karlis, D., & Hermans, E. (2012). *Time Series Models for Road Safety Accident Prediction*. <http://www.steunpuntverkeersveiligheid.be/sites/default/files/RA-MOW-2011-020.pdf>

- Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54, 159–178. [https://doi.org/10.1016/0304-4076\(92\)90104-Y](https://doi.org/10.1016/0304-4076(92)90104-Y)
- Lavrenz, S. M., Vlahogianni, E. I., Gkritza, K., & Ke, Y. (2017). Time series modeling in traffic safety research. *Accident Analysis and Prevention*, 117(November), 368–380. <https://doi.org/10.1016/j.aap.2017.11.030>
- Lin Ya, C., Dan Jeric, A. R., Chen Yi, L., & Ta Te, L. (2019). Modelling and Forecasting of Greenhouse Whitefly Incidence Using Time-Series and ARIMAX Analysis. *International Federation of Automatic Control*, 52(30), 196–201. <https://doi.org/10.1016/j.ifacol.2019.12.521>
- Meesmann, U., Wardenier, N., Torfs, K., Pires, C., Delannoy, S., & Van den Berghe, W. (2022). A global look at road safety. *Synthesis from the ESRA2 survey in 48 countries. ESRA project (E-Survey of Road users' Attitudes)*.
- Michalaki, P., Quddus, M., Pitfield, D., & Huetson, A. (2016). A time-series analysis of motorway collisions in England considering road infrastructure, socio-demographics, traffic and weather characteristics. *Journal of Transport and Health*, 3(1), 9–20. <https://doi.org/10.1016/j.jth.2015.10.005>
- Mikkonen, V., Peltola, H., & Group OECD Scientific Expert. (1997). *Road Safety Principles and Models: Review of Descriptive, Predictive, Risk and Accident Consequence Models* (Issue 97).
- Mills, T. C. (2019). Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting. In *Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting*. Candice Janco. <https://doi.org/10.1016/C2016-0-03956-6>
- Qiong, B., Zegang, Z., & Yongjun, S. (2022). Assessing Road Safety Development in European Countries: A Cross-Year Comparative Analysis of a Safety Performance Index. *Appl.Sci.*, 12(9813). <https://doi.org/10.3390/app12199813>
- Safarpour, H., Khorasani-Zavareh, D., Soori, H., Bagheri-Lankarani, K., Ghomian, Z., & Mohammadi, R. (2020). Vision Zero: Evolution History and Developing Trend in Road Safety: A Scoping Review. *Trauma Monthly*, 25(6), 275–286. <https://doi.org/10.30491/TM.2020.244740.1166>
- Said E., S., & David A., D. (1984). Testing for unit roots in autoregressive-moving average models of unknown order. *Biometrika*, 71(3), 599–607. <https://doi.org/10.1093/biomet/71.3.599>
- SARTRE 3 consortium. (2004). *European drivers and road risk*.
- Sen, P. K. (1968). *Estimates of the Regression Coefficient Based on Kendall's Tau*. 63(324), 1379–1389.
- Sharma, S., Swayne, D. A., Obimbo, C., & Ess, L. O. W. (2016). Trend analysis and change point techniques : a survey. *Energy, Ecology and Environment*, 1(3), 123–130. <https://doi.org/10.1007/s40974-016-0011-1>
- Shumway, R. H., & Stoffer, D. S. (2017). *Time Series Analysis and Its Applications: With R Examples*. (4th ed.). Springer.
- Silverans, P., & Vanhone, S. (2023). *Baseline conclusions and recommendations. Baseline project* (Issue January). https://road-safety.transport.ec.europa.eu/system/files/2023-03/Baseline_conclusions_and_recommendations.pdf
- The Swedish Transport Administration. (2018). *Analysis of road safety trends 2017. Management by objectives for road safety work towards the 2020 interim targets*.
- Theodor D., P. (2020). Time series analysis for assessing and forecasting of road traffic accidents - Case studies. *WSEAS Transactions on Mathematics*, 19(April), 177–185. <https://doi.org/10.37394/23206.2020.19.17>
- Tomašković, M., & Završki, I. (2024). Analysis of the road safety in the EU countries and the impact of PBM on its improvement. *Organization, Technology and Management in Construction*, 16(1), 123–135. <https://doi.org/10.2478/otmcj-2024-0010>
- Uyodhu Ameakauma, V.-E., & Isaac Didi, E. (2016). Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX) Model for Nigerian Non Oil Export. *European Journal of Business and Management*, 8(36), 29–34.
- Van den Bossche, F., Wets, G., & Brijs, T. (2004). A regression model with ARMA errors to investigate the frequency and severity of road traffic accidents. *83rd Annual Meeting of the Transportation Research Board*, 32(0), 15. www.vti.se/publications
- Walter, E. (1995). Applied Econometric Time Series. In *Technometrics*. John Wiley & Sons, Inc. <https://doi.org/10.1080/00401706.1995.10484400>
- Wandee, W., & Bright Emmanuel, O. (2020). Optimal time series model for forecasting monthly temperature in the southwestern region of Thailand. *Modeling Earth Systems and Environment*, 6(1), 525–532. <https://doi.org/10.1007/s40808-019-00698-5>
- Wang, X., Smith, K., & Hyndman, R. (2006). Characteristic-based clustering for time series data. *Data Mining and Knowledge Discovery*, 13(3), 335–364. <https://doi.org/10.1007/s10618-005-0039-x>
- Wayne A., F. (1996). Introduction to Statistical Time Series. In *Universitas Nusantara PGRI Kediri* (2nd ed., Vol. 01). John Wiley & Sons, Inc.
- Wegman, F. (2016). Road safety data collection, analysis, indicators and targets. *Halving the Number of Road Deaths in Korea, June*, 83–102.
- Wiklund, M., Simonsson, L., & Forsman, Å. (2012). *Traffic safety and economic fluctuation. Long-term and short-term analyses and a literature survey*. 32. www.vti.se/publications
- Wiratama, B. S., Chen, P., Chen, L., Saleh, W., Chen, S., Chen, H., Lin, H., & Pai, C. (2021). *Evaluating the Effects of Holidays on Road Crash Injuries in the United Kingdom*.
- World Health Organization. (2023). *Global status report on road safety*. <https://doi.org/10.1136/ip.2009.023697>
- Yannis, G., Papadimitriou, E., & Folla, K. (2014). Effect of GDP changes on road traffic fatalities. *Safety Science*, 63, 42–49. <https://doi.org/10.1016/j.ssci.2013.10.017>
- Zeileis, A., Leisch, F., Homik, K., & Kleiber, C. (2002). strucchange: An R Package for Testing for Structural Change. *Journal of Statistical Software*, 7(2), 1–38.