Bulletin of Yerevan University: Economics
2025, Vol. 16, No. 2(46), December, 105-112
https://doi.org/10.46991/BYSU.G.2025.16.2.105

IMPACT OF BONUS-MALUS SYSTEM REFINEMENTS ON TIME-TO-ACCIDENT IN ARMENIA'S CMTPL INSURANCE: A SURVIVAL ANALYSIS APPROACH

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Abstract: This article investigates the impact of recent reforms in Armenia's Bonus-Malus (BM) system on the time-to-accident among Compulsory Motor Third-Party Liability (CMTPL) policyholders. Specifically, it evaluates whether the 2022 introduction of claim severity adjustments influenced policyholder behavior across different risk groups. Utilizing survival analysis methods on a dataset comprising over 2.3 million insurance contracts, the research identifies statistically significant improvements in accident-free durations post-reform. Results reveal that policyholders in certain vehicle categories and risk classes exhibited behavioral shifts, while others, such as public transport drivers and individuals in extreme BM classes, did not. The policyholder's gender emerged as a statistically significant risk factor, with female drivers showing consistently lower accident-free times. The findings underscore the effectiveness of claim severity-based malus policies and suggest that further personalization for example through telematics, can enhance fairness and incentivize safer driving.

Key words: *Bonus-Malus System, CMTPL Insurance, Survival Analysis, Risk Classification, Behavioral Incentives*

Introduction

The implementation of CMTPL insurance in Armenia has played a pivotal role in shaping the motor insurance landscape. A fundamental component of this system is the Bonus-Malus mechanism, which serves as a behavioral incentive by adjusting insurance premiums based on individual claims history. Since its initial deployment in 2013, Armenia's BM system has evolved considerably. Most notably, in 2022, a significant structural reform introduced claim severity into the malus calculation framework mainly based on (Chitchyan & Gulyan, 2015). This study aims to investigate the behavioral consequences of this reform, particularly its impact on the time elapsed between the commencement of a policy and the occurrence of the first reported claim event.

This research utilizes a survival analysis framework to statistically test the hypothesis that the revised BM system has led to an elongation of accident-free durations among

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Received: 12.05.2025
Revised: 05.06.2025
Accepted: 23.12.2025

policyholders. The findings aim to contribute to the broader discourse on behavioral insurance modeling and the empirical assessment of incentive-based policy instruments.

The BM system was introduced in Armenia in 2013, two years following the adoption of mandatory CMTPL insurance. Initially modeled on the Belgian system, it employed a relatively straightforward structure primarily based on claim frequency. Over the following decade, iterative refinements were implemented:

- **2013–2022:** Introduction of additional bonus and malus classes; revisions to transition rules.
- **2022 Reform:** Integration of claim severity into malus scoring. Minor accidents incurred smaller penalties compared to serious ones, promoting proportionality (AMIB, 2025).
- **2017 Technological advances: The Armenian Single Window for Automotive facilitated data exchange and transparency between insurers, regulators, and insureds. In addition to exchanging information on contracts and accidents, this platform also calculates the policyholders' BM classes** (ASWA, 2025)**.**

These modifications were designed to foster fairness, mitigate adverse selection, and enhance market competitiveness. According to the Armenian Motor Insurers' Bureau, these developments significantly improved insurer-client engagement and incentivized safer driving practices.

The main objectives of this research are as follows:

- To quantify behavioral shifts in driving risk subsequent to the 2022 Bonus-Malus reform.
- To identify policyholder segments (defined by risk class, gender, and vehicle characteristics) most affected by the reform.
- To statistically test the significance of behavioral variation using time-to-event metrics.

This investigation is grounded in actuarial science and risk classification theory, drawing on empirical data to inform regulatory and pricing policy decisions in the Armenian insurance sector.

Methodology

When we speak about survival, we mean probabilities. The probability of not occurring an event till some time can be taken as survival probability. In other words, the probability of an event occurrence after a certain time is survival probability. One of the purposes of survival analysis is to find out this probability distribution. A lot of other domain-specific statistical inferences can also be drawn from this. It can be observed that survival probability decreases over time. It is a very important feature of distribution (Nag, 2022).

Most survival analyses must consider a very important analytical problem called censoring. It is caused by not observing some subjects for the full time till failure (or event). A problem occurs when the event happens in between, after the end of or before the study, and hence censoring occurs. There can be two primary reasons for this:

- The event does not happen before the study ends,
- The object of a study left out during the study period.

In all the above cases, true survival time is not equal to the observed survival time, as the actual time could not be marked. Depending on these situations, there can be three

types of censoring. Right censoring happens when a study ends but no event is observed. Left censoring happens when an event has already occurred before the start of the study. Interval censoring happens when an event occurs within the study period in between two possible time limits, and, as usual, the actual time could not be noted.

This study analyzes a comprehensive dataset comprising over 2.3 million insurance contracts, covering the starting period from April 2021 to the ending period of the contracts, April 2024. The following methodological choices were employed:

- **Event of Interest:** First occurrence of a reported accident post-contract initiation.
- **Time Variable:** Duration measured in days from policy start date.
- **Censoring:** Contracts without reported accidents or those terminated before the occurrence of a claim were treated as right-censored observations.
- **Analytical Tools:** Survival analysis via the life-table method was conducted using the SPSS statistical package. The Wilcoxon (Gehan) statistic was applied to test for statistically significant differences between survival curves.

The Wilcoxon test statistic is given as:

$$W = \frac{(N-1)\sum \frac{SS_i^2}{n_i}}{\sum U_j^2}$$

Where:

- $U_j = Unc_j$, for a censored case at time j
- $U_j = 2 * Unc_j - UncEq_j + Cen_j - CenEq_j - N$, for an uncensored case j, where $UncEq_j$ and $CenEq_j$ are the number of uncensored and censored cases at each time period and Unc_j and Cen_j are the number of uncensored and censored cases at all current and previous time periods.
- SS_i is the sum of scores for group i.

The Wilcoxon test statistic accounts for both censored and uncensored observations over time, making it appropriate for non-parametric comparison of survival distributions across groups (StatsDirect, 2025).

Results

This section presents the core findings of the study, structured by key risk-related factors that influence policyholder behavior. The empirical results are grouped to highlight variations across risk classes, demographic features, and vehicle characteristics.

Before discussing the overall behavioral effects of the BM reform, it is important to highlight several conceptual distinctions across policyholder risk groups. Some segments, such as high-frequency claimants or drivers of service vehicles, may exhibit inertia in behavioral change due to structural or occupational exposure. Conversely, moderate-risk policyholders on mid-range BM classes, typically using vehicles for personal purposes, are more likely to adjust their driving behavior in response to incentive structures. Understanding these group-specific dynamics is critical to interpreting the differential impact of the reform.

✓ **General Behavioral Trends**

The survival function for policyholders in the post-reform period was statistically higher compared to the pre-reform period. The p-value (Sig.) of the Wilcoxon test was less than 0.05, indicating that the difference is statistically significant. This suggests that the 2022 BM reform positively influenced policyholders' behavior by increasing accident-free intervals.

Table 1

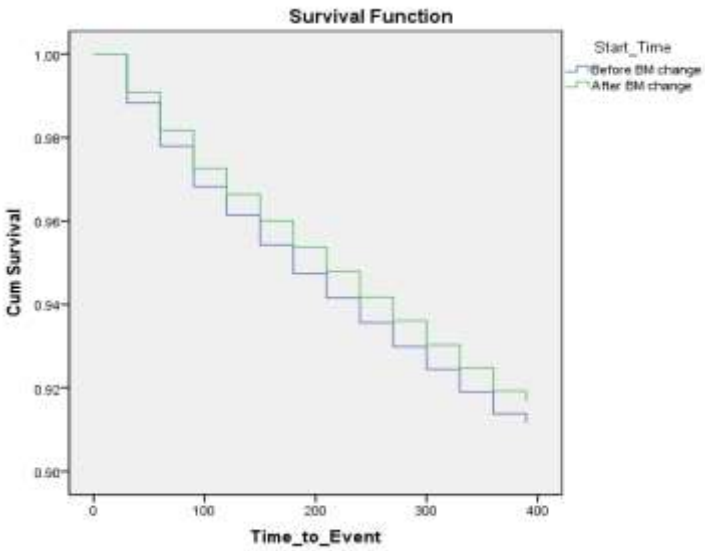
Wilcoxon (Gehan) test for comparison of survival changes before and after BM reform groups

Wilcoxon (Gehan) Statistic	df	Sig.
372.193	1	.000

Source: *Table created in SPSS by authors.*

Graph 1

Survival Function



Source: *Graph created in SPSS by authors*

Survival curve analysis shows that behavior change is in a positive direction as the survival curve before BM changes is lower than after that.

✓ **Behavior by Bonus-Malus Classes**

Insureds in the middle BM classes (classes 4-16) showed a statistically significant change in survival functions. Conversely, insureds in the extreme classes (the lowest BM levels 1-3 or the highest BM levels, 19-24) maintained stable behavioral patterns over both periods. This stability suggests that extreme risk groups may be less responsive to changes in incentive structures, possibly due to ingrained behavioral habits or structural risk factors.

Table 2

Wilcoxon (Gehan) test for comparison of survival changes by Bonus-Malus groups

		Wilcoxon (Gehan) Statistic	*df*	*Sig.*
BM Class	1	.064	1	.800
	2	.377	1	.539
	3	3.237	1	.072
	4	6.745	1	.009
	5	8.350	1	.004
	6	10.175	1	.001
	7	15.136	1	.000
	8	21.433	1	.000
	9	48.581	1	.000
	10	245.373	1	.000
	11	5.292	1	.021
	12	10.958	1	.001
	13	6.159	1	.013
	14	22.786	1	.000
	15	5.977	1	.014
	16	5.761	1	.016
	17	.436	1	.509
	18	6.938	1	.008
	19	.566	1	.452
	20	.028	1	.868
	21	3.518	1	.061
	22	13.570	1	.000
	23	.002	1	.967
	24	.024	1	.876
	25	4.662	1	.031

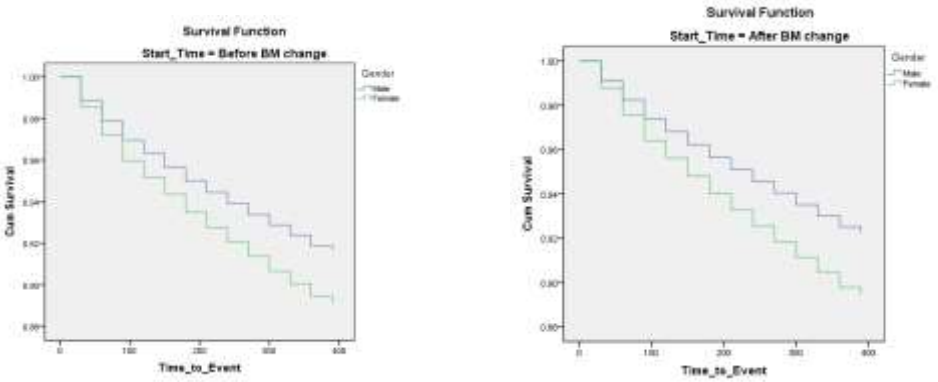
Source: *Table created in SPSS by authors*

✓ **Behavioral Differences Based on Gender and Other Personal Characteristics**

Across both pre-reform and post-reform datasets, female policyholders demonstrated consistently lower survival functions compared to male ones. This result was statistically significant (Sig. < 0.05), reinforcing gender as a material risk factor rather than a discriminatory pricing element. These findings align with prior studies in actuarial literature which document gender-based differences in claims frequency (OECD, 2021).

Graph 2

Survival Functions



Source: *Graph created in SPSS by authors.*

Table 3 shows that both males and females showed a positive change after the BM reform, with males experiencing a slightly higher increase (4.7 days) compared to females (3.2 days). This suggests that the BM reform had a generally beneficial effect on both groups, but the magnitude of the change was slightly greater for males.

Table 3

Average days to accident by gender

Gender	Before BM Change	After BM Change	Difference
Male	347.3	351.9	4.7
Female	341.8	345.0	3.2

Source*: Table created by authors.*

Gender as a valuation variable in insurance has been the subject of extensive debate. While statistical evidence supports its use as a relevant risk factor due to observed differences in accident frequency and severity, its application must balance actuarial accuracy with social fairness. Regulatory trends, such as the EU Test-Achats decision, prohibit gender-based pricing. This has led to a shift towards behavior-based personalization, which encourages individual driving patterns rather than relying on group classifications. Thus, gender as an insurance factor can be a fair and functional risk factor, but its application must be strictly controlled and based on proven differences, avoiding unjustified discrimination (Meyers & Hoyweghen, 2017).

The same suggestions can be made concerning other personal characteristics like the policyholder's citizenship and age group, which are also strong risk factors leading to change in the policyholder's behavior according to this study, but in some sense, they also can be discussed as discrimination factors.

✓ **Vehicle Type and Mark Effects**

In contrast to passenger, bus and truck drivers, motorcycle drivers showed no significant change in time-to-event metrics, indicating the reform did not alter their

behavioral risk profile. Among automobile models, Renault drivers were uniquely unaffected by the BM changes.

Table 4

Wilcoxon (Gehan) test for comparison of survival changes by vehicle mark groups.

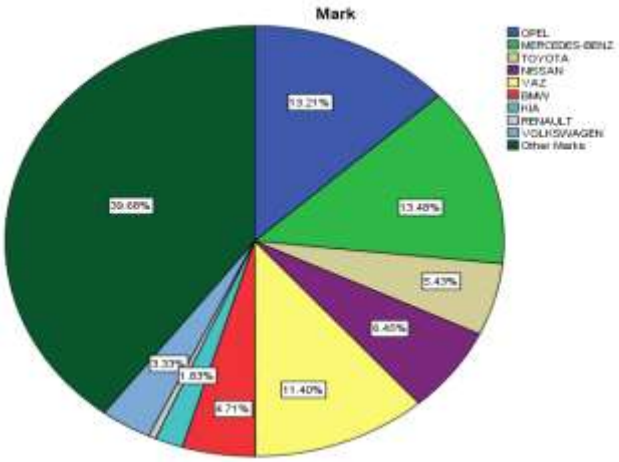
		Wilcoxon (Gehan) Statistic	Sig.
Mark	OPEL	59.452	.000
	MERCEDES-BENZ	36.062	.000
	TOYOTA	4.540	.033
	NISSAN	26.616	.000
	VAZ	113.452	.000
	BMW	7.418	.006
	KIA	10.839	.001
	RENAULT	**2.542**	**.111**
	VOLKSWAGEN	12.880	.000
	OTHER MARKS	108.245	.000

Source: *Table created in SPSS by authors.*

The distribution of vehicle marks in the study was as follows:

Graph 3

Distribution of vehicle marks



Source: *Graph created in SPSS by authors.*

Vehicle-related risk segmentation remains an important avenue for refinement in premium calculation.

✓ **Behavior by vehicle age, horsepower and use type**

According to the purpose of vehicle use, the analysis showed that there is no change in behavior in the case of public and service vehicles, which may be due to the fact that

the insurance premium for these vehicles is paid not directly by drivers, but by their employers or from the state budget. All other risk factors like vehicle age or horsepower significantly affect the change of policyholder's behavior in terms of time to event analysis.

Table 5

Wilcoxon (Gehan) test for comparison of survival changes by vehicle use type

		Wilcoxon (Gehan) Statistic	Sig.
Vehicle Use type	Personal	352.066	.000
	Commercial	21.685	.000
	Service	**.014**	**.904**
	Public transport	**.454**	**.500**
	Taxi or rental	24.213	.000

Source: *Table created in SPSS by authors.*

Conclusion

The empirical results affirm the effectiveness of Armenia's 2022 BM reform in extending accident-free durations among the general policyholder population. The incorporation of claim severity appears to have introduced greater behavioral sensitivity into the system, thereby enhancing its deterrent effect.

From a regulatory perspective, these findings support:

- Development of individualized premium models integrating telematics.
- Ongoing calibration of BM transition rules based on real-world behavioral data.
- Acknowledgement of gender and vehicle type as relevant, non-discriminatory risk factors.
- Continued development of transparent digital infrastructures like the Single Window platform to support data-driven supervision.
- Expansion of public policy tools that align insurance incentives with road safety objectives.

These insights may guide future refinements to the Armenian BM system and serve as a model for other emerging insurance markets.

References

AMIB. (2025). Retrieved from https://appa.am/

ASWA. (2025). Retrieved from https://aswa.am/

Chitchyan, R., & Gulyan, A. (2015). A Bonus-Malus System With Aggregate Claim Amount Component. *Journal of Contemporary Mathematical Analysis (Armenian Academy of Sciences)*, 74-88.

Meyers, G., & Hoyweghen, I. V. (2017). Enacting Actuarial Fairness in Insurance: From Fair Discrimination to Behaviour-Based Fairness. *Science as Culture*, 1-27.

Nag, A. (2022). *Survival Analysis with Python.* Taylor & Francis Group, LLC.

OECD. (2021). Retrieved from https://www.oecd.org/finance/Gender-Insurance-2021.pdf

StatsDirect. (2025). Retrieved from https://www.statsdirect.com/help/survival_analysis/logrank.htm