

Extremal Application of Underwriting Instruments in South African Medical Schemes, 2015–2024: A Peaks-Over-Threshold Analysis with Policy Implications

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ABSTRACT

Medical schemes in South Africa may apply three statutory underwriting instruments—general waiting periods, pre-existing-condition exclusions, and late-joiner penalties—to protect risk pools against anti-selection. However, their application varies, and extreme cases affecting large numbers of beneficiaries have not been formally modelled. This study applies extreme value theory (EVT) to underwriting cases across benefit options in South African medical schemes from 2015 to 2024, using national regulatory data, and interprets the findings in the context of policy debates on anti-selection and risk equalisation. The distribution of cases per option-year exhibited a heavy tail. A generalised Pareto distribution fitted to high-threshold exceedances yielded a positive shape parameter ($\xi \approx 0.18$ using maximum likelihood and ≈ 0.85 using the Hill estimator), placing the data in the Fréchet domain, with a tail index of approximately 1.2–3. Concentration was substantial: the most affected 10% of benefit options accounted for approximately three-quarters of all cases, while estimated return levels reached tens of thousands of cases for rare option-years. Trends varied by instrument: pre-existing-condition exclusions declined, general waiting periods peaked in 2024, and late-joiner penalties remained relatively stable but were concentrated in open schemes and older age groups. Extreme case counts were consistently higher in open schemes. These findings support policy discussions on risk equalisation and reducing reliance on underwriting. EVT offers regulators a systematic approach to identifying extreme underwriting case loads, although the results must be interpreted cautiously because counts depend on benefit-option size and do not measure application rates.

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1. INTRODUCTION

Voluntary health insurance markets that combine open enrolment with community rating are vulnerable to anti-selection, whereby higher-risk individuals are more likely to seek coverage, potentially eroding the risk pool if left unchecked [1,2,3]. South Africa's medical-scheme framework

addresses this tension by permitting three statutory underwriting instruments: general waiting periods, pre-existing-condition exclusions, and late-joiner penalties. These instruments provide limited protection against anti-selection [4,5,6]. However, their use is constrained because each also raises concerns about access and equity [3,7,8].

The extent to which these instruments are applied varies considerably across schemes and benefit options. The most extreme cases—those in which waiting periods, exclusions, or penalties affect very large numbers of beneficiaries—are of particular regulatory interest [6,8,9]. However, the distribution of underwriting applications, particularly its tail, has not been characterised statistically, leaving the most consequential observations insufficiently described [3,6,7].

Extreme value theory (EVT) provides a framework for analysing such tails by modelling exceedances over high thresholds and the heavy-tailed concentration often observed in insurance data [10,11,12]. Applying EVT to underwriting applications makes it possible to quantify concentration, estimate return levels for rare extremes, and identify the most affected options using a principled statistical approach [12,13,14].

This paper has three aims: to model the extremal distribution of underwriting cases across benefit options; to describe how these extremes have evolved over time and differ by scheme sector; and to connect the statistical findings to the regulatory recommendations on anti-selection and risk equalisation that have long shaped the South African debate [8,9,11]. Throughout, the analysis is explicit that case counts are size-dependent and that aggregate data cannot speak to the appropriateness of any individual instrument [6,14,15].

2. BACKGROUND

2.1 Underwriting Instruments under the Medical Schemes Act

The Medical Schemes Act of 1998 re-established open enrolment, community rating and prescribed minimum benefits, and in the same movement granted schemes limited protection against anti-selection through underwriting instruments [4,5,6]. General waiting periods may delay benefits for new members for a defined period; pre-existing-condition exclusions may withhold benefits for specified prior conditions; and late-joiner penalties impose contribution loadings on those who join later in life without sustained prior cover [4,5,6]. Each is permitted precisely because community rating and open enrolment would otherwise leave schemes defenceless against selective entry [3,4,7].

2.2 Anti-selection Theory and Risk Equalisation

The economic rationale is well established. Asymmetric information between insurers and applicants can lead to adverse selection, which classic analyses show can distort or destabilise insurance markets [1,2,16]. In health insurance, adverse selection threatens the viability of community-rated risk pools and creates a need for corrective mechanisms [3,17,18]. Risk-equalisation transfers are widely recognised as a corrective mechanism because they neutralise risk differences between funds, reducing the need for underwriting and the incentive to select healthier members [7,17,18]. South Africa developed policy reforms of this kind, but they have not been implemented. As a result, underwriting instruments remain an operative line of defence, and their application continues to be a policy concern [5,8,9].

2.3 Extreme Value Theory for Tail Concentration

The classical theory characterises the limiting behaviour of extremes: the Fisher–Tippett–Gnedenko theorem yields the generalised extreme value family for maxima, while the Pickands–Balkema–de Haan theorem yields the generalised Pareto distribution (GPD) for exceedances over a high threshold

[13,19,20,21]. For insurance and other concentrated data the peaks-over-threshold approach is standard, and a positive shape parameter signals a heavy, Pareto-type tail in which a few extreme units dominate the whole [10,11,14]. It is exactly this heavy-tailed concentration that the present application seeks to quantify [12,22,23].

3. DATA AND METHODS

3.1 Data

The data were obtained from the national underwriting extract compiled by the Council for Medical Schemes. For each scheme, benefit option, age band, gender, and year from 2015 to 2024, the extract records the number of beneficiaries subject to each of the three instruments [5,6,8]. It covers 83 schemes and 391 benefit options across the open and restricted sectors, the two main divisions of the medical-scheme market [6,7,9].

3.2 Variables and Unit of Analysis

The primary variable is the number of beneficiaries subject to any of the three underwriting instruments, aggregated by benefit-option year. This is the unit of analysis used to examine concentration across options [10,11,12]. Schemes are classified as open or restricted, and instrument-specific and demographic breakdowns are also [3,5,7]. Because case counts increase with option size, they measure the absolute scale of underwriting rather than its application rate, as discussed below [6,12,14].

3.3 Extreme Value Methods

A GPD was fitted to exceedances above a high threshold, selected from mean-residual-life and shape-stability diagnostics; for an exceedance $y = x - u$ the model is [13,24,25]:

$$H(y) = 1 - (1 + \xi y/\tilde{\sigma})^{-1/\xi}$$

with shape ξ governing tail heaviness. The shape was corroborated semi-parametrically by the Hill estimator over the upper order statistics [26,27,28]:

$$\hat{\xi}_{Hill} = (1/k) \Sigma [\ln X_{n-i+1} - \ln X_{n-k}], \quad \alpha = 1/\xi$$

with tail index $\alpha = 1/\xi$. High quantiles were summarised by return levels [11,29,30]:

$$x_N = u + (\tilde{\sigma}/\xi) [(N \zeta_u)^\xi - 1]$$

where the return level represents the case load expected to be exceeded, on average, once every N option-years. Concentration was measured as the share of all cases accounted for by the most affected options. Standard diagnostic procedures were used to support the threshold selection [15,31,32].

3.4 Limitations of the Data

Two limitations are intrinsic. First, the extract counts beneficiaries subject to each instrument but contains no denominator of all beneficiaries, so the analysis describes absolute case loads, which are size-dependent, rather than application rates [6,12,14]. Second, the data are aggregate and cannot reveal whether any instrument was applied appropriately in an individual case, so the findings describe the structure and scale of underwriting, not its justification [5,8,15].

4. RESULTS

4.1 Aggregate Trends by Instrument

The three instruments followed distinct trends over the decade (Table 1 and Figure 1). General waiting periods were consistently the most frequently applied instrument, affecting approximately 174,000 to 262,000 beneficiaries per year and reaching a clear peak in 2024 [5,6,8]. In contrast, pre-existing-condition exclusions declined from approximately 130,000 cases in 2015 to around 82,000

in 2024, while late-joiner penalties remained comparatively stable at about 40,000 cases per year [3,6,7].

Table 1. Beneficiaries subject to each underwriting instrument by year, 2015–2024.

Year	Waiting periods	Pre-existing	Late joiner	Total
2015	208,414	129,787	44,844	383,045
2016	173,558	106,903	41,733	322,194
2017	215,294	103,567	36,595	355,456
2018	188,682	78,197	38,006	304,885
2019	206,906	79,162	44,193	330,261
2020	181,490	70,592	40,695	292,777
2021	186,937	73,926	43,826	304,689
2022	195,862	70,537	40,451	306,850
2023	211,561	75,296	39,996	326,853
2024	261,872	82,220	47,278	391,370

Source: author's analysis of Council for Medical Schemes underwriting data.

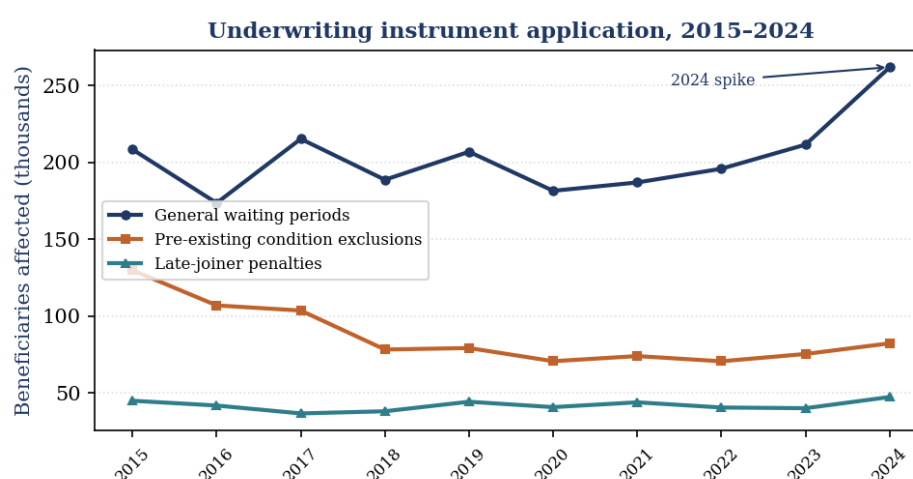


Figure 1. Application of the three underwriting instruments, 2015–2024. Source: author's analysis.

4.2 Sectoral Composition

The instruments differed sharply in their sectoral footprint (Table 2). Late-joiner penalties were overwhelmingly an open-scheme phenomenon roughly nine in ten cases arose in open schemes consistent with their purpose of deterring strategic late entry in the voluntary open market, which restricted, employment-based schemes largely avoid [3,7,9]. Pre-existing-condition exclusions were also open-skewed, whereas general waiting periods were applied in broadly comparable volumes across the two sectors [5,6,7].

Table 2. Total beneficiaries subject to each instrument by scheme sector, 2015–2024 pooled

Instrument	Open schemes	Restricted schemes
General waiting periods	1,002,367	1,028,209
Pre-existing-condition exclusions	557,447	312,740
Late-joiner penalties	374,105	43,512

Source: author's analysis.

4.3 Heavy-tailed Concentration of Underwriting Cases

The distribution of underwriting cases across option-years was extremely right-skewed, with a median of about 158 cases but a maximum exceeding 56,000 and a skewness above seven (Table 3). Fitted to exceedances above the ninetieth percentile, the GPD returned a positive shape of $\xi \approx 0.18$, while the Hill estimator gave a heavier $\xi \approx 0.85$; both place the data unambiguously in the Fréchet domain of heavy tails, with a tail index of roughly 1.2 to 3 (Figure 2; [13,26,28]). The divergence between the two estimates is a familiar small-sample feature of heavy-tailed inference and does not alter the qualitative conclusion that the tail is heavy [10,27,32]. The practical signature of this tail is concentration: the most affected tenth of options accounted for about three-quarters of all underwriting cases in 2024, a Pareto-like pattern in which a few options dominate the whole [10,14,30].

Table 3. Distribution summary and generalised-Pareto fit for underwriting cases per option-year

Quantity	Value	Note
Option-years (n)	3,020	2015–2024
Median cases	158	central location
95th / 99th percentile	5,857 / 13,016	
Maximum	56,171	
Skewness	7.3	heavy right tail
GPD shape ξ	0.18	Fréchet domain
Hill shape ξ	0.85	tail index $\alpha \approx 1.2$
Top-10% concentration	75.1%	share of all cases

Source: author's analysis.

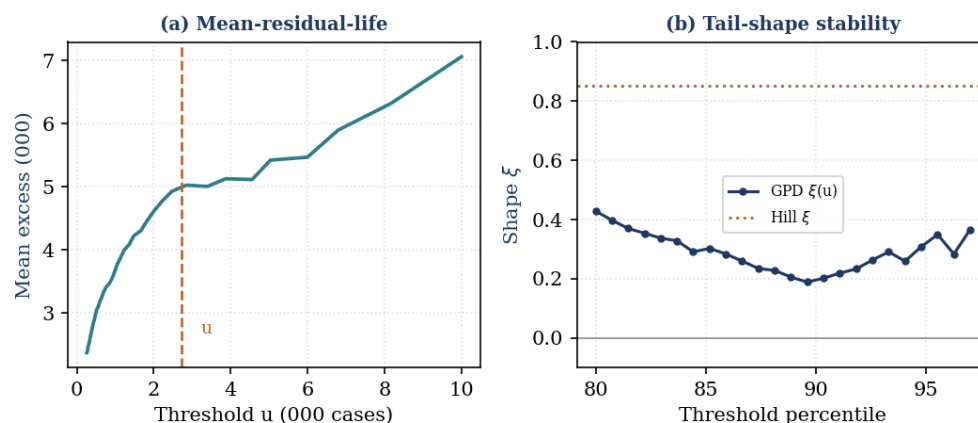


Figure 2. Extreme value diagnostics: (a) mean-residual-life plot and (b) tail-shape stability with the Hill estimate. The positive, stable shape indicates a heavy tail. Source: author's analysis.

4.4 Return Levels

Consistent with the heavy tail, the return-level curve rose steeply rather than saturating (Figure 3, Table 4). The case load exceeded once per hundred option-years was about 14,500, rising to roughly 26,000 per five hundred, 32,000 per thousand and 50,000 per five thousand evidence that extreme underwriting footprints grow rapidly in the rarest options rather than approaching any ceiling [11,12,30]. This escalating behaviour is the hallmark of a Fréchet-domain variable and contrasts with bounded indicators whose return levels flatten [10,11,14].

Table 4. Generalised-Pareto return levels for underwriting cases per option-year

Return period (1 in N option-years)	Return level (cases)
100	14,513
500	26,217
1,000	32,407
5,000	50,158

Source: author's analysis.

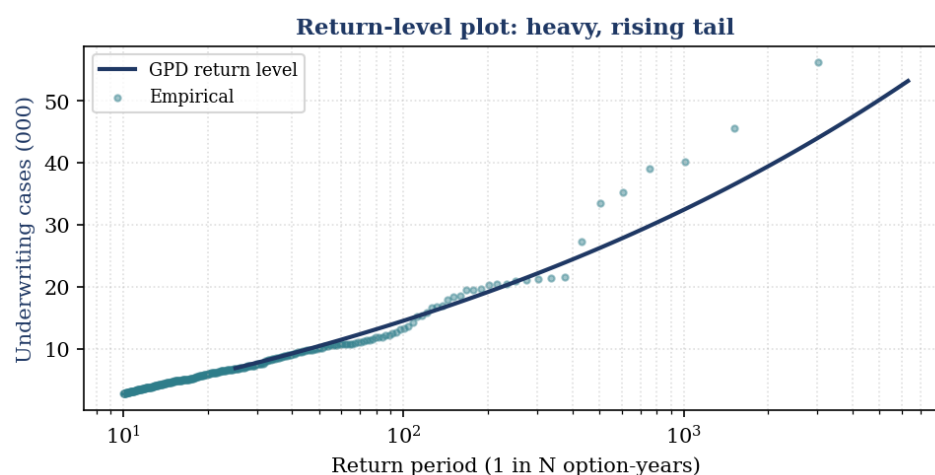


Figure 3. Return-level plot for underwriting cases, with empirical exceedances overlaid. Source: author's analysis.

4.5 Extremal Application over Time, by Sector

Tracking the extreme of the per-option distribution over time shows how the heaviest underwriting footprints evolved and differed by sector (Figure 4). The ninety-fifth percentile of option case loads was persistently higher in the open sector than the restricted sector throughout the decade, and rose toward the end of the period, mirroring the aggregate increase in general waiting periods [6,7,8]. The widening of the open-sector extreme is consistent with the greater exposure of open schemes to anti-selection and their correspondingly heavier reliance on underwriting [3,9,14].

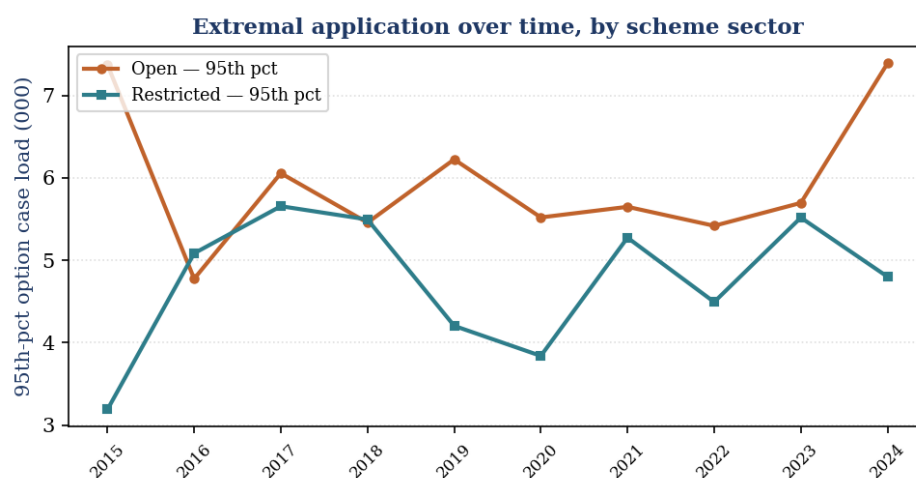


Figure 4. Extremal (95th-percentile) option-level underwriting case load by scheme sector, 2015–2024. Source: author's analysis.

4.6 Demographic Concentration of Late-joiner Penalties

Late-joiner penalties were concentrated not only in the open sector but also in older age bands, peaking among beneficiaries in their late forties and fifties and tapering thereafter (Figure 5). This profile follows directly from the instrument's design, which loads contributions for those joining later in life without sustained prior cover, and confirms that the penalty falls largely on older entrants [3,4,5]. The demographic concentration is itself a form of extremal structure, locating the instrument's impact in a specific and policy-relevant segment of the membership [6,7,9].

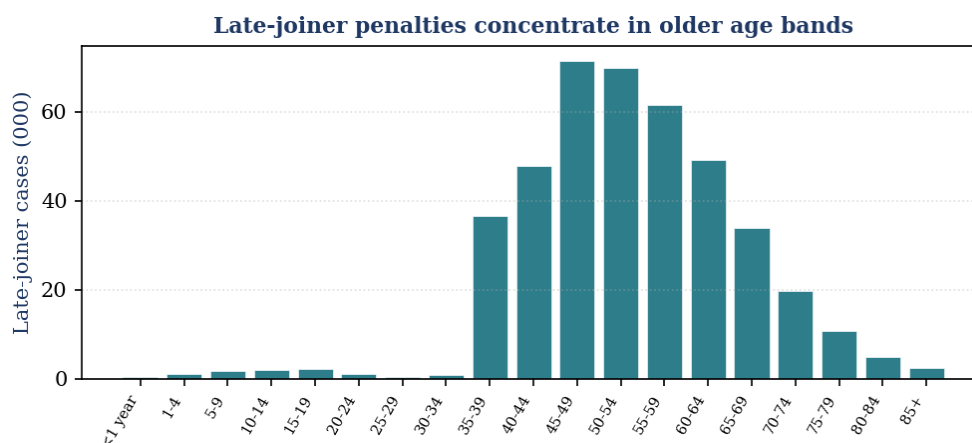


Figure 5. Late-joiner-penalty cases by age band, 2015–2024 pooled. Source: author's analysis.

5. DISCUSSION

5.1 The Meaning of Heavy-tailed Concentration

The main statistical finding is that underwriting applications have a heavy-tailed distribution and are highly concentrated: a small proportion of benefit options account for most cases, while the most extreme options have exceptionally high case counts [10,14,32]. For regulators, this concentration suggests that oversight and reform efforts could be focused on a small number of options with particularly high case counts, rather than being spread uniformly across the market [6,8,12]. EVT provides a statistical basis for identifying these options rather than relying on arbitrary thresholds [11,13,15].

5.2 Underwriting, Anti-selection and the Access Trade-off

Underwriting instruments sit at the heart of an unavoidable tension. Without them, community-rated open schemes are vulnerable to anti-selection that can destabilise the pool; with them, access is delayed or made costlier for exactly those who most need cover [1,2,3]. The concentration of late-joiner penalties among older entrants and in open schemes makes this trade-off concrete, since these are the members for whom the access cost of underwriting is most acute [3,33,34]. The instruments are therefore best understood not as ends in themselves but as second-best devices standing in for an absent risk-equalisation mechanism [7,9,17].

5.3 Policy and Regulatory Recommendations

The findings are relevant to existing regulatory recommendations concerning private health financing. The Health Market Inquiry and previous actuarial research have argued that implementing policy reforms alongside mandatory membership could reduce the structural drivers of anti-selection and, in turn, reliance on underwriting instruments [7,8,9]. The heavy-tailed concentration and increasing extremes in the open-scheme sector observed in this study are consistent with that argument. Underwriting appears to play a substantial role where anti-selection pressures are greatest, a gap that risk-equalisation transfers are intended to address [7,8,17]. In the interim, the concentration findings support closer regulatory monitoring of options with the highest application counts. The demographic findings also suggest that reforms should consider the access burden faced

by older late joiners [6,35,36]. EVT therefore complements the policy literature by quantifying where and to what extent these instruments are applied [5,8,11].

5.4 Limitations

The principal limitation is that case counts are size-dependent and lack a population denominator, so the extremes partly reflect option size rather than application intensity; an intensity analysis would require total-beneficiary data not present in the extract [6,12,14]. The data are also aggregate and cannot establish whether any instrument was applied appropriately, and the tail-index estimates carry the wide uncertainty usual in heavy-tailed inference, so the return levels are indicative magnitudes rather than precise forecasts [15,27,32]. These caveats temper the quantitative detail but not the qualitative findings of heavy concentration and divergent instrument trends [8,10,11].

6. CONCLUSION

The application of underwriting instruments in South African medical schemes has a heavy-tailed distribution and is highly concentrated. A positive extreme-value shape parameter places the data in the Fréchet domain, while the most affected 10% of benefit options account for approximately three-quarters of all cases. Return-level estimates for the rarest option-years reach tens of thousands of beneficiaries. The three instruments show different trends: pre-existing-condition exclusions declined, general waiting periods rose to a peak in 2024, and late-joiner penalties remained relatively stable but were concentrated in open schemes and older age groups. Extreme case counts were consistently higher in the open-scheme sector. These findings reinforce longstanding arguments for activating risk equalisation and reducing structural reliance on underwriting. They also illustrate how EVT can help regulators identify options with the highest application counts, subject to the limitations of size-dependent count data.

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