THE PRICE OF VEHICLE IMPACTS: A SIMULATION-BASED APPROACH FOR THE IDENTIFICATION OF PROPERTY-DAMAGE COSTS AND OCCUPANTS' INJURY RISK

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ABSTRACT

Vehicle safety is continuously improving and evolving, with numerous advances from both a passive and active features perspective. Nonetheless, on-road vehicle collisions still represent an important economic loss, both in terms of Bodily Injury (BI) and Property Damage (PD) costs. Insurance organizations cover these accident-related costs by appropriate and targeted compensations, on a case-by-case basis. Yet, the capability to predictively identify the link between PD costs and personal injuries before the occurrence of road accidents could be crucial. For one, it would allow insurers to propose efficient policies favoring the most virtuous vehicles in terms of both occupant protection and structural resistance to damages. It would also allow insurers to compare the injury-related claim amount with the PD costs of the same accident in order to verify the coherence between the two for anti-fraud purposes.

The aim of the present work is to highlight a relation between PD costs and Injury Risk (IR) of occupants in *car-to-car* accidents. To this end, repair and replacement costs have been extracted for different body parts of 507 vehicle models, belonging to different categories and in circulation on the European roads since 1990. Then, a simulation-based methodology has been introduced to reconstruct five of the most common impact configurations to which a vehicle can be subject during its entire life cycle, considering crashes with all possible vehicle body categories. The frequency of impact configurations has been determined from the analysis of real accident scenarios, based on an in-depth global accident database (IGLAD). From the simulations, crash-related parameters have been derived that can be associated with specific damage entities for the vehicle body parts involved in the intrusion (for PD costs calculation) as well as with the forces discharged on the occupants (for IR assessment).

The derived relation between PD costs and IR is in the form of a linear regression model, to be easily employable and interpretable by different recipients. Additionally, such a relation enables a ranking of vehicle categories by passive safety performances. This ranking highlights that Superior SUVs are the most crashworthy vehicles (low IR for the occupants when impacted); however, they exhibit the highest PD costs among all categories and feature the highest aggressiveness with respect to all vehicle categories (maximum IR for the occupants when they impact another vehicle, because of their high mass). Minivans are characterized by the lowest PD, while A segment vehicles feature the lowest crashworthiness and aggressiveness among all body categories.

Keywords Reduced-Order Dynamic Models (RODM) · impact reconstruction · velocity change (ΔV) · vehicle category · vehicle model · kerb weight

1 Introduction

The massive economic burden of vehicle accidents is a chief topic of interest in all major countries. In the last two decades, a vast number of countermeasures has been put in place to drastically decrease the number of accidents, their severity, as well as the Injury Risk (IR) for the involved people [1]. Although the introduction of better performing passive safety technologies and vehicle crashworthiness technologies have strongly influenced vehicle safety [2], the advent of Advanced Driver Assistance Systems (ADAS) and partial driving automation has bolstered that even further [3, 4]. Based on the European Transport Safety Council 2021 report, in the whole Europe, this has exemplarily led to the decrease from 52,880 road fatalities in 2000 to 37,840 in 2010, ultimately down to 18,844 in 2020[1]. Although these data are encouraging and tend towards the Zero Vision objective of the European Commission (*i.e.*, zero fatalities on EU roads by 2050), the increase in vehicle dimensions and the diffusion of electric cars are leading to a progressive increase in the average mass of the circulating fleet: this translates into a higher potential severity in the event of an accident, impact speed being the same [5]. A very heavy, structurally performing passenger car can be almost undamaged by an impact with a low-weight car, resulting in small Property Damage (PD) costs and no injuries for its occupants. However, the impact can be associated with a high Injury Risk (IR) for the opponent vehicle's occupants, who can consequently sustain severe or even fatal injuries. A comprehensive economic assessment on road accident-related outcomes must hence consider both material damages and personal harm potential.

The costs associated with PD can be obtained retrospectively or prospectively, following a convention that also applies to ADAS performance assessment methodologies [6, 7]. Retrospective analyses can use a dataset where the costs are linked to features of crashes (*i.e.*, the accident scenario, parameters like speed and offset between cars, the physical characteristics of the two cars as kerb masses, stiffness, inertial momentum). This approach is typically conducted to determine how the impact kinematics are linked to replacement and repair costs for the vehicle components involved in the intrusion. However, even if large datasets are considered, the identification of costs for a single vehicle model depends on the impact configurations that such a model has sustained, which provides limited information on the whole set of accidents that the vehicle can experience during its entire life cycle in terms of opponent and impact configuration. For instance, a prior study by Vaillancourt [8] determined a correlation between repair costs and the observed dive (*i.e.*, the roll angle of a vehicle decelerating before the impact). Despite being the sole scientific product on the topic, it has many limitations: the small dimension of the dataset (18 vehicle models), the focus on rear-end impacts only, and the irrelevance of the opponent features.

In general, a retrospective approach cannot provide indications regarding very recent or newly type-approved vehicle models for which accident data are unavailable. This limitation can be solved by proposing prospective approaches, where the outcomes of several impact scenarios for a specific vehicle model can be simulated before their occurrence in the real world. Simulations can involve a large set of impact conditions, whose difference can exemplarily lie in the impact configuration (front-to-front, front-to-rear, etc.) or speed of the involved parties. Since these vehicle-to-vehicle impact simulations are able to accurately identify the regions of the vehicle that sustain a deformation, they can also provide indications regarding the overall repair and replacement costs based on the intrusion entity and its location; impact reconstruction simulations are generally based on Finite Element (FE), Multi-body (MB), or Reduced-Order Dynamic Models (RODM) [9, 10, 11]. Recent literature includes several scientific papers on the costs associated with road accident-related injuries. A comprehensive review by Zaloshnja et al. [12] identified the costs for the treatment of different levels of injuries in all possible body segments following the classification of the *Abbreviated Injury Scale* (AIS, from 0 to 6). The study quantified an increasing trend in the treatment costs as the AIS increases. In particular, referring to the Maximum AIS through all body regions (MAIS), the sum of medical, work, administration, legal, and quality of life insurance costs for non-fatally injured highway crash victims summed to $411,606 Millions considering all MAIS levels. Shen and Neyens [13] examined the relationships between drivers' age, gender, and some crash characteristics (e.g., impact configuration, weather condition, not wearing a seatbelt, fatigued driving, etc.) on the crash related health care costs. Their analysis highlighted that rear-end collisions were associated with the lowest treatment costs and head-on crashes with the highest, in particular for male drivers older than 64. A more recent paper by Zakeri et al. [14] analyzed all direct and indirect costs of road traffic injuries, considering not only treatment costs but also factors like lost productivity. This work also highlighted that the average PD-related cost in the whole dataset is $1141, but no indication is given regarding the categories of the involved vehicles nor the features of the impact from which the damages resulted.

The objective of the present work is to provide a simulation-based, prospective methodology for the assessment of PD costs and IR linked to a specific vehicle model, with the goal of determining a relationship between PD costs and IR for a wide range of vehicles. This information can be important for several insurance purposes. First, knowledge on the capabilities of the vehicle to both protect the involved occupants and to withstand deformation is a fundamental step for proposing efficient insurance policies favoring the most virtuous vehicles. In addition, injury data and PD costs are

[1]Because of the Covid pandemic, the temporary estimates for 2021 of 19,750 victims should be more reliable.

often treated separately by insurers in case of compensation. An indication of the IR associated with the PD can be a preliminary step to harmonize repair costs and injury related figures for a comprehensive estimate of the total costs associated with the accidents. Finally, a relation between PD and IR can be an effective indicator of the coherence between injuries and vehicle damages. This relation can be a useful feature from an anti-fraud perspective, providing a direct indication about the likelihood that a severe injury could result from a certain PD cost-related accident.

The proposed simulation framework considers a vast set of *car-to-car* accident scenarios, where the vehicle whose PD costs are to be estimated (*subject*) is at a standstill and it is impacted by a second vehicle moving at 50 km/h (*opponent*).To perform an in-depth investigation of the complexity of the possible accident scenarios, the subject sustains crashes with opponents that belong to any possible body category.

Intuitively, small deformations should be linked to low PD costs; however, this does not always translate into low IR. For example, if the stiffness is high, accelerations tend to be directly transferred from the vehicle to the occupants [15]. A description of the methodology, with its constitutive elements, is highlighted in the first part of the paper. Such methodology is then applied to 507 vehicle models that have been circulating on EU roads since 1990. Finally, results in terms of PD costs and IR for all vehicle categories are provided, together with the relations linking the two variables, to give researchers a solid basis for future analyses. Also based on such a discussion, the novel contributions of the present work can be summarized as follows:

- Identification of the body parts of a vehicle that are most likely to be affected in the simulated impact configurations;
- Extraction of the repair and replacement costs for the body parts identified in the previous step;
- Use of a Reduced-Order Dynamic Model (RODM) algorithm for vehicle-to-vehicle crash reconstruction to virtually derive the deformations sustained by each body part of the vehicle;
- Estimation of the total PD cost using the simulated deformations together with the repair and replacement costs for each body part, as well as the impact-related variables that are directly linked to IR;
- Estimation of the IR of the occupants of both vehicles (subject and opponent);
- Ranking of vehicle categories based on expected IR for both the subject's and the opponent's occupants;
- Ranking of vehicle categories based on PD costs, as a function of the body category;
- Provision of high quality relations between PD and IR for the occupants, in the form of a linear regression model that also accounts for the mass and body category of the two vehicles.

2 Methodology description

This Section outlines the methodology used to retrieve PD costs associated with specific vehicle models. Firstly, the most frequent impact configurations on real roads have been obtained from an accidents database; secondly, repair and replacement costs for a wide number of vehicle body parts have been retrieved from a database used by auto body shops in Italy. Then, the simulation environment has been defined, which enabled the calculation of deformations of specific vehicle models. Finally, a relevant IR model enabling evaluations on injury outcomes for the impact configurations to be simulated has been defined. All the vehicles considered for the analyses have been anonymized for intellectual property reasons.

2.1 Information retrieval from databases

2.1.1 Analysis of real accidents

To determine representative indications on PD costs for specific vehicle models, it is initially required to identify the impact configurations that a generic vehicle can sustain during its entire life cycle. For this purpose, the IGLAD [2] database (version 2020) has been analyzed. This database was initiated by Daimler AG and the ACEA[3] in 2007 and it collects information on more than 8000 accident cases from all over the world. From the analysis of the IGLAD database, the five most frequent impact configurations have been identified:

- Front-to-rear
- Full front-to-front
- Front-to-front with offset or reduced overlap
- Front-to-side where the impact with the side is in correspondence of the compartment
- Front-to-side where the impact with the side is in correspondence of the front wheel

The impact configurations are listed in order of decreasing frequency.

[2] *Initiative for the GLobal harmonization of Accident Data*, http://www.iglad.net/.
[3] European Automobile Manufacturers Association.

2.1.2 Extraction of repair costs

Once the impact configurations to be simulated are known (Section 2.1.1), it is necessary to rely on costs for the main components that may be damaged in the crash. The extraction of repair and replacement costs was obtained from a database that is currently in use in Italian auto body shops, but includes vehicle models in circulation throughout Europe. Data were extracted for the vehicle components in Table 1, based on the impact categories to be simulated.

	Impact configuration				
Part	Front-to-rear	Front-to-front (full)	Front-to-side (compartment)	Front-to-front (offset)	Front-to-side (wheel)
Crossbeam - rear bumper	X				
Rear bumper	X				
Complete front chassis leg		X			
Front chassis leg		X			
Complete motor		X			
Headlight		X		X	
Radiator		X			
Crossbeam - front bumper		X			
Front bumper		X		X	
Sill			X		
Exterior door panel			X		
Interior door panel			X		
Front suspension strut					X
Front mudguard					X

Table 1: List of parts whose repair and replacement costs have been extracted; the impact configurations in which these costs are employed for total calculation of PD costs for the subject vehicle are marked by a "X" symbol.

Repair and replacement costs were extracted for each of the listed components, according to the internal clustering of the database: costs were collected for "LIGHT", "MEDIUM", "SEVERE" damages, as well as for the "REPLACE" procedure. For the calculation of costs linked to the reported levels of damage, the database reports the work time in hours required for painting, sheet metal refinements, and mechanic adjustments associated with each part repair; total repair costs can be then obtained including a specified hourly cost for the employees involved in the repair procedure. In case of "REPLACE", also the cost of the object to be substituted is included.

2.2 Simulation environment

To reconstruct the accident and infer the damage to the vehicles in several impact configurations, a 2D accident reconstruction software has been employed. The algorithms regulating the software have been described in-depth in previous research [10]. The reconstruction of the impact phase is obtained by a RODM where the vehicle perimeter is represented by a set of 200 nodes that are elastically connected to a central solid element (representing the whole vehicle inertial properties). The elastic connection is obtained by springs featuring an elastic constant b_1 according to the McHenry model [16]. The value of b_1 depends on the node position on the perimeter (front, side, and back), and the specific stiffness features of the vehicle under analysis. The b_1 values are typically retrieved from in-depth analysis of crash tests like those by New Car Assessment Programs (NCAP) [4]; they are obtained, as described in [17], based on impact velocity and dynamic crush (maximum intrusion during the impact, *i.e.*, at the time when compression ends and restitution begins). To calculate the b_1 values of the vehicles considered in the present analysis, data from crash tests conducted both internally and externally (US/Euro NCAP) have been employed.

For the purposes of the present work, the algorithms of the simulation environment described in [10] have not been varied; rather, the software routines have been enriched to consecutively simulate multiple impacts with multiple opponents in all the configurations identified in Section 2.1.1. In particular, each opponent represents a different vehicle body category, to obtain a total cost estimate for each subject vehicle that is as representative as possible of the effect of actual collisions it may experience on the road. The considered opponent body categories are summarized in Table 2.

[4] https://en.wikipedia.org/wiki/New_Car_Assessment_Program

For each body category, a single representative vehicle model has been selected for the impact simulations, whose kerb mass is also reported in Table 2.

Category	Description	Kerb mass [kg]
Average EU [5]	Average Car	1397
A segment	Mini Car	810
B segment	Small Car	1087
C segment	Medium Car	1190
D segment	Large Car	1500
E segment	Executive Car	1790
Coupé/Cabriolet	Sport Car	1505
Minivan	Minivan	1538
MPV	Multi Purpose Vehicle	1245
Compact SUV	Compact SUV	1172
Medium SUV	Medium SUV	1520
Big SUV	Big SUV	1620
Superior SUV	Superior SUV	1980

Table 2: Body category and description of the considered opponent vehicles; kerb mass is also reported for a single vehicle model that represents the specific category in the simulated impacts.

In every simulated accident, the vehicle under test is stationary while the opponent vehicle collides against it at a speed of 50 km/h, corresponding to the average of the reported collision speeds in real car-to-car accidents ([18]).

2.3 Calculation of property damage costs for individual components

Depending on the simulated intrusion sustained by the subject vehicle over the various impact configurations, different PD costs result. For each vehicle and for each crash configuration detailed in Section 2.1.1, computations have been carried out to identify the position of the components (Section 2.1.2) affected by the crash. Each individual component has been represented in 2D as a rectangle of width W and height H.

The simulated damage of each individual component can be classified into one of the following categories based on the percentage of intrusion:

- if the intrusion reaches the position of the component and involves up to one third of the area of the rectangle, the damage is classified as "LIGHT";
- if the intrusion reaches the position of the component and involves between one third and two thirds of the area of the rectangle, the damage is classified as "MEDIUM";
- if the intrusion reaches the position of the component and involves between two thirds and 100% of the area of the rectangle, the damage is classified as "SEVERE";
- if the intrusion reaches the position of the component and totally covers the area of the rectangle, the damage is classified as "REPLACE".

This subdivision of damages is adopted to make them coherent with the classification of repair and replacement costs described in Section 2.1.2. Consequently, the repair and replacement costs of the parts can be directly derived from the corresponding database as a function of the intrusion entity. There are two exceptions to this rule, the motor and the headlight, which must be replaced as soon as the intrusion reaches them.

2.4 Calculation of Injury Risk (IR)

A large amount of IR models is available in literature for *car-to-car* impacts. These models span from logistic regression curves [19] to machine learning algorithms such as the Support Vector Machines or the Random Forests [18]. Besides modeling approaches, IR models differ from each other because they consider different injury scores, like Abbreviated Injury Scale (AIS), Maximum Abbreviated Injury Scale (MAIS), or Injury Severity Score (ISS) [20]. In this study, a logistic regression model for IR based on MAIS 3+ is employed (Figure 1 [21]) where the IR is a function of both the velocity change ΔV sustained by the vehicle in the impact and the intrusion region. In this approach, the IR is the

[5] The European average of the circulating fleet. EUROPEAN VEHICLE MARKET STATISTICS, Pocketbook 2019/2020, International Council of Clean Transportation (ICCT).

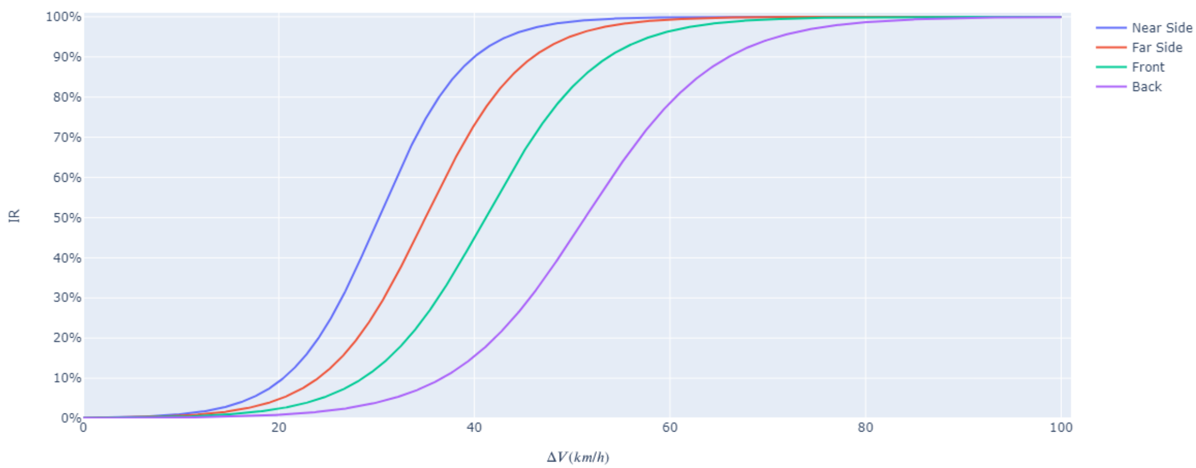


Figure 1: Employed Injury Risk (IR) model [21].

probability, expressed as a function of the ΔV, that an occupant of the car incurs in a MAIS injury level equal to or higher than level 3, where the levels are defined as in Table 3.

Injury Level	Description
1	Minor injury
2	Moderate injury
3	Serious injury
4	Severe injury
5	Critical injury
6	Fatal injury

Table 3: Description of the levels of injuries according to the Abbreviated Injury Scale (AIS) coding system.

Such a model entails the classification of crashes in four different configurations: if the front and back portion of the vehicle are subjected to intrusion, they are respectively defined as *front* and *back* impacts for the vehicle; crashes where the lateral portions of the vehicle are involved can be further divided into *near side* and *side* impacts. The *near side* cases refer to lateral impacts where the compartment is intruded on the same side of the occupant position, while the *side* cases cover impacts where the remaining lateral portions of the vehicle sustain a deformation. In the remainder of this paper, all the simulated impacts with the involvement of the compartment are *near side* impacts. This is equivalent to impose that both front seats of the involved cars are occupied.

Under this model, for instance, occupants of a vehicle subjected to a rear impact will have a 40% probability of sustaining a serious injury ($i.e.$, MAIS equal to or higher than 3) when ΔV reaches 50 km/h [21]. ΔV is well-established as the primary indicator of impact severity, being directly linked to the accelerations experienced by the vehicle's occupants during a crash.

Using the simulation environment described in Section 2.1.1, ΔV can be obtained by simulating the impact dynamics, which mainly depends the mass of the involved vehicles and on the stiffness of the impacted vehicle regions.

3 Results

Figure 2 portrays the five different impact configurations (Section 2.1.1) that are simulated for a single subject vehicle. The opponent moves at a speed of 50 km/h (a mean value for the impact closing speed that is extracted from accident databases [18]) towards the subject, which is standstill. Simulations were conducted for 507 subject vehicle models,

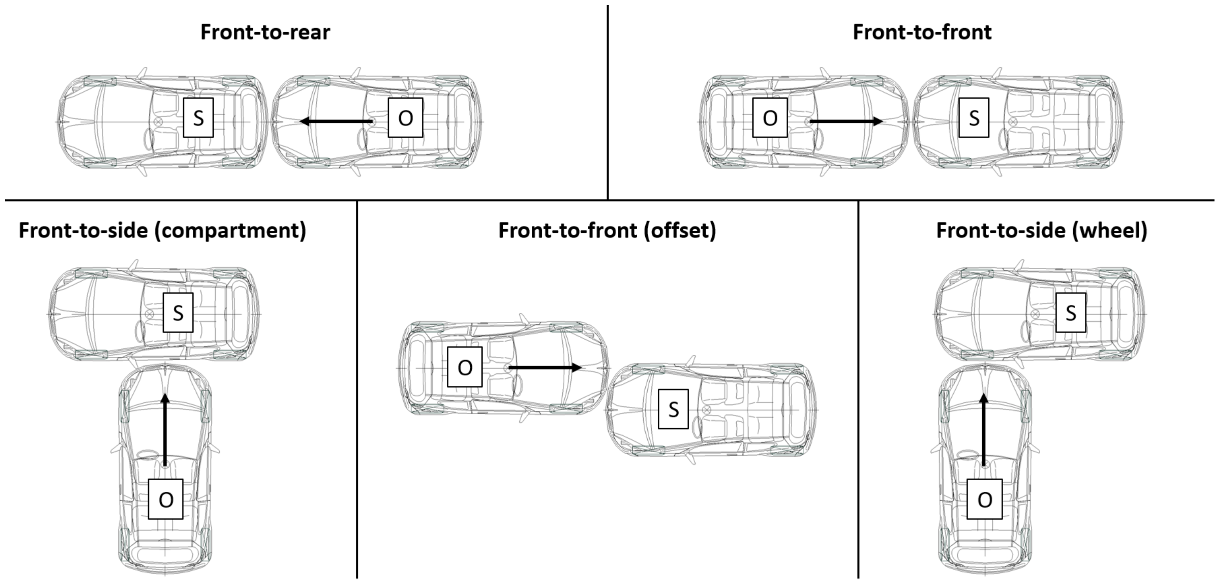


Figure 2: Summary of the five simulated impact configurations (O stands for opponent, while S indicates the subject).

whose characteristics were retrieved as discussed in Section 2.1.2. IR values and PD costs for the subject vehicles and the IR values for the opponents were obtained. Such values represent a weighted sum of the results obtained across the five simulated impact configurations. By simultaneously considering the concepts introduced in Section 2.1.1 and in Section 2.4, regarding the IR for their occupants, the following highlights can be provided for the two vehicles in the different simulated impacts:

- Front-to-rear impact: the subject's occupants sustain a *back* impact, the opponent's occupants sustain a *front* impact;
- Front-to-front: the occupants of both vehicles sustain a *front* impact;
- Front-to-side (compartment): the subject's occupants sustain a *near side* impact, the opponent's occupants sustain a *front* impact;
- Front-to-front (offset): the occupants of both vehicles sustain a *front* impact;
- Front-to-side (wheel): the subject's occupants sustain a *side* impact, the opponent's occupants sustain a *front* impact.

To derive a relation between PD and IR for the occupants of the involved vehicles, a linear regression model has been applied to the data. The dependent variables considered in the regression are IR for the subject's occupants ($IR_{subject}$) and IR for the opponent's occupants ($IR_{opponent}$), while the independent variables are listed below:

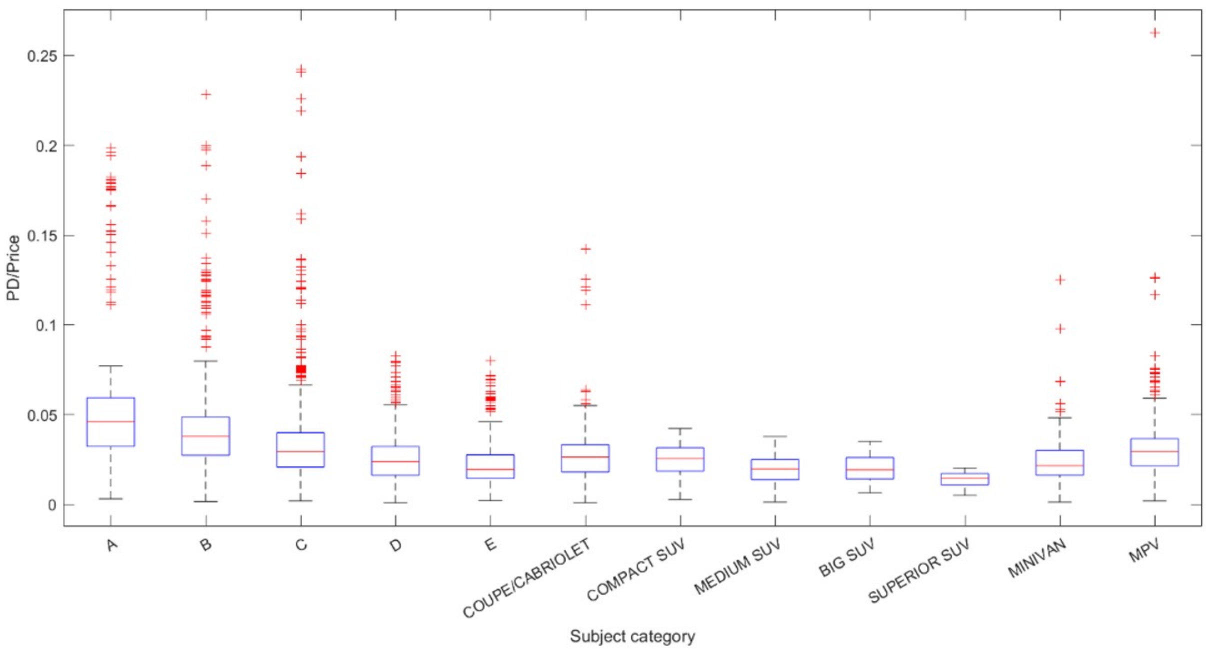
- Opponent category;
- Subject category;
- M_s/M_o (ratio between subject mass and opponent mass, dimensionless);
- PD/Price (ratio between PD and purchase price of the subject, dimensionless).

Rather than separately use M_s, M_o, PD, and Price as independent variables for the regression, the dimensionless parameters were chosen because of their deeper information content:

- M_s/M_o is directly linked to the ratio between the ΔV of the subject and the opponent, consequently affecting IR for the vehicles' occupants
- Since vehicles of specific body categories feature high purchase price and costs for the components to be repaired or replaced (e.g., E segment or Superior SUVs), the employment of PD/Price enable the comparison of PD among vehicles belonging to diverse categories

3.1 Data distribution

Data distribution for PD/Price among the different subject and opponent categories is reported in the boxplots of Figure 3. The total number of entries for the dataset is 6591, with each of the 507 subject vehicles impacted with 13 opponents. PD/Price is always lower than 1. Based on the provided visualization of quartiles, it can be preliminarily shown that



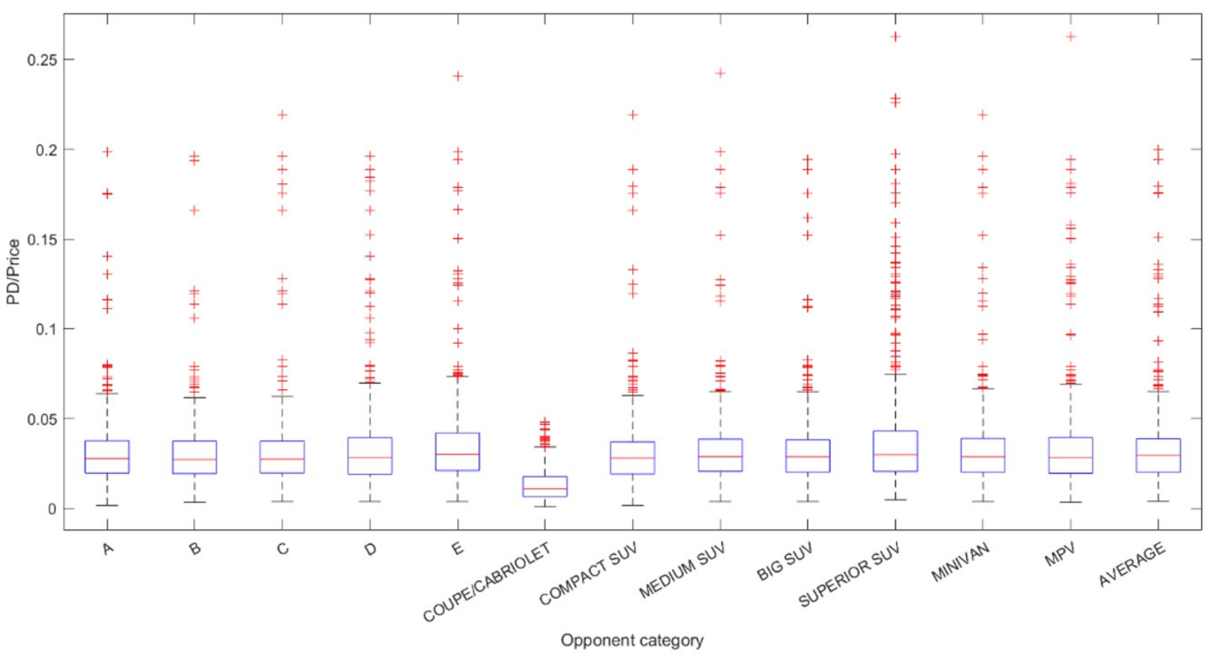


Figure 3: Boxplots of PD/Price based on Subject category (above) and Opponent category (below).

PD/Price slightly decreases as the subject size increases for both sedans and SUVs (*i.e.*, moving from the A to the E segment and from compact to superior SUVs, with Superior SUVs exhibiting the lowest value of PD/Price among all categories). Such a difference is not seen for the different opponent categories, with similar consequences on the subject in terms of PD/Price. Only Coupé/Cabriolet opponents are linked to a significantly lower value of PD/Price, indicating that they tend to produce less relevant damages on the subjects compared to other categories. This is likely caused by a particularly low stiffness of the Coupé/cabriolet vehicle (Table 2) used to represent this Opponent category.

The boxplots in Figure 4 display the trend of M_s/M_o based on the category of the subject and the opponent. As expected, M_s/M_o generally increases with the subject size for both sedans and SUVs. Overall, A segment and Superior SUVs are associated with the lowest and highest values of M_s/M_o, respectively. The opposite trend can be highlighted

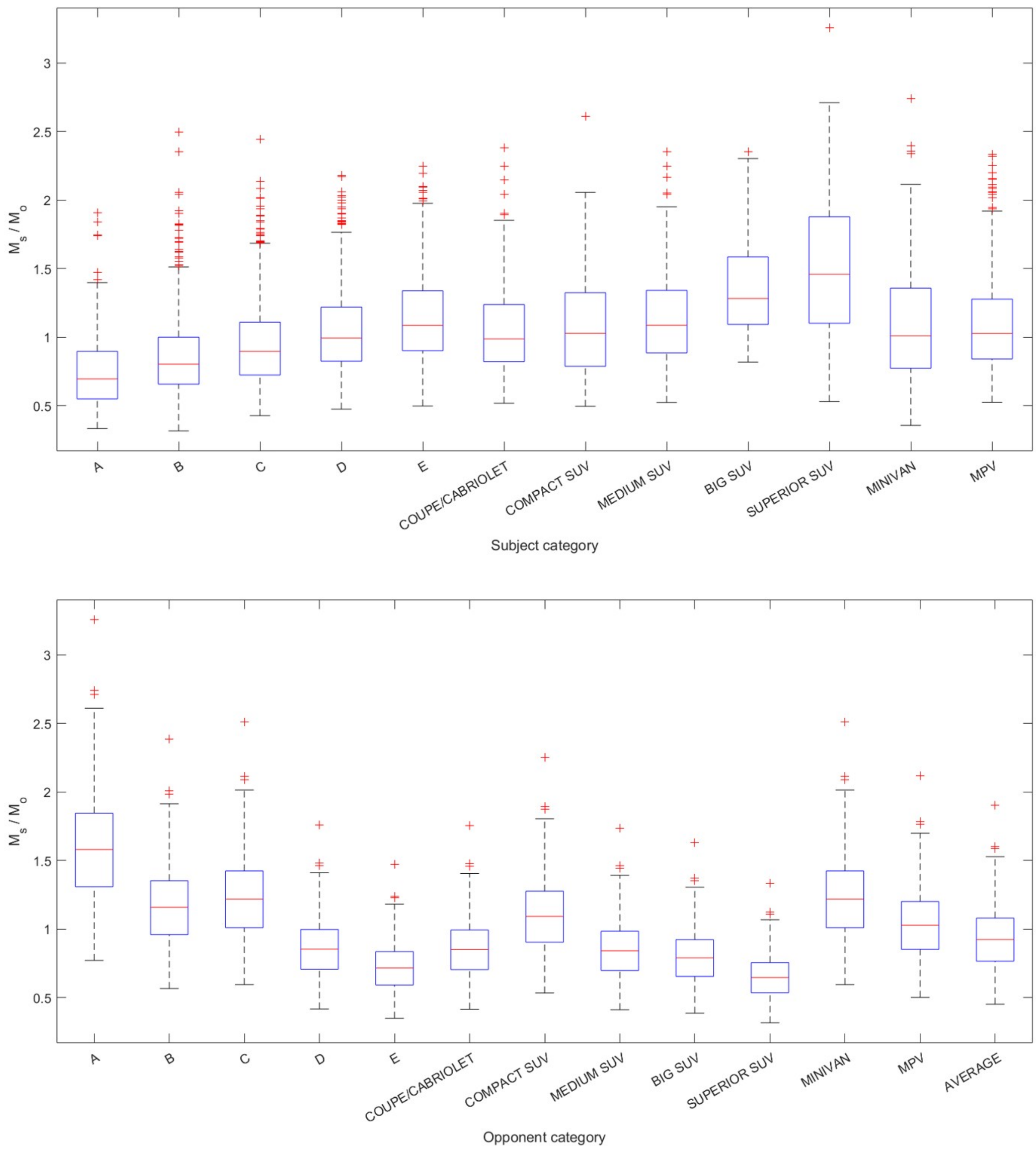


Figure 4: Boxplots of M_s/M_o based on Subject category (above) and Opponent category (below).

for the Opponent category, *i.e.*, M_s/M_o decreases for both sedans and SUVs as the size of the opponent increases. As expected, M_s/M_o for the Average EU car (the leftmost one) is intermediate among those for the different opponent categories.

Based on the data distribution of $IR_{subject}$ among the different subject and opponent categories in Figure 5, a decreasing trend can be highlighted as the subject size increases for both sedans and SUVs (linked to an increase in the vehicle masses). The opposite trend can be highlighted when the opponent is considered, with an increase in the size (or mass, equivalently) that corresponds to a higher $IR_{subject}$. Superior SUVs preliminarily appear as the most protective vehicles with respect to their occupants, while A segment vehicles perform poorly compared to other subject categories. Conversely, A segment opponents are linked to low $IR_{subject}$, demonstrating low aggressiveness with respect to other

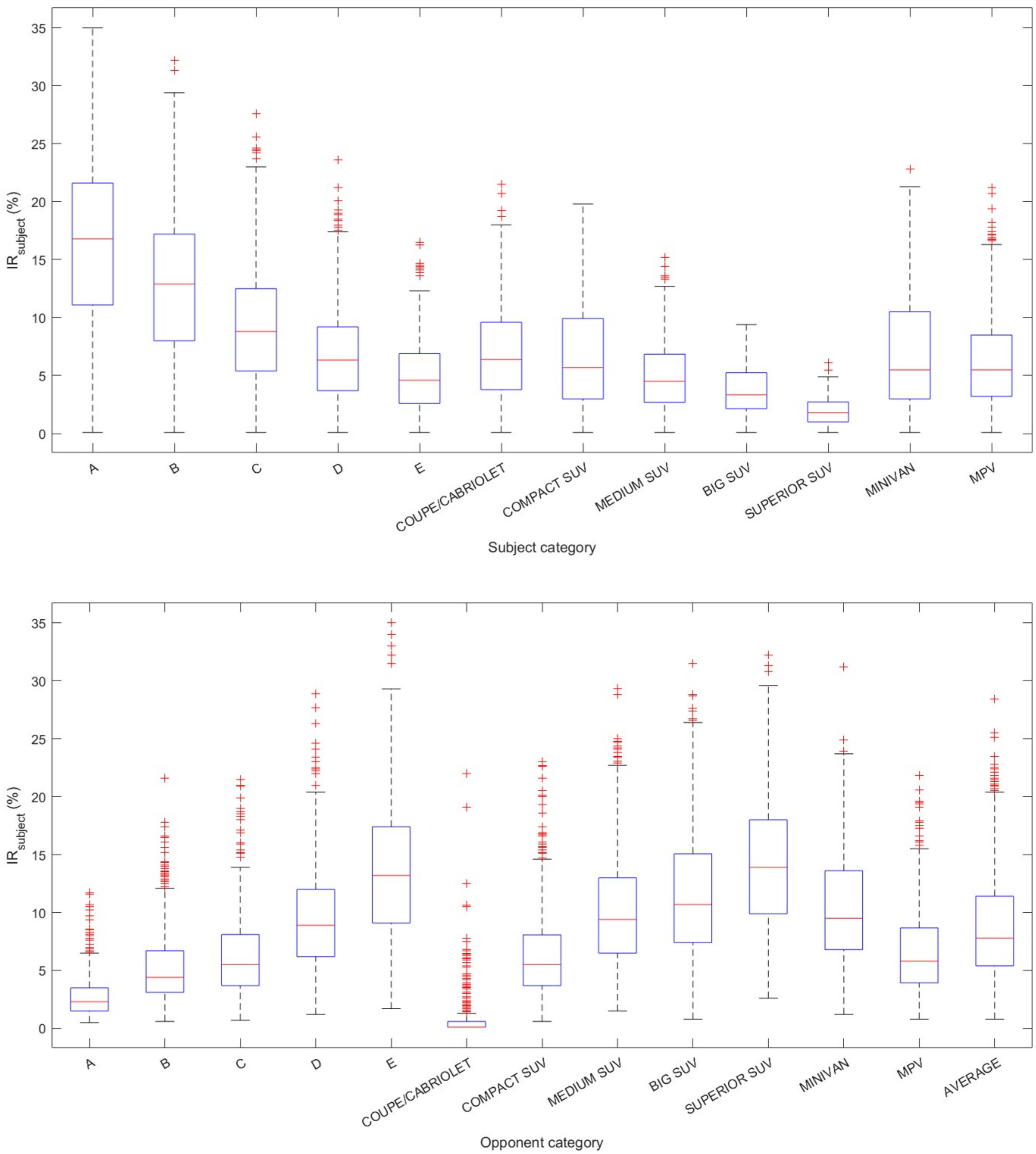


Figure 5: Boxplots of $IR_{subject}$ based on Subject category (above) and Opponent category (below).

vehicles. As a consequence of the low stiffness of the Coupé/Cabriolet vehicle employed to represent this Opponent category, Coupé/cabriolet are associated with the lowest value of $IR_{subject}$.

Data distribution for $IR_{opponent}$ among the different subject and opponent categories is reported in Figure 6. The trends are in line with those found for $IR_{subject}$, mainly due to the momentum conservation that rules over the impact physics (ΔV for the opponent can be directly derived once ΔV for the subject and the mass ratio of the vehicles are known).

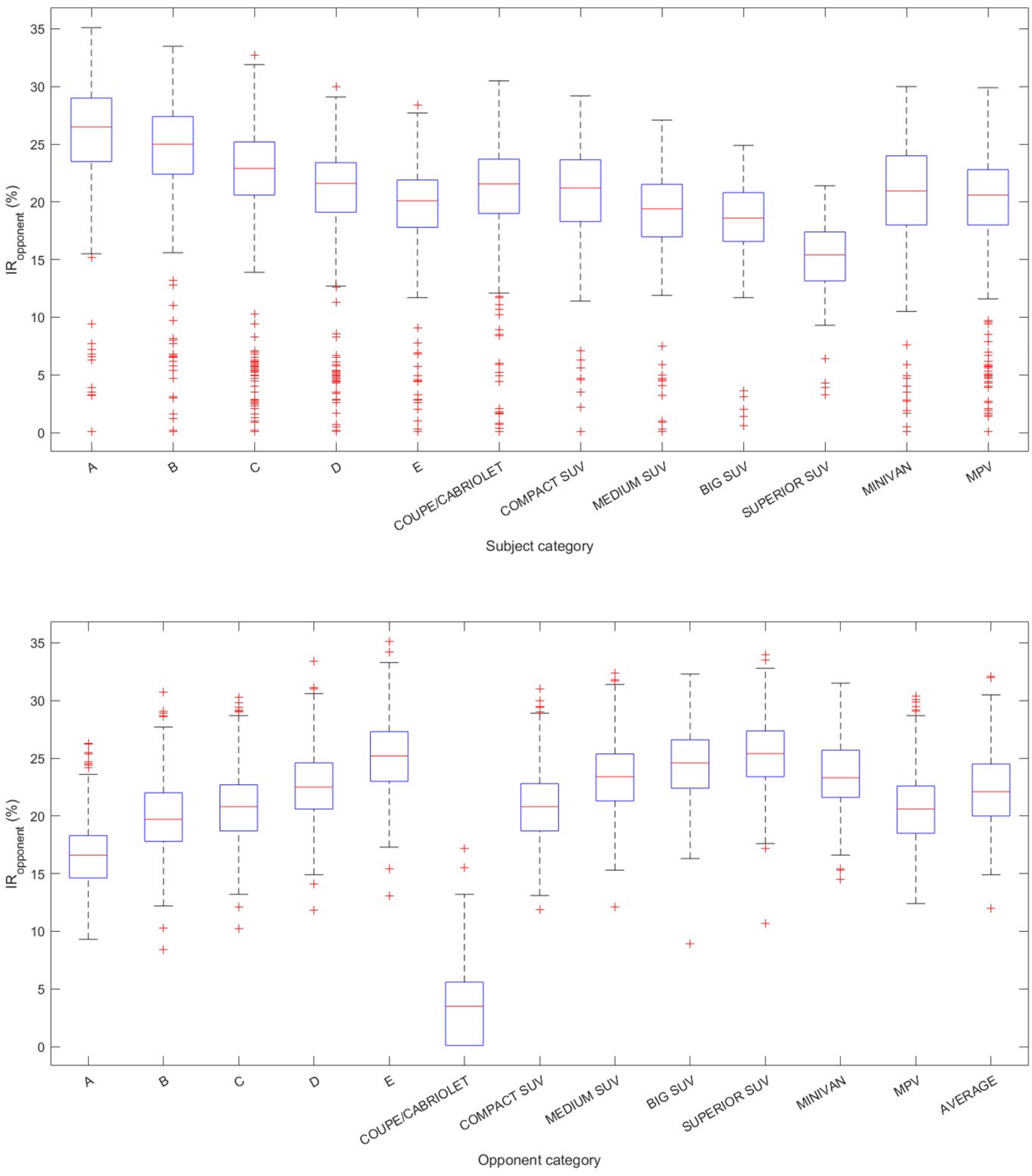


Figure 6: Boxplots of $IR_{opponent}$ based on Subject category (above) and Opponent category (below).

3.2 Linear regression

For simplicity and interpretability reasons, a linear regression model has been employed to describe the relationship between the data and the two injury risks, obtaining a R^2 of 75.1% for the $IR_{subject}$ and of 88.9% for the $IR_{opponent}$. In the following, the obtained models and their related features are reported. Independent variables are considered to influence a dependent variable if their p-value is lower than 5%.

3.2.1 Model for $IR_{subject}$

The resulting linear, first order hierarchical best-fit model for $IR_{subject}$ is reported below:

$$IR_{subject}(\%) = 15.569 + 16.44 \cdot PD/Price - 4.339 \cdot M_s/M_o + a_0 + a_1 \quad (1)$$

Table 4 reports the values of a_0, a_1, and p-value associated with each Subject category and Opponent category. For this model, R^2=75.1% with a p-value lower than 0.001 for both M_s/M_o and PD/Price .

From the model statistics, it can be initially shown that all parameters M_s/M_o, PD/Price, Subject category, and Opponent category are influential on $IR_{subject}$ (p-value < 0.001). Additionally, the values reported in Table 4 demonstrate the possibility of ranking different vehicle categories in terms of safety for both vehicles' occupants:

1. A significant difference between all subject categories exists in terms of IR for the subject's occupants (p-value<0.05);
2. All subject categories provide higher protection to their occupants compared to the reference A segment (negative coefficients, so that IR is lower when a category differing from the A segment is considered);
3. $IR_{subject}$ for both sedans and SUVs decreases as the subject size increases, *i.e.*, passing from segment A to E and from Compact SUV to Superior SUV;
4. Superior SUVS, Big SUVs, and E segment cars are the three Subject categories that provide the highest protection to their occupants, *i.e.*, they are the most crashworthy vehicles;
5. A significant difference between all opponent categories exists in terms of IR for the subject's occupants (p-value<0.05);
6. Opponents belonging to the Coupé/Cabriolet and A segment categories perform best in terms of protection of the subject's occupants (negative coefficient), *i.e.*, they feature low aggressiveness with respect to other vehicles;
7. Excluding the Coupé/Cabriolet category, all opponent categories tend to increase $IR_{subject}$ compared to the A segment. In these terms, Superior SUVs, E segment, and Minivans appear as the most aggressive opponent categories;
8. $IR_{subject}$ gets higher as the opponent size (and mass) increases, *i.e.*, passing from segment A to E and from Compact SUV to Superior SUV for the opponent. This is because the opponent collision speed is always 50 km/h, so that the impact energy (*i.e.*, the kinetic energy) is higher as its mass increases.

The 3D graph in Figure 7 reports the obtained regression function, considering the case where both the subject and the opponent belong to the A segment (a_0=a_1=0.000). It can be seen that $IR_{subject}$ increases as PD/Price increases, while it

Subject category	**a_0**	***p*-value**
A segment	0.000	-
B segment	-2.749	<0.001
C segment	-5.865	<0.001
D segment	-7.624	<0.001
E segment	-8.920	<0.001
Coupé/Cabriolet	-7.531	<0.001
Compact SUV	-7.564	<0.001
Medium SUV	-8.886	<0.001
Big SUV	-9.197	<0.001
Superior SUV	-10.141	<0.001
Minivan	-6.972	<0.001
MPV	-8.093	<0.001

Opponent category	$\mathbf{a_1}$	***p*-value**
A segment	0.000	-
B segment	0.742	<0.001
C segment	2.007	<0.001
D segment	3.631	<0.001
E segment	7.124	<0.001
Coupé/Cabriolet	-4.796	<0.001
Compact SUV	1.555	<0.001
Medium SUV	4.221	<0.001
Big SUV	5.443	<0.001
Superior SUV	7.392	<0.001
Minivan	6.009	<0.001
MPV	1.442	<0.001
Average	3.262	<0.001

Table 4: Values of a_0, a_1, and *p*-value associated with each Subject category and Opponent category, for the derived linear regression model of $IR_{subject}$.

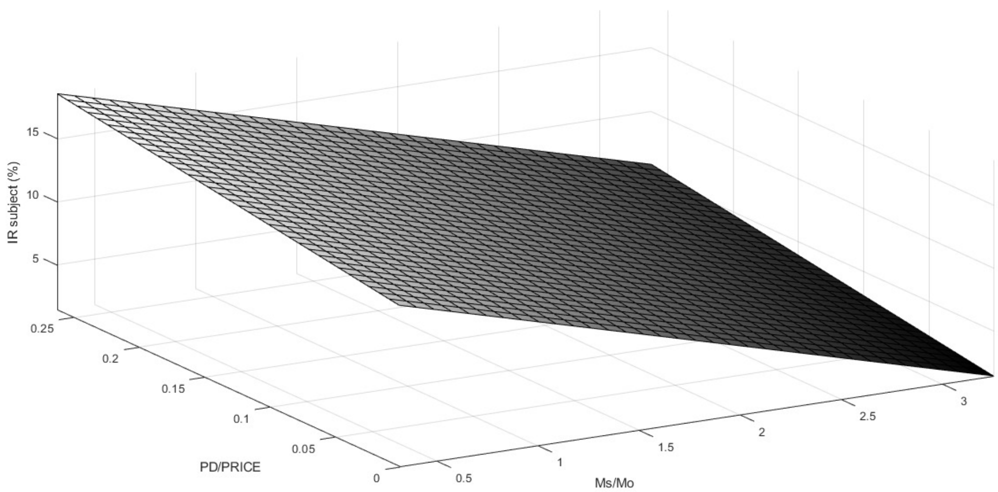


Figure 7: Derived regression model for $IR_{subject}$.

decreases as the mass of the subject increases compared to that of the opponent (ΔV for the subject is lower than ΔV of the opponent). In the considered range of values for the independent variables, the maximum changes in $IR_{subject}$ that can be associated with PD/Price and M_s/M_o variations are 3.25% and 8.24%, respectively.

The results in Table 4 are in line with the information provided by the boxplots in Figure 5. The added value of the derived model in Figure 7 is the possibility of quantifying the influence of PD/price on $IR_{subject}$, combined with the effects from M_s/M_o, the Subject category, and the Opponent category.

3.2.2 Model for $IR_{opponent}$

The resulting linear, first order hierarchical best-fit model for $IR_{opponent}$ is reported below:

$$IR_{opponent}(\%) = 25.626 + 9.55 \cdot PD/Price - 4.060 \cdot M_s/M_o + b_0 + b_1 \tag{2}$$

Table 5 reports the values of b_0, b_1, and *p*-value associated with each Subject category and Opponent category. For this model, R^2=88.9% with a *p*-value lower than 0.001 for both M_s/M_o and PD/Price.

Subject category	b_0	*p*-value
A segment	0.000	-
B segment	-0.720	<0.001
C segment	-2.181	<0.001
D segment	-3.190	<0.001
E segment	-4.195	<0.001
Coupé/Cabriolet	-3.233	<0.001
Compact SUV	-3.032	<0.001
Medium SUV	-4.448	<0.001
Big SUV	-4.473	<0.001
Superior SUV	-6.563	<0.001
Minivan	-2.951	<0.001
MPV	-3.741	<0.001

Opponent category	b_1	*p*-value
A segment	0.000	-
B segment	1.522	<0.001
C segment	2.706	<0.001
D segment	2.986	<0.001
E segment	4.899	<0.001
Coupé/Cabriolet	-17.273	<0.001
Compact SUV	2.195	<0.001
Medium SUV	3.680	<0.001
Big SUV	4.603	<0.001
Superior SUV	4.781	<0.001
Minivan	5.474	<0.001
MPV	1.724	<0.001
Average	2.895	<0.001

Table 5: Values of b_0, b_1, and *p*-value associated with each Subject category and Opponent category, for the derived linear regression model of $IR_{opponent}$.

The model statistics indicate that all parameters M_s/M_o, PD/Price, Subject category and Opponent category are influential on $IR_{opponent}$ (*p*-value < 0.05). From the values reported in Table 5, the following highlights can be derived:

1. A significant difference between all subject categories exists in terms of IR for the opponent's occupants (*p*-value lower than 0.05);
2. All subject categories provide higher protection to the opponent's occupants compared to the reference A segment (negative coefficients);
3. Superior SUVs, Big SUVs, and Medium SUVs are the three subject categories that provide the highest protection to the opponent's occupants. While this may be counterintuitive considering that these categories are typically associated with high mass (Figure 4), it must be noted that the values reported in Table 5 already account for differences in M_s/M_o among subject and opponent categories: this denotes a high crashworthiness for this vehicle category and capabilities to dissipate the impact energy;
4. $IR_{opponent}$ for both sedans and SUVs decreases as the subject size increase, *i.e.*, passing from segment A to E and from Compact SUV to Superior SUV;
5. A significant difference between all opponent categories exists in terms of IR for their occupants (*p*-value<0.05);
6. Opponents belonging to the Coupé/Cabriolet category perform best in terms of protection of their occupants (negative coefficient);
7. Excluding the Coupé/Cabriolet category, all Opponent categories tend to increase $IR_{opponent}$ compared to the A segment; in these terms, Minivans, E segment, and Superior SUVs appear as the most aggressive Opponent categories;
8. $IR_{opponent}$ for both sedan and SUV opponents gets higher as the opponent size increase, *i.e.*, passing from segment A to E and from Compact SUV to Superior SUV; this is because the opponent collision speed is always 50 km/h, so that the impact energy (*i.e.*, the kinetic energy) is higher as its mass increases.

These highlights are in line with the highlights obtained from the *IR$_{subject}$*-related model. This is a direct consequence of the momentum conservation that rules over the impact dynamics (ΔV of the subject is proportional to the opponent's ΔV).

The 3D graph in Figure 8 reports the obtained regression function for *IR$_{opponent}$*, considering the case where both the subject and the opponent belong to the A segment (b_0=b_1=0.00). It can be seen that *IR$_{opponent}$* increases as PD/Price increases, while it decreases as the mass of the subject increases compared to that of the opponent (ΔV for the subject is lower than ΔV of the opponent, and IR as a consequence). In the considered range of values for the independent variables, the maximum changes in *IR$_{subject}$* that can be associated with PD/price and M_s/M_o variations are 1.90% and 7.77%, respectively. These latest independent variables have hence less influence on *IR$_{opponent}$* than in the case of *IR$_{subject}$*. The fitting quality for *IR$_{opponent}$* is higher than in the case of *IR$_{subject}$* because of the simpler accident dynamics for the opponent: while the subject's occupants experience different impact configurations in terms of intrusion location (near side, side, front, and rear), the opponent's ones always sustain front impacts. This makes IR values for the opponent more coherent among the different simulated impacts compared to the subject.

Overall, the derived linear regression models and the related statistical indicators clearly indicate that, in case of an accident, a strong correlation exists among IR for the vehicles' occupants and PD for the subject vehicle. The provided models are characterized by high goodness-of-fit, enabling technicians to directly derive IR for the vehicles' occupants based on the PD, the subject and opponent categories, as well as the mass ratio of the two vehicles. Based on the coefficients of regression for the Subject category and Opponent category, it has been demonstrated that Superior SUVs tend to be both the most crashworthy and aggressive vehicles: when impacted at a standstill, the vehicle protects its occupants and those of the other party (low *IR$_{subject}$* and *IR$_{opponent}$*); when it moves towards a still vehicle, *i.e.*, it is the main actor of the impact, it has high aggressiveness (high *IR$_{subject}$* and *IR$_{opponent}$*) because of its high mass (and, consequently, kinetic energy). Both aspects should be considered to derive appropriate values of IR based on PD/price, M_s/M_o, Subject category and Opponent category. Conversely, A segments are demonstrated to be the less crashworthy vehicles, while Coupé/Cabriolets are identified as the less aggressive ones.

4 Discussion

Figure 9 exemplarily shows the trend of IR for the two vehicles involved in the impacts, considering the average EU vehicle as the opponent. As the plot shows, the IR for the average EU vehicle (*IR$_{average}$*) is always higher than *IR$_{subject}$*, regardless of the Subject category. This behavior results from the combination of the following factors:

- Some impact configurations are characterized by low IR for the subject compared to those for the opponent (*i.e.*, rear versus front). The opponent is the main actor in the various impacts, *i.e.*, it has a speed of 50 km/h once it contacts the subject vehicle at standstill, and always sustains a front impact (refer to Figure 2). In particular, the impact configuration with the lowest possible *IR$_{subject}$* (rear) is the most frequent impact configuration

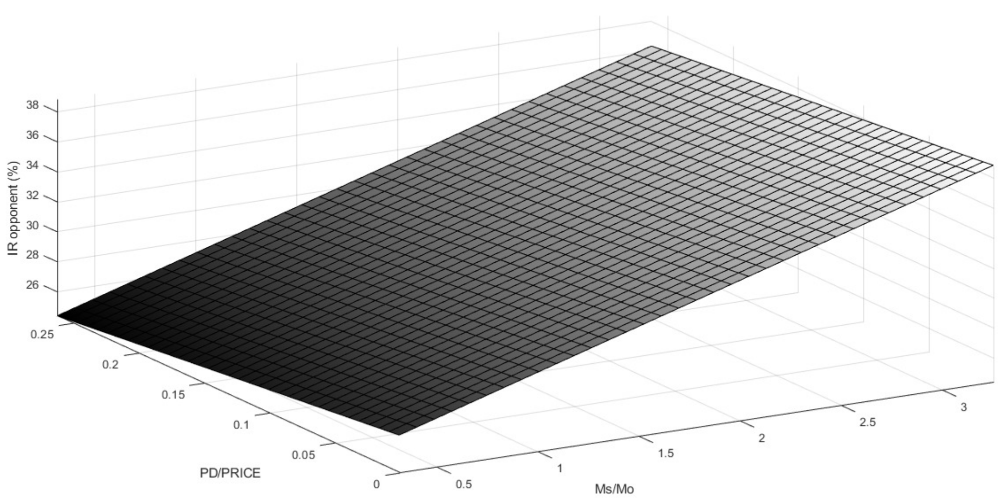


Figure 8: Derived regression model for *IR$_{opponent}$*.

encountered in the IGLAD database, 3 times more frequent than the more severe near-side impact; since the results in terms of IR are weighted considering the representativeness of each impact configuration, the data reported in Figure 9 are predominantly influenced by such a factor.
- The front impacts to which the average vehicle is always subjected are characterized by low eccentricity, *i.e.*, the Principal Direction Of Forces (PDOF[6]) tends to pass through the center of gravity for the opponent but not for the subject, giving rise to a high value of ΔV for the opponent alone.

Overall, Figure 9 highlights that the IR for the opponent vehicles (the EU average, in this case) is not negligible compared to the IR for the subject, but rather is the major one among the two vehicles. Moreover, $IR_{subject}$ is highest for the A, B, C segments and lowest for Superior SUVs, in accordance with Figure 5 and Table 4.

For completeness, Table 6 reports the average values of PD costs[7] for the subject and the maximum IR for the occupants of both vehicles, as a function of the Subject category and with the Average EU as the opponent in all cases. As apparent in the table, Superior SUVs have the highest PD costs when impacted by the average of the EU fleet, but also have the lowest values of IR among all subject categories. Overall, the lowest PD costs are associated with Minivans, that also perform better than categories like A, B, and C segments in terms of IR.

Subject Category	Opponent Category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
A segment	Average EU	708.50	19.1%	26.6%
B segment	Average EU	585.10	14.2%	25.5%
C segment	Average EU	674.20	10.0%	23.3%
D segment	Average EU	664.80	7.1%	21.6%
E segment	Average EU	802.70	4.9%	19.9%
Coupé/Cabriolet	Average EU	864.80	7.5%	21.5%
Minivan	Average EU	478.20	8.0%	22.1%
MPV	Average EU	688.20	6.2%	20.5%
Compact SUV	Average EU	621.10	6.9%	21.8%
Medium SUV	Average EU	651.80	4.8%	19.4%
Big SUV	Average EU	898.60	3.6%	18.4%
Superior SUV	Average EU	1,065.00	2.0%	15.6%

Table 6: Cost and IR for accidents between an opponent average car and several categories of the subject vehicle.

Further insights can be gained by considering a specific Subject category and varying the Opponent category: Table 7 reports the case of the A segment when subjected to all possible impacts (Section 2.1.1) against all possible categories (Table 2) of opponent. More tables reporting the cases of other segments when subjected to impacts against all possible opponents can be found in the Appendix A. When modifying the Opponent category from A segment up to E segment, IR for both the subject and the opponent increases, in contrast with the trend highlighted in Table 6. As already highlighted in Section 3, the main reason for this is that the opponent is the only moving participant in the impacts. Hence, the pre-impact energy solely depends on the opponent, which possesses a kinetic energy proportional to its mass. Since the opponent speed is kept fixed for this study (*i.e.*, 50 km/h) and vehicles from upper segments typically possess higher mass, IR values for both the subject and the opponent increase. Coupé/Cabriolets exhibit low values of PD costs and IR, mainly because of the low stiffness of the vehicle employed to represent this specific opponent category. Due to the significant discrepancy between the PD and IR values when the Coupé/Cabriolets are Subject or Opponent, further investigations should be performed for this category to more clearly demonstrate both Subject and Opponent perspectives. The analysis involving the remaining categories of subject vehicles leads to similar takeaways.

5 Limitations

This paper demonstrates interesting highlights regarding both IR and PD costs, which are the first of their kind to be presented. However, the present work has several limitations. For instance, the method considers a synthetic set of components that are more likely to be affected in a crash. To provide a more complete estimate of the PD cost, upcoming works should focus on additional impacted components. Secondly, although PD costs and IR have been linked through a high quality model, proper figures regarding medical care costs based on the derived IR are still missing. Next steps should link these two elements, so that evaluations regarding the overall costs related to a specific

[6] The direction of the collision forces on the two vehicles.

[7] A preset value of 50 €/hour for labor cost has been applied for cost calculation of all vehicle makes and models.

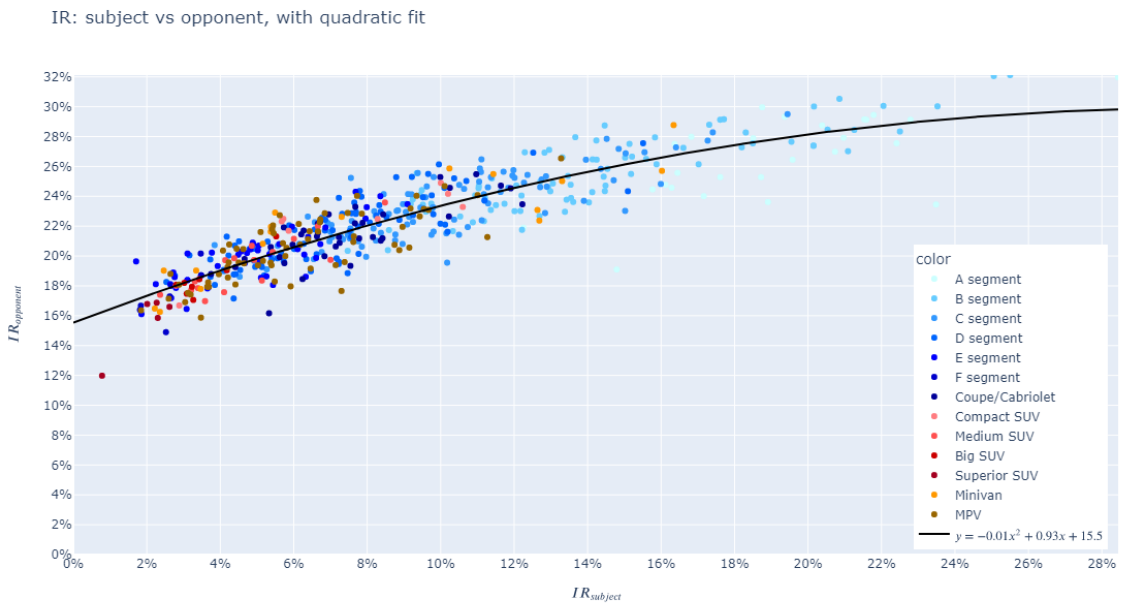


Figure 9: IR for the average vehicle as a function of IR for the subject vehicle and the subject's category (parabolic regression with $R^2 = 81.4\%$).

Subject Category	Opponent Category	PD [€]	IR^{subj}_{avg}	IR^{opp}_{avg}
A segment	A segment	773.4	6.6%	21.2%
A segment	B segment	608.0	12.2%	24.8%
A segment	C segment	688.6	13.9%	25.4%
A segment	D segment	747.8	18.4%	27.1%
A segment	E segment	766.5	25.1%	29.5%
A segment	Coupé/Cabriolet	208.4	2.7%	3.5%
A segment	Minivan	652.5	19.3%	27.4%
A segment	MPV	769.5	13.5%	24.3%
A segment	Compact SUV	716.9	14.7%	25.6%
A segment	Medium SUV	653.4	19.3%	28.0%
A segment	Big SUV	714.4	22.2%	28.8%
A segment	Superior SUV	606.8	24.3%	29.0%

Table 7: Cost and IR for accidents between different categories of the opponent car and a sample subject vehicle, belonging to the A segment.

vehicle model can be proposed for insurance purposes. In addition, another shortcoming of the present model lies in the fact that a worldwide accident dataset is employed to estimate the relative frequency of the accident scenarios, while the repair and replacement costs are extracted for a single country. Since global estimates on the proportion of the circulating fleet in terms of body categories were not available, no weighting has been applied to the data from this standpoint. Furthermore, a representative speed for the opponent has been set to 50 km/h but future analyses should account for different speed values (also considering motion of the subject). Finally, the discrepancy found for the Coupé/Cabriolet category for PD costs and IR when considered as subject or opponent will be the object of new investigations and verification, with the aim of harmonizing the obtained results among all vehicle categories.

6 Conclusions

This work presented an overall framework to retrieve both the Property Damage (PD) costs of a specific vehicle model when subjected to a road impact with another vehicle, and the Injury Risk (IR) for the occupants of both vehicles involved in the crash. After the extraction of PD and IR data for 507 vehicles in circulation from the 1990s in the EU, a high quality linear relation was found between PD and IR, which also accounts for the body category and mass of the two involved vehicles. The demonstration of this relation has three uses in insurance-related analyses. First, it indicates the capabilities of the vehicle to both protect the occupants involved in the impacts and to withstand deformation. This information can be used to propose efficient insurance policies favoring the most virtuous vehicles. Secondly, while bodily injury and PD claims are often treated separately by insurers, evaluating them simultaneously provides a comprehensive estimate of the costs associated with the accidents. Finally, a relation between PD and IR is an effective indicator of the coherence between injuries and vehicle damages, which can be used for anti-fraud purposes.

The results demonstrate that PD costs are significantly related to the IR for the occupants of both vehicles. PD costs are the highest for Superior SUVs. This category of vehicles is simultaneously the most crashworthy (*i.e.*, it offers high protection to the occupants when a moving vehicle impacts it) and the most aggressive (*i.e.*, it is linked to high IR values when it impacts another vehicle because of its high mass and, consequently, kinetic energy, speed being the same). Conversely, A segment vehicles are seen to be the less crashworthy, while Minivans are associated with the lowest PD costs.

The present work proposed novel contributions that can be summarized as follows:

- Identification of the body parts of a vehicle that can be damaged in the most frequent *car-to-car* accident scenarios from real world observations, with subsequent extraction of repair and replacement costs for such body parts;
- Combined use of an impact simulation algorithm and the costs of the body parts to estimate the expected PD cost for a vehicle based on the deformations it sustains in the identified accident scenarios;
- Use of an IR model to estimate the expected IR for the occupants of each vehicle based on the impact dynamics derived from the simulation;
- Ranking of vehicle models based on PD costs;
- Ranking of vehicle models based on IR for both the vehicle's and the opposing party's occupants.
- Provision of high quality relations between PD and IR for the occupants involved in the impact, in the form of a linear regression model that also accounts for the mass and the body category of the two vehicles.

Acknowledgments

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A Appendix

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
B segment	Average	585.1	14.2%	25.5%
B segment	A segment	505.2	4.5%	19.5%
B segment	B segment	483.6	8.9%	23.1%
B segment	C segment	510.2	10.4%	23.9%
B segment	D segment	576.2	14.9%	25.8%
B segment	E segment	592.5	20.3%	28.2%
B segment	Coupé/Cabriolet	208.0	1.3%	2.0%
B segment	Minivan	556.5	15.7%	26.8%
B segment	MPV	600.9	10.7%	23.5%
B segment	Compact SUV	506.6	10.3%	23.7%
B segment	Medium SUV	542.8	15.7%	26.2%
B segment	Big SUV	527.1	17.4%	27.5%
B segment	Superior SUV	799.4	20.8%	27.9%

Table 8: PD and IR for accidents between the B segment subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
C segment	Average	674.2	10.0%	23.2%
C segment	A segment	628.0	2.9%	17.5%
C segment	B segment	633.5	5.8%	20.8%
C segment	C segment	623.3	6.8%	21.6%
C segment	D segment	677.5	10.5%	23.4%
C segment	E segment	723.1	15.3%	26.2%
C segment	Coupé/Cabriolet	272.7	0.9%	2.1%
C segment	Minivan	669.2	11.4%	24.6%
C segment	MPV	649.4	7.4%	21.6%
C segment	Compact SUV	612.8	7.0%	21.9%
C segment	Medium SUV	668.8	11.4%	24.5%
C segment	Big SUV	646.4	12.8%	25.5%
C segment	Superior SUV	768.6	15.8%	26.2%

Table 9: PD and IR for accidents between the C segment subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
D segment	Average	664.8	7.1%	21.6%
D segment	A segment	638.1	2.1%	15.8%
D segment	B segment	642.2	4.1%	19.1%
D segment	C segment	641.7	5.1%	20.4%
D segment	D segment	646.5	7.8%	21.8%
D segment	E segment	712.4	11.6%	24.2%
D segment	Coupé/Cabriolet	303.1	0.4%	2.2%
D segment	Minivan	661.2	8.8%	23.0%
D segment	MPV	623.1	5.5%	20.2%
D segment	Compact SUV	613.8	5.1%	20.3%
D segment	Medium SUV	684.7	8.1%	22.4%
D segment	Big SUV	668.5	9.8%	23.9%
D segment	Superior SUV	681.6	12.5%	25.1%

Table 10: PD and IR for accidents between the D segment subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
E segment	Average	802.7	4.9%	19.9%
E segment	A segment	771.3	1.5%	14.7%
E segment	B segment	781.7	2.9%	17.6%
E segment	C segment	779.5	3.5%	18.6%
E segment	D segment	744.1	6.0%	20.4%
E segment	E segment	816.7	8.4%	22.8%
E segment	Coupé/Cabriolet	371.2	0.4%	1.9%
E segment	Minivan	799.4	6.6%	21.5%
E segment	MPV	791.2	3.8%	18.7%
E segment	Compact SUV	792.6	3.6%	18.7%
E segment	Medium SUV	784.3	6.2%	21.0%
E segment	Big SUV	855.9	7.5%	22.4%
E segment	Superior SUV	780.3	9.7%	23.4%

Table 11: PD and IR for accidents between the E segment subject vehicle car and several categories of the opponent vehicle.

Table 12: PD and IR for accidents between the F segment subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Coupé/Cabriolet	Average	864.8	7.5%	21.5%
Coupé/Cabriolet	A segment	823.0	2.3%	16.3%
Coupé/Cabriolet	B segment	823.7	4.0%	19.0%
Coupé/Cabriolet	C segment	823.7	4.9%	19.9%
Coupé/Cabriolet	D segment	855.2	8.0%	21.7%
Coupé/Cabriolet	E segment	962.0	11.3%	24.6%
Coupé/Cabriolet	Coupé/Cabriolet	271.2	0.6%	1.5%
Coupé/Cabriolet	Minivan	828.9	8.7%	22.8%
Coupé/Cabriolet	MPV	933.7	5.4%	20.4%
Coupé/Cabriolet	Compact SUV	839.5	5.3%	20.4%
Coupé/Cabriolet	Medium SUV	853.4	8.8%	22.8%
Coupé/Cabriolet	Big SUV	846.1	10.1%	23.9%
Coupé/Cabriolet	Superior SUV	1,157.2	12.4%	24.5%

Table 13: PD and IR for accidents between the Coupé/Cabriolet subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Minivan	Average	478.2	8.0%	22.0%
Minivan	A segment	451.3	2.1%	15.5%
Minivan	B segment	493.9	4.3%	18.8%
Minivan	C segment	506.1	5.3%	20.1%
Minivan	D segment	534.7	8.0%	22.1%
Minivan	E segment	488.8	11.1%	23.3%
Minivan	Coupé/Cabriolet	153.7	1.3%	3.4%
Minivan	Minivan	525.9	9.1%	23.3%
Minivan	MPV	502.9	5.7%	19.8%
Minivan	Compact SUV	506.6	5.6%	20.3%
Minivan	Medium SUV	481.4	9.2%	22.4%
Minivan	Big SUV	480.8	10.3%	23.7%
Minivan	Superior SUV	458.4	12.5%	24.5%

Table 14: PD and IR for accidents between the Minivan subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
MPV	Average	688.2	6.1%	20.5%
MPV	A segment	642.0	1.8%	15.2%
MPV	B segment	640.9	3.6%	18.4%
MPV	C segment	644.9	4.5%	19.4%
MPV	D segment	641.7	7.3%	21.4%
MPV	E segment	736.7	11.2%	24.2%
MPV	Coupé/Cabriolet	257.1	0.8%	2.5%
MPV	Minivan	657.3	7.9%	22.1%
MPV	MPV	752.9	4.7%	19.3%
MPV	Compact SUV	650.7	4.4%	19.0%
MPV	Medium SUV	656.5	7.8%	22.2%
MPV	Big SUV	661.7	8.9%	22.9%
MPV	Superior SUV	775.2	11.6%	24.1%

Table 15: PD and IR for accidents between the MPV subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Compact SUV	Average	621.1	6.9%	21.8%
Compact SUV	A segment	615.4	2.0%	16.0%
Compact SUV	B segment	517.8	4.0%	19.4%
Compact SUV	C segment	536.2	4.7%	20.2%
Compact SUV	D segment	549.4	8.3%	21.9%
Compact SUV	E segment	564.3	10.7%	23.8%
Compact SUV	Coupé/Cabriolet	182.2	1.0%	3.8%
Compact SUV	Minivan	578.6	8.4%	22.5%
Compact SUV	MPV	584.7	4.9%	18.8%
Compact SUV	Compact SUV	517.4	5.1%	20.1%
Compact SUV	Medium SUV	580.8	7.9%	22.6%
Compact SUV	Big SUV	618.8	10.0%	24.2%
Compact SUV	Superior SUV	602.5	12.0%	24.5%

Table 16: PD and IR for accidents between the Compact SUV subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Medium SUV	Average	651.8	4.8%	19.4%
Medium SUV	A segment	613.5	1.5%	14.3%
Medium SUV	B segment	627.6	2.8%	17.1%
Medium SUV	C segment	649.6	3.4%	18.1%
Medium SUV	D segment	592.5	5.9%	20.3%
Medium SUV	E segment	701.1	8.9%	22.6%
Medium SUV	Coupé/Cabriolet	230.5	0.7%	2.9%
Medium SUV	Minivan	676.5	6.0%	20.9%
Medium SUV	MPV	635.7	3.7%	17.9%
Medium SUV	Compact SUV	644.1	3.5%	18.0%
Medium SUV	Medium SUV	666.3	6.3%	21.1%
Medium SUV	Big SUV	610.9	6.9%	21.8%
Medium SUV	Superior SUV	669.4	10.0%	23.0%

Table 17: PD and IR for accidents between the Medium SUV subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Big SUV	Average	898.6	3.6%	18.4%
Big SUV	A segment	847.4	1.1%	13.2%
Big SUV	B segment	825.9	2.2%	16.6%
Big SUV	C segment	754.5	2.4%	16.9%
Big SUV	D segment	837.8	4.2%	19.3%
Big SUV	E segment	811.5	7.3%	22.1%
Big SUV	Coupé/Cabriolet	387.9	0.1%	1.3%
Big SUV	Minivan	794.5	4.6%	19.8%
Big SUV	MPV	930.2	2.5%	16.9%
Big SUV	Compact SUV	810.5	2.7%	17.7%
Big SUV	Medium SUV	838.6	4.7%	19.9%
Big SUV	Big SUV	774.7	5.4%	20.9%
Big SUV	Superior SUV	897.1	7.2%	22.4%

Table 18: PD and IR for accidents between the Big SUV subject vehicle car and several categories of the opponent vehicle.

Subject category	Opponent category	PD [€]	IR_{avg}^{subj}	IR_{avg}^{opp}
Superior SUV	Average	1,065.0	2.0%	15.6%
Superior SUV	A segment	871.7	0.7%	10.4%
Superior SUV	B segment	927.8	1.1%	12.9%
Superior SUV	C segment	866.5	1.2%	13.7%
Superior SUV	D segment	990.8	2.5%	16.4%
Superior SUV	E segment	948.8	4.1%	18.4%
Superior SUV	Coupé/Cabriolet	517.8	0.4%	3.6%
Superior SUV	Minivan	981.5	2.3%	16.3%
Superior SUV	MPV	1,063.3	1.4%	14.5%
Superior SUV	Compact SUV	836.8	1.5%	14.6%
Superior SUV	Medium SUV	951.0	2.6%	17.2%
Superior SUV	Big SUV	830.9	2.7%	17.7%
Superior SUV	Superior SUV	1,017.8	3.9%	18.8%

Table 19: PD and IR for accidents between the Superior SUV subject vehicle car and several categories of the opponent vehicle.