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MODERNIZING MOTOR INSURANCE PRICING IN TUNISIA: A GENERALIZED LINEAR MODELS APPROACH FOR EMERGING MARKETS

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ABSTRACT:

The Tunisian motor insurance market confronts critical actuarial challenges following seven years of frozen tariffs (2016-2023) despite persistent claims inflation and evolving risk landscapes. This empirical case study develops and validates a Generalized Linear Models (GLM) framework for risk-based motor insurance pricing within regulatory-constrained emerging market contexts. Using 148,505 motor insurance policies from a leading Tunisian insurer, we implement frequency-severity modeling: Poisson regression for claim frequency and Gamma regression for claim severity across 13 key risk variables. Key findings demonstrate substantial risk differentiation (87.2% coefficient of variation) between low-risk and high-risk profiles, enabling actuarially justified premium segmentation. Bonus-malus class exhibits 14.8-fold variation, driver age shows 3.64× elevation for young drivers, vehicle age follows U-shaped patterns, and fuel type generates 14% frequency differential. International comparison validates alignment with published literature while revealing Tunisian-specific nuances. Implementation projects 3-5 percentage point combined ratio improvements while maintaining regulatory compliance. This research contributes to African insurance modernization by demonstrating evidence-based GLM implementation in constrained emerging markets, providing a transferable framework for other African insurers seeking actuarial advancement.

Keywords: Generalized Linear Models, motor insurance, emerging markets, pricing, risk segmentation, frequency-severity, Africa, regulatory constraints, actuarial science

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I. INTRODUCTION

1.1 Problem Context and Market Conditions

The Tunisian motor insurance market represents a foundational component of the country's insurance sector, mandatory for all vehicle owners and critical for economic risk transfer. However, the sector faces acute actuarial challenges stemming from regulatory tariff freezes implemented in 2016 that remain unchanged despite significant shifts in underlying claims experience. This seven-year stagnation creates systematic actuarial inadequacy: premium levels cannot reflect evolving risk landscapes shaped by claims inflation, demographic shifts in driver populations, vehicle technology evolution, and changing driving patterns.

Motor insurance constitutes approximately 52% of total non-life insurance premiums in Tunisia, making pricing modernization significant for both sector stability and consumer protection. The regulatory constraint—tariffs frozen under Ministry of Finance Circular 2016-12—prevents insurers from implementing risk-differentiated pricing despite global consensus regarding best practices. This constraint creates cross-subsidies between low-risk and high-risk policyholders, undermining incentive structures and financial stability.

1.2 International Context: GLM as Global Standard

Generalized Linear Models have become the international standard for insurance pricing over the past three decades, adopted across developed and emerging markets. GLMs provide transparent, statistically justified methodologies enabling regulators, consumer advocates, and insurers to engage constructively on pricing principles. Recent empirical evidence from multiple markets demonstrates GLM implementations achieve 3-6 percentage point combined ratio improvements through enhanced risk segmentation.

However, GLM adoption remains limited in African insurance markets, particularly in contexts combining regulatory constraints, limited data infrastructure, and market-specific complexities. This gap represents both a challenge and an opportunity: African insurers seeking modernization can adapt proven methodologies while addressing local market realities.

1.3 Research Objectives and Contributions

This case study pursues five interconnected objectives:

1. Develop a rigorous, statistically validated GLM-based pricing framework incorporating 13 key risk variables relevant to Tunisian motor insurance

2. Quantify predictive power of bonus-malus class, driver demographics, vehicle characteristics, and policy tenure on claims outcomes

3. Implement frequency-severity modeling enabling separate analysis of claim count and claim amount dynamics

4. Generate actuarially justified premium recommendations with transparent risk differentiation

5. Evaluate implementation feasibility within Tunisian regulatory and operational constraints

The research contributes across three dimensions: For Tunisian insurers, it provides evidence for regulatory engagement and modernization planning. For African insurance markets, it demonstrates GLM adaptation to regulatory-constrained emerging market contexts. For the actuarial profession, it expands empirical evidence regarding GLM applications in African insurance sectors.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Generalized Linear Models: Theoretical Foundations

Generalized Linear Models, developed by Nelder and Wedderburn (1972), extend classical linear regression to accommodate non-normal response distributions characteristic of insurance data. Unlike ordinary least squares regression assuming normally distributed outcomes with constant variance, GLMs provide flexible distributional frameworks enabling appropriate modeling of count data (Poisson, negative binomial) and positive continuous outcomes (Gamma, lognormal) through specified link functions [1][2].

In insurance applications, GLMs offer methodological advantages. They provide flexibility accommodating empirical insurance claims characteristics: non-negative values, right-skewed distributions, and heterogeneous variance. They enable transparency with regression coefficients directly representing multiplicative risk factors, facilitating regulatory justification and stakeholder communication. They maintain regulatory alignment, with coefficients representing actuarially justified factors defensible before regulators. They handle scalability efficiently, managing large datasets with multiple categorical and continuous variables through maximum likelihood estimation.

The theoretical specification rests on:

$$\eta_i = \mathrm{x}_i^T \beta$$

where η_i represents the linear predictor, $\mathbf{x}_i$ contains predictors, $\boldsymbol{\beta}$ represents coefficients, and the link function g relates expected value $\mu_i = \mathbb{E}(Y_i)$ to the predictor:

$$g(\mu_i) = \eta_i$$

2.2 Frequency-Severity Decomposition in Insurance

International actuarial practice decomposes pure premium (expected claim cost per exposure unit) into two components [3][4]:

$$\text{Pure Premium} = \mathbb{E}[\text{Claim Frequency}] \times \mathbb{E}[\text{Claim Severity}]$$

This decomposition reflects that claim count and claim amount are often driven by different risk factors with distinct distributional properties. Frequency modeling employs Poisson or negative binomial distributions with logarithmic links; severity modeling typically uses Gamma or lognormal distributions. This approach accommodates heterogeneous risk structures while maintaining interpretability.

Frequency specification:

$$\log \mathbb{E}[\text{Claim Count}_i] = \mathbf{x}_{i,\text{freq}}^T \boldsymbol{\beta}_{\text{freq}}$$

Severity specification:

$$\log \mathbb{E}[\text{Claim Amount}_i] = \mathbf{x}_{i,\text{sev}}^T \boldsymbol{\beta}_{\text{sev}}$$

Combined pure premium:

$$\text{Pure Premium}_i = \exp\left(\mathrm{x}_{i,\text{freq}}^T \beta_{\text{freq}}\right) \times \exp\left(\mathrm{x}_{i,\text{sev}}^T \beta_{\text{sev}}\right)$$

2.3 International Empirical Evidence: Comparative Literature Review

Driver Age Effects

International studies consistently demonstrate strong age-frequency relationships. Choi and Hardin (2023) report 3-4× frequency elevation for drivers under 25 years across emerging markets, with exponential relationships typical. Bajorunas et al. (2008) found age-related violations and accident involvement follow power-law distributions. This study's Tunisian results (31.58% frequency for drivers <20 years, 3.64× portfolio average) align with international patterns while revealing local market-specific dynamics.

Bonus-Malus System Discrimination

Lemaire (2015) documents bonus-malus systems across European markets achieving 8-15× discrimination between best and worst classes, validating claims history as a fundamental risk predictor. The Tunisian system demonstrates 14.8-fold variation (Class 1: 6.27% to Class 11: 92.59%), placing it within the international range and suggesting the system effectively incentivizes safe driving behavior.

Vehicle Age Patterns

Zarkadoulas et al. (2020) identify non-linear vehicle age patterns across European markets, with quadratic effects common. Wilson (2023) meta-analysis of 50 empirical studies confirms U-shaped patterns with peak risk typically at 5-10 years of age. This study's Tunisian data (peak frequency 9.42% at 5-10 years) validates the international pattern while confirming local applicability.

Fuel Type and Usage Patterns

Choi and Hardin (2023) report diesel vehicles exhibit 10-15% higher frequency than gasoline vehicles, primarily reflecting higher annual mileage and commercial usage patterns. The Tunisian result (14% differential, 9.30% diesel vs. 8.15% gasoline) falls squarely within this international range, suggesting fuel type captures consistent usage patterns across markets.

Summary Comparative Table

Risk Factor	Tunisian Results	International Literature	Alignment Assessment
Driver Age <20	31.58% frequency (3.64× avg)	Choi & Hardin (2023): 3-4×	Within international range; strong alignment
Bonus-Malus Range	14.8× (6.27%-92.59%)	Lemaire (2015): 8-15×	Within international range; effective discrimination
Vehicle Age Peak	9.42% at 5-10 years	Zarkadoulas et al. (2020); Wilson (2023): U-shaped peaks at 5-10y	Confirms international patterns
Fuel Type Diesel	14% higher frequency	Choi & Hardin (2023): 10-15%	Within international range; reflects usage patterns

This comparative analysis demonstrates that while Tunisian coefficients reflect local market conditions, risk factor relationships align fundamentally with international actuarial evidence, supporting the validity and generalizability of GLM methodology across market contexts.

2.4 African Insurance Market Context

African insurance sectors, while growing rapidly, face distinct challenges limiting GLM adoption. Limited data infrastructure constrains modeling capabilities; regulatory

frameworks often lag international best practices; actuarial capacity remains concentrated in South Africa; and emerging market characteristics create specific implementation barriers. This Tunisian case study addresses these constraints directly, demonstrating that rigorous GLM methodology remains feasible and valuable within African market realities.

2.5 Research Gap and Study Positioning

Despite extensive international GLM literature, empirical studies demonstrating GLM implementation in African insurance markets with regulatory constraints remain limited. This study addresses that gap by providing rigorous methodological implementation combined with realistic assessment of Tunisian-specific implementation challenges and opportunities. The research bridges international best practices with African market realities, contributing both to Tunisian insurance development and broader African actuarial modernization.

III. DATA AND METHODOLOGY

3.1 Data Source and Preparation

This study utilizes motor insurance policy data from a major Tunisian insurer. The dataset comprises 154,537 initial policy records representing the universe of active motor insurance policies during this period.

Data Cleaning Protocol: A structured cleaning approach ensured data quality while retaining analytical credibility. Extreme outliers inconsistent with plausible insurance experience were removed: policyholders aged 80+ years (0.8% of records) and vehicles aged 30+ years (0.3% of records). Missing values in key variables received mode imputation for categorical variables and median imputation for continuous variables, affecting less than 2% of records.

The final analytical dataset comprises 148,505 policy records representing 89,747 unique exposure units (individual policyholders tracked across multiple years).

3.2 Variable Specification

The analysis incorporates 13 key risk variables across four domains: driver characteristics, vehicle attributes, policy features, and geographic factors, selected per international actuarial practice and Tunisian market knowledge.

Driver Variables:

- Driver Age (7 categories): <20, 20-29, 30-39, 40-49, 50-59, 60-69, 70-80 years
- Bonus-Malus Class (11 categories): 1 (best) to 11 (worst)
- Policy Tenure (continuous): years with current insurer

Vehicle Variables:

- Vehicle Age (6 categories): 0-5, 5-10, 10-15, 15-20, 20-25, 25-30 years
- Fuel Type (2 categories): Diesel, Gasoline
- Vehicle Category (2 categories): Commercial, Personal

Geographic Variables:

- Region (Urban/Rural classification)
- Area (Administrative subdivision)
- Density Index (Regional population density proxy)

Outcome Measures:

- Claim Count: Total claims filed during exposure period (frequency model response)
- Claim Amount: Total claim cost in Tunisian Dinars (severity model response)

3.3 Statistical Methodology

Stage 1 – Descriptive Analysis: Frequency distributions and crosstabulations characterize relationships between risk factors and claim outcomes, establishing baseline patterns and identifying anomalies.

Stage 2 – Model Specification: Separate Poisson regression models for claim frequency and Gamma regression models for claim severity via maximum likelihood estimation. Poisson specification is standard for count data; Gamma distribution is appropriate for right-skewed, positive-valued claim amounts.

Stage 3 – Model Validation: Deviance residuals assessment examines model fit across predicted value ranges. Out-of-sample validation assesses predictive performance on held-out test data. Coefficient stability analysis compares estimates across subsamples to assess robustness.

IV. RESULTS

4.1 Descriptive Analysis

Claims Frequency by Fuel Type: Analysis of 89,747 exposure units with 7,777 total claims reveals fuel type differential. Diesel vehicles (40,066 units) generated 9.30% frequency; gasoline vehicles (49,682 units) generated 8.15% frequency—a 14% differential reflecting higher mileage and commercial usage.

Claims Frequency by Driver Age: Driver age exhibits pronounced risk gradient. Drivers <20 years (336 units) generated 31.58% frequency, representing 3.64× portfolio

average. Frequency declines systematically with age: 20-29 years (11.52%), 30-39 years (8.01%), 40-49 years (8.88%), 50-59 years (8.28%), 60-69 years (7.33%), 70-80 years (6.75%). This pattern aligns with international evidence regarding age-related driving risk.

Claims Frequency by Bonus-Malus Class: Bonus-malus classification demonstrates exceptional predictive power. Class 1 comprises 65,844 units at 6.27% frequency; Class 11 comprises 4 units at 92.59% frequency—a 14.8-fold variation validating system effectiveness.

Claims Frequency by Vehicle Age: Vehicle age exhibits U-shaped pattern with peak frequency at 5-10 years (9.42%), declining for older vehicles (3.63% for 25-30 years). Pattern reflects interplay of mechanical condition and usage intensity.

4.2 Frequency Model Results

Poisson regression achieves excellent fit with residual deviance 8,247.23 on 89,732 degrees of freedom. All major risk factors demonstrate statistical significance ($p < 0.001$).

Bonus-Malus Classes 2-9 exhibit monotonically increasing coefficients from 0.520 (Class 2) to 1.750 (Class 7), indicating progressive risk increase. Fuel Type (Gasoline) coefficient of -0.139 indicates 13.0% lower frequency relative to diesel. Vehicle Age 5-10 coefficient of 0.279 indicates 32.2% higher frequency for mid-age vehicles. Driver Age coefficients for 20-29 and 30-39 years show negative values, indicating lower frequency for these groups compared to baseline.

Baseline intercept of -2.164 corresponds to baseline frequency approximately 11.49% for reference policyholder (age 40-49, vehicle 0-5 years, Bonus-Malus Class 1, gasoline fuel).

4.3 Severity Model Results

Gamma regression intercept of 8.749 corresponds to baseline expected claim amount approximately 6,319 Tunisian Dinars. Fuel Type (Gasoline) achieves statistical significance ($p = 0.001$) with coefficient -1.002 indicating 63.3% lower claim amounts for gasoline vehicles. Dispersion parameter of 7.261 reflects high inherent variability in individual claim amounts.

4.4 Risk Differentiation and Pure Premium Calculations

Combining frequency and severity estimates generates pure premium predictions for representative risk profiles:

- **Low-Risk Profile** (age 60-69, vehicle 0-5 years, Bonus-Malus Class 1, gasoline): Frequency 6.27%, Severity 3,580 TND, Pure Premium 224 TND, Loading Factor 0.34

- **Medium-Risk Profile** (age 40-49, vehicle 10-15 years, Bonus-Malus Class 1, diesel): Frequency 8.67%, Severity 6,319 TND, Pure Premium 548 TND, Loading Factor 1.00
- **High-Risk Profile** (age 20, vehicle 5-10 years, Bonus-Malus Class 7, diesel): Frequency 48.90%, Severity 8,742 TND, Pure Premium 4,270 TND, Loading Factor 7.79

19-fold variation in pure premiums between low-risk and high-risk profiles (4,270 ÷ 224) demonstrates substantial risk differentiation. Coefficient of variation of 87.2% between low-risk and high-risk profiles enables actuarially justified premium segmentation impossible under uniform regulatory tariffs.

V. DISCUSSION AND IMPLICATIONS

5.1 Model Performance and Actuarial Implications

The frequency model demonstrates excellent predictive power across all major risk dimensions. Bonus-malus class, the most significant predictor, aligns with international actuarial evidence regarding claims history as a fundamental risk indicator. The 14.8-fold risk variation from Class 1 to Class 11 validates system discrimination capacity and suggests potential for further refinement through logarithmic transformation or polynomial effects.

Driver age exhibits expected age-frequency relationship with 3.64× elevation for very young drivers. Interestingly, the model reveals local Tunisian effect: drivers aged 20-39 show lower frequency than intermediate age groups (40-49), potentially reflecting differences in driving behavior, vehicle selection, or usage patterns specific to Tunisian market. This local nuance warrants future investigation with telematics and behavioral data.

Vehicle age effects confirm U-shaped pattern from descriptive analysis, with mid-age vehicles representing peak risk. Gradual decline for very old vehicles likely reflects survivor bias (only well-maintained vehicles remain in service) or differential usage patterns.

5.2 Comparative Analysis: Tunisian Results in International Context

Tunisian model results demonstrate strong alignment with international empirical evidence across all major risk dimensions, validating GLM methodology's cross-market applicability while revealing market-specific nuances.

Age Effects: Tunisian young driver elevation (3.64×) aligns closely with international patterns (Choi & Hardin 2023: 3-4×; Bajorunas et al. 2008), confirming that age-related risk relationships transcend market contexts. The local 20-39 year age effect suggests Tunisian-specific behavioral or vehicle selection patterns meriting future investigation.

Bonus-Malus Performance: Tunisian system's 14.8-fold discrimination falls comfortably within international ranges (Lemaire 2015: 8-15×), confirming effective incentive structures. The non-linear acceleration beyond Class 5 suggests potential for advanced segmentation strategies tested internationally.

Vehicle Age Patterns: U-shaped pattern with 5-10 year peak matches international findings (Zarkadoulas et al. 2020; Wilson 2023), supporting hypothesis that mechanical aging and usage intensity create universal risk dynamics across markets.

Fuel Type Effects: Tunisian 14% diesel differential sits within international range (Choi & Hardin 2023: 10-15%), suggesting fuel type consistently captures usage and mileage patterns globally. This consistency indicates reliable risk factor for multi-market modeling.

This comparative alignment strengthens confidence in model validity and suggests that Tunisian results—while grounded in local data—represent broader actuarial principles applicable across emerging markets.

5.3 Regulatory and Market Implications

Coefficient of variation of 87.2% demonstrates actuarial inadequacy of uniform pricing under current Ministry of Finance tariffs frozen since 2016. Uniform premiums systematically overprice low-risk and underprice high-risk policyholders, creating cross-subsidies undermining risk-based principles.

GLM implementation would enable: (1) Risk-based pricing reflecting underlying claims distribution across 13 risk variables; (2) Loss ratio stabilization improving underwriting results through better segmentation, reducing combined ratios by estimated 3-5 percentage points based on international evidence; (3) Market competitiveness enabling data-driven positioning while maintaining profitability; (4) Regulatory compliance ensuring transparent, actuarially justified pricing.

5.4 Implementation Strategy

Successful implementation requires seven-phase structured approach:

Phase 1 – Stakeholder Engagement: Meetings with Ministry of Finance, competitors, and consumer advocates build consensus regarding actuarial principles and international best practices.

Phase 2 – Data Infrastructure: Investment in data governance, system integration, and analytical capabilities supports ongoing model maintenance.

Phase 3 – Model Refinement: Advanced segmentation testing, interaction term exploration, and external data integration enhance predictive power.

Phase 4 – Pricing Implementation: Gradual transition from regulatory tariffs enables market adaptation with careful policyholder communication.

Phase 5 – Staff Training: Development of internal actuarial capabilities ensures long-term model maintenance independent of external consulting.

Phase 6 – Performance Monitoring: Establishment of key performance indicators tracks implementation success.

Phase 7 – Continuous Refinement: Annual model updates incorporate emerging claims trends and regulatory changes.

5.5 Limitations and Future Research

Limitations: Single-insurer data may not fully represent market-wide characteristics (multi-insurer analysis recommended). Eight-year observation period (2014-2022) is shorter than preferred 10+ years for credibility assessment. Severity model pseudo-R^2 of 0.027 (typical for insurance claims) indicates room for improvement through additional variables (accident circumstances, injury type). Absence of telematics data, driving behavior indicators, and vehicle safety features limits modeling scope.

Future Directions: Machine learning extensions (GAMs, Gradient Boosting) could capture complex non-linear relationships. Dynamic pricing using telematics and behavioral data would enable granular assessment. Comparative multi-insurer analysis would enable industry benchmarking. Emerging risk integration (climate change, autonomous vehicles) would ensure model relevance. Fairness assessment research evaluating pricing equity regarding gender, geography, and socioeconomic factors would ensure ethical implementation.

VI. CONCLUSION

This case study develops and validates a Generalized Linear Models framework for Tunisian motor insurance pricing within regulatory-constrained emerging market contexts. Using 148,505 policies and 13 key risk variables, we demonstrate four key findings:

First, substantial risk differentiation (87.2% coefficient of variation) enables actuarially justified premium segmentation impossible under current uniform regulatory tariffs. International comparison validates fundamental alignment of Tunisian risk patterns with global evidence, while revealing market-specific nuances enriching our understanding of emerging market insurance dynamics.

Second, all major risk factors demonstrate statistical significance with excellent model fit, validating frequency-severity framework for Tunisian data while confirming international actuarial principles' cross-market applicability.

Third, results align with published international studies while appropriately incorporating Tunisian market characteristics, demonstrating that international best practices remain relevant in local contexts.

Fourth, structured implementation approach addresses regulatory constraints and operational challenges specific to Tunisia, providing realistic roadmap for market transition.

GLM methodology enables Tunisian insurers to modernize pricing practices while maintaining regulatory compliance and market competitiveness. Projected 3-5 percentage point combined ratio improvements, coupled with enhanced customer trust through transparent pricing, create substantial business value justifying implementation investment.

This research contributes to African actuarial development by demonstrating that rigorous, evidence-based pricing frameworks can be successfully implemented in emerging market contexts with regulatory constraints, providing an operational model for other African insurance markets seeking modernization while respecting local regulatory and market realities.

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