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Ex-Post Evaluation of Road Safety Regulations in Belgium Using Causal Inference Methods

Assessing the Impact of the EU Cross Border Enforcement Directive and the 2022 Road Code Reform for Motorized Personal Mobility Devices

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Summary

This report examines two use cases to explore the application of casual inference models in the context of road safety. Policy interventions are introduced with the expectation that they will improve road safety outcomes or influence behaviour in a targeted way, such as reducing driving speeds. The reasoning behind such policy interventions rests on assumed cause-effect relationships. By introducing these interventions, a change in outcomes (e.g. number of crashes) will be effected (or caused).

Ex-post evaluation therefore aims to assess whether observed changes can truly be attributed to the intervention itself. However, simple before/after comparisons often fail to capture the causal effect though they are easy to apply. Changes in outcomes may occur for reasons unrelated to the intervention, such as natural fluctuations over time, mobility trends, seasonal effects, or changes in exposure. When these factors are not taken into account, a change in the outcomes may simply coincide with the intervention rather than be caused by it. This is a well-known principle that correlation does not necessarily imply causation.

Causal inference methods address this challenge by explicitly estimating or constructing a counterfactual (what would have happened in the absence of the intervention). By comparing this counterfactual with the observed outcome, these methods aim to isolate the causal effect of the intervention (which is called as treatment) and provide decision-makers with more reliable evidence on the impacts of policy measures on road safety outcomes.

EU Cross Border Enforcement (CBE Directive)

The first use case evaluates the impact of the EU Cross Border Enforcement (CBE) Directive implemented in Belgium in May 2015 on road safety outcomes involving foreign registered vehicles. The CBE Directive enables EU countries to share vehicle and driver information to enforce road safety traffic violations (like speeding, drunk-driving, phone use) committed by non-resident drivers. The analysis draws on a detailed panel dataset of all police recorded crashes from May 2012 to April 2018, supplemented with monthly weather indicators. By comparing trends for Belgian registered and foreign registered vehicles before and after the CBE Directive was introduced, the study analyses whether improved cross border enforcement led to measurable changes in road safety outcomes.

Although foreign registered vehicles account for only a small share of crashes in Belgium, they might differ from Belgian registered vehicles in important ways, including travel patterns, seasonal mobility, and underlying crash risk. The descriptive evidence shows clear seasonal variation and distinct crash patterns between two groups. To help account for these differences, the study relies on a difference-in-differences (DiD) approach that focuses on comparing foreign and Belgian crash involvement over time. The main specification employs a saturated fixed-effects model comparing number of crashes within same province and month, complemented by models based on the share of crashes involving foreign registered vehicles. We conduct a series of robustness checks, including pre-intervention trend analysis, event-study models, and placebo tests. These checks support the validity of DiD approach, even though baseline crash levels differ between two groups.

After controlling for provincial and monthly fixed effects, temperature, precipitation, and seasonal mobility cycles, the results indicate that the CBE Directive significantly improved road safety outcomes. The CBE Directive is associated with a reduction of approximately 0.5 percentage points in the share of crashes involving foreign registered vehicles, relative to Belgian registered vehicles using complementary share-based model. The main specification suggests an approximate 5% decline following May 2015, corresponding to a decline from approximate 9% to about 8.5% of crashes involving foreign registered vehicles. Although this magnitude might seem modest, the direction of the effect is in line with the objective of the CBE Directive. When the estimate is extrapolated nationwide using average crash counts per province before the implementation of the policy, this reduction corresponds to 130-150 fewer crashes per year involving foreign registered vehicles. Taking statistical uncertainty into account, the 95% confidence interval suggests that this reduction would range approximately between 20 and 250 crashes per year. This reduction varies across provinces, ranging from about 2-6 crashes per year in less densely populated provinces such as Luxembourg and Namur to more than 20 crashes per year in provinces with higher density such as Antwerp and East Flanders.

Therefore, the results show that the CBE Directive produced clear, measurable, and statistically significant road safety improvements, even if the magnitude of the effect is small. The Directive reduced the enforcement gap that previously allowed foreign registered offenders to evade sanctions, and this increase in enforcement certainty appears to have influenced driver behaviour.

PMDs regulation

The second empirical investigation examines the July 2022 reform governing e-scooter use in Belgium, which introduced age restrictions, clarified rules for riding and parking, and restricted e-scooter circulation in pedestrian areas. Using an interrupted time-series design with extensive placebo testing, the analysis reveals a sharp and immediate decline in monthly victims following the reform, suggesting that the policy successfully altered mobility conditions in a way that reduced injury risk. However, the underlying long-term trend in e-scooter casualties, which is driven by broader adoption of micromobility, remains upward, indicating that the reform mitigated but did not reverse or reduce the overall increase. The reduction in shared e-scooter usage observed after the reform is consistent with part of the safety improvement arising from reduced exposure rather than solely behaviour change. These findings illustrate that targeted behavioural regulations can deliver rapid safety gains, but sustained improvements depend on infrastructure design, user practices, and longer-term mobility patterns.

Overall, the report demonstrates the value of causal inference methods which is supported by extensive pre-trend diagnostics and robustness checks in evaluating road safety policies. The findings suggest that continued improvements in cross border enforcement, combined with targeted communication strategies, and coordinated safety initiatives across Member States, are likely to yield further safety gains. At the same time, the results from the e-scooter reform underline that behavioural policies can produce rapid changes but must be supported by safe infrastructure and ongoing monitoring. Strengthening the integration of crash, victim, enforcement, and exposure data across domains would further enhance Belgium's capacity to implement and evaluate effective road safety interventions.

1 Introduction

Improving road safety remains a central priority for both the European Union and Belgium. Although substantial progress has been made over recent decades, recent years have witnessed slower declines in fatalities and the emergence of new challenges linked to evolving mobility patterns. The rapid growth of novel modes such as shared e-scooters, as well as persistent enforcement gaps linked to international traffic flows, underline the need for evidence-based regulatory responses. Policymakers increasingly require not only ex-ante assessments of proposed measures but also robust ex-post evaluations that determine whether implemented regulations achieve their intended effects in real-world conditions. This emphasis is consistent with recent global road safety monitoring, which highlights that progress has slowed in many settings and that sustained, evidence-based interventions remain necessary (WHO, 2023).

Evaluating the impact of regulations is inherently challenging. Road crashes are rare and highly stochastic events, shaped by a complex combination of behavioural, environmental and structural factors, including weather, road use patterns, vehicle technologies, demographic trends, and the intensity of enforcement. Traditional before/after comparisons cannot distinguish whether observed changes are caused by the intervention or by other factors. For example, (Auerbach et al., 2019) show that a before/after analysis of New York City's Vision Zero policy overestimated its effect, and that they find that the more realistic estimate was only two-thirds the size of the initially reported reduction when accounting for external factors using causal analysis. As widely recognized in the road safety literature, credible evaluation requires causal inference methods capable of accounting for seasonality, regression to the mean¹ and other confounding factors that can obscure the true impact of a regulatory change.

This report applies two causal inference designs which are difference-in-differences (DiD) and interrupted time series (ITS) to evaluate the effects of two road safety regulations relevant to Belgium. The first use case examines the impact of the EU Cross Border Enforcement (CBE) Directive, established under Directive (EU) 2015/413, which facilitates the cross border exchange of vehicle registration data for the follow-up of road safety related traffic offences. Automated enforcement systems and police checks identify violations through license plate recognition, meaning that authorities can immediately observe the country in which the vehicle is registered. Prior to the Directive, fines issued to vehicles registered abroad were less likely to be successfully delivered or recovered, resulting in lower sanction certainty for foreign registered vehicles compared with Belgian registered vehicles. To assess whether the Directive influenced road safety outcomes, this report compares the evolution of crashes involving at least one foreign registered vehicle relative to Belgian registered vehicles, applying a DiD design that aligns with established enforcement research. The main specification compares crash counts within same province and month using a saturated fixed-effects structure, complemented by models based on the share of crashes involving foreign registered vehicles. DiD is widely used in causal inference analysis of regulations and is considered a robust quasi-experimental approach when suitable control groups are available and pre-intervention trends are comparable (see Section 2.2 for a definition and discussion of quasi-experimental methods). Previous studies have consistently shown that the certainty of sanction, rather than its severity, is a key determinant of compliance with traffic laws (Bailey & Smith, 1973; Blais & Carnis, 2015; Kudła et al., 2024; Kundro et al., 2023). As the CBE Directive increases the chances that a fine actually reaches the driver, the evaluation should allow us to detect an effect.

The second use case evaluates the 2022 reform of the Belgian Road Code for motorized personal mobility devices (PMDs), including e-scooters. The reform introduced clearer PMD classifications, reclassified e-scooter users as cyclists, established a minimum age requirement and restricted riding on pavements to improve pedestrian safety (Mobilité et Transports, 2022). These measures were introduced in response to a rapid rise in PMD-related injuries, increasing interactions between riders and pedestrians and the operational growth of shared e-scooter fleets (Chambre des Représentants de Belgique, 2021; Sloomans, 2024). Using detailed monthly data on e-scooter injury victims, the evaluation applies an ITS model to assess whether the reform produced measurable changes in injury levels or trends. ITS is widely used in the road safety literature and is considered as a robust quasi-experimental approach for evaluating national level legal reforms, as it captures both immediate and longer-term effects while controlling for trends and seasonality.

Hence, these two analyses illustrate how causal inference can strengthen Belgium's regulatory cycle by providing transparent, data driven evidence on the real-world impacts of road safety regulations. The report

¹ **Regression to the mean:** Statistical phenomenon where, if the measurement of a random variable is extreme (i.e. very high or low), the next measurement of the same random variable is likely to be closer to its mean (Upton & Cook, 2011).

combines legal context, empirical data and rigorous statistical methods to support policymakers in developing and refining effective road safety policy.

The rest of this report is organized as follows: Section 2 covers the theoretical foundation of causal inference by means of a literature review. Section 3 covers the use case where we study the impact of the CBE Directive on road safety outcomes, followed by Section 4 which contains the use case where we study the effect of reform on PMDs on road safety outcomes. Conclusions and recommendation are presented in Section 5.

2 Literature Review

Evaluating the real-world impacts of road safety regulations requires methodology capable of distinguishing policy effects from the wide range of external factors that influence crash and injury outcomes. Road safety outcomes are shaped by behavioural, demographic, environmental, technological and structural factors. Extensive literature shows that weather conditions and seasonal patterns, mobility behaviour and demographic shifts, vehicle fleet composition and technological developments, as well as variation in enforcement intensity all contribute to observed crash patterns within road safety (Blais & Dupont, 2005; Elvik, 2009, 2012; Evans, 2004; Lie & Tingvall, 2002; OECD/ITF, 2018; Qiu & Nixon, 2008; Wegman & Aarts, 2006; World Health Organization, 2019). These forces generate natural fluctuations that complicate the identification of causal relationships. This has led to a growing interest in causal inference to estimate what would have occurred had the intervention not been implemented which is the counterfactual at the centre of any meaningful policy evaluation. Detailed review can be found in section 2.3.

Before reviewing the studies that apply causal inference, we first briefly explain what causal inference is and outline the counterfactual framework. We then present and describe the main causal inference methods. In the last subsection, we discuss the use of causal inference methods in road safety research.

2.1 Causal Inference and the Counterfactual Framework

Ex-post analysis is done after a decision is made and implemented. It enables decision-makers to estimate the effects caused by an intervention, rather than simply relying on the absolute difference in outcomes before and after the intervention, in which many external factors can play a role. It can also shed light on whether the impacts of the intervention were as expected, and provide explanation for why there was any variation from expectations (Angrist & Pischke, 2009; Meyer, 1995; Rossi et al., 2004; Schiff et al., 2017; Weiss, 1998).

In order to estimate the effects caused by an intervention, we need a counterfactual against which post-intervention outcomes are compared. The counterfactual represents the state of the world without the intervention. The effects caused by the intervention are estimated using differences between actual and counterfactual outcomes. The issue is that a counterfactual cannot be observed directly; it is not possible to observe outcomes for a given place or group with and without an intervention at the same time. The counterfactual must therefore be estimated using data and statistical models, and some assumptions are required when comparing the counterfactual with post-intervention outcomes (Angrist & Pischke, 2009; Gertler et al., 2016; Holland, 1986; Morgan & Winship, 2014; Rubin, 1974; Schiff et al., 2017).

One common approach to construct a counterfactual is to compare outcomes in a 'treatment' group, which are units such as places or populations that are affected by the intervention, with the outcomes in a 'control' group of units where the intervention was not applied. The idea is that, in the absence of the intervention, the treatment group would have followed a similar trajectory to the control group. Thus, observed outcomes in the control group serve as an estimate of the counterfactual outcome for the treatment group (Meyer, 1995; Schiff et al., 2017; Shadish et al., 2002). The treatment effect is then calculated as the difference between the actual post-intervention outcome in the treatment group and the estimated counterfactual based on the control group. This logic is central to quasi-experimental designs, which exploit naturally occurring or policy driven variation to approximate the conditions of a randomized experiment, allowing researchers to estimate causal effects using observational data (Meyer, 1995; Shadish et al., 2002). Designs such as difference-in-differences use control groups to provide the best available approximation of what would have happened to the treated groups had the intervention not occurred.

Because this counterfactual state is not directly observable, estimating it becomes the central challenge of causal inference (Morgan & Winship, 2014). Simple descriptive before/after comparisons implicitly assume that, without intervention, past trends would have continued unchanged. Yet this assumption rarely holds in road safety, where collision counts show a long-term decline due to safer vehicles and infrastructure, fluctuate yearly due to a strong seasonal pattern, and fluctuate randomly due to episodic influences such as tourism cycles, extreme weather or targeted enforcement operations (Elvik, 2002; Hauer, 1997; Lian et al., 2025; Qiu & Nixon, 2008). These sources of instability make road safety outcomes especially vulnerable to confounding, where external factors influence both the intervention and the outcome, thereby creating spurious or exaggerated effects if not properly controlled (Elvik, 2002; Hauer, 1997; Shadish et al., 2002). They can mimic or mask the impact of an intervention, and often interact with regression to the mean and time-varying exposure (e.g. changes in traffic flow over time) to further alter simple before/after comparisons (Hauer, 1997;

Qiu & Nixon, 2008). For this reason, quasi-experimental designs are well suited to credible evaluation, as they aim to approximate the counterfactual and to distinguish true intervention effects from background trends and unobserved heterogeneity² (Angrist & Pischke, 2009; Lopez Bernal et al., 2016; Meyer, 1995). These approaches are widely used in transport and road safety research when drawing causal conclusions from observational data.

2.2 Causal Methods

This subsection provides most commonly used causal methods and explains the assumptions behind the methods which play a crucial role in choosing the appropriate model for each use case in our report.

The strongest approach is to use a well-designed randomised experiment for addressing the fundamental problem of causal inference and producing unbiased estimates of treatment effects (Rubin, 1974; Shadish et al., 2002). In such experiments, observational units are randomly assigned either to receive the treatment (intervention) or to serve as a control group. Because randomisation ensures that, on average, the treatment and control groups are comparable on both observed and unobserved factors, differences in outcomes between the groups can be attributed to the intervention itself. In this setup, the outcomes observed in the control group provide a credible approximation of the counterfactual, which is what would have happened to the treated units in the absence of the intervention (Holland, 1986).

However, true randomized experiments are often infeasible in transport and road safety interventions, as well as in social policy more broadly. Ethical, legal, logistical, or political constraints may prevent the random allocation of interventions. Policymakers may also choose to target measures toward the areas or populations that appear to need them most, making random assignment impossible (Gertler et al., 2016; Schiff et al., 2017; Shadish et al., 2002). In such situations, analysts must rely on additional assumptions to approximate the counterfactual. Yet these assumptions, especially when they cannot be empirically tested, mean that resulting estimates of the treatment effect carry less certainty than those obtained from a well-designed randomized experiment (Morgan & Winship, 2014; Schiff et al., 2017). When pure randomization is not possible, it may still be feasible to design a quasi-experiment through careful analysis of how the intervention is implemented. When carefully applied, these approaches can provide credible evidence of intervention impacts even in a complex, real-world transport and road safety context. Although not exhaustive, we present here methods that have shown their relevance in the domain of road safety and mobility.

Difference-in-differences (DiD) has become one of the most widely used approaches for evaluating transport and road safety interventions. DiD estimates causal effects by comparing changes in outcomes over time between a group exposed to an intervention (treatment group) and a comparable group that remains untreated (control group) (Angrist & Pischke, 2009; Meyer, 1995). The credibility of the design depends on the parallel trends assumption which means that if the intervention had not occurred, both groups would have continued to evolve along similar trajectories. When this assumption is reasonable, and when the treated group is uniquely exposed to an intervention or regulatory change while the control group provides a stable baseline, DiD offers a robust strategy for isolating the impact of the intervention (Lechner, 2010; Wing et al., 2018). Recent work in applied econometrics has further clarified how to implement DiD and event-study designs in a transparent way when effects may be dynamic, reinforcing the importance of explicit pre-trend diagnostics and careful specification choices (Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Roth, 2022; Sun & Abraham, 2021). This makes it especially valuable in road safety context where policy implementation varies across populations, locations or vehicle types over time. Examples may be given as penalty-point systems that apply only to specific driver groups, the staggered rollout of speed limit enforcement technologies, or targeted enforcement campaigns that apply unevenly across space or time. More detailed information on the DiD design, including a schematic illustration, is provided in Section 3.4.1 (Figure 1).

Interrupted time series (ITS) designs are particularly well suited to evaluating population-wide interventions that take effect at a clearly defined point in time. ITS models assess whether an intervention is associated with an immediate change in the level of an outcome, a change in the trend, or both, while explicitly adjusting pre-existing trends, seasonality, and autocorrelation³ (Linden, 2015; Lopez Bernal et al., 2016). A major strength of ITS is its ability to distinguish abrupt effects from more gradual behavioural or systemic responses,

² **Unobserved heterogeneity:** Variation in the population that is not captured by the measured variables and thus cannot be accounted for in the statistical model.

³ **Autocorrelation:** measure of the correlation between the observations with a delayed copy of itself. It quantifies the similarity between observations of a variable at different points in time.

providing a nuanced picture of how an intervention unfolds over time (Wagner et al., 2002). These features make ITS especially valuable in road safety and transport research, where interventions such as legal reforms, large-scale enforcement operations, alcohol availability restrictions, or national regulatory changes often apply simultaneously to entire populations and cannot be evaluated using randomized designs (Kontopantelis et al., 2015; Taljaard et al., 2014).

Regression discontinuity (RD) designs play an important role in evaluating transport and road safety interventions that hinge on clear thresholds: for example, age-based licensing requirements, point system penalties, or abrupt policy changes tied to specific implementation dates. When units just above and below the cutoff are comparable, RD can yield highly credible causal estimates by exploiting the discontinuity created at the threshold (Imbens & Lemieux, 2008; Lee & Lemieux, 2010).

Propensity score methods offer a practical way to evaluate transport and road safety interventions when random assignment simply is not possible. The basic idea is that instead of comparing treated and untreated (control) units that may differ in important ways, researchers first model the probability of receiving the intervention based on observed characteristics. This probability, which is called the propensity score, is then used to balance the observations using different implementation strategies such as matching, weighting, or grouping units so that the treated and control groups look more similar on the factors that likely influenced treatment assignment (Austin, 2011; Rosenbaum & Rubin, 1983). In road safety research, this is especially helpful because interventions are often targeted at high risk locations or specific populations, creating strong selection biases. Studies applying propensity score methods to traffic safety improvements, for example, show that balancing treated and untreated sites on variables such as baseline crash history, road design, or traffic volumes can substantially improve the credibility of estimated effects (Sasidharan & Donnell, 2013). When used carefully, propensity score methods help address confounding on observed characteristics and provide a more reliable basis for estimating how much an intervention actually changed safety outcomes.

Beyond these methods, other quasi-experimental approaches are also widely used in road safety evaluation. Panel fixed-effects models, for example, are frequently used in transport policy evaluation to control for unobserved characteristics of regions that do not change over time such as infrastructure quality, enforcement culture, or socio-economic conditions. By comparing changes within the same region over time, rather than differences across regions, fixed-effects models help isolate the effect of policy changes from stable geographic differences that otherwise confound the analysis (Wooldridge, 2010). At the site level, Empirical Bayes (EB) techniques are widely applied in safety analyses of traffic cameras, blackspot remediation, and engineering treatments, where they mitigate regression to the mean by combining observed crash data with prior information to produce more reliable estimates of expected crash frequencies (Elvik, 2002; Hauer, 1997). Together, these approaches provide powerful tools for drawing robust causal conclusions in road safety research when randomized experiments are not feasible.

These considerations help explain why simple before/after comparisons are widely viewed as insufficient for evaluating real-world transport and road safety interventions. The methodological literature strongly recommends the use of quasi-experimental designs including difference-in-differences, interrupted time series, regression discontinuity, and propensity-based methods which are explicitly designed to approximate the unobserved counterfactual and isolate the causal effect of an intervention (Angrist & Pischke, 2009; Lopez Bernal et al., 2016; Meyer, 1995). This broad consensus provides the foundation for modern evaluations of complex road safety regulations, offering a coherent framework for analysing interventions such as the EU Cross Border Enforcement Directive or Belgium’s 2022 PMD reform, where randomized experimental assignment is impossible but rigorous causal inference remains essential. An overview of commonly used causal inference methods discussed in this section is presented in Table 1.

Table 1 Overview of commonly used causal inference methods.

Method	Typical use case	Key strengths	Key limitations
Randomized experiments	Pilot interventions with controlled implementation	Strong internal validity; minimal reliance on modelling assumptions	Often infeasible due to ethical, legal, or political constraints
Difference-in-differences (DiD)	Interventions affecting some groups but not others over time	Controls for time-invariant unobserved heterogeneity; intuitive interpretation	Relies on parallel trends assumption; sensitive to group-specific shocks

Interrupted time series (ITS)	Population-wide interventions with a clear start date	Adjusts for pre-existing trends and seasonality; suitable without control group	Vulnerable to concurrent interventions or shocks
Regression discontinuity (RD)	Policies based on sharp eligibility thresholds (e.g. age, points)	Strong local causal identification near the cutoff	Limited external validity; requires a clear cutoff
Propensity score methods	Targeted interventions with rich covariates	Improves balance on observed factors	Cannot address unobserved confounding factors
Empirical Bayes (EB)	Site level safety treatments (e.g. black spots, cameras)	Addresses regression to the mean	Not designed for policy wide or behavioural effects
Panel fixed-effects models	Panel data with repeated observations over regions or units	Controls for time-invariant unobserved heterogeneity; intuitive	Cannot address time-varying unobserved confounding factors

While a range of quasi-experimental methods are available for causal evaluation in road safety, their suitability depends on how an intervention is implemented and on the structure of the available data. In this report, we focus on difference-in-differences (DiD) and interrupted time series (ITS) designs because they closely match the characteristics of the two policy interventions examined. The evaluation of the EU Cross Border Enforcement (CBE) Directive adopts a DiD design, as the Directive affects foreign registered vehicles while Belgian registered vehicles provide a natural comparison group whose outcomes can be observed over the same period. By contrast, the evaluation of Belgium’s 2022 PMD reform adopts an ITS approach, as the reform was implemented nationwide at a clearly defined point in time and does not offer an untreated control group.

Other quasi-experimental approaches discussed in Section 2.2 were carefully considered but found to be less suitable in this context. Regression discontinuity designs require a clearly defined eligibility threshold that assigns treatment discontinuously; however, neither the CBE Directive nor the PMD reform generates such a cutoff. Propensity score methods are most effective when rich individual level data are available to model treatment assignment, whereas the analyses in this report rely on aggregated crash data that limit the scope for balancing on observed characteristics. Empirical Bayes techniques are primarily designed for evaluating site level safety treatments rather than for assessing behavioural or regulatory changes at the national or group level. Panel fixed-effects models do not on their own provide a causal identification strategy and are therefore used as supporting tools rather than as stand-alone evaluation designs. These considerations justify the focus on DiD and ITS as the most appropriate approaches for evaluating the causal impacts of the interventions examined in this report.

2.3 Road Safety and Mobility Related Regulations and Causal Inference

Subsection 2.3 summarizes existing research that employs the previously described models to analyse how mobility and road safety related interventions or regulations affected road safety outcomes. We first summarize causal inference studies linked to our two use cases, CBE Directive and e-scooters regulation. We then present the broader literature on other mobility and road safety regulations.

2.3.1 Causal Inference Evaluation of the CBE Directive

The EU Cross Border Enforcement (CBE) Directive creates a shared legal and technical system that helps Member States identify and follow-up with drivers of foreign registered vehicles who commit road safety related offences while travelling abroad. Through this framework, countries can access each other’s vehicle registration databases, making it possible for the state where an offence occurred to obtain the name and address of the vehicle owner or holder involved. The Directive applies to a defined set of key offences such as speeding, not wearing a seat belt, running a red light, driving under the influence, using a mobile phone while driving, or illegal lane use and was introduced to address the longstanding issue of ‘impunity’ for foreign drivers. Its broader aim is to ensure that drivers of foreign registered and state registered vehicles are treated equally and to encourage greater compliance with road safety rules across the EU (European Parliament and Council of the European Union, 2015).

Although the literature on causal evaluation in road safety is growing rapidly, research on the CBE Directive remains methodologically limited. The existing studies on the CBE Directive focus on administrative

performance such as cross border identification rates, follow-up of notices, and payment behaviour rather than estimating road safety outcomes. As a result, there is no credible causal evidence on whether the directive reduced collisions, injuries, or fatalities (European Parliamentary Research Service, 2025; European Transport Safety Council, 2022).

The impact of enforcement certainty (how likely one is to be caught if breaking the law) on road safety outcomes was however successfully studied in the context of road safety, using causal inference (see section 2.3.3). As certainty of the sanction is one of the key aspects of the CBE Directive, we expect that quasi-experimental methods can be applied on this policy.

2.3.2 Causal Inference Evaluation of E-Scooter Regulations

When it comes to causal inference studies on the impact of e-scooter related regulations on road safety outcomes, the literature is quite limited. Cloud et al. (2023) provide one of the first robust causal estimates of e-scooter safety impacts using a staggered difference-in-differences design across 93 cities in six European countries. Exploiting quasi-experimental variation in rollout timing and using a DiD design, they show that the introduction of shared e-scooter services increased police reported accidents involving personal injury by 8.2% on average, with substantially larger effects during summer months of around 11.5% and negligible effects in winter. This study demonstrates that causal inference is feasible in the micromobility domain when natural variation is available. Edwards et al. (2025) study the introduction of e-scooter rental schemes in selected districts in England on bicycle accidents using a natural experiment. They show that e-scooter schemes reduced bicycle collisions by 20%.

While causal evidence on e-scooter safety is scarce, quasi-experimental research designs have been used to study modal shift. One example is the study by Kazemzadeh and Sprei (2024) who examine how shared e-scooter programs affect modal shift in Sweden. They estimate the impact of being an e-scooter user on the probability of substituting other modes for e-scooter trips. They apply propensity score matching to construct an artificial control group of non-users with similar observable characteristics, explicitly aiming to obtain unbiased estimates of e-scooter usage impacts on modal substitution. They find that being an e-scooter user increases the probability of shifting short-range trips to e-scooters from other modes by around 46%. Luo et al. (2021) study the impact of e-scooter trips on the bus system using difference-in-differences models in Indiana as a case study. They show that the competing relationship leads to reduction in bus ridership and that the shared e-scooter system can complement the bus system where bus coverage is low. Yang et al. (2021) analyse the impact of e-scooter sharing on the usage of bike sharing in Chicago using a difference-in-differences modelling approached based on the propensity score matching method. Their findings show that the introduction of e-scooter sharing decreased the weekly usage of bike sharing by 10.2%.

Although causal evaluations of PMD regulations remain limited, studies presented in the next section suggest that classification rules, speed restrictions, age requirements and riding environment regulations can meaningfully influence safety outcomes. Because PMD-related behaviours and risks can shift rapidly following regulatory changes, ITS methods offer a particularly valuable framework for detecting policy effects such as Belgium's 2022 PMD regulation.

2.3.3 Causal Inference for Other Road Safety Regulations

In contrast, quasi-experimental evaluations are increasingly common for other mobility and road safety regulations. The literature on speed enforcement provides some of the strongest evidence available regarding the effectiveness of road safety interventions. The speed at which a vehicle travels is an important determinant of injury; the faster the vehicle is travelling, the greater the energy inflicted on the occupants during a crash, and the greater the injury. Hence, it is essential to study the impact of speed cameras or automated enforcement on road safety outcomes to evaluate the effectiveness of speed related interventions.

Numerous studies have demonstrated that speed cameras and automated enforcement lead to significant reductions in fatal and serious crashes. Wilson et al. (2010) review studies that focus on the impact of speed cameras on speeding and road safety outcomes using randomized controlled trials (RCT), interrupted time series (ITS) and controlled before/after studies. They show that studies analysing speed outcomes reported a reduction in average speeds post-intervention with speed cameras. They also indicate that all studies found a lower number of crashes in the speed camera areas after implementation of the program. Willardsen (2021) exploits a rare natural experiment in Dayton which courts repeatedly forced cameras to be deactivated and reactivated over time causing three exogenous shocks. Using a before and after and a difference-in-differences

estimator, the study reveals that operational cameras consistently reduced total crashes, angle crashes and severe injuries.

Li et al. (2020) study how the effects of speed cameras on road accidents change over time by analysing a total of 771 camera sites and 4787 potential control sites for a period of 18 years (1999 – 2016) across England. They apply a difference-in-differences (DiD) based propensity score matching (PSM) method and find that speed cameras have significantly reduced the number of road accidents near camera sites. However, the effects vary across different time periods. They indicate that the reduction becomes smaller over the long period. They emphasize that appropriate road traffic regulations and management, as well as proper camera sites selection criterion, are important to maintain the effectiveness of speed cameras.

Gehrsitz (2017) estimates the effects of temporary driver's license suspensions on driving behaviour in Germany where drivers who commit a series of speeding offenses within 365 days have their licenses suspended for 1 month. Regression discontinuity design is used to exploit the quasi-random assignment of license suspensions caused by the 365-day cutoff and the analysis shows that 1-month license suspensions lower the probability of recidivation within a year by 20%. Blais and Carnis (2015) investigate the effect of the French Automated Speed Enforcement Program (ASEP) on casualties involving different types of road users. They use an interrupted time series (ITS) design and show that overall, the ASEP was associated with a decrease of 19.7% in traffic fatalities and crashes with injuries.

Another area of research where quasi-experimental designs are used widely is alcohol related interventions. Yu and Kaffine (2011) use a regression discontinuity design to estimate the effect of Colorado Blue Laws on alcohol related accidents and traffic DUI (drinking under the influence) citations. Blue Laws are restrictions aiming to promote moral codes, including the ban of alcohol sales on Sunday, and were repealed on July 1, 2008. Yu and Kaffine find no evidence that the repeal of Colorado Blue Laws had an impact on alcohol related accidents and traffic citations.

Nistal-Nuno (2017) also applies ITS models to evaluate the effect of a new law introduced in March 2012 which decreased the BAC limit for driving while impaired from 1 to 0.8 (g/L) and the legal BAC limit for driving under the influence of alcohol from 0.5 to 0.3 (g/L) on mortality outcomes in Chile. The study shows that the number of traffic fatalities decreased; however this decrease was not statistically significant. Wright and Lee (2021) exploit quasi-random variation in state laws to estimate the causal effect of alcohol related traffic laws on the frequency of fatal accidents. They show that the most effective penalties to reduce alcohol-induced fatal crashes are zero tolerance alcohol use restrictions on underage drivers, prohibiting open alcoholic beverages in motor vehicles, and restricting vehicle use for past DUI offenders (license suspensions and mandating ignition interlock devices). They also indicate that the conclusion changes significantly across various empirical approaches.

Otero and Rau (2017) analyse the effects of lowering the legal BAC limit for drivers from 0.5 to 0.3 (g/L) and increasing license suspension periods for offenders using a regression discontinuity design. They show that even though there is a significant decrease of 32% in alcohol related car accidents right after the law was approved, the effects are only moderate over time with a 15% reduction after three years. Chamlin (2016) investigates the impact of New Jersey's BAC legislation on total and disaggregated crash fatalities. The results from the ITS analyses show that reducing the BAC limit to 0.8 (g/L) has no effect on total or driver fatalities, but results in a lasting decline of passenger fatalities.

Haghpanahan et al. (2019) take advantage of the change in the BAC limit for drivers from 0.8 to 0.5 (g/L) in Scotland in December 2014 which creates a natural experiment since England and Wales experienced no change in the BAC limit for drivers and could therefore be used as a control group. They find that lowering the driving BAC limit in Scotland was not associated with a reduction in road traffic accidents. Liang and Huang (2008) analyse how zero tolerance laws, which make it illegal for anyone under age 21 to drive with any measurable amount of blood alcohol, influences individual alcohol use and driving under the influence behaviours using a difference-in-differences design. They use older college students in their sample as the control group. They show that zero tolerance laws reduce drinking and driving among college students.

The consistency of results across multiple methods, contexts and time periods provides strong evidence that alcohol regulations are among the most effective road safety interventions when implemented with adequate enforcement.

Research on distracted driving has produced mixed findings, largely due to variability in enforcement and compliance. Abouk and Adams (2013) provide one of the most salient examples: using DiD, they found that

texting bans were only effective when categorized as primary offences, enabling officers to stop drivers solely for texting. However bans enforced as secondary offense, thus requiring a driver to be stopped for a separate infraction, showed no measurable impact. Rocco and Sampaio (2016) also analyse whether bans for texting and handheld cell phone are effective in reducing the number of fatalities occurring using US county-level data. They show that states that enacted primary cell phone bans experienced a significant reduction in the number of fatalities.

Penalty-point systems represent another major area of enforcement research. De Paola and Scoppa (2013), using a regression discontinuity design, estimate the effects of the introduction of a penalty-points system for driving offences in July 2003 on road safety outcomes in Italy. They find that the introduction of the penalty-point system has led to a reduction of about 9% in road accidents and of about 30% in traffic fatalities. Their analysis demonstrates that increasing penalty consistency and visibility induces measurable behavioural adaptation. It is important to note that penalty-point systems are not applied in every country. A systematic analysis concluded that the probability of offense detection in Belgium was far too low for a points-based system to have any effect in our country, highlighting once again the importance of sanction consistency (Silverans et al., 2018).

Theoretical and empirical work in deterrence theory provides strong support for applying causal inference methods such as difference-in-differences to evaluate the effects of enforcement policies like the CBE Directive. Deterrence research consistently shows that increases in the certainty of punishment rather than severity alone, are the primary mechanism through which enforcement influences behaviour (Nagin, 2013). This insight is echoed in evaluations of distracted driving legislation. Studies by Chamlin (2016) and Nistal-Nuno (2017) show that laws that exist on paper but lack credible enforcement produce minimal behavioural change. These findings align with broader behavioural economics evidence indicating that road users respond not just to fines or legal prohibitions, but to the perceived likelihood of detection.

All these examples show that causal inference models are essential for evaluating road safety regulations, particularly those targeting behavioural change or implemented at scale. By drawing on these established methods, the present report ensures a rigorous and credible evaluation of two major Belgian road safety interventions.

3 Did Cross Border Enforcement Improve Road Safety? A Difference-in-Differences Analysis

3.1 Background

Foreign registered vehicles represent a persistent challenge in road safety enforcement across the European Union. Before 2015, national authorities faced major obstacles in identifying owners of foreign registered vehicles when traffic offences were detected through automated systems such as speed cameras or red light enforcement. EU Member States relied on different bilateral agreements to obtain foreign vehicle registration data. This meant that in practice, the offences committed by foreign registered vehicles could not be followed up effectively, especially if there was no such agreement. This created what EU institutions described as a form of relative impunity for road users of foreign registered vehicles. Compared to drivers of domestically registered vehicles, the probability of receiving a fine for the same offence was substantially lower.

In response, the European Union adopted the Cross Border Enforcement (CBE) Directive (European Parliament and Council of the European Union, 2015), which aimed to reduce this enforcement gap by establishing a harmonised system for cross border information exchange. Most EU Member States were required to transpose the Directive into national law by May 2015, with the exception of Denmark, Ireland and UK (then a member of EU) which were given until May 2017 to adjust to the Directive. Despite these exceptions, the Directive substantially expanded the ability of countries such as Belgium to identify and pursue foreign registered vehicles involved in traffic offences through the EUCARIS information exchange system. When an automated enforcement device detects an offence in Belgium, the system can request registration data from Member States and issue a follow-up penalty notice. As a result, empirical evaluation appropriately focuses on crashes involving foreign registered vehicles, which represent the group directly exposed to the increased certainty of sanction.

Existing evaluations of the CBE Directive are largely administrative and legal in nature, focusing on enforcement capacity, follow-up mechanisms, and fine payment rates, with little empirical assessment of impacts on road safety outcomes (European Commission, 2023). Drivers of foreign registered vehicles account for approximately 5% of road traffic in the EU, and a foreign registered car is around three times more likely to commit a traffic offence than a domestically registered one (European Transport Safety Council, 2022). According to the European Commission (2023), in 2019 approximately 14.5 million traffic offences committed with a vehicle registered abroad and not identified on the spot were detected. Of these, around 8.2 million payments were made for the offences (8 million voluntarily, 200,000 following successful enforcement). While around 6.3 million offences resulted in the offender not being held accountable. Hence 40% of the cross border offences were committed with impunity, either because the investigation failed (and the presumed offender never received a penalty notice) or because the enforcement failed (the fine was not paid). This is relatively high, in particular compared to the general level of impunity for comparable intra-national offences (mostly speeding detected by speed cameras), which ranges from 5% in the most successful countries (the Netherlands, Sweden, Poland) to 10-20% on average (Luxembourg, Latvia, Ireland, Spain, Estonia, Hungary). It is also indicated that although the share of detected offences with foreign registered vehicles differs significantly between Member States, on average around 18% of all speeding offences are committed by drivers of foreign registered vehicles.

The European Commission's ex-post evaluation reports substantial increases in the number of cross border cases investigated. Although effectiveness varies across Member States, the CBE Directive reduced anonymity for foreign offenders and narrowed the enforcement gap. On an EU level the voluntary payment rate (i.e. payment upon reception of the penalty notice) for foreign offenders, which was about 50% in 2016, increased to 70%. This is a meaningful improvement compared with conditions before the CBE Directive took place (European Commission, 2023).

Independent organizations such as the European Transport Safety Council (2022) have concluded that the CBE Directive enhanced cross border enforcement, although there is still a gap. These findings contributed directly to the 2025 revision of the Directive. The revision goes beyond its original focus on data exchange by strengthening procedural cooperation, expanding the scope of coverable offences, and improving mechanisms for mutual assistance and enforcement across Member States. The updated Directive also clarifies transparency and procedural rights for non-resident drivers and seeks to address weaknesses in enforcement identified in the 2016 evaluation (EPRS, 2025). While enforcement outcomes have improved, the

consequences of these changes for driver behaviour and broader road safety outcomes have not yet been fully empirically assessed.

Despite progress on enforcement, no peer-reviewed evaluation has examined the impact of the CBE Directive on road safety outcomes, and EU impact assessments explicitly acknowledge this evidence gap. This absence is notable given the expectation that increased certainty of enforcement should affect driver behaviour. Deterrence theory emphasises that when the perceived certainty of sanction increases, compliance improves (Nagin, 2013). While behavioural adaptation is rarely observed directly in road safety research, a substantial empirical literature documents reductions in violations and crashes following enforcement interventions that increase the likelihood of being caught. For example, Italy's penalty-point system reduced violations and contributed to a reduction in fatalities (De Paola & Scoppa, 2013); automated speed enforcement reduced speeding and injury crashes substantially (Pérez et al., 2007); Willardsen, 2021); and mobile phone bans reduced distraction related crashes in states with strong enforcement (Abouk & Adams, 2013). Rebollo-Sanz et al. (2021) show that introducing Spain's penalty-point system had a strong deterrent effect, reducing traffic offenders by about 14%, with larger reductions for more severe violations, consistent with economic theories of deterrence. This behavioural change translated into substantial road safety gains, including persistent reductions of roughly 14–16% in accidents, injuries, and fatalities, indicating that non-monetary sanctions can be a highly effective and cost-efficient road safety policy. Although these studies infer behavioural change from crash and violation outcomes rather than measuring compliance directly, they collectively demonstrate that when detection becomes more certain, drivers modify their behaviour accordingly which is precisely the mechanism the CBE Directive seeks to activate. The CBE Directive directly targets this mechanism for foreign registered vehicles. The behavioural expectation is that closing the enforcement gap should lead to safer driving behaviour and fewer crashes among foreign registered vehicles.

This report provides the first causal assessment of whether the CBE Directive led to improved road safety outcomes in Belgium. Using official police reported crash data from 2012-2018 and a difference-in-differences design, the analysis compares foreign registered vehicles which is treated group affected by the CBE Directive and Belgian registered vehicles which is the control group that is not affected by the CBE Directive. The choice of a DiD framework follows directly from the structure of the policy intervention. By increasing the certainty that foreign registered vehicles would face enforcement for traffic offences, the CBE Directive altered incentives in a manner consistent with deterrence theory. Foreign registered vehicles therefore constitute the population directly exposed to the policy change, while Belgian registered vehicles provide a natural comparison group whose enforcement conditions remained unchanged. Comparing changes in crash involvement between these groups before and after the implementation of the Directive allows us to construct a credible counterfactual trend and isolate the effect of the policy on road safety outcomes.

The rest of the chapter presents the data, definitions, empirical strategy, descriptive patterns, pre-trend diagnostics, and the main results.

3.2 Data and Definitions

The analytical dataset combines police reported crashes with weather information for the period May 2012 to April 2018.

3.2.1 Data Source

The primary data source for this study is the national database on road accidents resulting in death or injury. This database is based on crash reports filled in by the Federal Police/DGR/DRI/BIPOL following an accident. The crash reports contain the accidents identified on the spot as well as the accidents reported to the police station. The data are then provided to Statbel (Directorate-general Statistics - Statistics Belgium) that checks and approves them. The fatally injured people are added by the Federal Police and Statbel based on death certificates from the prosecutors and information from the MaCH database. In addition, the number of fatalities is also checked on the basis of the national register of natural persons which describes the characteristics of deceased persons.

For each recorded crash, the database contains detailed information on:

- date and time of the collision,
- geographical location (province, arrondissement),
- road and environmental characteristics,

- vehicle characteristics (e.g., vehicle type, country of registration),
- driver characteristics
- crash severity and victim counts

The variable we are interested in for this study is an indicator identifying whether a crash involved at least one foreign registered vehicle. This variable reflects the enforcement mechanism targeted by the CBE Directive, which aims to increase the likelihood that traffic offences committed by drivers of foreign registered vehicles to result in effective sanctioning.

Ideally, an evaluation of the CBE Directive would also examine traffic offences, as the Directive directly targets enforcement and is likely to affect offence behaviour and perceived impunity. However, offence data by vehicle registration status are not readily available, which limits their use for causal analysis in this context. For this reason, the present study focuses on road safety outcomes. Although the effect on crashes is indirect, it remains highly policy relevant, as improved compliance with traffic rules is ultimately expected to translate into safer driving behaviour and fewer accidents. Future research combining offence and crash data would provide a more complete picture of the behavioural and safety impacts of cross border enforcement.

3.2.2 Data Preparation

The empirical dataset covers the period from May 2012 to April 2018. This period spans a symmetric window of three years before and after the implementation of the EU Cross Border Enforcement (CBE) Directive, which became applicable in Belgium in May 2015. The chosen period provides a sufficiently long pre-treatment period to assess dynamics before policy took place and supports the identification of post-policy changes associated with the Directive.

For the analysis, we aggregated the number of crashes per province per month. The data are aggregated at the monthly level for two main reasons. First, foreign registered vehicle crashes constitute a relatively small share of all crashes, and finer temporal aggregation (e.g. daily or weekly) would lead to excessive zero counts and unstable estimates at the province level. Second, monthly aggregation allows us to capture seasonal patterns in traffic and weather conditions while preserving sufficient variation to identify policy effects around the implementation of the CBE Directive.

All crashes involving at least one motorised vehicle were included. We focus on passenger cars, lorries, vans, and motorcycles because passenger cars account for the largest share of road traffic and therefore offer the greatest statistical power for detecting behavioural responses. Lorries are involved in fewer crashes numerically but pose higher severity risks due to their mass and kinetic energy, and they account for a substantial share of cross border freight traffic. Vans exhibit a distinct risk profile because they are commonly used for commercial and delivery activities, often involving higher mileage, time pressure, and intensive urban driving, which are associated with elevated crash risk. Motorcyclists face particularly high vulnerability due to the lack of physical protection and greater exposure in collisions.

Crashes involving mopeds are excluded from the causal analysis. As of 31 March 2014, Belgium introduced mandatory registration for all mopeds, accompanied by a regularisation procedure for vehicles already in circulation. Prior to this reform, a substantial portion of mopeds circulating in Belgium were unregistered, meaning that reliable information on their registration country was not systematically recorded. This change created a discontinuity in the data. After 2014, a large number of mopeds newly appear as Belgian registered, not because of changes in underlying mobility or safety patterns, but solely as a result of the administrative requirement. Such an abrupt shift in the measurement of the treatment variable directly violates the parallel trends assumption required for the difference-in-differences design and prevents the construction of a consistent pre-policy counterfactual. For this reason, mopeds are not included in the DiD models.

The main specification compares crash counts for foreign and Belgian registered vehicles within the same province and month using a saturated fixed-effects structure, which absorbs all province specific shocks in a given month (including seasonal patterns and time-varying exposure). In addition to analysing crash counts, the causal analysis focuses on the relative involvement of foreign registered vehicles in crashes. As a complementary and easily interpretable measure, we also report results using the share of crashes involving at least one foreign registered vehicle in a given province and month. This normalised outcome captures changes in relative involvement and is less sensitive to aggregate fluctuations in traffic volume, reporting intensity or overall crash risk that affect all road users simultaneously. Hence, for each province and month, the share outcome is constructed as:

- *foreign_share* = the ratio of crashes in which at least one involved vehicle was registered abroad in Europe to the total number of crashes.

The spatial unit of analysis consists of Belgium's ten provinces plus the Brussels-Capital Region. A categorical variable (*prov*) is used to identify these 11 locations.

For the difference-in-differences analysis, we need to define a treatment variable. The treatment corresponds to the implementation of the CBE Directive, which became operational in Belgium in May 2015. Hence, a binary variable is created to capture this timing:

- *post_cbe* = 1 for months from May 2015 onward
- *post_cbe* = 0 for months before May 2015

The identifying variation therefore comes from changes in crash involvement for foreign registered vehicles relative to Belgian registered vehicles before and after the introduction of the CBE Directive.

To examine the dynamics of the policy effect and assess potential anticipation or delayed responses, an event-time variable is also created:

- *rel_month* = the number of months relative to May 2015, with negative values indicating pre-treatment periods and positive values indicating post-treatment periods.

To account for environmental conditions that may influence crash risk and seasonal patterns, the following time-varying controls are included:

- *avg_tem*: mean monthly temperature ($^{\circ}\text{C}$)
- *avg_pre*: monthly average of daily precipitation totals (*mm*)

Finally, the empirical models include province fixed effects (*prov*) to absorb structural differences across provinces, such as road infrastructure, traffic density patterns, urbanisation, and enforcement capacity. In addition, month fixed effects are included to capture common seasonal patterns in crashes and driving conditions.

3.3 Methodology

This section describes the empirical strategy used to estimate the impact of the EU Cross Border Enforcement (CBE) Directive on the involvement of foreign registered vehicles in road crashes in Belgium. The analysis is implemented using a difference-in-differences (DiD) design comparing foreign and Belgian registered vehicles before and after May 2015. The main specification compares crash counts within the same province and month using a saturated fixed-effects structure, which reduces sensitivity to province specific seasonality, exposure fluctuations, and other time-varying confounders. As a complementary analysis, we also estimate DiD models using the share of crashes involving at least one foreign registered vehicle per province and month, which provides an intuitive normalised measure of relative involvement.

A difference-in-differences (DiD) design is well suited to this setting because it compares changes over time in the treated group with changes in the control group before and after the CBE Directive. The central challenge in assessing the impact of the CBE Directive is to isolate whether the involvement of foreign registered vehicles in crashes changed after the policy was introduced in May 2015, relative to Belgian registered vehicles. Because the CBE Directive targets vehicles whose registration originates outside Belgium, foreign registered vehicles form the treatment group. Therefore, the control group consists of Belgian registered vehicles. Our assumption is that if the CBE Directive was effective in changing the behaviour of drivers of foreign registered vehicles thanks to the increased certainty of enforcement; then crashes involving foreign registered vehicles should evolve differently after May 2015 compared with those involving Belgian registered vehicles.

It should be noted that the DiD design does not require treatment and control groups to have identical outcome levels or perfectly overlapping trends. It allows differences between foreign and Belgian registered vehicles and for common shocks affecting both groups. It is, however, required that the outcomes for foreign and Belgian registered vehicles follow similar trends prior to May 2015 (the parallel trends assumption). This is the key assumption of DiD design which is called parallel trends assumption. Under this assumption, any systematic divergence observed after May 2015 can be attributed to the policy intervention rather than to pre-existing differences or common shocks. We have conducted an event-study that allows to analyse the parallel trends assumption and detect of anticipation effects or gradual policy responses. Hence, DiD design, event-study

specifications and placebo tests ensure both validity and robustness in estimating the effect of the Directive on road safety outcomes and obtaining credible causal estimates.

3.3.1 Complementary Share-Based Difference-in-Differences (DiD) Model: Crash Share of Foreign Registered Vehicles

The Difference-in-Differences (DiD) approach compares how an outcome changes over time between an intervention (treatment) group and a comparison (control) group. In Figure 1, both groups exhibit their own outcome levels before the intervention. It is important to note that they follow similar trends, which is the core parallel trends assumption. This means that, without the intervention, the difference between the two groups would have remained constant over time. After the intervention occurs, the comparison group continues along its original trend, while the intervention group shows a sharper increase in the outcome. The dotted red line represents the unobserved counterfactual meaning what the intervention group's outcome would have been had the intervention never been implemented. The DiD estimate is obtained by comparing the actual post-intervention outcome of the intervention group to this counterfactual trend and subtracting the change observed in the comparison group. In this way, DiD isolates the causal impact of the intervention by removing both baseline differences and general time trends that affect both groups.

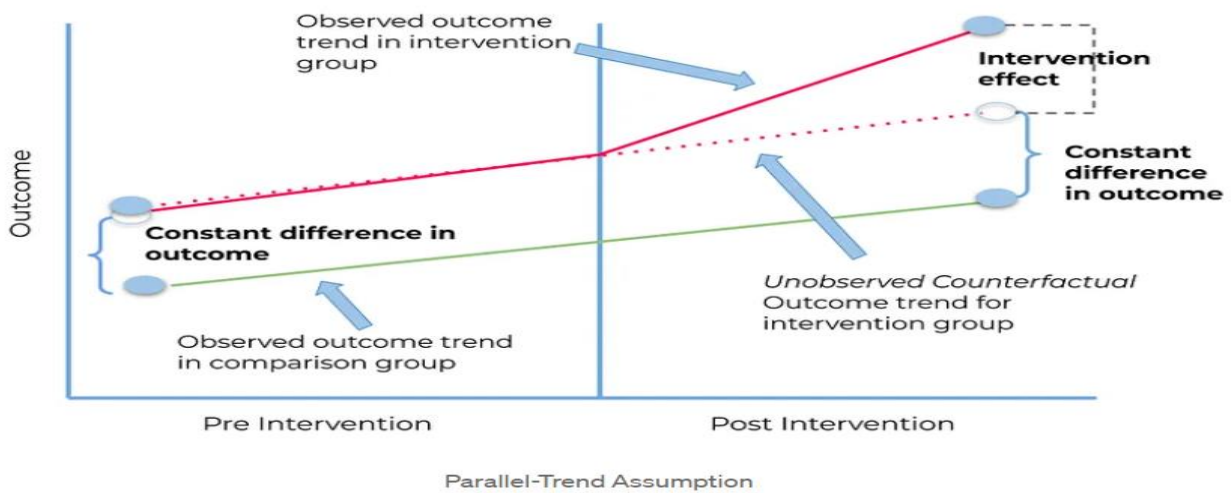


Figure 1 Difference-in-Differences (DiD) Design and Parallel Trend Assumption.

Source: <https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation>

The complementary specification evaluates whether the share of crashes involving foreign registered vehicles changed after the implementation of the CBE directive. The model equation is defined as follows:

$$foreign_share_{pt} = \beta_0 + \beta_1 post_cbe_t + \gamma X_{pt} + \alpha_p + \lambda_m + \varepsilon_{pt}$$

where:

- $foreign_share_{pt}$ = the proportion of crashes involving at least one foreign registered vehicle in province p , month t ;
- $post_cbe_t$ = binary indicator equals to 1 for months from May 2015 onward and 0 otherwise;
- X_{pt} = monthly weather controls (temperature and precipitation);
- α_p = province fixed effects (to control for unobserved time-invariant differences across provinces);
- λ_m = month fixed effects capturing common seasonal patterns shared across provinces;
- ε_{pt} = standard error term clustered at the province level to allow for serial correlation and arbitrary within-province dependence.

In this model, the coefficient of interest is β_1 which measures the average change in the share of crashes involving foreign registered vehicles after the CBE Directive took place relative to the pre-policy period.

Because the outcome is a share rather than a count, the estimated effect should be interpreted as a change in percentage points in the relative involvement of foreign registered vehicles in crashes.

Although the empirical analysis is conducted using the share of crashes involving foreign registered vehicles as the outcome variable, the identification strategy follows a two-way fixed effects difference-in-differences framework. The treatment is defined by the implementation of the CBE Directive in May 2015, which affects foreign registered vehicles but not Belgian registered vehicles. Belgian registered vehicles serve as the implicit control group embedded in the outcome through normalization by total crashes. This formulation therefore compares changes over time in the relative involvement of foreign vehicles before and after the policy, while using Belgian vehicles as the counterfactual group.

While informative, the share-based specification remains a normalized outcome measure. The main empirical specification relies on a saturated difference-in-differences model using crash counts, which is presented in the next subsection.

3.3.2 Saturated Difference-in-Differences (DiD) Specification

To estimate the causal impact of the CBE Directive, the main specification relies on a saturated difference-in-differences (DiD) model using the number of crashes rather than crash shares. This specification strengthens identification and aligns the analysis with a standard DiD framework by comparing crashes involving foreign registered and Belgian registered vehicles per province and month.

The main specification is:

$$y_{ptg} = \exp(\beta (\text{foreign}_g * \text{post_cbe}_t) + \gamma X_{pt} + \alpha_g) + \varepsilon_{ptg}$$

where:

- y_{ptg} = the number of crashes province p , month t , and registration group g (foreign or Belgian) ;
- foreign_g = equals to 1 for foreign registered vehicles and 0 for Belgian registered vehicles;
- post_cbe_t = binary indicator equals to 1 for months from May 2015 onward and 0 otherwise;
- X_{pt} = are province by month fixed effects (i.e., province * year-month), absorbing all time-varying shocks common to both groups within the same province and month;
- α_g = captures persistent level differences between foreign and Belgian registered vehicles;
- ε_{ptg} = standard error term clustered at the province level to allow for serial correlation and arbitrary within-province dependence.

This saturated model absorbs all province specific monthly shocks, including seasonality, macroeconomic fluctuations, enforcement intensity changes, and other time-varying confounders common within the same province and month. Identification therefore comes from within-province comparisons between number of crashes involving foreign and Belgian registered vehicles before and after the introduction of the CBE Directive.

We estimate a log-linear OLS specification as our primary model and a Poisson model as a robustness check. In the log-linear specification, the coefficient on the interaction term $\text{foreign}_g * \text{post_cbe}_t$ (denoted β) measures the percentage change in crashes involving foreign registered vehicles relative to Belgian registered vehicles after the introduction of the CBE Directive. More precisely, the estimated effect can be interpreted as $\exp(\beta) - 1$, which approximates the proportional change in number of crashes involving at least one foreign registered vehicle relative to the control group. The Poisson specification, estimated with the same fixed-effects structure, provides a complementary count-based robustness check under a different functional form.

3.3.3 Event-Study Specification for Parallel Trends Diagnostics

To assess the validity of the parallel trends assumption and to explore the dynamic evolution of the policy effect, an event-study specification is estimated aligned with the saturated difference-in-differences model:

$$\log(y_{ptg}) = \sum_{k \neq -1} \delta_k [\text{foreign}_g * 1(\text{rel_month}_t = k)] + \gamma X_{pt} + \alpha_g + \varepsilon_{ptg}$$

Where y_{ptg} denotes the number of crashes in province p , month t , and registration group g (foreign or Belgian); $I()$ in the equation denotes an indicator function that equals to one if the condition inside the brackets holds and zero otherwise. The model is estimated in logarithmic form, so coefficients can be interpreted as approximate percentage changes. Here, rel_month measures the number of months relative to May 2015, with -1 serving as the omitted reference period (April 2015). Each coefficient δ_k represents the relative difference in crashes involving foreign registered vehicles compared with Belgian registered vehicles in month k relative to the reference period (April 2015), tracing the dynamic evolution of the policy effect before and after the introduction of the CBE Directive. The specification also accounts for province fixed effects, month fixed effects, and weather conditions.

If the DiD assumptions hold, the pre-treatment coefficients ($k < 0$) should fluctuate randomly around zero without displaying systematic upward or downward patterns. If the event-study estimates were consistently positive or negative prior to May 2015, this would indicate that the crashes involving foreign registered vehicles were already trending differently before the Directive took effect. Such a pattern could reflect anticipation effects meaning behavioural changes in response to earlier announcements or discussions of the Directive, or other contemporaneous developments affecting drivers of foreign registered vehicles. In that case, a simple DiD model might incorrectly attribute pre-existing dynamics to the policy intervention.

In contrast, post-treatment coefficients ($k > 0$) describe how crashes involving foreign and Belgian registered vehicles evolved following implementation. A sustained negative pattern after May 2015 would be consistent with a relative decline in crashes involving foreign registered vehicles compared with Belgian registered vehicles following the introduction of the CBE Directive, whereas estimates close to zero would suggest limited or no measurable impact on relative crash involvement.

Overall, the event-study estimates serve both as a diagnostic tool by assessing the plausibility of the parallel trend assumption and as a descriptive illustration of the timing, and direction of any policy related changes in road safety outcomes (Goodman-Bacon, 2021).

3.3.4 Robustness and Alternative Specifications

Several robustness checks are conducted to assess the sensitivity of the results. These include placebo tests using alternative policy dates and alternative samples based on complementary share-based models. A saturated fixed-effects model is also estimated using Poisson regression. In addition, models based on crash counts are presented in the Annex to provide complementary evidence to illustrate how the results compare across outcome definitions.⁴

Models are estimated using *R version 4.0.2* and the *fixest* package, which is designed for high dimensional fixed-effects regression and robust DiD estimation (Berge, 2018).

3.4 Descriptive Patterns and Pre-Trend Diagnostics

Before estimating the causal effect of the Cross Border Enforcement (CBE) Directive, it is important to describe the underlying crash patterns involving Belgian registered and foreign registered vehicles. Descriptive analysis provides essential context for interpreting the DiD results, highlighting long-term trends, seasonal variation, traffic composition, and differences across vehicle categories. These descriptive patterns also help assess whether the evolution of crashes among foreign registered vehicles prior to the implementation of the Directive is broadly comparable to that of Belgian registered vehicles which is an important consideration for the credibility of the subsequent causal analysis.

This section, hence, presents descriptive patterns and pre-trend diagnostics in monthly crashes involving Belgian and foreign registered vehicles between over the period 2012-2018. Figures for all vehicles (aggregating cars, lorries, vans and motorcycles) are presented in this section.

⁴ The analysis was also conducted separately by vehicle type (cars, motorcycles, lorries and vans). The corresponding results are available upon request but are not included in the report due to their length.

Crashes involving Belgian registered vehicles dominate the aggregate numbers, reflecting their much larger share in the vehicle fleet in Belgium.

Monthly crashes involving Belgian and foreign registered vehicles

All vehicles, Belgium (2012–2018)

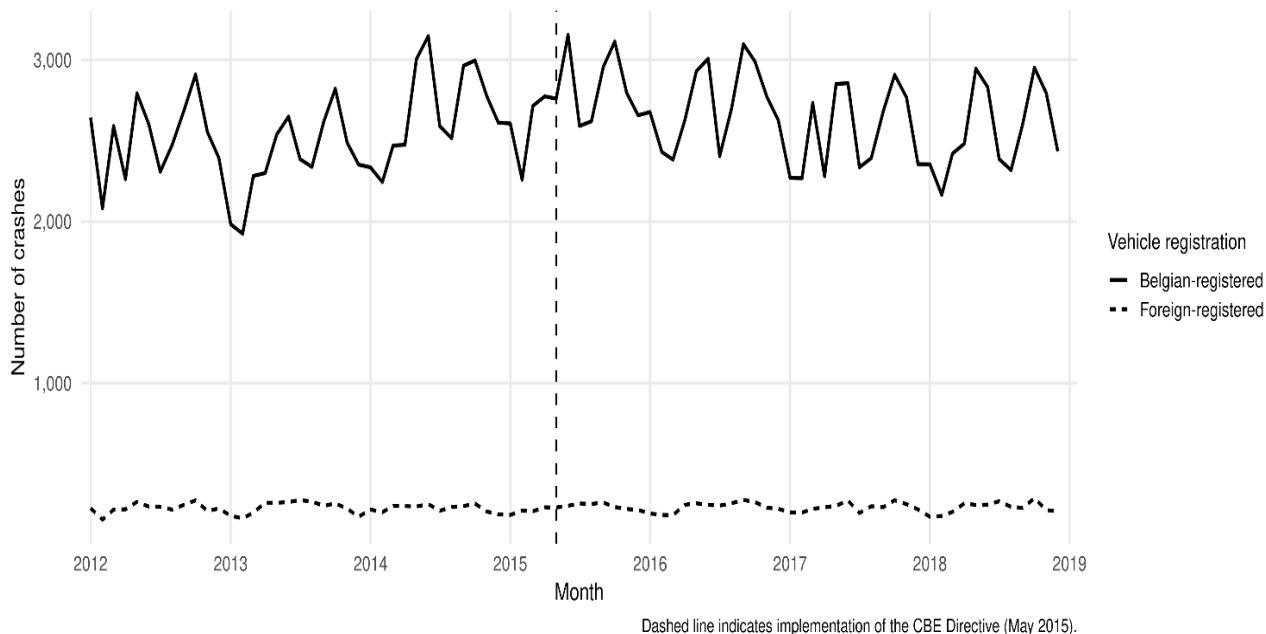


Figure 2 Monthly crashes involving Belgian and foreign registered vehicles (2012 - 2018).

As shown in Figure 2, monthly number of crashes involving Belgian registered vehicles range between 2,000 and 3,000, whereas crashes involving foreign registered range around between 200 and 400 per month. Both series show seasonal fluctuations, with higher crash counts in spring and summer and lower counts in winter. They also exhibit similar cyclical movements in the pre-policy period which suggests no obvious divergence in pre-policy dynamics and motivating the formal parallel trends assumption presented later using event-study models. Finally, we do not see an abrupt discontinuity around May 2015 at the descriptive level, which is consistent with a policy effect that is modest relative to underlying seasonal and structural variation.

Share of crashes involving foreign registered vehicles

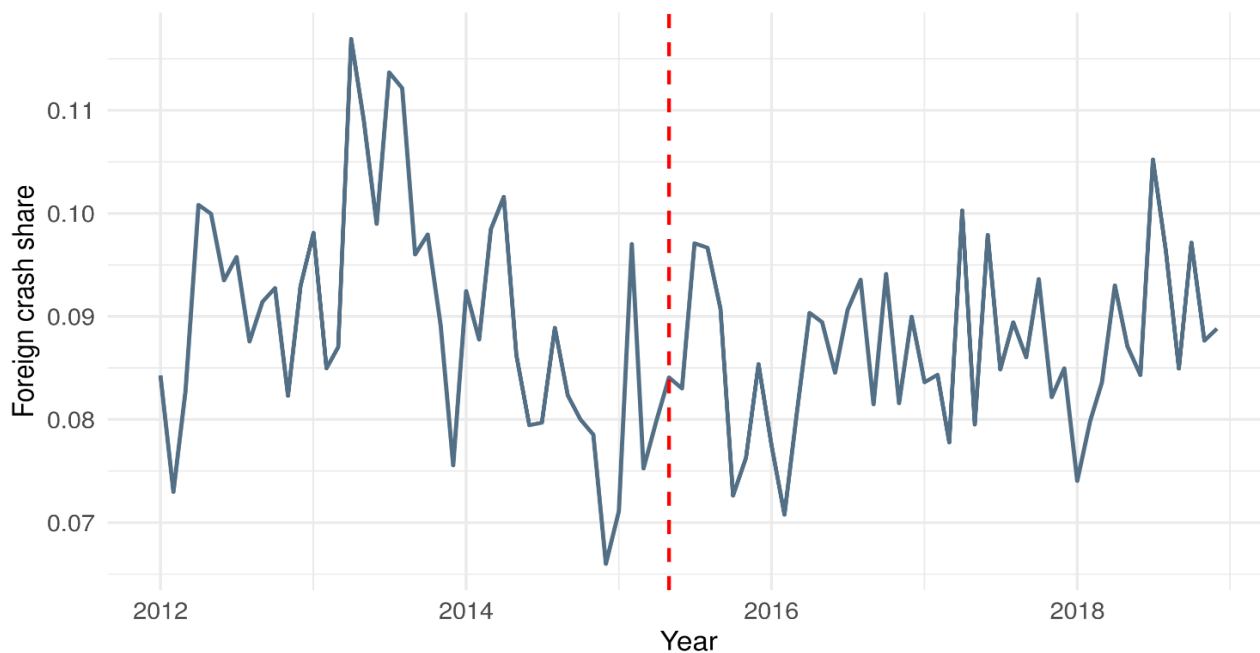


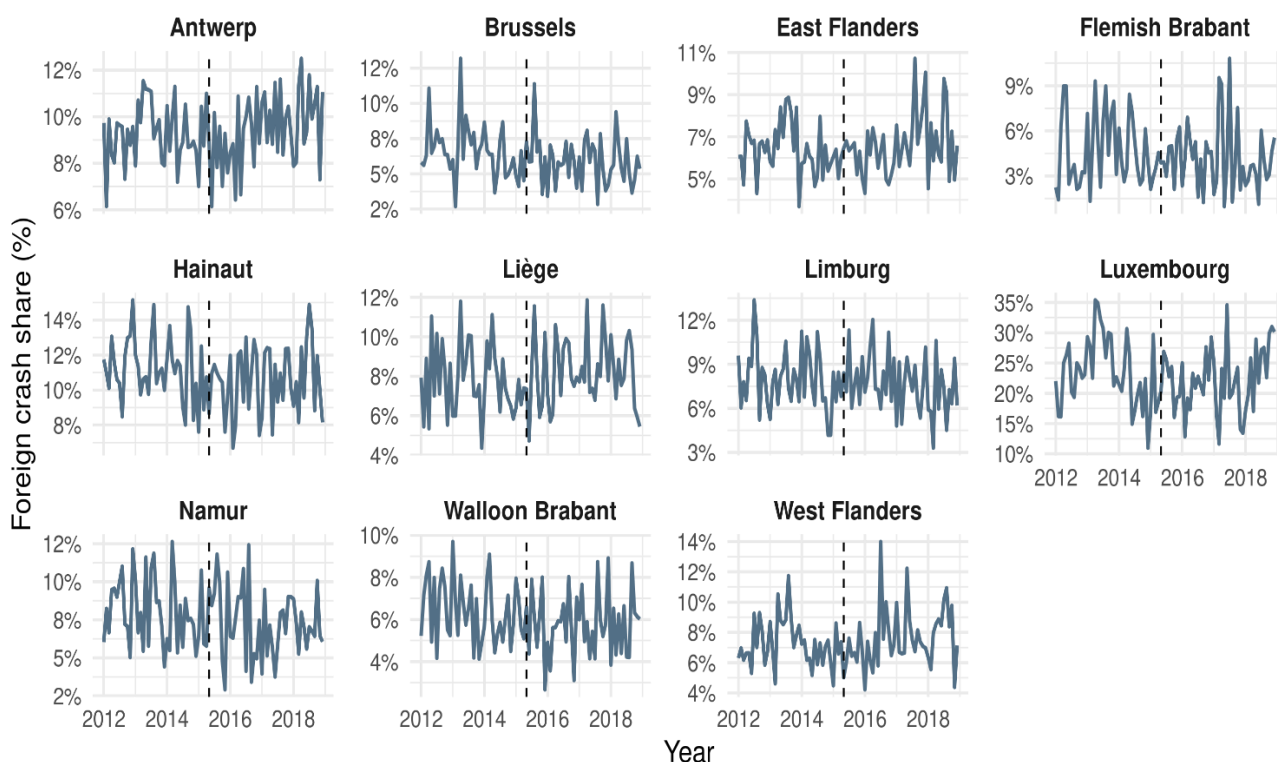
Figure 3 Share of crashes involving foreign registered vehicles.

Figure 3 depicts the monthly evolution of the share of crashes involving at least one foreign registered vehicle in Belgium over the period 2012-2018. It can be seen from this figure that foreign registered vehicles represent a small proportion of total crashes varying between 7% and 11% over the period. However, they account for a measurable proportion of crashes, and the series show seasonal variation, with higher shares in months during summer and spring, due to increased tourist traffic and the presence of cross border visitors. Figure 3 also shows that before the introduction of the CBE Directive in May 2015, the foreign crash share fluctuates within a relatively stable range without following a sustained increasing or decreasing trend. While short-run increases and decreases are visible, these movements do not follow a consistent directional pattern.

When we look at the time of implementation (dashed line in the figure), there is no visible abrupt discontinuity suggesting that any policy effect is likely to be small relative to underlying seasonal and structural variation. This strengthens the credibility of comparing foreign registered and Belgian registered vehicles crash trends over time, as there is no evidence of systematic pre-policy divergence that would undermine the counterfactual comparison. This supports the suitability of a DiD design.

Foreign crash share by province

Monthly evolution in Belgium (2012–2018)



The dashed vertical line indicates implementation of the CBE Directive (May 2015).

Figure 4 Provincial foreign crash shares (2012 - 2018).

Figure 4 shows the monthly evaluation of the share of crashes involving at least one foreign registered vehicle, disaggregated by province over the period of 2012–2018. It can be seen that there is heterogeneity across provinces in the level of foreign crash involvement. Border provinces display higher foreign crash shares. In particular, Luxembourg province stands out with 15-30% of crashes, reflecting its role as a major transit highway and border region. Brussels and Antwerp also exhibit relatively high shares compared to other provinces, consistent with their international connectivity and high volumes of non-residence traffic. It is also seen that seasonality is visible across nearly all provinces, with higher foreign crash shares typically occurring spring and summer months. The fact that similar seasonal cycles appear both before and after May 2015 underscores the importance of controlling for month fixed effects in the empirical analysis.

Looking at Figure 4, we also see that there is no strong continuous increasing or decreasing trend prior to the introduction of the CBE Directive in May 2015. Looking at the monthly numbers, we see that there are fluctuations, however these movements do not display pre-policy divergence. This stability is particularly visible in provinces such as Antwerp, East Flanders, Liege, Limburg, and West Flanders. Finally, we do not see an

abrupt or structural break in these provinces around May 2015. This suggests that any impact of the CBE Directive is likely to be moderate relative to underlying seasonal and provincial variation. Overall, even though the proportions differ across provinces, the pre-policy evolution of foreign crash shares seems to be broadly parallel across provinces. All these support the need for a DiD design rather than relying on descriptive analysis and the credibility of the identification strategy.

Table 2 Mean foreign share before and after the introduction of the CBE Directive.

Period	Mean	SD
Pre	9 %	5.43%
Post	8.67 %	5.17%

Table 2 reports the mean and standard deviation of the foreign crash share before and after the introduction of the CBE Directive. On average, the share of crashes involving foreign registered vehicles declines from 9% in the pre-policy period to 8.7% in the post policy period. While this difference is small in magnitude and descriptive, it indicates a modest reduction in the relative involvement of foreign registered vehicles after May 2015. The high variability implies that simple before/after comparisons are insufficient and motivates the use of a DiD design that explicitly controls for seasonality, provincial heterogeneity and common month effects. These descriptive statistics there provide useful context but do not by themselves establish a causal impact of the Directive.

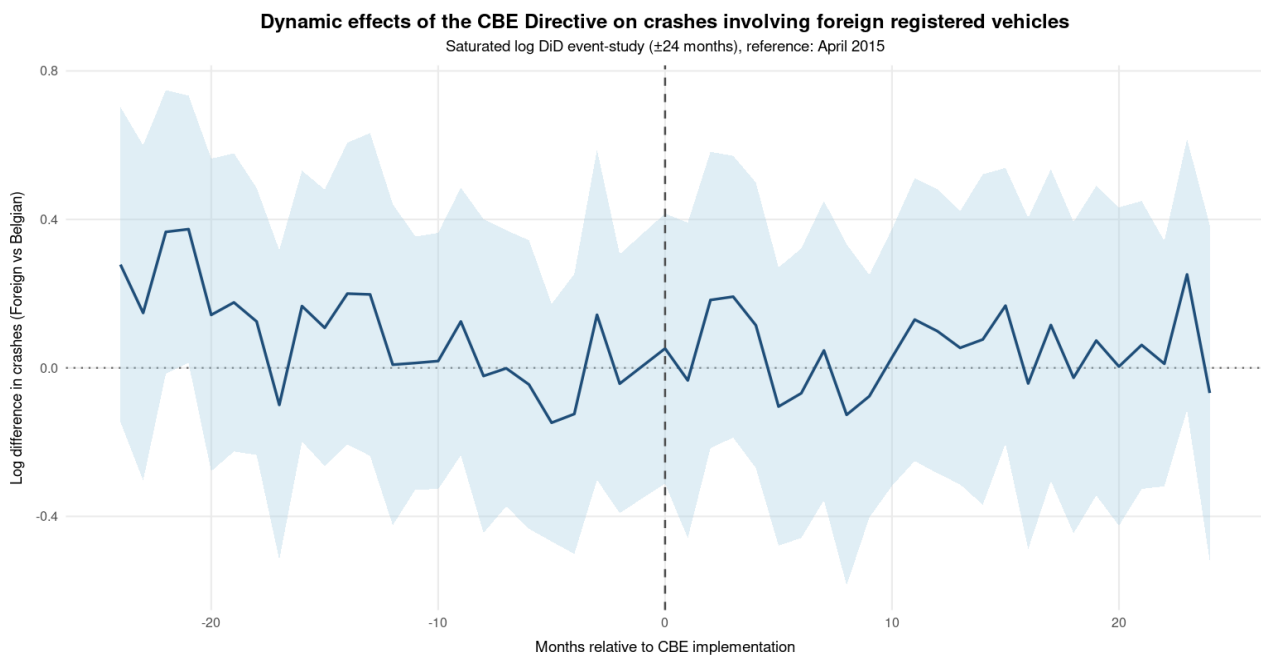


Figure 5 Saturated log-DiD event-study estimates.

A key identifying assumption of the DiD design is that, in the absence of the CBE Directive, crashes involving foreign registered vehicles would have evolved in parallel with those involving Belgian registered vehicles. In order to diagnose whether this assumption holds, one of the methods is to conduct an event-study specification as mentioned before. After the estimation of the event-study specification, we need to check the slope of the pre-treatment coefficients rather than their level. A monotonic increase or decrease, a clean nonlinear trajectory or a structural break can be considered as evidence of the violation of parallel trends assumption and indication of differences in pre-policy slopes between treatment and control groups. In contrast, coefficients that are consistently positive or negative but stable over time reflect level differences rather than divergent trends and do not invalidate the difference-in-differences design.

Figure 5 presents the dynamic event-study estimates based on the saturated log difference-in-differences specification, focusing on the 24 months before and after the introduction of the CBE Directive in May 2015. It can be seen from Figure 5 that the pre-treatment coefficients fluctuate around zero without exhibiting a monotonic increasing or decreasing patterns. While individual monthly estimates vary and confidence intervals

are relative wide reflecting the limited number of clusters and highly saturated fixed-effects structure; there is no evidence of a sustained or monotonic divergence between crashes involving foreign and Belgian registered vehicles prior to implementation. Following implementation of the CBE Directive, the estimates remain modest in magnitude and fluctuate around zero, with confidence intervals that frequently overlap zero, suggesting that any post-policy changes in the crashes involving foreign registered vehicles relative to Belgian registered vehicles are small relative to overall variability. The event-study therefore serves both as a diagnostic tool validating the identification strategy and as a descriptive figure that illustrates the timing and persistence of potential policy effects.

Overall, the dynamic estimates do not display a clear or sustained pre-policy divergence between foreign and Belgian registered vehicles. While individual monthly coefficients vary and reflect the inherent volatility of the data, there is no evidence of a systematic upward or downward pre-treatment trend that would suggest a structural break prior to implementation. Taken together, the graphical evidence supports the interpretation of the main difference-in-differences results as reflecting a modest post-policy adjustment rather than pre-existing divergence.

3.5 Results

This section presents the main empirical findings of the impact of the CBE Directive on crashes involving foreign registered vehicles in Belgium. The analysis uses a difference-in-differences (DiD) design applied to monthly province-level data from May 2012 to April 2018. Our primary specification is a saturated difference-in-differences model and the outcome variable is the number of crashes in a given province and month that involve at least one foreign registered vehicle and Belgian registered vehicles. The coefficient of interest measures the change in the number of crashes involving foreign registered vehicles after May 2015, relative to Belgian registered vehicles. The model includes province by month fixed effects to control for regional differences and common seasonal patterns, and standard errors are clustered at the province level.

As complementary evidence, we also report a complementary share-based specification that examines changes in the proportion of crashes involving at least one foreign registered vehicle and a Poisson version of the saturated count model as robustness checks.

Table 3 Effect of the CBE Directive on crashes involving foreign registered vehicles.

	Share Did	Log Saturated DiD
post_cbe	-0.0050+ (0.075)	-
Foreign * post_cbe	-	-0.0526* (0.018)
temperature	-0.0001 (0.6315)	-
precipitation	-0.0020 (0.2493)	-
province fixed effects	yes	Province by month fixed effects
month fixed effects	yes	Province by month fixed effects
observations	792	1584
Adjusted R2	0.796	0.931

+p ≤ 0.10; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001

Table 3 reports the estimates from the DiD models. The values inside the brackets are *p-values*. Column (1) presents the complementary specification using the foreign crash share as the outcome, while Column (2) reports the saturated count-based specification using log number of crashes with province by month fixed effects.

In the complementary share model (Column 1), the coefficient *post_cbe*, which is the key variable of interest, is negative and statistically significant at the 10% level. The estimated coefficient is -0.0050 which implies that following the introduction of the CBE Directive in May 2015, the share of crashes involving foreign registered vehicles decreased by approximately 0.5 percentage points relative to the pre-policy period.

As shown in Table 1 in the previous section, average pre-policy foreign crash share is calculated approximately as 9%. Hence, DiD estimate corresponds to a 5-6 % relative reduction in the involvement of foreign registered vehicles in crashes. Although this magnitude is modest and statistically significant at the 10% level, the direction of the effect is consistent with the objective of the CBE Directive which aims to strengthen

enforcement incentives for drivers of foreign registered vehicles by facilitation cross border information exchange. Hence, this estimate provides initial evidence that the Directive may have reduced the relative involvement of foreign registered vehicles in crashes.

Column (2) presents the saturated log-linear DiD specification, which compares crashes involving foreign and Belgian registered vehicles within the same province and month while absorbing all province-specific monthly shocks. The estimated interaction coefficient is -0.0526 ($p = 0.018$). Interpreted as $\exp(\beta) - 1$, this implies an approximate 5.1% relative reduction in crashes involving foreign registered vehicles compared to Belgian registered vehicles following the Directive. This does not mean that the foreign crash share fell by 5 percentage points. Rather, given a pre-policy average foreign crash share of about 9%, a 5.1% relative decline corresponds to a reduction from roughly 9% to approximately 8.5–8.6% of crashes involving foreign registered vehicles. The magnitude is modest but statistically significant at the 5% level and closely aligned with the share-based results.

While the estimated effects are expressed in relative terms, it is useful to translate the results into approximate crash counts to facilitate interpretation. The preferred saturated log specification suggests an approximate 5% relative reduction in crashes involving foreign registered vehicles following the introduction of the CBE Directive. Based on average pre-policy crash counts involving foreign registered vehicles, this estimate corresponds to roughly 130–150 fewer crashes per year nationwide involving foreign registered vehicles. The magnitude of this reduction varies across provinces, ranging from approximately 3–6 crashes per year in provinces with lower population density, such as Luxembourg and Namur, to more than 20 crashes per year in highly trafficked provinces, such as Antwerp and East Flanders.

Accounting for statistical uncertainty, the 95% confidence interval suggests a reduction of between approximately 1% and 9% in crashes involving foreign registered vehicles relative to Belgian registered vehicles. Although these numbers should be interpreted as approximate, they indicate that even a relatively small change in crash shares can translate into a non-negligible number of avoided crashes at the national level.

The estimated coefficients on temperature and precipitation are small and statistically insignificant. This suggests that, once seasonal effects are absorbed by month fixed effects, short-run variation in weather conditions does not systematically affect the relative involvement of foreign registered vehicles in crashes, even though weather may influence overall crash risk.

As a robustness check, a Poisson specification using the same fixed-effects structure yields a similarly sized negative effect (approximately -2.7%), although statistical significance weakens ($p \sim 0.10$). Full Poisson results are reported in the Annex. The consistency in direction across specifications strengthens confidence in the main findings.

As discussed in the previous section, the event-study estimates show no systematic divergence in trends prior to May 2015, supporting the plausibility of the parallel trends assumption. Post-treatment coefficients are generally negative, suggesting that the reduction in crashes involving foreign registered vehicles emerged around the time of implementation and persisted thereafter rather than reflecting a sharp one-time break. Given that discussions and preparatory steps for the CBE Directive preceded its formal entry into force, this pattern may reflect a combination of gradual implementation effects and behavioural responses to increased enforcement certainty.

Overall, these results indicate that the introduction of the CBE Directive is associated with a statistically detectable decline in the relative crash involvement of foreign registered vehicles, consistent with a behavioural response to increased enforcement certainty. The results support ETSC's (2022) view that cross border enforcement mechanisms enhance compliance and road safety while highlighting the need for continued cross border cooperation and targeted interventions. This points to the value of maintaining and strengthening EU-wide coordination on traffic enforcement.

As a complementary analysis, we also estimated DiD models using the share of crash victims (fatal and non-fatal) involving foreign registered vehicles as the outcome. Given the lower frequency and greater volatility of victim outcomes, the analysis focuses on the share-based specification rather than the saturated count-based model. While the estimated coefficient is negative, it is not statistically significant once province and month fixed effects are included (please refer to Figure 13 in Annex). This indicates that although the CBE Directive is associated with a modest reduction in the relative involvement of foreign registered vehicles in crashes, this change does not translate into a statistically detectable shift in the distribution of crash victims. Given the

greater volatility and complexity of victim outcomes, the main analysis therefore focuses on crash involvement rather than victim shares.

3.5.1 Robustness Checks and Sensitivity Analysis

Several robustness checks were conducted to assess the credibility of the main DiD estimates and to evaluate the sensitivity of the results to alternative modelling choices. These additional analyses are primarily implemented using the share-based specification, which provides a normalized outcome measure and facilitates comparison across modelling variants. First, all share-based specifications include province and month fixed effects. Province fixed effects absorb persistent provincial differences in traffic exposure, infrastructure, and mobility patterns, while month fixed effects capture common seasonal variation in crashes and driving conditions. Weather controls are included to account for environmental conditions that may influence crash risk. The estimated coefficients on these controls are stable across specifications and do not materially affect the estimated policy effect.

Second, standard errors are clustered at the province level to account for serial correlation and unobserved shocks within provinces over time. This conservative approach widens confidence intervals but reduces the risk of spurious statistical significance.

Third, as part of the robustness analysis, we estimate versions of the DiD model that allow each registration group (Belgian vs. foreign registered vehicles) to follow its own linear time trend. In line with best practices in applied DiD research, we assess the robustness of the estimated effects by allowing treatment and control groups to follow group-specific linear trends. This approach relaxes the standard parallel trends assumption by permitting differences in underlying pre-treatment trajectories. The use of differential linear trends as a diagnostic is well established in the DiD literature and is recommended when researchers suspect underlying heterogeneity in slopes (Angrist & Pischke, 2009; Duflo & Mullainathan, 2004; Goodman-Bacon, 2021). Recent methodological contributions further emphasize that examining sensitivity to group-specific trends is an important way to assess violations of the parallel trends assumption (Clarke & Schythe, 2021; Roth, 2022; Sun & Abraham, 2021).

Finally, we conducted placebo timing tests to examine whether the estimated post-2015 decline in the foreign crash share could be driven by spurious timing or unrelated secular trends. Using an extended sample covering 2008–2019, we re-estimated the complementary model while assigning fictitious implementation dates in several pre-policy years (2011–2014) and one post-policy year (2016). Most placebo coefficients are small and statistically insignificant, although a modest negative effect is detected for one placebo year. Importantly, placebo estimates do not display a systematic or monotonic pattern as the fictitious implementation date approaches May 2015. This suggests that while the foreign crash share exhibits some gradual long-run variation, the timing and persistence of the decline remain most closely aligned with the actual introduction of the CBE Directive. As a sensitivity check, we also estimated the complementary share-based DiD model after excluding vehicles registered in the United Kingdom, Ireland, and Denmark. These countries differ institutionally from the core EU-27 and account for a relatively large share of foreign traffic in Belgium. The estimated post-CBE effect remains negative and of similar magnitude (–0.36 percentage points), although statistical significance weakens to the 10% level. This indicates that the main result is not driven by a small number of high-volume foreign countries, while also reflecting reduced statistical power in the restricted sample. Results can be found in the Annex.

Taken together, these robustness checks indicate that the complementary share-based results are not driven by seasonal effects, province-specific confounders, spurious timing, or differential pre-treatment trends. Instead, they support the interpretation that the observed post-2015 decline in the foreign crash share reflects a modest but statistically detectable response to the introduction of the CBE Directive.

3.6 Discussion

This study examines the impact of the EU Cross Border Enforcement (CBE) Directive on road safety outcomes in Belgium, focusing on crashes involving at least one foreign registered vehicles. Using a rich dataset that allows us to exploit variation between Belgian and foreign registered vehicles per month per province, we applied a difference-in-differences model. The main specification employs a saturated fixed-effects structure comparing number of crashes involving foreign and Belgian registered vehicles per month per province,

complemented by share-based models and additional robustness checks such as placebo tests and alternative DiD specifications.

Our findings indicate that the CBE Directive was associated with a measurable and meaningful improvement in road safety in Belgium. We find that the CBE Directive is associated with a reduction of approximately 0.5 percentage points in the share of crashes involving foreign registered vehicles, relative to Belgian registered vehicles under the complementary share-based specification. Given a pre-policy average foreign crash share of about 9%, this corresponds to a decline to roughly 8.5% of crashes involving foreign registered vehicles. The preferred saturated log specification suggests an approximate 5% relative reduction in crashes involving foreign registered vehicles compared with Belgian registered vehicles following implementation. In practical terms, this relative reduction is consistent with the share falling from about 9% to approximately 8.5–8.6%, rather than a 5 percentage-point decline. Although this magnitude might seem modest, the direction of the effect is in line with the objective of the CBE Directive.

When the estimate is extrapolated nationwide using average crash counts per province before the implementation of the policy, this reduction corresponds to roughly 130-150 fewer crashes per year involving foreign registered vehicles. Taking statistical uncertainty into account, the 95% confidence interval suggest that this reduction would range approximately 1% to 9%. Looking into provinces in detail, it can be seen that this reduction varies across provinces, ranging from about 2-6 crashes per year in less populated provinces such as Luxembourg and Namur to more than 20 crashes per year in provinces with denser traffic such as Antwerp and East Flanders.

Importantly, these figures should not be interpreted as a reduction in total crashes, but rather as a decline in the relative involvement of foreign registered vehicles, consistent with the mechanism through which the CBE Directive operates. The results therefore suggest that cross border enforcement together with other EU Member States can yield measurable safety benefits, even in settings where foreign registered vehicles account for a relatively small share of overall traffic. Overall, the results align with the assessment of ETSC (2022) that cross border enforcement plays a role in promoting compliance with traffic regulations. The findings further point to the importance of ongoing cooperation between national authorities to ensure the effective functioning of EU-wide enforcement frameworks.

These findings add new empirical evidence to the broader literature on cross border traffic enforcement and deterrence. The current literature lacks empirical analysis of the impact of the CBE Directive on road safety outcomes, which makes this study a contribution to the literature. Overall, the study demonstrates that harmonizing and strengthening cross border enforcement can meaningfully improve road safety outcomes. As mobility within the European Union continues to rise, ensuring that traffic laws apply consistently regardless of vehicle registration remains a crucial component of effective and equitable road safety policy. Future research could build on these results by investigating behavioural channels, enforcement intensity, and the heterogeneity of effects across road types, enforcement technologies, and driver populations.

3.7 Limitations

Although the DiD models provide a structured and widely used approach to estimating the causal effect of the CBE Directive, several limitations should be acknowledged when interpreting the results. First, the analysis cannot fully rule out the influence of other road safety measures introduced around the same time as the Directive. Belgium expanded the use of average speed cameras, ANPR (Automatic Number-Plate Recognition) enforcement and regional traffic policing during the study period, and improvements in motorway infrastructure occurred in several provinces. If such interventions disproportionately affected foreign drivers, for example because they were concentrated on major interurban motorways; the estimates may partially attribute these effects to the CBE Directive. The models isolate relative changes between foreign and Belgian registered vehicles, but they cannot disentangle overlapping reforms that differentially influenced the two groups.

The results are also shaped by the data available. While the administrative crash records provide comprehensive coverage of all reported crashes, they do not include measures of exposure such as vehicle-kilometres travelled, border-crossing flows, tourism intensity or freight volumes. If the mobility of foreign drivers increased or decreased for reasons unrelated to the Directive, changes in crash or victim counts may reflect shifts in exposure rather than behavioural responses. Victim data are particularly volatile due to multi-victim crashes. Aggregation at the monthly province level further masks within province variation, and the

data do not include information on offence detection, fine payment or compliance, limiting the ability to identify mechanisms. In addition, sample size constraints affect the robustness of some estimates.

Taken together, these limitations do not invalidate the empirical strategy, but they imply that the estimated effects should be interpreted as capturing the net relative change associated with the CBE Directive rather than isolating the reform from all other contemporaneous influences. The findings provide policy relevant evidence on how crashes and victims involving foreign registered vehicles evolved after the Directive, but they cannot fully separate the effect of CBE from broader changes in enforcement, mobility or road safety conditions during the same period.

3.8 Recommendations

The findings point to several avenues through which policymakers could strengthen the impact of cross border road safety enforcement. Since the CBE Directive appears to have improved road safety outcomes, it would be beneficial to further expand and support the mechanisms that enable cross border follow-up of traffic offences. It is essential for enforcement authorities in EU Member States to have timely access to reliable vehicle registration data. The technical and administrative infrastructure that makes it possible to exchange cross border information can be extended and improved by further investment to help reduce remaining enforcement gaps that allow offenders to escape liability.

In December 2024, the European Commission adopted a revised version of the CBE Directive to address the enforcement gap of the previous rules: around 40% of cross-border offences remained unpunished because of difficulties in identifying offenders or enforcing fines. In addition to an improved offender identification, the scope of offences subject to CBE was broadened to include additional dangerous behaviours such as failing to keep a safe distance, dangerous overtaking, or hit-and-run. Once Member States have transposed this regulation into their national legislation and accident data are available, a similar study could investigate the added value of the revision and quantify any shortcomings of the original CBE Directive.

In addition to policy measures, a crucial step would be to develop more comprehensive datasets that combines administrative crash records with detailed information on enforcement activity such as alcohol and drug checks, the timing and location of speed camera deployments, and exposure data such as traffic volume per province. Linking these datasets would make it possible to more precisely identify how the CBE Directive affects driver behaviour and to disentangle its impact from other interventions (such as deployment of new speed cameras) introduced during the same period. Data harmonization between Member States that ensures the similar definitions of severity of injuries, classification of vehicles, offence types would allow a more robust cross country comparative analyses. Besides, the direct effect of the CBE Directive is on traffic offences. Hence, it would be interesting to conduct a causal analysis using offence data upon availability. In this report, we study the indirect effect of the CBE Directive on road safety outcomes.

From a modelling perspective, richer data that have information such as exposure metrics (e.g. number of kilometres travelled) would allow us to improve the causal design. Incorporating spatial dependence and cross border spillovers would be particularly valuable, as traffic behaviour in border provinces may be influenced by enforcement levels in neighbouring countries. As better data become available, future evaluations could benefit from combining DiD with structural or behavioural models that capture how drivers respond to changes in the likelihood of being sanctioned.

Finally, the results highlight the importance of sustained cross border cooperation in road safety. Mobility within the EU continues to increase, and enforcement frameworks must adapt in parallel. Reinforcing the consistency of penalties, shortening response times for cross border notifications, and enhancing public awareness of the enforceability of road rules across borders could all help ensure that drivers of foreign registered vehicles face the same deterrents as drivers of Belgian registered vehicles.

4 Did 2022 Regulation on Mobility Devices Reduce the Number of E-Scooter Victims? An Interrupted Time Series Analysis

4.1 Background

4.1.1 E-Scooters and Road Safety

Despite their advantages, e-scooters come with risks due to the device itself (smaller wheels, underpowered brakes,...) (Störmann et al., 2020), the user behaviour (riding on the sidewalk, not wearing a helmet,...), or other users (lack of awareness) (Slootmans, 2024).

Since 2019, police’s records of crashes with bodily injuries allows to identify e-scooter users. The data show that both the number of crashes involving an e-scooter and the number of injured victims in such crashes have been increasing steadily since then, with the exception of 2023.

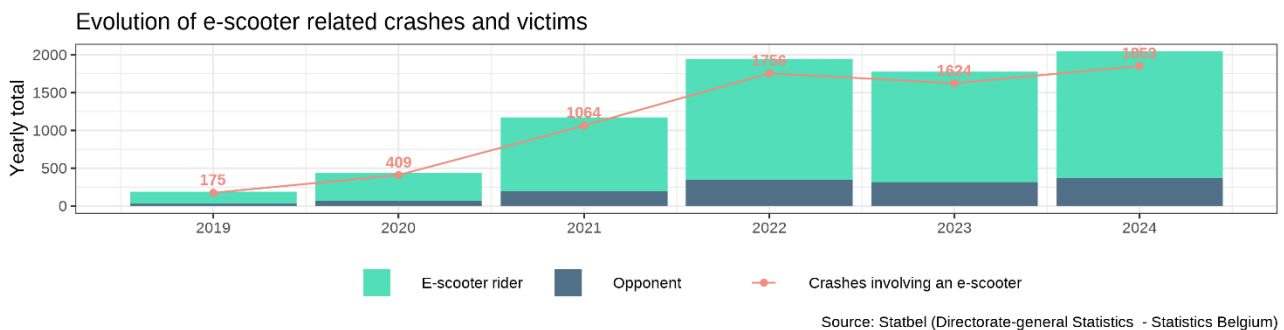


Figure 6 Evolution of crashes and victims related to e-scooters.

In 2024 the overall number of victims in e-scooter crashes was 2044, this is 10.8 time higher compared to 2019 (189 victims). The number of crashes followed a similar trend reaching 1853 in 2024, exceeding the 2019 level by a factor of 10. Table 4 gives a breakdown of this evolution by degree of injury. Serious injuries increased the most, suggesting that e-scooter accidents are not only happening more often but are also growing in severity. Although the number of deaths increased as well, the low incidence makes the interpretation uncertain. These numbers should be interpreted in light of the increased use of e-scooters in the same period (+ 139% between 2020 and 2024; Vias Institute, 2023).

Table 4 Evolution of the number of victims in crashes involving an e-scooter by level of severity between 2019 and 2024.

	2019	2024	Evolution 2019-2024
Slightly injured	180	1921	+967%
Seriously injured	8	119	+ 1387%
Fatalities 30 days	0	3	+ 3
All victims	189	2044	+ 982%

International literature reveals a similar trend. In Vienna, the number of injured patients increased approximately 19-fold from 2018 to 2021 (Frank et al., 2024). In the US, the number of e-scooters victims increased by more than 45% annually between 2017 and 2022 (Fernandez et al., 2024).

Another way to look at the impact of e-scooters on road safety is to consider the severity of the accident. It is usually computed as (number of deaths/number of crashes)*1000, however the low number of deaths make this indicator unstable. As an alternative, we also considered the number of seriously injured victims to get a more accurate estimate. For the period 2019-2024, the severity of e-scooter crashes was 221. For reference, during the same period, the severity of bicycle accidents was 259. The severity for opponents is similar in both

groups but we observe a large difference for the rider: the crash severity is 57 for e-scooter users compared to 102 for cyclists.

Table 5 Modified severity of crashes for riders and opponents of e-scooters and bicycles for the period 2019-2024.

	E-scooter	Bicycle
Rider	57	102
Opponent	165	158
General	221	259

An analysis of one hundred police reports of road accidents involving at least one electric scooter and occurring in the Brussels Region in 2020 shows that the electric scooter user is responsible for the accident in 46% of the cases (De Vos et al., 2023). Liability is shared in 35% of accidents. In most cases, these are accidents between electric scooters and motor vehicles.

The Statbel crash data gives a more detailed picture of e-scooter opponents in crashes with bodily injury. Figure 7 shows a breakdown of the opponents' type in crashes with injured/killed e-scooter users and compares it with bicycle users. In 72% of the crashes resulting in an injured e-scooter user, the opponent was a motorized vehicle. The opponent was a pedestrian in 3.2% of the cases, which is similar to cyclists. Finally, 15% of the injured e-scooter users had no opponent, slightly more than the injured cyclists (12.7%). Statbel data and police records show however only part of the reality, since they only cover crashes with bodily injury that were reported to/by the police.

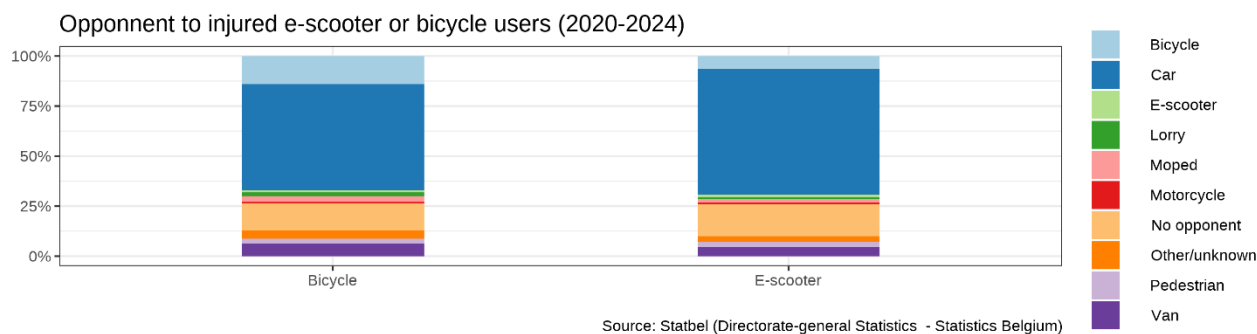


Figure 7 Opponent types for bicycles and e-scooters.

Hospital data show a different picture. Based on 8 studies using hospital data, the OECD concluded in 2020 that only 4% of the e-scooter crashes involved another road user (ITF & OECD, 2020). Studies in Spain, Israël and Germany (Coelho et al., 2021; Shichman et al., 2022; Störmann et al., 2020) find a large predominance of falls over collisions with another road user as the cause of accidents. The analysis of 3,331 patients' record admitted to the emergency department for e-scooter related injury reveal that only 4.8% of the patients were pedestrians hit by an e-scooter (Shichman et al., 2022).

Despite the relatively low number of fatalities associated with e-scooter accidents, a considerable proportion of injured victims require serious medical intervention, frequently necessitating surgery or admission to the Intensive Care Unit (ICU) (Dhillon et al., 2020; Liew et al., 2020). The most striking pattern observed across multiple U.S. studies is the high frequency of head injuries, which often account for roughly one-third of all documented lesions (Aizpuru et al., 2019; Bauer et al., 2020; Bresler et al., 2019; Störmann et al., 2020). A comprehensive German study involving 538 accident victims further highlights the severity, reporting that 83% suffered a severe injury to the head or face (Abbreviated Injury Scale [AIS] ≥ 2) (Hartz et al., 2025). The most common severe injuries included subarachnoid haemorrhage, skull base fracture, and serial rib fractures. A study from Poland also includes the extremities as the most frequent injury site (51%), before the head and face (36%) (Kłosiewicz et al., 2024). Hospital data from Belgium confirm this trend, revealing that 60% of seriously injured e-scooter users sustained a severe head trauma, with 24% also suffering injuries to the hip and upper legs (Bouwen, 2024).

The prevalence of severe head injuries can be explained by the low rate of helmet use among e-scooter riders. Observational data underscores this safety gap. When comparing accident victims admitted to the Emergency Room (ER) in Washington D.C., e-scooter riders were dramatically less likely to be wearing a helmet than cyclists (2% vs. 66.4%) (Cicchino et al., 2021). Another U.S. study noted that users of shared e-scooters wore

helmets 70% less often than riders of private devices (Frye et al., 2024). This behavioural pattern directly contributes to injury severity.

Overall, the data clearly establishes that while e-scooters may not cause a high volume of fatalities, they pose a significant risk of severe, resource-intensive, and life-altering injuries. These severe injuries also incur substantial healthcare costs, with a median hospitalization cost estimated at \$291 in Poland (Kłosiewicz et al., 2024).

Although they play an important role in the development of mobility, e-scooters have a documented impact on the road safety. In July 2022, a new regulation came into effect to alleviate this burden. The purpose of this use case is to evaluate the impact of this new law on the monthly number of victims in e-scooter accidents (both riders and opponents; both privately owned and shared) in Belgium, by comparing the trajectory from January 2019 to June 2022, with the trajectory between July 2022 and December 2024.

4.1.2 Policy Context

Since 2007 the Road Code introduced a specific category for motorized “mobility devices”, regrouping motorized vehicles with one or more wheels and a maximum speed of 25km/h. Among those devices appear the electric scooters (e-scooter), similar to conventional kick scooters although they have a battery powering an electric motor.

E-scooters users either own their own device or, in most major cities, can use their smartphone to unlock a shared-device owned by a rental company. Although the users’ profile and motivation differs, both private and shared device have grown popular in the recent years thanks to their functional convenience (affordability, urban accessibility, multimodality,...) as well as the core values and needs they fulfil (reduced environmental impact, freedom, health and well-being,...) (Espinoza et al., 2019; Vandael Schreurs et al., 2023).

In reaction to the increased usage, and subsequently the increased number of victims, the authorities amended the Road Code to include more specific regulations concerning “motorized personal mobility devices” such as electric scooters. This law, which came into effect on July 1, 2022⁵, classifies users of these devices as cyclists rather than pedestrians, making them subject to cyclist road regulations. The main consequences and provisions of this new regulation are :

1. The ban on riding e-scooters on the sidewalks, they must now use the cycle lane (or the pavement if there is no lane).
2. A maximum speed limited to 25 km/h, with more specific limitations in Brussels-Capital region (8 km/h in some pedestrian areas, 20km/h for the rest of the territory).
3. A minimum age of 16 year to ride an e-scooter (except in residential, pedestrian, and meeting areas, as well as paths and streets reserved for play).
4. The interdiction to transport a passenger.
5. E-scooters must be parked out of the roadway and parking area, expect for dedicated parking spots designated by M21 to M24 traffic signs.
6. The extension of required equipment: reflectors, side reflector, brakes and audible warning device.

This regulation aims to limit dangerous behaviours and clarify the legal framework governing these new urban mobility devices. Additionally, e-scooters must be compliant with the EN17128 norms regulating safety features for personal light electric vehicles (such as speed, braking system and battery management) and national legislation. E-scooters must be equipped with reflector, sound indicator, adapted braking system, and have a maximum width of 1 meter.

Other traffic regulations such as the interdiction to use the phone while driving or driving under the influence of alcohol also apply to e-scooters users.

Although other type of micromobility devices such as monowheels, hoverboards or e-skateboards are also concerned by the regulations mentioned, their use remains very marginal (Mobilians & Smart Mobility Lab, 2025; SPF Mobilité et Transports, 2020). Most often, they are excluded or grouped in a generic “Others” category in mobility surveys ((Eurostat, 2021; Ipsos & Europ Assistance, 2025; Vias Institute, 2023). This is

⁵ 15 MAI 2022. - Loi modifiant l'arrêté royal du 1^{er} décembre 1975 portant sur le règlement général de la police de la circulation routière et de l'utilisation de la voie publique, en ce qui concerne la réglementation des appareils de locomotion, BS 15 juin 2022, bl. 50763.

also true for police reports in which they can't be clearly identified. For these reasons, our analysis focuses only on e-scooters.

4.2 Data and Definition

The national database on road accidents resulting in death or injury is the primary data source used here. It is described in section 3.2.1. From this database, we extracted the monthly number of killed or injured victims in a crash involving at least one e-scooter between the 1st of January 2019 and the 31st of December 2024.

The Automatic Weather station (AWS) open dataset from IRM/KMI was used to control for meteorological effect (Royal Meteorological Institute of Belgium, 1995). Hourly weather reports between 8AM and 8PM from Uccle-Ukkel were extracted for the full period. The average temperature (*TEMP_AVG*) and level of precipitation (*PRECIP_QUANTITY*) were averaged by month to create two external regressors.

As the COVID-19 pandemic hit during our study period, the Oxford COVID-19 Government Response Tracker (OxCGRT) was used to derive a third external regressor (Hale et al., 2021). Using the OxCGRT_simplified dataset, we extracted the daily score for the variables *C1* to *C8* (School closing, Workplace closing, Cancel Public events, Restrictions on gathering size, Close public transport, Stay at home requirements, Restrictions on internal movement, Restrictions on international travel) for Belgium. The values were then averaged altogether by month to reflect the strictness of closure and containment policies in response to COVID-19 pandemic. The dataset covers the period from the 1st of January 2020 to the 30th of December 2022. Outside of this period (i.e. for 2019, 2023 and 2024) the index was set to 0, reflecting the absence of containment policy.

To estimate via proxy the usage of e-scooters, we use the monthly number of trips reported by shared e-scooters company operating in Brussels (*Évolution mensuelle de la mobilité*, n.d.). As there were no available number prior 2021, we imputed missing values assuming a linear increase starting from 0 in January 2019 and ending at 2726 (first available value) in January 2021.

4.3 Methodology

To answer this question, an interrupted time series (ITS) was used. ITS is a quasi-experimental approach that evaluates whether a policy produces measurable changes by comparing trends before and after the intervention while accounting for underlying temporal patterns and external influences such as seasonality, mobility trends, or weather conditions (Linden, 2015; Lopez Bernal et al., 2016). The studies using ITS to evaluate alcohol policy, speed enforcement and licensing evaluations (see section 2.2.3) provide an ideal template to evaluate the PMD road code reform. The reform's clearly defined implementation date, nationwide scope and comprehensive nature make ITS an ideal tool for identifying both immediate and longer-term effects on PMD injury trends.

In this framework, the effect of the intervention is captured through changes in both the level and the slope of the time series.

- A significant change in level indicates an immediate shift—either an abrupt decrease or increase—in the number of e-scooter victims right after the policy came into force.
- A significant change in slope reflects whether the long-term trajectory has been altered. This may signal a reversal of trend (e.g., a previously increasing trend begins to decline) or a change in the rate of growth (e.g., a steep rise becomes more moderate, or an already decreasing trend accelerates).

By modelling these components simultaneously, the ITS approach not only identifies whether the intervention had an effect, but also clarifies *how* and *when* the effect materialized to distinguish rapid, short-term impacts from gradual, structural changes in e-scooter injury patterns.

A SARIMAX model was used to analyse and forecast data. An ARIMA model, which stands for AutoRegressive Integrated Moving Average, is a statistical approach used to analyse and forecast time series data by capturing patterns in the series' past values, trends, and error structures. It combines three components. The autoregressive part (AR) models the relationship between the current value and the previous observations, with the parameter p indicating how many past values are used. The integrated component (I) represents the differencing applied to the series to remove trends or non-stationarity, and its parameter d specifies how many

times the data are differenced. The moving average part (MA) captures the influence of past forecast errors on current values, with q indicating the number of lagged errors included.

For time series that show seasonal patterns, such as monthly or weekly cycles, the model can be extended to a Seasonal ARIMA, written as

$$ARIMA(p, d, q)(P, D, Q)_m$$

In this version, the parameters P, D and Q mirror the non-seasonal ones but operate at the seasonal frequency, while m defines the length of the seasonal cycle (in our case, 12 for monthly data with yearly seasonality). Altogether, these parameters allow the ARIMA framework to account for short-term dynamics, long-term trends, and recurring seasonal behaviours, making it a flexible tool for forecasting and understanding time-dependent processes (Box et al., 2016). Both the literature (Frank et al., 2024; Kłosiewicz et al., 2024; Slotmans, 2024) and our data suggest the seasonality of e-scooters crashes (with a peak in summer), leading us to choose a model accounting for seasonality.

The three external regressor described in section 4.2 (level of precipitation, temperature and Stringency index) were added to the model as a way to take into account the impact of external factors.

The models' parameters were selected using *auto.arima* from the R package *forecast* v8.15 (Hyndman & Khandakar, 2008). The function explores different model combinations and selects automatically the best one. The performance of a model is based on the evaluation of various information criteria like the Akaike information criterion (AIC) or the Bayesian information criterion (BIC), which balance goodness of fit against model complexity. The search process (rather than stepwise) was used to select the model with the lowest information criterion value as the optimal specification. For both the search and the stepwise process, the non-seasonal d and seasonal D parameters are first chosen by testing the series for stationarity and, if the series is not stationary, incrementing the parameters value by one until stationarity is attained. Once d and D are fixed, the stepwise process would select AR and MA orders (p, q, P, Q) by using a algorithm. The algorithm starts by 4 predefined models and selecting the one with the lowest AIC. Up to 17 variations of the current model are then tested and whenever a model with a lower AIC is found, it becomes the "new" current model, and the procedure is repeated. The process stops when it cannot find another model close to the current one with a lower AIC. On the other hand, the search process is exhaustive and explicitly fits every valid combination for p, q, P and Q before selecting the model with the lowest AIC. This method has a much higher computational cost but does not depend on starting values, local improvements, or incremental moves, so it cannot get stuck in a local minimum.

Two ad-hoc analysis were performed to assess the robustness of our results and give more insight on their interpretation. First, we conducted a "placebo test" using fictive intervention dates (one year before and after the actual implementation of the law). Comparing those results with the actual date helps confirming that our model is actually picking up the direct impact of the law and not some seasonal anomalies or random fluctuations. Second, using the same model, we predicted the number of trips using shared e-scooters in Brussels to assess, via proxy, the impact of the regulation on e-scooter usage⁶.

4.4 Results

4.4.1 Main ITS: Impact on the Number of Victims

The estimated model is an $ARIMA(0,1,1)(1,0,0)_{12}$. Figure 7 compares the fitted values (i.e. the number of victims estimated by the model on each time point) with the actual values as reported in the crash data.

⁶ As data were not collected prior to January 2021, the number of trips was interpolated for the period January 2019-December 2020.

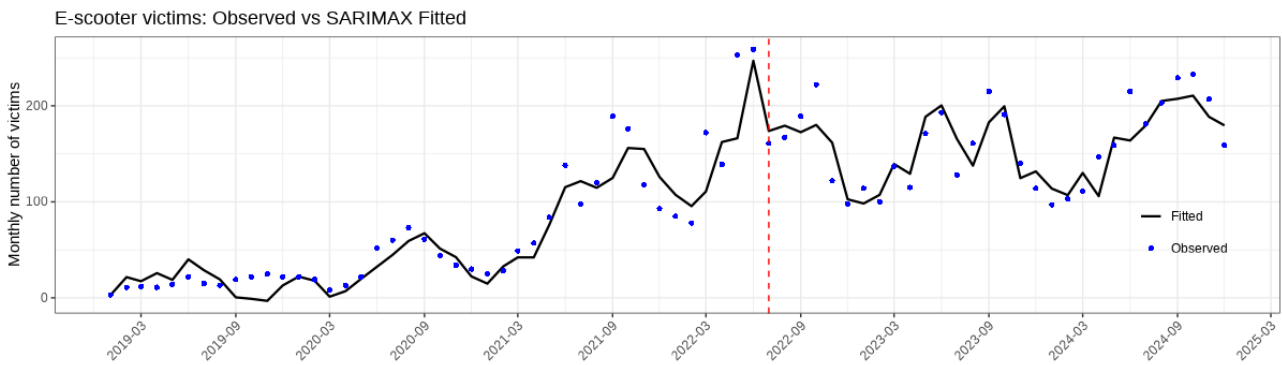


Figure 8 SARIMAX fitted numbers of e-scooters victims.

The estimated error variance was 629.4, with a log-likelihood of -327.84 . Model selection criteria were AIC = 671.69, and BIC = 689.79 (Table 6).

Table 6 Selection criteria of the main ITS model.

Statistic	Value
Sigma²	629.40
Log-likelihood	-327.84
AIC	671.69
AICc	674.01
BIC	689.79

The estimates for each parameter of the model are summarized in table 7. The moving-average term (MA1) was negative and statistically meaningful (-0.33), while the seasonal autoregressive term at lag 12 (SAR1) was positive (0.53). Among the regressors, temperature was significantly and positively associated with the outcome ($\beta = 3.88$), whereas precipitation quantity and Stringency Index showed no significant association. Finally, regarding the impact of the policy, the level shift parameter was negative and significant ($\beta = -78.11$), while the slope change term was small and non-significant ($\beta = -1.67$). This indicates an immediate effect of the policy but no changes in the long-term trajectory.

Table 7 Summary statistics of the main ITS model parameters.

Parameter	Estimate	Std. Error	p-value
MA(1)	-0.325	0.129	0.01**
SAR(1)	0.525	0.106	0.001***
Temperature	3.875	0.946	0.001***
Precipitation	-3.244	3.889	0.4
Stringency Index	-18.607	10.018	0.06
Level shift	-78.113	22.512	0.001***
Slope change	-1.673	4.404	0.7

*p ≤ 0.5; **p ≤ 0.01; ***p ≤ 0.001

4.4.2 Robustness Checks

The estimates for the placebo models are presented in table 8. The models were fitted using the same parameters and the same external regressors. The level shift and slope change were adapted to reflect a fictive implementation date on the 1st of July 2021 or 2023. The models show good fits ($AIC_{2021} = 683.02$; $AIC_{2023} = 682.75$) and similar estimate for the temperature, precipitation and Stringency Index. The level and slope are however non-significant for both fictive dates, meaning that no difference was found comparing the period before and after the cut-off dates.

Table 8 Estimates and level of significance of ITS placebo models.

Parameter	July 2021		July 2023	
	Estimate	p-value	Estimate	p-value
MA(1)	-0.414	0.016*	-0.386	0.023*
SAR(1)	0.501	0.001***	0.489	0.001***
Temperature	3.622	0.001***	3.754	0.001***
Precipitation	0.993	0.82	2.118	0.618
Stringency index	-18.848	0.07	-19.667	0.067
Level shift	21.811	0.37	-0.358	0.988
Slope change	1.604	0.66	5.280	0.241

* $p \leq 0.5$; ** $p \leq 0.01$; *** $p \leq 0.001$

4.4.3 Impact on Exposure

The last model tested looks at a different outcome and focuses on the impact of the policy on the number of trips on shared e-scooters in Brussels. The estimates indicate that the number of trips significantly decreased after July 2022 (-10 133 trips per month, $p = 0.004^{**}$). However, we should keep in mind that the moderately high estimated variance of the one-step-ahead forecast error ($\sigma^2 = 15\,671\,755$) indicates substantial remaining noise in the data, suggesting the strong impact of other factors that were not accounted for in the model. The full model specifications and estimates are available in the annex.

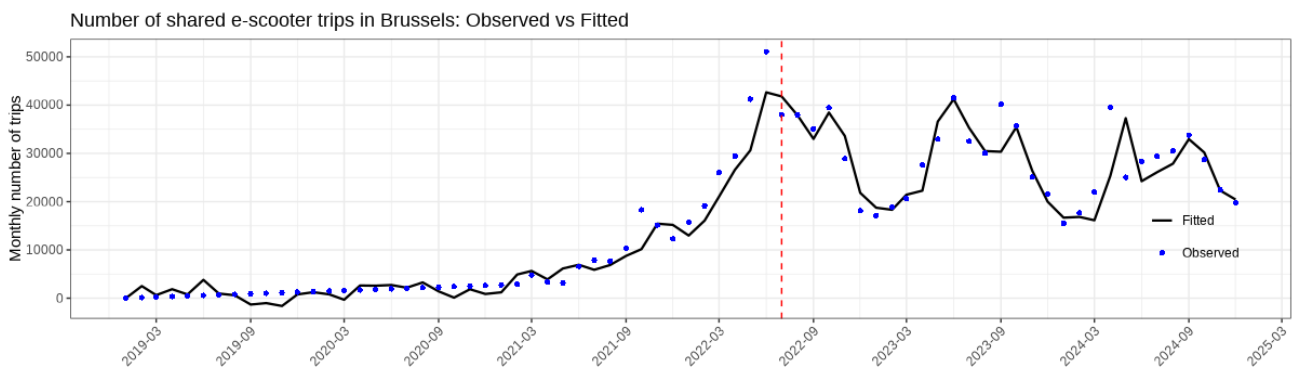


Figure 9 SARIMAX fitted numbers of shared e-scooters trips.

4.5 Discussion

This study aimed to evaluate the impact of the July 2022 reform of the Belgian Road Code on the number of monthly victims in e-scooter crashes in Belgium, using an ITS design with a SARIMAX specification accounting for weather, COVID-19 restrictions, and seasonality. The “regulation impact” should be understood here in its broader sense rather than the simple act of enacting a new law. It also encompasses other core components to law compliance, such as education, communication, awareness and enforcement efforts (R. D. Cooter & Gilbert, 2022; Roy, 2021; Van Rooij, 2021).

The results suggest that the new regulation produced an immediate and measurable reduction in the number of victims but did not generate a detectable long-term change in the trend. On Figure 9 the step effect is visually indicated by the observed values (black) being systematically lower than the expected values (blue) right after the intervention. The lack of slope effect is shown by the fact that expected and observed values remain roughly parallel post-intervention. The light blue area shows the 95% confidence interval around the predicted values and the increasing uncertainty over time.

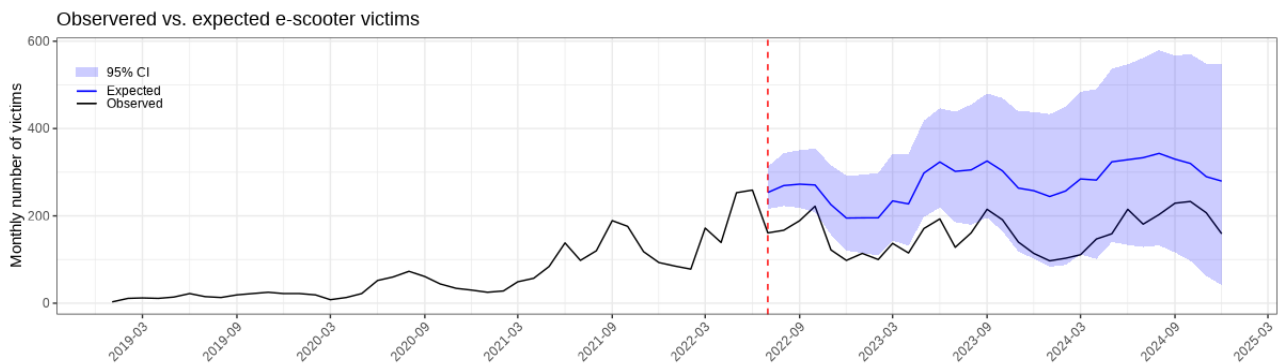


Figure 10 Expected numbers of e-scooter victims without policy change.

The model indicates a level shift of approximately 78 victims per month following the implementation of the regulation. This effect is substantial, particularly considering the rapid growth in e-scooter usage and the rising number of injuries observed between 2019 and 2024. However, the absence of a significant slope change implies that the underlying upward trajectory of e-scooter injuries remains broadly intact, meaning that the law mitigated but did not reverse long-term risk.

The two placebo analyses support the credibility of the results. Neither produced significant level or slope effects, indicating that the detected change in July 2022 is unlikely to be attributable to seasonal peaks, random fluctuations, or broader mobility patterns. This strengthens the causal interpretation that the observed reduction is linked to the policy itself.

In parallel, the analysis of shared e-scooter trip data in Brussels shows that the regulation was associated with a significant decrease in the number of trips. This result suggests that the reduction in victims may be partially mediated by lower exposure, rather than by improvements in user behaviour or inherent safety of the devices. This distinction is important for policy interpretation: while fewer injuries are desirable, reductions driven only by decreased usage may not reflect a safer mobility environment or behaviour. In contrast, changes in riding behaviour, compliance, or infrastructure could generate longer-term benefits.

The nature of injuries observed in Belgian and international hospital data underscores the importance of this issue. Although fatalities remain relatively rare, e-scooters are associated with a high burden of severe injuries such as head trauma and other conditions requiring ICU care (Bouwen, 2024; Dhillon et al., 2020; Liew et al., 2020). Helmet use remains very low and shared device users appear even less likely to wear a helmet than private riders (Cicchino et al., 2021; Frye et al., 2024). Given that falls are the leading mechanism of injury, the design of the device, rider protective behaviour, and infrastructure are central determinants of risk.

At the same time, public knowledge of the regulation appears uneven. The ESRA survey indicates that rules related to intoxication, mobile-phone use, and mandatory use of cycle lanes are relatively well known, but awareness of rules about helmet use, earphones, or the transport of goods remains limited (Delavary et al., 2024). The level of knowledge regarding these rules is similar in Belgium compared to other European countries. A more specific survey about the 2022 law changes would help evaluating its impact and whether it reached its full potential. The level of knowledge and the level of conformance among those knowing the law are crucial information to decide if more efforts are needed, and whether we should focus on awareness-raising communication, enforcement, or both. Finally, international evidence suggests that urban infrastructure moderates the safety effect of e-scooters. Cities with limited cycling infrastructure experienced larger increases in crashes when e-scooters are introduced, whereas cities with high bike-lane density show little to no effect (Cloud et al., 2022, 2023). This heterogeneity highlights the broader context in which the 2022 law operates: regulation alone is not sufficient, and must be accompanied by investments in infrastructure, vehicle design, and safe-riding behaviour.

4.6 Limitations and Future Research

It is difficult to account for all factors that may have influenced the number of victims around the time the new regulation came into force. In addition, other, simultaneous changes may have contributed to the observed decrease. The lack of detailed exposure data is a key limitation, as it restricts the ability to calibrate the model more accurately and to disentangle whether the reduction reflects safer conditions or simply changes in usage.

Moreover, e-scooter accidents are substantially underreported in police data, particularly unilateral accidents and crashes resulting in minor injury, making it difficult to obtain a comprehensive picture. Even if the regulation would have a major effect on those events, we cannot measure it with the available data.

The regulation also altered several dimensions at once, such as rider behaviour through age limits and device performance through speed restrictions, which makes it impossible to determine which specific component drove the observed effect or to estimate the relative magnitude of each. Finally, as there are prerequisites to compliance with the law (communication, education, enforcement,...), it is difficult to disentangle how each element plays a role in the (lack of) impact the law change. The decreased number of victims is reflecting the cumulative impact of all the prerequisites on all of the dimensions (behaviour and device changes).

A more detailed breakdown of regulatory impacts by injury severity (e.g., slightly vs. seriously injured) and by victim type (rider vs. opponent) would help determine where the benefits of the regulation are concentrated and which user groups remain at higher risk. Continued longitudinal evaluation is essential to determine whether the immediate decline observed in 2022 persists, diminishes, or evolves with user adaptation. Future studies should also examine the impacts of targeted measures, such as infrastructure upgrades or helmet-use policies, and assess whether they produce stronger or more sustained safety improvements. Analysis including exposure measurement, such as fleet size, active user counts and kilometres travelled, would also allow more meaningful comparison over time. An analysis focusing on geographical differences (by regions, type of infrastructure, level of urbanization,...) would also provide valuable insights.

4.7 Recommendations

Most of the recommendations from previous Vias studies (De Vos et al., 2023; Sloomans, 2024) are still relevant in the perspective of e-scooter victims reduction.

First, improving device safety remains essential, especially given the high prevalence of falls and severe head injuries. Efforts could focus on enhancing stability and braking systems, implementing geofencing to enforce speed limits and no-ride zones, and encouraging the adoption of advanced safety features. Second, the development of safe, continuous, and well-maintained micromobility infrastructure is critical. Evidence (Cloud et al., 2022, 2023) shows that cities with dense cycling networks experience fewer severe e-scooter crashes, suggesting that infrastructure investment may produce larger and more lasting safety benefits than regulation alone. Third, promoting safer user behaviour remains a priority. Awareness campaigns, training initiatives, and incentives or mandates to improve helmet use could help reduce the burden of severe head injuries. Enforcement measures (alcohol checks, speed control, and monitoring compliance with sidewalk and parking rules) should complement educational initiatives to reinforce safer riding norms.

Finally, from a broader policy perspective, routine evaluation of new mobility regulations should become standard practice. Supporting data systems with stronger exposure metrics, integrated hospital–police linkages, and access to operator data would enable more reliable policy assessments and help identify when regulatory adjustments or targeted interventions are needed. Collectively, these measures can help ensure that the benefits observed after the 2022 reform translate into sustained improvements in e-scooter safety.

5 Conclusions

The two empirical cases presented in this report examine, in different contexts, how regulatory interventions shape road safety outcomes in Belgium. Although they target distinct mobility domains which are cross border enforcement for motor vehicles and the regulation of e-scooter use; they provide together a broader picture of how changes in legal frameworks, enforcement certainty, and user behaviour translate into measurable safety effects.

We have assessed the impact of the EU Cross Border Enforcement (CBE) Directive on crashes involving foreign registered vehicles in Belgium. The CBE Directive aimed to close an enforcement gap by making it easier to identify and sanction traffic offences committed by foreign registered vehicles in Belgium. Using monthly province level data and a difference-in-differences design, we find that the introduction of the CBE Directive is associated with a small but statistically significant decrease in crashes involving foreign registered vehicles. After May 2015, complementary share-based estimates indicate that the foreign crash share fell by around 0.5 percentage points relative to Belgian registered vehicles. Given a pre-policy average of approximately 9%, this corresponds to a decline to about 8.5% of in the relative involvement of foreign registered vehicles in crashes. The preferred saturated specification suggests an approximate 5% relative reduction in crashes involving foreign registered vehicles compared with Belgian registered vehicles. In practical terms, this relative reduction is consistent with the share falling from roughly 9% to around 8.5–8.6%, rather than a 5 percentage point decline. While modest in size, this pattern is consistent with a behavioural response to increased enforcement certainty and remains robust across specifications. In contrast, when the analysis is repeated using the share of crash victims involving foreign registered vehicles, the estimated effect is negative but not statistically significant. This suggests that the observed change in crash involvement does not clearly translate into measurable changes in injury outcomes, which are more volatile and influenced by additional factors beyond enforcement. Overall, the findings indicate that strengthening cross border enforcement can affect driving behaviour, but that enforcement alone is unlikely to generate large safety gains across all outcomes or road user groups.

From a policy perspective, the results support continued cooperation between Member States on traffic enforcement. Further progress may depend on increasing the visibility and perceived certainty of sanctions for foreign drivers, as well as on continued investment in efficient and interoperable enforcement systems. Ongoing monitoring of crash patterns involving foreign registered vehicles will be important to assess the longer-term effects of recent and future revisions of the CBE Directive.

The July 2022 e-scooter reform, by contrast, offers a clearer example of a regulatory intervention generating an immediate and measurable safety impact. The interrupted time series analysis identified a sharp reduction in monthly victims following the tightening of rules governing age limits, riding behaviour, and prohibited areas. Placebo tests support that this drop cannot be explained by unrelated temporal shifts or the particular structure of the data. It also appears that shared e-scooter usage in Brussels declined after the reform. If this change extends to private devices and the other regions, the observed safety improvement may stem from reduced exposure rather than exclusively safer practices among remaining riders. At the same time, the long-term upward trend in e-scooter victim counts was not reversed, highlighting that short-term gains do not automatically translate into sustained risk reduction if underlying growth in micromobility demand continues and behaviour or infrastructure remain unchanged.

The evidence highlight that regulatory changes alone are not sufficient to ensure enduring safety gains even as micromobility adoption continues to expand. On the one end, they could be strengthened by targeted communication on safe riding practices, alcohol use, distraction and helmet use. On the other hand, more continuous and better-designed micromobility infrastructure, particularly protected lanes and clearer separation from pedestrian spaces and motorized vehicles, remains central to reducing conflicts.

From the research perspective, these use cases show the importance and the feasibility of using causal inference to evaluate the impact of policies on road safety. Strengthening available data would improve policy evaluation and future safety planning. Integrating police crash data with hospital injury records, accessing exposure metrics such as traffic volumes, and harmonizing reporting practices across regions would enable more precise identification of risk patterns. Linking enforcement data such as the deployment of speed cameras, mobile patrol operations, or alcohol checks to crash outcomes would allow policymakers to disentangle the effects of enforcement from those of regulatory reforms.

Taken together, the findings point to an overarching conclusion: successful road safety regulation requires more than legal amendments or technological upgrades to enforcement systems. Consistent with the Safe System approach which is developed and promoted by the ITF (2022) and adopted in European policy frameworks (European Commission, 2022), meaningful and lasting improvements arise when policies recognize that humans make mistakes, that the transport system must be resilient to those mistakes, and that responsibility for safety is shared across road users, infrastructure providers, vehicle systems, and enforcement agencies. In practice, this means that regulatory reforms are most effective when they strengthen enforcement certainty, align with behavioural incentives, and are supported by safe road design, forgiving infrastructure, clear communication, and post-crash care. Continuous monitoring, integrated data, and robust evaluation are essential to support adaptive and evidence-based policy in an evolving multimodal transport system.

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Annex

Annex 1: Use Case 1

Annex 1.A: Additional Checks

Table 9 Results for Poisson Saturated DiD.

	Poisson Saturated DiD
foreign	-2.41 (0.0002)
Foreign * post_cbe	-0.028 (0.108)
province fixed effects	Province by month fixed effects
month fixed effects	Province by month fixed effects
observations	1584
Adjusted Pseudo R2	0.9421

Dependent Var.:	placebo_2011 foreign_share	placebo_2012 foreign_share	placebo_2013 foreign_share	placebo_2014 foreign_share	placebo_2016 foreign_share
Post (placebo cutoff)	-0.0016 (0.0025)	-0.0018 (0.0025)	-0.0031 (0.0022)	-0.0062* (0.0024)	-0.0015 (0.0020)
avg_temp	-0.0009* (0.0003)	-0.0009* (0.0004)	-0.0007* (0.0003)	-0.0006 (0.0003)	-0.0009* (0.0004)
avg_pre	-0.0002 (0.0003)	-0.0002 (0.0003)	-0.0002 (0.0003)	-0.0001 (0.0003)	-0.0003 (0.0002)
Fixed-Effects:					
prov	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered by: prov					
Observations	1,584	1,584	1,584	1,584	1,584
R2	0.80865	0.80873	0.80919	0.81154	0.80863
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					

Figure 11 Placebo tests using complementary share-based models.

did_share_all	
Dependent Var.: foreign_share	
Post (true CBE)	-0.0036. (0.0018)
avg_temp	-0.0001 (0.0006)
avg_pre	-0.0022 (0.0018)
Fixed-Effects:	
prov	Yes
month	Yes
S.E.: Clustered by: prov	
Observations	924
R2	0.81151

Figure 12 Share-based model results excluding UK, Ireland and Denmark.

```

did_share_all
Dependent Var.: foreign_share

Post (true CBE)      -0.0022
                    (0.0021)

avg_tem              -0.0006
                    (0.0008)

avg_pre              -0.0028
                    (0.0023)

Fixed-Effects:
prov                 Yes
month                Yes

S.E.: Clustered by: prov
Observations         924
R2                   0.76034

```

Figure 13 Share-based model results for the victims.

```

           placebo_2011 placebo_2012 placebo_2013 placebo_2014 placebo_2016
Dependent Var.: foreign_share foreign_share foreign_share foreign_share foreign_share

Post (placebo cutoff)  0.0010      -0.0007      -0.0019      -0.0048      -0.0003
                    (0.0030)      (0.0032)      (0.0028)      (0.0029)      (0.0024)

avg_temp              -0.0014*     -0.0013*     -0.0012*     -0.0010*     -0.0014*
                    (0.0005)      (0.0004)      (0.0004)      (0.0004)      (0.0005)

avg_pre               -0.0008     -0.0007     -0.0008     -0.0007     -0.0008
                    (0.0006)      (0.0006)      (0.0006)      (0.0006)      (0.0005)

Fixed-Effects:
prov                  Yes           Yes           Yes           Yes           Yes
month                 Yes           Yes           Yes           Yes           Yes

S.E.: Clustered by: prov
Observations          1,584       1,584       1,584       1,584       1,584
R2                    0.75966     0.75964     0.75981     0.76094     0.75962

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 14 Placebo tests for the victims.

Annex 1.A.1: Descriptive/Pre-Diagnostic Figures for absolute values

Annex 1.A.1.1: Crashes

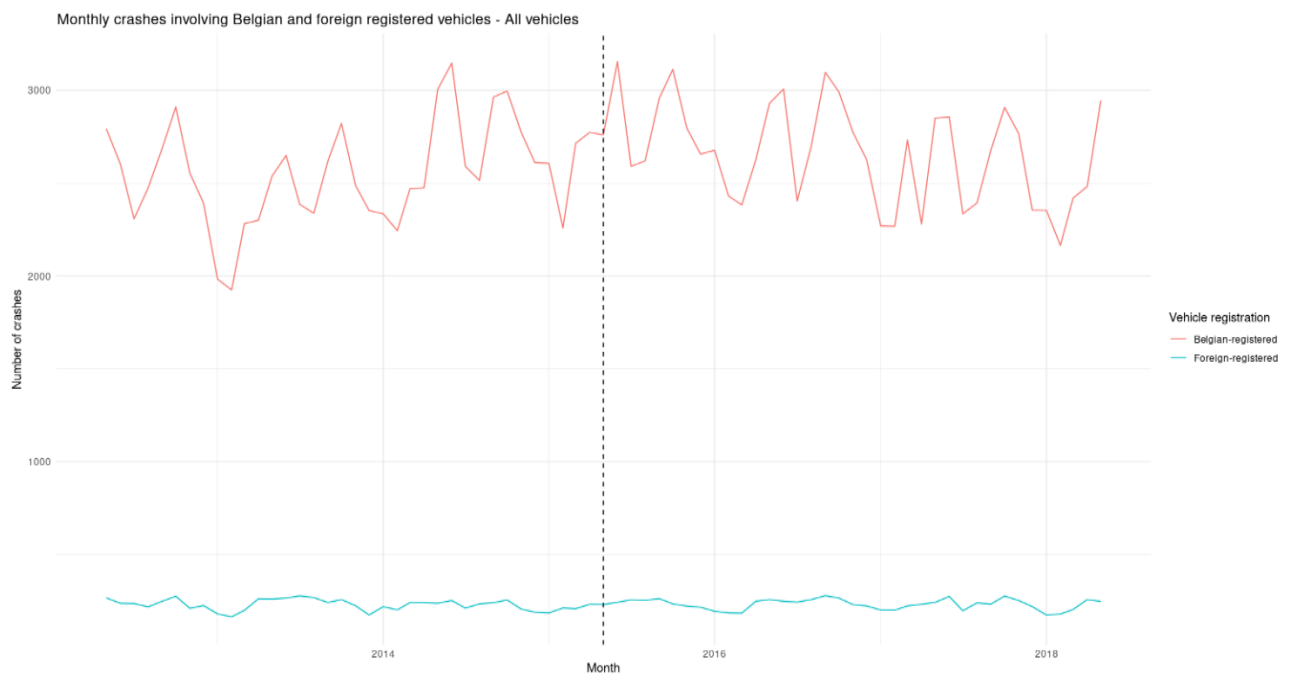
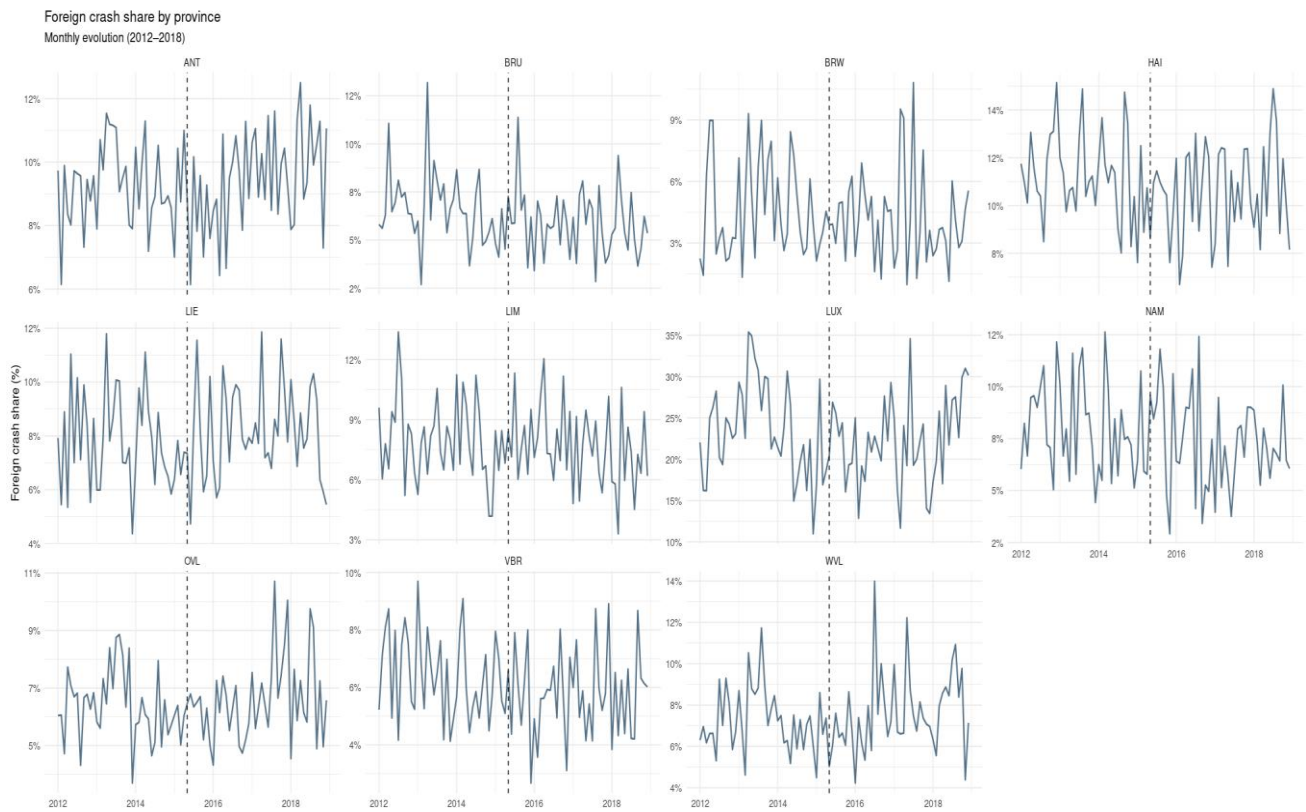


Figure 15 Monthly crashes involving Belgian and foreign registered vehicles involving all vehicle types.

Annex 1.A.1.2 Victims

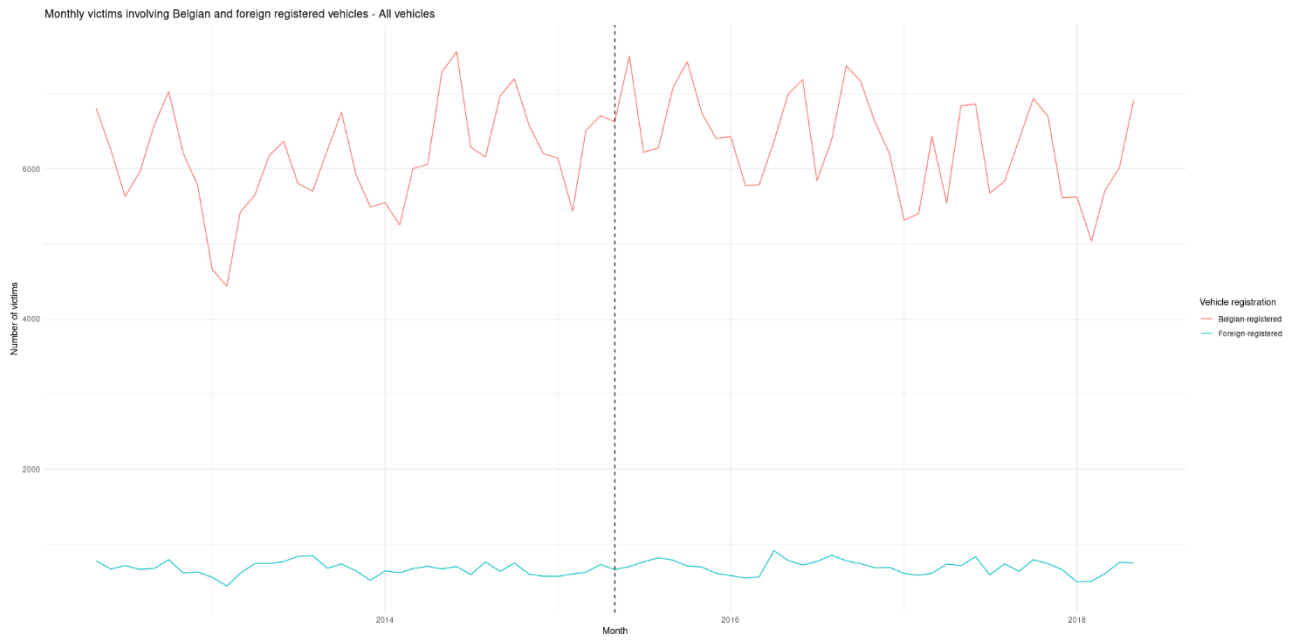


Figure 16 Monthly victims involving Belgian and foreign registered vehicles – All vehicles.

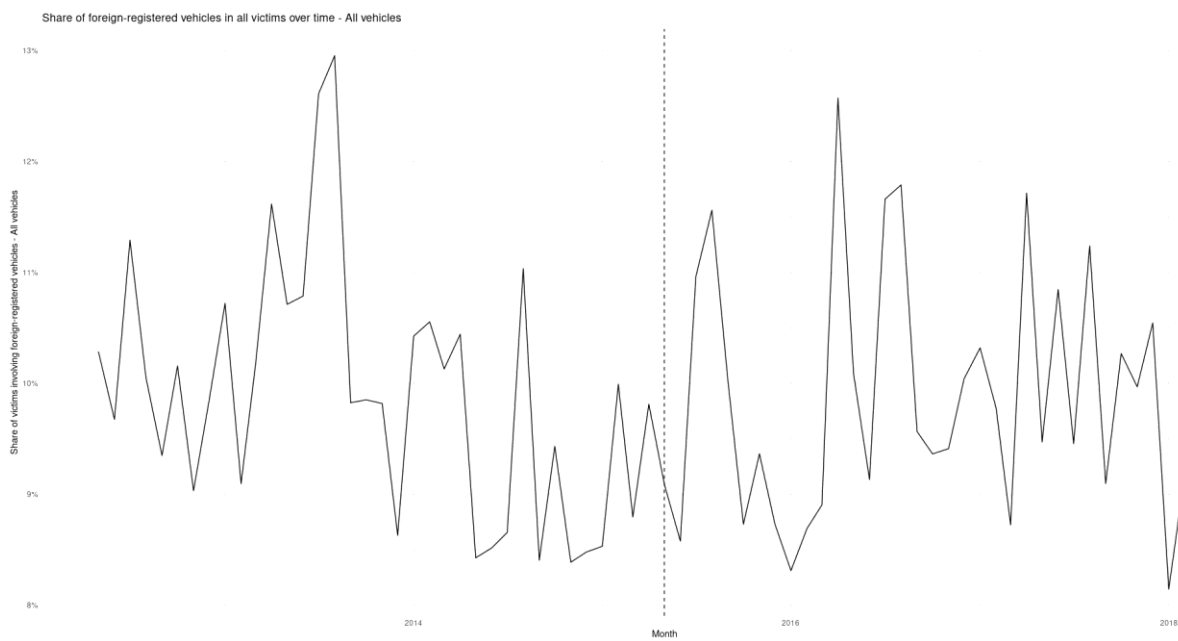


Figure 17 Share of foreign registered vehicles in all victims over time – All vehicles.

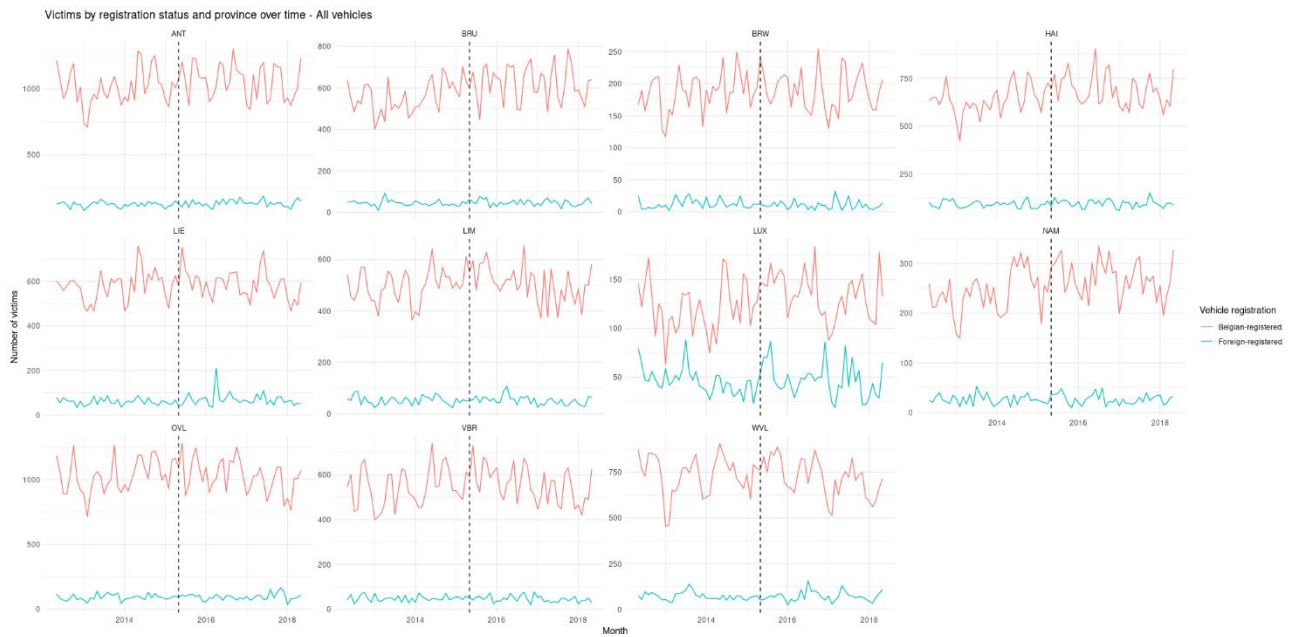


Figure 18 Victims by registration status and province over time – All vehicles.

Annex 1.B: Difference-in-Differences Model for Absolute Crash Counts

Annex 1.B.1: Model

The primary model evaluates whether the treatment group experienced a change in crash involvement after the Directive:

$$accidents_{ipt} = \beta_0 + \beta_1 post_t + \beta_2 treatment_i + \beta_3 (post_t * treatment_i) + \gamma X_{pt} + \alpha_p + \varepsilon_{ipt}$$

Where:

- $accidents_{ipt}$: monthly number of crashes involving foreign or Belgian registered vehicles in province p at time t
- $post_t$: equal to 1 after May 2015
- $treatment_i$: equal to 1 for foreign registered vehicles
- $post_t * treatment_i$: the DiD estimator capturing the effect of the CBE Directive
- X_{pt} : monthly weather controls (temperature and precipitation)
- α_p : Province fixed effects (to control for unobserved time-invariant differences across provinces)
- ε_{ipt} : Standard errors: clustered at the province level

The coefficient of interest, β_3 , measures the relative change in crashes involving foreign registered vehicles after the CBE came into force.

This model is estimated separately for all vehicles combined (excluding mopeds) and for each vehicle type separately (cars, lorries, vans, motorcycles).

Trend-Adjusted Difference-in-Differences Model for Absolute Crash Counts

In cases where pre-treatment differences are not stable, the standard DiD estimator may confound the effect of the Directive with pre-existing divergence. For such cases, a group-specific linear time trend is added:

$$accidents_{ipt} = \beta_0 + \beta_1 post_t + \beta_2 treatment_i + \beta_3 (post_t * treatment_i) + \beta_4 (treatment_i * time_t) + \gamma X_{pt} + \alpha_p + \varepsilon_{ipt}$$

Where:

- $time_t$: is the monthly time index
- The interaction $treatment_i * time_t$ captures systematic pre-policy divergence
- The coefficient β_3 now measures the treatment effect net of this pre-existing divergence

Other coefficients have the same interpretation as before. This specification is used only when justified by event-study diagnostics.

This selective application of adjusted models follows best practices in applied DiD research.

Annex 1.B.2: Full Regression Outputs

Annex 1.B.1: Crashes

Cars		
Dependent Var.:	did_model accidents	did_trend accidents
Post-policy	7.941* (3.120)	7.940* (3.121)
Foreign-registered vehicle	-193.22*** (31.15)	-214.1*** (44.44)
Average temperature	0.7587*** (0.1796)	0.7658*** (0.1842)
Average precipitation	0.7971** (0.2225)	0.8145** (0.2273)
Foreign × Post (CBE effect)	-8.259* (2.976)	-9.715* (3.086)
Foreign × Time trend	---	0.0013 (0.0010)
Fixed-Effects:		
prov	Yes	Yes
S.E.: Clustered	by: prov	by: prov
Observations	1,606	1,606
R2	0.81831	0.81831
Within R2	0.77140	0.77141
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Figure 19 DiD Results for Cars – Number of Crashes.

Lorries		
Dependent Var.:	did_model accidents	did_trend accidents
Post-policy	0.0421 (0.3967)	0.0417 (0.3966)
Foreign-registered vehicle	-4.995*** (1.082)	-12.85 (7.312)
Average temperature	0.0621** (0.0145)	0.0648*** (0.0160)
Average precipitation	0.0242 (0.0608)	0.0307 (0.0630)
Foreign × Post (CBE effect)	0.2554 (0.3502)	-0.2904 (0.6994)
Foreign × Time trend	---	0.0005 (0.0004)
Fixed-Effects:		
prov	Yes	Yes
S.E.: Clustered	by: prov	by: prov
Observations	1,606	1,606
R2	0.74534	0.74561
Within R2	0.34526	0.34595
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Figure 20 DiD Results for Lorries – Number of Crashes.

Vans

Dependent Var.:	did_model accidents	did_trend accidents
Post-policy	1.319* (0.4906)	1.319* (0.4908)
Foreign-registered vehicle	-19.77*** (4.106)	-27.68** (6.228)
Average temperature	0.0819** (0.0261)	0.0845** (0.0266)
Average precipitation	0.0830 (0.1209)	0.0896 (0.1205)
Foreign × Post (CBE effect)	-0.9326 (0.4579)	-1.482* (0.5008)
Foreign × Time trend	---	0.0005* (0.0002)
Fixed-Effects:		
prov	Yes	Yes
S.E.: Clustered		
Observations	by: prov 1,606	by: prov 1,606
R2	0.74139	0.74144
Within R2	0.63765	0.63773
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Figure 21 DiD Results for Vans – Number of Crashes.

Motorcycles

Dependent Var.:	did_model accidents	did_trend accidents
Post-policy	-0.1220 (0.4610)	-0.1232 (0.4611)
Foreign-registered vehicle	-19.05*** (2.990)	-42.14*** (7.476)
Average temperature	0.7029*** (0.0716)	0.7108*** (0.0726)
Average precipitation	-1.031*** (0.1520)	-1.012*** (0.1520)
Foreign × Post (CBE effect)	-0.3082 (0.3829)	-1.912** (0.6031)
Foreign × Time trend	---	0.0014** (0.0003)
Fixed-Effects:		
prov	Yes	Yes
S.E.: Clustered		
Observations	by: prov 1,606	by: prov 1,606
R2	0.70804	0.70859
Within R2	0.66073	0.66137
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1		

Figure 22 DiD Results for Motorcycles – Number of Crashes.

Annex 1.B.2: Victims

All Vehicles Dependent Var.:	did_model total_victims
Post-policy	19.02* (7.721)
Foreign-registered vehicle	-496.7*** (82.23)
Average temperature	3.156*** (0.6192)
Average precipitation	1.077. (0.5907)
Foreign × Post (CB effect)	-18.20* (7.181)
Foreign × Time trend	
 Fixed-Effects:	
prov	Yes

S.E.: Clustered by: prov	
Observations	1,606
R2	0.81623
Within R2	0.76214

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

Figure 23 DiD Results for All Vehicles – Number of Victims.

Cars Dependent Var.:	did_model total_victims
Post-policy	16.55* (6.931)
Foreign-registered vehicle	-464.1*** (76.18)
Average temperature	2.410*** (0.5225)
Average precipitation	1.992** (0.5333)
Foreign × Post (CBE effect)	-16.67* (6.354)
Foreign × Time trend	
 Fixed-Effects:	
prov	Yes

S.E.: Clustered by: prov	
Observations	1,606
R2	0.81782
Within R2	0.76581

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

Figure 24 DiD Results for Cars – Number of Victims.

```

Lorries
Dependent Var.:          did_model
                          total_victims

Post-policy              -0.0050 (0.8812)
Foreign-registered vehicle -10.65** (2.399)
Average temperature      0.2201** (0.0574)
Average precipitation     0.1951 (0.2402)
Foreign x Post (CBE effect) 1.924. (0.9096)
Foreign x Time trend

Fixed-Effects:
prov                      Yes
-----
S.E.: Clustered by: prov
Observations              1,606
R2                        0.69134
Within R2                 0.19839
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 25 DiD Results for Lorries – Number of Victims.

```

Vans
Dependent Var.:          did_model
                          total_victims

Post-policy              3.051* (1.196)
Foreign-registered vehicle -50.79*** (10.66)
Average temperature      0.2219* (0.0783)
Average precipitation     0.2719 (0.3407)
Foreign x Post (CBE effect) -1.453 (1.191)
Foreign x Time trend

Fixed-Effects:
prov                      Yes
-----
S.E.: Clustered by: prov
Observations              1,606
R2                        0.73811
Within R2                 0.61986
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Figure 26 DiD Results for Vans – Number of Victims.

```

Motorcycles
Dependent Var.:          did_model
                          total_victims

Post-policy              -0.4388 (0.9719)
Foreign-registered vehicle -39.24*** (6.295)
Average temperature      1.488*** (0.1533)
Average precipitation     -2.256*** (0.3194)
Foreign x Post (CBE effect) -0.4137 (0.8029)
Foreign x Time trend

Fixed-Effects:
prov                      Yes
-----
S.E.: Clustered by: prov
Observations              1,606
R2                        0.69377
Within R2                 0.64230
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

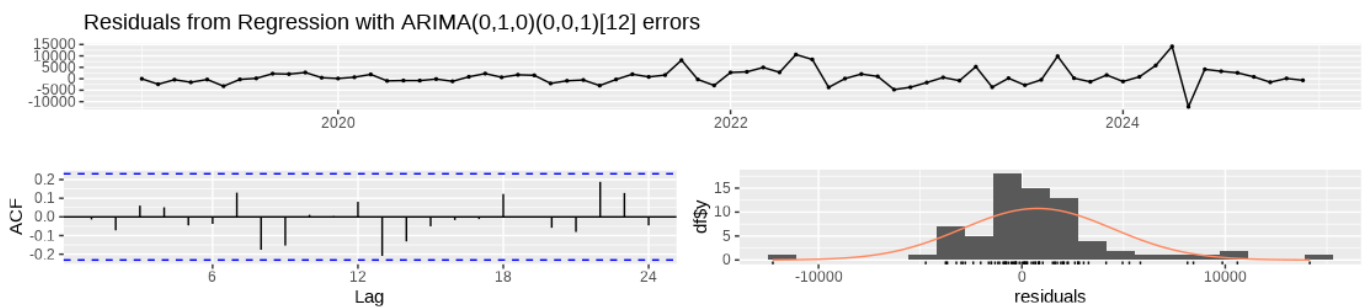
Figure 27 DiD Results for Motorcycles – Number of Victims.

Annex 2: Use Case 2

Annex 2.A. Statistics of the SARIMAX model on the number of trips using shared e-scooters in Brussels.

Statistic	Value
Sigma²	629.40
Log-likelihood	-690.59
AIC	1395.18
AICc	1396.96
BIC	1411.02

Parameter	Estimate	Std. Error	p-value
SAR(1)	0.750	0.232	0.001***
Temperature	588.631	135.641	0.001***
Precipitation	-56.426	433.858	0.89
Stringency index	-1987.949	1869.325	0.29
Level shift	-10133.125	3542.185	0.004**
Slope change	-1877.498	1192.225	0.12





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