

Backtesting Split Frequency–Severity Models in Motor third-party liability (MTPL) Insurance Under Claims Inflation

Ondřej Vít[†], Lubomír Seif[‡]

[†]ORCID: 0009-0003-7317-5856

[‡]ORCID: 0009-0003-7444-9425

Department of Statistics and Probability

Faculty of Informatics and Statistics

Prague University of Economics and Business

W. Churchill's square 4, 13067 Prague, Czech Republic

[†]Email: ondrej.vit@vse.cz

[‡]Email: lubomir.seif@vse.cz

Lubomír Štěpánek^{1, 2, 3}

ORCID: 0000-0002-8308-4304

¹Department of Statistics and Probability

²Department of Mathematics

Faculty of Informatics and Statistics

Prague University of Economics and Business

W. Churchill's square 4, 13067 Prague, Czech Republic

Email: lubomir.stepanek@vse.cz

&

³Institute of Biophysics and Informatics

First Faculty of Medicine

Charles University

Salmovská 1, 12000 Prague, Czech Republic

Email: lubomir.stepanek@lf1.cuni.cz

Abstract—Frequency–severity models in motor third-party liability (MTPL) insurance commonly partition claims into size buckets separated by a fixed monetary threshold. While this split improves model fit by allowing different distributional assumptions for small and large claims, it introduces a methodological challenge for backtesting: nominal claims inflation causes claims to migrate across the threshold boundary over time. We formalise the *spillover effect* that arises when an inflation-adjusted claim crosses from the small into the large bucket, and propose an additive decomposition of aggregate severity changes into a *within-bucket inflation* component and a *cross-bucket migration* component. We derive closed-form approximations under a lognormal severity assumption and validate the framework on a Czech MTPL portfolio spanning 2022–2025 with a threshold of 100 000 CZK. Our results show that ignoring the spillover effect overestimates large-claim frequency by 5–35% depending on the assumed inflation rate, and that the cross-bucket migration component dominates the observed severity increase, accounting for 85–100% of the total change. A sensitivity analysis across threshold levels and inflation rates demonstrates that the effect is robust and practically relevant for a wide range of model configurations.

Index Terms—MTPL, claims inflation, frequency–severity model, backtesting, threshold migration, non-life insurance

I. INTRODUCTION

MOTOR third-party liability (MTPL) pricing models are typically structured as frequency–severity models, where the expected risk premium μ is decomposed as

$$\mu = \lambda \cdot c, \quad (1)$$

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with λ denoting the claim frequency and c the expected claim severity [1], [2]. To improve model fit and capture the heavy-tailed nature of claim-size distributions, practitioners commonly split the severity component at a predetermined threshold τ , modelling small claims ($X \leq \tau$) and large claims ($X > \tau$) separately [3], [4]. This yields a decomposed risk premium

$$\mu = \lambda_S \cdot c_S + \lambda_L \cdot c_L, \quad (2)$$

where the subscripts S and L denote small and large components, respectively.

Although this split is well-motivated actuarially, it introduces a subtle problem when the model is backtested across multiple accident years. Claims inflation – driven by repair cost increases, medical inflation, and judicial trends – shifts the entire severity distribution upward over time. If the threshold τ is kept fixed in nominal terms, claims that would have been classified as “small” in earlier years increasingly migrate into the “large” bucket. This *threshold spillover effect* contaminates observed trends in λ_S , λ_L , c_S , and c_L with artefactual changes that do not reflect genuine risk evolution.

The problem is exacerbated in Central European MTPL markets, where claims severity inflation has been running at 4–10 % annually in recent years [5], yet pricing thresholds are often calibrated infrequently. In the Czech market, thresholds of 100 000–200 000 CZK are common, placing them squarely in a region of the severity distribution with non-negligible probability mass.

In this paper we:

- 1) formalise the spillover effect mathematically and decompose the observed change in aggregate severity into

a within-bucket component and a migration component (Section III),

- 2) derive tractable approximations under a lognormal severity assumption (Section IV),
- 3) demonstrate the practical impact on a Czech MTPL portfolio (Section V),
- 4) present a sensitivity analysis across threshold levels and inflation rates (Section VI),
- 5) discuss implications for backtesting methodology (Section VII).

II. RELATED WORK

Split frequency–severity models with a fixed monetary threshold are standard practice in non-life pricing. The actuarial treatment of heavy-tailed claim-size distributions and the separate modelling of attritional and large losses is developed in the classical loss-models literature [3], [4], while the statistical theory of the tail beyond a high threshold rests on extreme-value methods [6]. The choice of the splitting threshold is typically motivated by reinsurance and large-loss considerations rather than by backtesting stability [7].

A second strand concerns claims inflation and its propagation into reserving. Stochastic claims-reserving frameworks [8] and the broader loss-reserving literature [9] recognise that severity trends distort development patterns, and triangle-free approaches [10] were proposed partly to mitigate the compositional instability of size-banded triangles. These works treat inflation as a driver of the severity level, but do not address the classification artefact it induces at a fixed nominal threshold.

To the best of our knowledge, the interaction between these two strands has not been formalised: namely, the contamination of a backtested split model by the migration of claims across a fixed nominal threshold under inflation. Existing treatments either fix the threshold and model the buckets independently, or adjust for inflation at the aggregate level without isolating its effect on bucket membership. The present paper fills this gap by decomposing the observed severity change into a within-bucket and a cross-bucket migration component, and by proposing a deflation-first classification that removes the artefact.

III. METHODOLOGY

A. Setup and Notation

Let X denote a generic claim severity random variable with cumulative distribution function (CDF) F_t in accident year t . We assume a fixed nominal threshold $\tau > 0$ that separates small and large claims throughout the observation period. For a portfolio with N_t total claims in year t , define

$$N_{S,t} = \#\{i : X_{i,t} \leq \tau\}, \quad N_{L,t} = \#\{i : X_{i,t} > \tau\}, \quad (3)$$

$$\bar{X}_{S,t} = \frac{1}{N_{S,t}} \sum_{i: X_{i,t} \leq \tau} X_{i,t}, \quad \bar{X}_{L,t} = \frac{1}{N_{L,t}} \sum_{i: X_{i,t} > \tau} X_{i,t}. \quad (4)$$

The aggregate risk premium in year t is estimated as

$$\hat{\mu}_t = \hat{\lambda}_{S,t} \bar{X}_{S,t} + \hat{\lambda}_{L,t} \bar{X}_{L,t}, \quad (5)$$

where $\hat{\lambda}_{S,t} = N_{S,t}/E_t$ and $\hat{\lambda}_{L,t} = N_{L,t}/E_t$ are the observed frequencies and E_t the earned exposure.

B. Inflation Model

Assume that claims inflation acts multiplicatively: a claim that would have cost x in the base year t_0 costs $x \cdot (1 + \pi)^{t-t_0}$ in year t , where π is the annual inflation rate. Denoting the cumulative inflation factor by $\phi_t = (1 + \pi)^{t-t_0}$, the severity CDF in year t relates to the base-year CDF by

$$F_t(x) = F_{t_0}\left(\frac{x}{\phi_t}\right). \quad (6)$$

Under this model, the small-claim probability evolves as

$$p_{S,t} = \Pr(X_t \leq \tau) = F_{t_0}\left(\frac{\tau}{\phi_t}\right), \quad (7)$$

which is *decreasing* in t since ϕ_t grows over time. The “lost” probability mass migrates to the large-claim bucket. Fig. 1 illustrates this mechanism: as the severity distribution shifts rightward under inflation, a growing mass of probability crosses the fixed threshold τ .

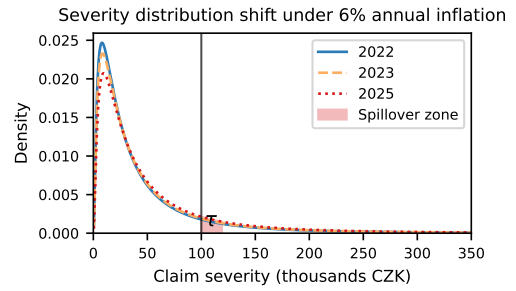


Fig. 1. Lognormal severity densities under 6% annual inflation. The shaded region marks the spillover zone: claims that exceed $\tau = 100\,000$ CZK in 2025 but would not have in 2022.

C. Decomposition of Aggregate Severity Changes

We propose the following additive decomposition of the change in aggregate expected severity between years t and t_0 ,

$$\Delta\mu_t = \underbrace{\Delta\mu_t^{\text{within}}}_{\text{within-bucket inflation}} + \underbrace{\Delta\mu_t^{\text{cross}}}_{\text{cross-bucket migration}}, \quad (8)$$

where

$$\begin{aligned} \Delta\mu_t^{\text{within}} &= p_{S,t_0} (\mathbb{E}[X_t | X_t \leq \tau] - \mathbb{E}[X_{t_0} | X_{t_0} \leq \tau]) \\ &\quad + p_{L,t_0} (\mathbb{E}[X_t | X_t > \tau] - \mathbb{E}[X_{t_0} | X_{t_0} > \tau]), \end{aligned} \quad (9)$$

$$\Delta\mu_t^{\text{cross}} = \Delta p_{L,t} \cdot (\mathbb{E}[X_t | X_t > \tau] - \mathbb{E}[X_t | X_t \leq \tau]), \quad (10)$$

with $p_{L,t} = 1 - p_{S,t}$ and $\Delta p_{L,t} = p_{L,t} - p_{L,t_0}$.

The within-bucket term (9) captures the severity growth experienced by claims that remain in their original bucket (pure inflation effect holding category composition fixed). The cross-bucket term (10) captures the compositional shift:

claims migrating from the small to the large bucket change the average severity of both buckets simultaneously. Notably, the cross-bucket term is proportional to the gap $\mathbb{E}[X_t | X_t > \tau] - \mathbb{E}[X_t | X_t \leq \tau]$, which is large by construction in split models – this is precisely why the effect can dominate even for moderate inflation rates.

Note that the decomposition (8) is a two-term approximation of an exact three-term identity. The full shift-share expansion reads

$$\begin{aligned} \Delta\mu_t = & \underbrace{p_{S,t_0}\Delta\bar{X}_S + p_{L,t_0}\Delta\bar{X}_L}_{\text{within}} + \underbrace{\Delta p_L(\bar{X}_{L,t_0} - \bar{X}_{S,t_0})}_{\text{cross}} \\ & + \underbrace{\Delta p_L(\Delta\bar{X}_L - \Delta\bar{X}_S)}_{\text{interaction}}, \end{aligned} \quad (11)$$

where $\Delta\bar{X}_S = \bar{X}_{S,t} - \bar{X}_{S,t_0}$ and analogously for L . The interaction term captures claims that simultaneously migrate across τ and experience differential severity inflation. Our formulation (10) uses end-period conditional means, which absorbs the interaction into the cross-bucket component. This is a deliberate choice that simplifies the decomposition to two terms, but it implies that the cross-bucket share reported in Table III is an upper bound on the pure compositional effect.

D. Inflation-Adjusted Backtest

For a consistent backtest, we propose a *deflation-first* classification. All historical claim amounts are deflated to the base-year monetary level before bucket assignment,

$$\tilde{X}_{i,t} = \frac{X_{i,t}}{\phi_t}, \quad \text{classify } \tilde{X}_{i,t} \text{ against } \tau. \quad (12)$$

Equivalently, one may inflate the threshold to $\tau_t^* = \tau \cdot \phi_t$ and classify the nominal amounts against τ_t^* . Both approaches yield identical bucket assignments and eliminate the migration artefact, ensuring that the bucket composition remains stable across accident years.

IV. LOGNORMAL APPROXIMATION

Assume the base-year severity follows a lognormal distribution, $\ln X_{t_0} \sim \mathcal{N}(\nu, \sigma^2)$. Under inflation (6), $\ln X_t \sim \mathcal{N}(\nu + \ln \phi_t, \sigma^2)$. Define $z_t = (\ln \tau - \nu - \ln \phi_t)/\sigma$. Then

$$p_{S,t} = \Phi(z_t), \quad (13)$$

$$\mathbb{E}[X_t | X_t \leq \tau] = \exp\left(\nu + \ln \phi_t + \frac{\sigma^2}{2}\right) \cdot \frac{\Phi(z_t - \sigma)}{\Phi(z_t)}, \quad (14)$$

$$\mathbb{E}[X_t | X_t > \tau] = \exp\left(\nu + \ln \phi_t + \frac{\sigma^2}{2}\right) \cdot \frac{1 - \Phi(z_t - \sigma)}{1 - \Phi(z_t)}, \quad (15)$$

where $\Phi(\cdot)$ denotes the standard normal CDF.

The migration rate from the small to the large bucket between years t_0 and t is

$$\Delta p_{L,t} = \Phi(z_{t_0}) - \Phi(z_t). \quad (16)$$

For small inflation rates, a first-order Taylor expansion yields

$$\Delta p_{L,t} \approx \frac{\varphi(z_{t_0})}{\sigma} \cdot \ln \phi_t, \quad (17)$$

where $\varphi(\cdot)$ is the standard normal density. This approximation is obtained by expanding $\Phi(z_{t_0} - \delta)$ in $\delta = \ln \phi_t/\sigma$; the second-order correction adds a term $\frac{z_{t_0}}{2\sigma^2}\varphi(z_{t_0})(\ln \phi_t)^2$, whose relative magnitude is $z_{t_0} \ln \phi_t/(2\sigma)$. For the parameters in our dataset ($z_{t_0} \approx 1.2$, $\sigma \approx 1.1$, $\ln \phi_3 \approx 0.18$), this ratio is below 10%, justifying the first-order approximation. The key implication is that the spillover magnitude is governed by two factors: the density of claims near the threshold (captured by $\varphi(z_{t_0})$) and the cumulative log-inflation $\ln \phi_t$. The density factor $\varphi(z_{t_0})/\sigma$ can be interpreted as the “sensitivity” of the bucket composition to inflationary shocks—it is maximised when τ falls near the mode of the severity distribution, which is often the case in MTPL portfolios.

V. EMPIRICAL ILLUSTRATION

A. Data Description

We use an MTPL claims dataset from a Czech insurer covering accident years 2022–2025. The dataset is restricted to the personal vehicles segment (ČKP [11] categories 5–9, standard usage), which constitutes the core of the MTPL book. Claims are filtered by line of business (MTPL property damage and bodily injury, coded as B10y) with positive total incurred estimates. After deduplication at the claim level, the dataset contains approximately 19 400 individual claims. We set the threshold at $\tau = 100\,000$ CZK¹, a level commonly used in practice for separating attritional from large claims in Czech MTPL pricing. Table I presents summary statistics by accident year.

TABLE I
CLAIMS SUMMARY BY ACCIDENT YEAR ($\tau = 100\,000$ CZK)

Year	N	N_S	N_L	$\bar{X}_S$	$\bar{X}_L$	p_L (%)
2022	1 894	1 774	120	30 561	270 231	6.3
2023	4 586	3 898	688	33 358	272 142	15.0
2024	6 473	5 456	1 017	33 020	232 272	15.7
2025	6 492	5 446	1 046	35 174	268 237	16.1

N = total claims, N_S (N_L) = small (large) claims count, $\bar{X}_S$ ($\bar{X}_L$) = average small (large) severity in CZK, $p_L = N_L/N$.

The proportion of large claims (p_L) more than doubled from 6.3 % in 2022 to 16.1 % in 2025. Note that the average large-claim severity $\bar{X}_L$ does not increase monotonically: it drops from 270 231 CZK in 2022 to 232 272 CZK in 2024 before recovering. This non-monotone pattern reflects the compositional heterogeneity within the large-claim bucket – as the spillover pushes claims with severities just above τ into the large category, it dilutes the conditional mean $\bar{X}_L$ downward, illustrating that the migration effect operates on both sides of the threshold simultaneously. Whether this rise reflects a genuine increase in the frequency of large losses or is partly an artefact of threshold migration is the central question of this paper.

¹Czech koruna (CZK); 1 EUR $\approx$ 25 CZK as of 2025, i.e. $\tau \approx 4\,000$ EUR.

B. Inflation Estimation

Estimating claims inflation from the data is itself non-trivial in a growing portfolio. The overall median severity rose from 27 400 CZK in 2022 to 35 500 CZK in 2025, suggesting an annualised inflation of approximately 9 %. However, this figure conflates genuine severity inflation with compositional changes in the claim mix. The median of attritional claims (those below 50 000 CZK) grew more modestly, from 20 900 CZK to 21 900 CZK (approximately 1.6 % per annum), while the 75th percentile of the full severity distribution grew at 14.5 % per annum. This challenge of extracting a reliable signal from heterogeneous, high-dimensional financial data is well-recognised in the broader forecasting literature; for instance, Zukanović et al. [12] demonstrate that the choice of dimensionality reduction technique substantially affects predictive accuracy in financial time series.

In the remainder of this section, we present results for a central inflation estimate of $\hat{\pi} = 6\%$ and explore sensitivity to this assumption in Section VI.

C. Threshold Spillover Quantification

To isolate the spillover effect, we construct a counterfactual by deflating all claims to 2022 CZK using $\hat{\pi} = 6\%$. A claim of nominal amount $X_{i,t}$ is deflated to $\tilde{X}_{i,t} = X_{i,t}/1.06^{t-2022}$ and then classified against $\tau = 100\,000$ CZK. Table II compares the nominal and deflated large-claim counts.

TABLE II
NOMINAL VS. DEFLATED LARGE-CLAIM COUNTS ($\hat{\pi} = 6\%$)

Year	N_L (nominal)	N_L^* (deflated)	Spillover	Spillover (%)
2022	120	120	0	0.0
2023	688	635	53	7.7
2024	1 017	853	164	16.1
2025	1 046	791	255	24.4

N_L^* is the count when all claims are deflated to 2022 CZK before classification.

By 2025, approximately one quarter of the observed large claims would have fallen below the threshold at 2022 price levels. Fig. 2 visualises the decomposition of large-claim counts and the dependence of the spillover share on the assumed inflation rate.

D. Decomposition Results

Applying the decomposition (8) to the 2023–2025 period relative to the 2022 base year, we obtain the results in Table III.

The results are striking: the cross-bucket migration component accounts for 85–100 % of the total observed severity increase. The within-bucket component is comparatively negligible – in 2024 it is even slightly negative, indicating that the average severity *within* each bucket barely changed while the overall average severity rose by nearly 19 000 CZK purely due to the shift in bucket composition.

This finding has a clear intuitive explanation. The gap $\bar{X}_L - \bar{X}_S \approx 200\,000$ CZK is very large relative to the within-bucket severity changes (a few thousand CZK per year). Even

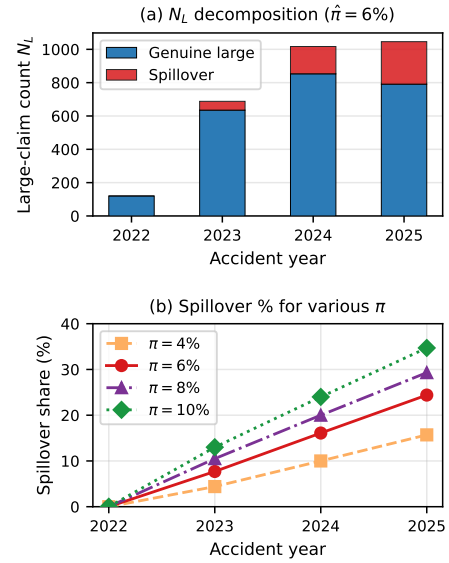


Fig. 2. (a) Stacked decomposition of observed large-claim counts into genuine large claims and threshold spillover ($\hat{\pi} = 6\%$). (b) Spillover as a percentage of total N_L for various inflation assumptions.

TABLE III
SEVERITY CHANGE DECOMPOSITION (CZK PER CLAIM, 2022 BASE)

Year	$\Delta\mu^{\text{within}}$	$\Delta\mu^{\text{cross}}$	$\Delta\mu$ (total)	Cross (%)
2023	2 740	20 694	23 434	88.3
2024	−103	18 681	18 579	>99
2025	4 194	22 785	26 979	84.5

a modest increase in p_L of 10 percentage points therefore produces a cross-bucket effect of $0.10 \times 200\,000 = 20\,000$ CZK, which dwarfs the within-bucket inflation. This observation generalises: in any split model where the threshold creates a large gap in conditional expectations, the migration effect will dominate under even moderate inflation. It should be noted, however, that the dominance of the cross-bucket component is partly a structural consequence of the model design. The gap $\bar{X}_L - \bar{X}_S$ is determined by the choice of τ , which separates the lognormally distributed severities into segments with vastly different conditional means. The decomposition result is therefore not independent of the threshold specification: a lower τ amplifies the gap and thus the cross-bucket share, while a threshold set closer to the tail would reduce it. The sensitivity analysis in Section VI partially addresses this dependency.

VI. SENSITIVITY ANALYSIS

The spillover effect depends on two parameters that the modeller controls or estimates: the threshold τ and the assumed inflation rate π . To assess robustness, we compute the spillover share for 2025 (relative to 2022) across a grid of (π, τ) combinations. Fig. 3 presents the results.

Several patterns emerge from the heatmap. First, the spillover share increases monotonically in π , as expected –

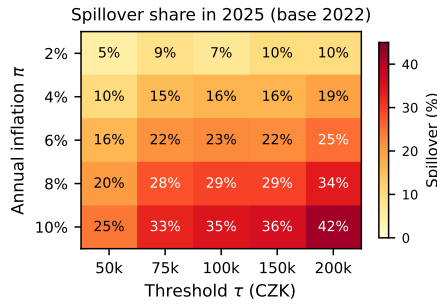


Fig. 3. Spillover share in 2025 (base 2022) across various inflation rates and threshold levels. Cells show the percentage of observed N_L attributable to threshold migration.

higher inflation pushes more claims across any given threshold. At $\pi = 10\%$ and $\tau = 100\,000$ CZK, over one third of observed large claims are spillover artefacts. Second, the effect also increases with τ : higher thresholds sit in thinner tails of the distribution, but the compound inflation over a three-year horizon produces substantial migration even there. At $\tau = 200\,000$ CZK with $\pi = 8\%$, the spillover exceeds 30%. Third, even at conservative inflation estimates ($\pi = 2\%$), the spillover is non-negligible at 5–10% over a three-year horizon, suggesting that the deflation adjustment is warranted in virtually all practical configurations.

The sensitivity to π highlights the importance of accurate inflation estimation. As discussed in Section V, the choice of inflation estimator introduces substantial uncertainty: estimates ranging from 1.6% (attritional median) to 14.5% (75th percentile) can be extracted from the same dataset. We therefore recommend that backtesting exercises report results for a range of inflation scenarios rather than relying on a single point estimate.

VII. DISCUSSION

A. Practical Implications for Backtesting

Our analysis reveals that backtesting a split frequency–severity model with a fixed nominal threshold conflates two distinct phenomena: genuine claims inflation within each bucket and artefactual migration across the threshold. This conflation distorts the backtest in several ways.

First, large-claim frequency appears to trend upward more steeply than the true underlying process would suggest, potentially leading to overpricing of the large-claim layer. In our data, the naive p_L rises from 6.3% to 16.1% over three years; after deflation adjustment, the growth is substantially more moderate.

Second, the average small-claim severity is biased downward because the migrating claims – which are by definition the most expensive small claims – exit the small bucket. This can mask genuine inflationary pressure in the attritional layer.

Third, IBNR development factors estimated separately for each bucket inherit these biases, as the claim-size composition within each bucket shifts over the development period. A claim

that is “small” at early development stages may become “large” as reserves are revised upward, creating inconsistencies between the development triangles of the two buckets [8], [9].

B. Recommended Approach

We recommend a four-step deflation procedure for backtesting split models:

- 1) Estimate the annual claims inflation rate $\hat{\pi}$ from the data, preferably from the median severity trend of attritional closed claims to minimise the impact of compositional changes.
- 2) Deflate all historical claim amounts to a common base year using $\tilde{X}_{i,t} = X_{i,t}/\hat{\phi}_t$.
- 3) Classify deflated claims against the threshold τ .
- 4) Re-inflate the bucket-level aggregates for reporting purposes.

This procedure ensures that the bucket composition remains stable across accident years, isolating genuine trends in frequency and severity from threshold artefacts. When separate IBNR development patterns are applied to small and large claims, the deflation-first approach prevents the patterns from being contaminated by the changing mix of claims near the threshold during the development period.

C. Limitations and Extensions

The main limitation of our approach is the assumption of a uniform multiplicative inflation factor across the entire severity distribution. In practice, the Czech MTPL market exhibits markedly different inflation dynamics across claim types: material damage claims are driven by repair costs and spare parts prices, while bodily injury claims are subject to medical cost inflation, evolving judicial precedent on pain-and-suffering awards, and legislative changes to compensation limits. These components may inflate at substantially different rates. Consequently, the single parameter π used in our deflation procedure represents an aggregate approximation that may distort the decomposition in Table III – particularly the within-bucket component, which absorbs any residual misspecification of the inflation model. A natural extension would be to allow bucket-specific or peril-specific inflation rates, which complicates the decomposition but may be necessary for portfolios with heterogeneous inflation dynamics.

Furthermore, the decomposition in Table III is presented as point estimates without uncertainty quantification. Given the stochastic nature of the claims process, bootstrap confidence intervals around $\Delta\mu^{\text{within}}$ and $\Delta\mu^{\text{cross}}$ would strengthen the inferential validity of the results. In particular, the near-zero within-bucket component observed in 2024 (−103 CZK) may not be statistically distinguishable from a moderately positive value. We leave the construction of such intervals, along with a sensitivity analysis of the decomposition to the inflation estimator $\hat{\pi}$, to future work.

Additionally, our empirical illustration is based on a single Czech insurer’s portfolio that experienced rapid growth during 2022–2025. This growth compounds the inflation effect with changes in portfolio composition. While the methodology

is general, the quantitative results are portfolio-specific and should be re-estimated for each application.

Finally, we assumed a fixed threshold throughout. An adaptive threshold strategy – where τ is explicitly indexed to an inflation measure – would eliminate the spillover by construction, but requires agreement on the appropriate index and introduces additional complexity into the pricing and reserving framework.

VIII. CONCLUSION

We have formalised the threshold spillover effect in split frequency–severity MTPL models and proposed an additive decomposition into within-bucket inflation and cross-bucket migration components. Under a lognormal severity assumption, both components admit closed-form expressions that are straightforward to implement. Our empirical analysis on Czech MTPL data with $\tau = 100\,000$ CZK confirms that the spillover effect is quantitatively dominant: the cross-bucket migration accounts for 85–100 % of the observed severity increase, and up to one quarter of large-claim counts are attributable to threshold migration at moderate inflation rates. A sensitivity analysis demonstrates that the effect is robust across a wide range of threshold levels and inflation assumptions.

We recommend a deflation-first classification approach for backtesting, which eliminates the migration artefact and produces cleaner frequency and severity trends for pricing and reserving. Future work will extend the framework to non-uniform inflation across the severity distribution and investigate the interaction between threshold migration and IBNR development patterns in more detail.

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