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RETHINKING FAIR PRICING:

Balancing Actuarial Risk and Social Equity -

by Shereen Francis



INTRODUCTION

South Africa's financial industry is sophisticated and highly regulated, yet it operates against the backdrop of deep, persistent socio-economic inequality. Many in the insurance sector already know the principle that premiums should reflect risk - the core idea of actuarial fairness. But in a society where wealth and risk factors are unevenly distributed, often along historical racial and economic lines, this principle alone does not answer the bigger question: is pricing truly fair in practice? When risk factors mirror structural inequality, technical risk-based pricing can unintentionally entrench exclusion. Vulnerable households may find themselves priced out of cover altogether, left exposed to shocks they are least able to absorb. So, while this tension is well known to

industry professionals, it is worth asking what fair pricing really means - and why it matters now more than ever.

At its heart, fair pricing asks insurers and actuaries to look beyond statistical risk and consider whether premiums genuinely uphold fairness, transparency, and social justice. In South Africa, where insurance access can determine who recovers from loss and who falls deeper into poverty, this is not abstract - it is a question of trust and the long-term sustainability of the market.

Ultimately, this article aims to show why pricing is never just a technical exercise but part of a wider conversation about how insurance can genuinely include, protect, and support people in South Africa.'s

DEFINITIONS AND FRAMEWORKS OF ETHICAL PRICING

Balancing Actuarial Fairness and Social Fairness

Ethical pricing can be seen as the ongoing pursuit of fairness in how insurance premiums are determined and allocated. Traditionally, actuarial fairness - sometimes called actuarial equity - means that each customer should pay a premium proportionate to their individual risk. In practice, this means that individuals or groups with similar risk profiles are charged similar rates that reflect the expected cost of their claims. From an insurer's perspective, risk-based pricing is economically necessary: voluntary insurance markets rely on risk differentiation to stratify the risk pool into more homogeneous groups, helping to limit cross-subsidisation and prevent adverse selection. In this sense, underwriting - the process of classifying and rating risk - is justified as the mechanism that keeps the insurance pool financially viable and sustainable.

A central ethical dilemma in insurance is the trade-off between risk-based pricing and wider ideas of fairness or equity. In practice, risk-based pricing uses factors like age, driving record, location, health status, and credit history to estimate risk and set premiums. This keeps risk pools more predictable and discourages adverse selection. Insurers argue that these factors do not unfairly discriminate but ensure that policyholders with similar risks pay similar premiums.

However, fairness in a broader sense raises important questions about the social consequences of large premium disparities. When taken to extremes, purely risk-based pricing can produce outcomes that appear plainly unjust - for example, when healthier, wealthier policyholders receive generous cover for premiums that buy only minimal protection for those who are older, sicker, or poorer. Even when these differentials are supported by credible risk data, they clash with a wider social principle - seen in taxation and social security - that the better-off help protect the more vulnerable. Here, actuarial fairness (charging according to risk) can conflict with social fairness (ensuring

adequate protection for those least able to absorb shocks).

Insurance as Social Function

However, an ethical pricing lens brings in broader ideas of fairness that extend beyond purely reflecting risk costs. Insurance is not merely a private commodity; it also serves a vital social function by providing financial security and peace of mind. Some scholars describe private insurance as a non-primary social good that people should have reasonable access to, rather than access being determined solely by individual risk or ability to pay. This perspective is rooted in the principles of solidarity and mutuality: while risk pooling allows individuals to share risks they cannot bear alone, it also implies a moral commitment to mutual aid - we insure not only for ourselves, but with the understanding that we all contribute to protecting each other from misfortune.

Solidarity vs Fair Lottery Principle

This balance is delicate. Solidarity ensures that everyone shares in the collective safety net, but actuarial fairness requires that prices still reflect differences in risk exposure; otherwise, the system risks becoming financially unsustainable. Social insurance schemes lean further into solidarity by using community rating or mandatory participation to spread costs broadly. By contrast, South Africa's private insurance relies on risk differentiation, justified by actuarial equity and economic efficiency.

Scanlon's Contractualism:

Marais' framework sets out three interlinked principles: the Insurance Solidarity Principle, which captures the core reason private insurance exists at all: people come together to pool risks they cannot bear alone, creating a collective commitment to share losses they could not manage individually. This justifies the pooling of risks without discrimination in social insurance schemes, ensuring that the burden of misfortune is spread fairly across the community. The Fair Lottery Principle then illustrates the industrial logic for fair risk differentiation in private insurance. Just as in

a fair lottery, where every ticket must cost the same for the same chance of winning, so too in life insurance should each insured contribute a premium proportionate to their expected risk. If insured A's risk of death is statistically twice that of insured B, then A effectively holds the equivalent of two lottery tickets versus B's one and should therefore pay double to maintain actuarial equity. Otherwise, low-risk individuals would unfairly subsidise higher-risk participants, creating adverse selection that threatens the sustainability of the pool.

However, this analogy also highlights the practical challenge: unlike a perfect lottery where tickets can be counted exactly, an insurer cannot quantify each individual's risk with absolute precision. Actuarial risk assessment is not an exact science - it relies on grouping individuals into reasonably homogeneous risk pools using significant underwriting factors supported by credible statistical evidence. The challenge, then, is to ensure that this necessary risk classification remains fair in principle and practice.

This is where Marais' Fair Discrimination Principle completes the framework: it defines the contractualist standard for acceptable premium discrimination, requiring that no reasonable person should be able to reject the use of any underwriting factor that genuinely contributes to actuarial equity. According to this principle, discrimination between insurance applicants is ethically defensible only if three conditions are met: the statistical evidence must be strong and reliable; the allocation of each applicant to a particular risk group must be unambiguous; and the effect of the factor on the insured risk - for example, mortality - must have a reasonable causal explanation. The formulation "in terms of its contribution to actuarial equity" builds directly on the Fair Lottery Principle's logic: ignoring significant risk factors would unfairly subsidise higher-risk participants and encourage adverse selection.

If any underwriting factor fails these conditions - if its statistical basis is weak, its application ambiguous, or its causal link unconvincing - then its contribution to fairness is doubtful and should be rejected. Together, these principles

ensure that fair discrimination in underwriting is grounded in robust evidence, clear grouping, and genuine causation - maintaining the balance between solidarity and actuarial fairness, protecting the insurance pool's sustainability, and avoiding unjust harm to vulnerable groups.

EQUITY AND ACCESS IN THE SOUTH AFRICAN CONTEXT

The Legacy of Inequality and Risk-Based Pricing

Any discussion of ethical insurance pricing in South Africa must grapple with the country's profound socio-economic disparities and enduring legacy of inequality. South Africa remains one of the most unequal societies in the world, with a history in which access to financial services, including insurance, was shaped by race and class. This means that neutral risk-based pricing can produce unequal impacts across communities. Many common risk factors are still correlated with historical disadvantage. For example, property and motor insurers may charge higher premiums in areas with higher crime or accident rates and lower premiums in safer, well-resourced areas. Yet many of the highest-risk areas remain predominantly Black townships. So, geography-based pricing, though rooted in valid loss statistics, can result in Black South Africans paying more for cover than white South Africans in wealthier suburbs - raising fairness concerns even when race is not explicitly used.

Proxy Discrimination and Unintended Exclusion

Equity and access also raise a deeper question: does everyone who needs insurance have a fair chance to obtain it at a reasonable cost? For many low-income households in South Africa, the answer is still no. While the country's insurance penetration is high for an emerging market - thanks largely to the middle and upper classes - most low-income adults remain uninsured or underinsured. Many rely only on funeral insurance (which has cultural priority), while

uptake of other cover such as life, disability, or property insurance remains low. The reasons are complex: affordability, lack of trust, and poor product fit all play a role. Pricing factors like income, education, or occupation can also mean that people with lower or unstable incomes face relatively higher premiums or stricter terms.

The historical context still matters. Under apartheid, access to jobs, education, and assets was systematically restricted for Black South Africans. Decades later, these inequalities persist in socio-economic data: average income and education levels remain lower for the Black population than for the white population. When insurers use factors like education, occupation, or credit scores to price cover, they risk indirectly penalising groups that suffered past exclusion. This is why proxy discrimination is a critical ethical concern: even if insurers do not use race explicitly, some proxies can still produce outcomes that systematically disadvantage historically marginalised groups.

Policy Moves to Expand Access

To promote equity and access, South Africa has made policy moves in recent years. A major milestone was the introduction of a dedicated microinsurance framework under the Insurance Act of 2017 and accompanying Prudential Standards. This created a new category of microinsurers with lower capital requirements and simple, standardised products designed to make insurance more affordable for the mass market. Under these standards, insurers can offer low-sum assured policies - funeral, life, or small asset cover - with simplified terms, capped premiums, and minimal exclusions. The clear goal is to "enhance financial inclusion and expand insurance penetration for a large, uninsured population." In this context, fair pricing can mean accepting thinner profit margins or less detailed risk segmentation to include groups that have long been left outside the formal insurance net.

The Protection Gap and Structural Risk

The tensions around fair insurance pricing are clearly visible in South Africa's daily realities. In motor insurance, only around 35% of vehicles on the road are insured, leaving nearly two-thirds of drivers - often lower-income - uninsured and unable to absorb the financial shock of an accident. Premium structures that factor in vehicle value, driver profile, claims history, and residential area often make comprehensive cover unaffordable for people living in high-crime or high-accident zones - areas that remain predominantly Black townships shaped by apartheid-era settlement patterns.

Property insurance shows the same place-based dynamic. While middle- and upper-income households routinely insure their homes and valuables, many low-income households - especially in informal settlements or rural areas - lack any cover. Premiums in higher-risk neighbourhoods are naturally higher, and some insurers have historically avoided underwriting in informal areas altogether due to risk control challenges. The result: families living where risks are greatest often have the least protection, leaving them unable to rebuild after fires, floods, or theft - trapped in cycles of loss.

Funeral insurance illustrates this affordability-necessity tension most starkly. Funerals hold deep cultural significance in South Africa and can cost tens of thousands of rands - far beyond what many households can save. Funeral policies are nearly universal among low-income households because they fill a crucial cultural and financial gap, yet even microinsurance funeral plans with premiums as low as R35 per month can strain households living on social grants or informal incomes. Many families juggle multiple policies across family members or community burial schemes, stretching tight budgets further. Despite reforms under the Insurance Act to lower costs, the poorest households often still rely on loans or burial societies to meet funeral costs. This raises a fundamental question: if a dignified funeral is a social and cultural necessity, should the market alone decide who can afford it?

Beyond funeral cover, modern insurance increasingly uses personal data - such as residential area, income level, or credit history - to segment risk. While statistically predictive, these factors often act as proxies for protected characteristics like race or class. Geography and wealth remain deeply intertwined with race in South Africa because of the legacy of segregation and unequal opportunity. Area-based pricing - adjusting premiums for local crime rates, accident frequency, or poor infrastructure - can replicate racial and socio-economic disparities even when race is not explicitly used. International parallels show the same concern: in the US, ZIP code-based pricing has been scrutinised for perpetuating redlining - the historical denial of financial services to certain communities based on racial demographics.

Credit-based insurance scoring poses a similar challenge. Many South African short-term insurers factor in credit history when underwriting, echoing trends elsewhere. Insurers argue that a credit score predicts payment reliability, but credit scores themselves reflect structural barriers to financial stability. Poorer communities may face higher premiums or stricter terms not because they pose a higher claims risk, but because of entrenched socio-economic disadvantage. International research backs this up: a US Federal Trade Commission study found insurance credit scores correlate strongly with race, with minority communities tending to have lower scores. In response, some jurisdictions have pushed back - for example, Washington State's insurance commissioner proposed banning credit score use in insurance pricing, arguing that it "institutionalises racism and hurts low-income consumers." While South Africa has yet to see such bans tested in court, the ethical question remains: is it fair to charge someone more because of a score that reflects systemic barriers, not personal risk?

Even seemingly neutral factors like income or occupation can raise similar questions. Premiums for professional liability, motor insurance, or household cover often depend on one's job and income level. High-income professionals' benefit from lower rates

because they own safer cars or live in secure estates, while low-income workers often pay proportionally more for lower-value assets - a pattern that can mirror race and class divides. South Africa's Promotion of Equality and Prevention of Unfair Discrimination Act (PEPUDA) explicitly prohibits unfair discrimination in the provision of insurance, but area-based or credit-based pricing can still produce outcomes that disproportionately harm historically disadvantaged groups.

A critical but often overlooked dimension of fairness in insurance pricing is not only who can afford coverage, but who is meaningfully protected when shocks occur. Research from both developed and developing countries shows that social inequality directly shapes an individual's and household's ability to withstand health, climate, and economic shocks - and that unequal access to insurance worsens this vulnerability. Inequality is not just a moral concern; it is a systemic economic risk. High levels of inequality undermine long-term economic growth, weaken productivity, and increase the likelihood of social and political instability. The more unequal a society, the more likely it is to experience slower development, poor policy choices, unrest, and fragility - all of which shape the operating environment for insurers. Structural inequality erodes trust in formal financial systems and reduces household and SME (Small and Medium Business (SME) resilience, which in turn suppresses insurance take-up and can even result in more severe and frequent claims. Unequal access to insurance contributes to inequality, but inequality in turn destabilises the insurance market itself.

It is vital to acknowledge that inequality is structural - shaped by broader social and historical forces such as past discrimination, unequal access to quality education, and intergenerational wealth gaps - and not merely a product of individual choice or effort. Insurance pricing that relies purely on current risk factors often overlooks how those risks are historically and socially produced. Actuarial models that price using proxies like education, income, or occupation can unintentionally entrench systemic disadvantage, because these factors reflect deeper structural

inequalities. In South Africa, where the legacy of apartheid continues to shape socio-economic opportunity, insurers should be especially mindful that the use of such proxies may perpetuate intergenerational economic exclusion - even if statistically defensible- and should test each factor's impact, seek fairer alternative's where possible, and balance actuarial logic with the moral responsibility not to deepen structural inequalities.

Inequality undermines micro-level resilience in profound ways. Poorer households are more exposed to health risks and disasters yet have less access to insurance or alternative protection mechanisms. This means they are more likely to face catastrophic financial consequences when shocks strike. Disparities in access to healthcare, early diagnosis, and medical cover contribute to stark life expectancy gaps. Climate and disaster risks hit poorer communities hardest - they often live in more exposed areas, lack property or catastrophe insurance, and take far longer to recover from losses, if they recover at all. Low-income households and informal settlements are disproportionately at risk from floods, fires, and droughts, yet they are the least likely to hold any form of cover for these events. The result is a deep, persistent protection gap, where most economic losses go uninsured. According to Munich Re, in low-income countries the protection gap for natural disasters is nearly 100% - meaning virtually all losses are absorbed directly by families and governments. The intergenerational consequences are severe: when families are forced to sell productive assets to survive, they sacrifice future income potential and perpetuate cycles of poverty. Climate change threatens to intensify this dynamic, increasing the likelihood that vulnerable populations will fall back into poverty with each successive shock.

The implications are clear: risk-based pricing structures that systematically exclude the poor also exclude them from resilience. If left solely to the market, insurance may not bridge these divides - it may even amplify them. This reality calls for a deeper redefinition of fairness in insurance. Rather than asking only whether a premium aligns with individual

risk, insurers and actuaries must also ask: Does this product meaningfully protect the people who need it most? How we answer that question will shape not just the fairness of our pricing but the long-term resilience of our communities and economy.

THE ROLE OF PRIVATE INSURANCE IN STRENGTHENING SOCIAL PROTECTION

Why Private Insurance Matters

Insurance alone cannot resolve deep socio-economic divides - but it must not worsen them either. At its best, insurance acts as a quiet pillar of resilience: it transforms unpredictable, devastating losses into manageable risks that households, businesses, and communities can survive. By pooling risk across the many to support the few who suffer losses, insurance provides a financial buffer that helps families stay in their homes after a fire, cover medical costs after illness or accident, or bury loved ones with dignity. Without access to fair and affordable insurance, vulnerable households often rely on loans or informal coping mechanisms that can push them deeper into poverty when disaster strikes. This is why insurance - when designed well - is more than a private contract; it becomes a public good that stabilises communities and helps families rebuild rather than slip backward.

While social insurance, funded and run by the state, is designed to pool risks widely and redistribute income through universal schemes, private insurance plays an important complementary role. It can offer tailored, efficient protection to groups who might otherwise fall through the cracks. Crucially, private insurance does not need to replace public safety nets - it can fill gaps, provide choice, and extend protection where government schemes cannot reach.

Innovation is a key enabler. In many developing countries, large segments of the population work outside formal payroll systems - including informal traders, domestic workers, and seasonal labourers. These groups are often excluded from state social protection like unemployment funds. By leveraging

technology - mobile phones, digital wallets, simplified claims processes - private insurers can cost-effectively reach people without bank accounts or stable formal employment. Mobile premium collection and payouts, for example, make it possible for millions of South Africans to participate in formal insurance markets for the first time. This helps widen the safety net and supports broader financial inclusion.

However, both systems have structural limits that point to the need for collaboration. Social insurance is more equitable in theory but faces significant challenges in practice. In many developing contexts, weak taxation capacity limits governments' ability to sustain universal coverage. Trust deficits can hinder uptake, especially in societies where corruption, poor delivery, or political instability have undermined faith in public programmes. Even well-intentioned subsidies often fail to reach those who need them most due to poor targeting or administrative inefficiency.

At the same time, private insurance is prone to classical market failures. Moral hazard can arise when coverage reduces incentives for risk prevention. Adverse selection remains a challenge - when mostly high-risk individuals buy insurance while low-risk people opt out, premiums spiral upwards, shrinking the pool further. Certain risks, such as large natural disasters or pandemics, are highly correlated and difficult for private markets to diversify alone at an affordable price. Social insurance systems can tolerate these risks more easily due to compulsory participation and broad pooling. However, they often lack the data sophistication, customer focus, or incentives for innovation that private insurers can bring.

Public-Private Partnerships for Inclusive Solutions.

The most promising way to overcome these limitations is through well-designed public-private partnerships (PPPs). By combining the reach and redistributive mandate of the public sector with the product design agility, operational efficiency, and technology of private insurers, PPPs can help close

In South Africa's context, private insurance cannot stand apart from the national project of resilience.

protection gaps at scale. They can enlarge risk pools across income groups and risk classes, make targeted subsidies viable for vulnerable segments, and harness real-time data to price, deliver, and service microinsurance products more effectively. Crucially, they align incentives between commercial sustainability and social resilience outcomes.

In South Africa, such partnerships could unlock more inclusive solutions. Examples include municipal disaster risk pools that spread the cost of climate-related losses across households and businesses; state-subsidised health or funeral insurance bundled with social grants to reach informal workers; or climate-smart agricultural insurance that combines private underwriting with public data and partial reinsurance. International models reinforce what is possible: weather-index crop insurance in East Africa, for instance, uses public weather data to enable private insurers to offer affordable parametric cover to smallholder farmers; national disaster risk pools blend public funds with reinsurance to protect vulnerable regions against floods and storms.

For private insurance to truly support fair pricing and inclusive growth, however, products must be affordable, simple, and relevant. Administrative costs and profit margins must stay below what risk-averse, low-income households are willing and able to pay. Innovation must be combined with clear oversight and aligned incentives to prevent the mistakes of the past - where low-income consumers sometimes paid proportionally more for poor value cover.

In South Africa's context, private insurance cannot stand apart from the national project of resilience. Whether through product design, pricing, partnerships, or innovation, the private sector has a vital role to play in closing protection gaps - not widening them.

BALANCING PREDICTIVE POWER AND FAIRNESS: THE ROLE OF MACHINE LEARNING IN EQUITABLE INSURANCE

The Power and Risk of Data-Driven Pricing

As machine learning rapidly transforms how insurers set premiums and underwrite risk, a profound challenge is coming into focus: the same data-driven precision that makes models powerful can also quietly reproduce - and even amplify - deep social inequalities hidden within that data. While actuarial fairness aims to align with risk, this principle can backfire when risk factors reflect a world shaped by structural disadvantages: unequal access to healthcare, unsafe neighbourhoods, or histories of discrimination. In such cases, pure risk-based pricing can end up embedding social fairness under the guise of mathematical neutrality.

Fairness-Aware Machine Learning

Modern regulators and civil society are increasingly unwilling to accept this as inevitable. There is a growing consensus that fairness in insurance pricing cannot mean only statistical fit to past loss ratios; it must also ensure that protected groups - whether defined by race, gender, age or other traits - are not systematically disadvantaged by the models' insurers deploy. This tension between predictive accuracy and non-discrimination has pushed the insurance sector into the rapidly advancing field of fairness-aware machine learning, which aims to systematically detect, measure and correct unfair bias in algorithmic predictions.

Key Fairness Metrics and Approaches

Fairness metrics are a critical tool in this evolving pricing toolbox. Data scientists and actuaries now look beyond traditional measures like Gini coefficients or mean squared error, and test models for group fairness with metrics such as demographic parity - which checks whether the probability of receiving a favourable outcome (like a lower premium or policy approval) is independent of membership in a protected group. In practice, however,

simple demographic parity can be blunt: for example, a model that blindly equalises approval rates across groups might ignore genuine differences in risk, driving up loss costs and forcing insurers to raise prices for everyone. To balance predictive accuracy with fairness, many actuaries and data scientists may build or adjust models to meet more nuanced tests such as equalised odds. The goal of the equalised odds fairness metric is to ensure that a model performs equally well for different groups by requiring not only that its predictions are independent of sensitive group membership, but also that its false positive rates and true positive rates are similar across groups. This distinction matters because a model could technically achieve demographic parity - ensuring the same overall approval rate for all groups - yet still reach that parity by making more mistakes for one group than another, such as wrongly approving higher-risk cases just to balance the numbers. So, although the outcomes look equal, the errors are unevenly spread - failing equalised odds. By focusing on equal error rates rather than just equal outcomes, equalised odds avoid the blunt selection problem that pure demographic parity can create. While both equalised odds and demographic parity originate in binary classification tasks - like deciding whether to accept or reject a claim - their principles adapt to continuous pricing too. In insurance, this means examining whether prediction errors or average premiums systematically differ across groups, revealing whether an apparently 'accurate' model still replicates structural disadvantage under the guise of risk-based fairness.

Individual fairness goes even deeper: it says that each person should be treated consistently relative to comparable individuals, regardless of irrelevant traits. But defining who is comparable is no small task. In practice, it means deciding how similar two people are in a high-dimensional space of policyholder characteristics - a problem that quickly becomes mathematically and ethically complex. For example, two drivers with identical claims histories and driving patterns, but who live in different

neighbourhoods, should in theory pay the same premium - yet if neighbourhood acts as a subtle proxy for income or race, the model may pull them apart unfairly. "Fairness through unawareness", simply dropping race or gender from the input variables, does not solve this if other features stand in as proxies. Achieving true individual fairness often requires actively removing or controlling the statistical links between legitimate risk factors and protected traits - a process known as orthogonalizing the data - or explicitly constraining the learning algorithm to ensure its predictions do not change when only a protected attribute varies.

Bias Mitigation in Practise

Bias mitigation happens at three critical intervention points: before training, during training, or after. Preprocessing aims to fix the data itself. One basic method is reweighting: if the training dataset under-represents claims from certain communities, the model may learn to systematically underprice their risk or over-rely on proxies like ZIP code. By resampling or weighting training examples, insurers can give equal "voice" to all groups. More sophisticated pre-processing involves transforming features: removing or modifying attributes that act as stand-ins for race, gender, or class. Tools like the disparate impact remover help reduce unfair links to protected traits while keeping useful risk signals intact. Going a step further, some approaches build new "fair" versions of the data that still predict losses well but hold as little information as possible about sensitive traits.

In-processing methods take a more direct approach by building fairness rules into the model's training process itself. Here, fairness constraints are added straight into the algorithm's loss function, so the model learns to balance prediction accuracy with fairness goals. A well-known example is the Prejudice Remover, which adds a penalty if the model's predictions start to depend too much on a protected characteristic. A more advanced technique is adversarial debiasing, where a second "adversary" network tries to detect protected traits like race or gender from the

model's internal signals. The two networks compete: if the adversary can easily guess a sensitive trait, the main model is penalized and forced to adjust. Over time, this process teaches the model to predict claims or premiums accurately while minimizing the risk of leaking hidden bias.

Trade-offs and Governance Challenges

Yet real deployment is rarely so clean. Many insurance models are "black box" vendor tools or legacy systems that cannot be easily retrained. In cases where retraining a model from scratch is impractical - for example, when an insurer relies on a third-party black-box model or when time and budget constraints prevent a rebuild - post-processing methods offer a practical way to correct unfair bias in insurance pricing and underwriting. Post-processing works by taking the model's predictions and adjusting them after the fact to meet specified fairness criteria, without changing the model's internal logic. Common techniques include threshold adjustment, where insurers set different decision thresholds for different groups to equalize approval rates or error rates; output perturbation, where predictions near the decision boundary are probabilistically flipped to improve fairness for disadvantaged groups; or score adjustment, where final premium estimates are nudged up or down to ensure no group systematically pays more without justified risk differences. For example, a post-processing step might lower predicted premiums for a minority community if an audit finds that neighbourhood-based proxies inadvertently inflated their risk scores. While relatively straightforward to implement, post-processing does require clear governance: insurers must be able to explain to customers and regulators why adjustments were made, demonstrate that corrections do not distort legitimate risk signals, and ensure that the fairness fix itself does not introduce new inconsistencies or unintended consequences.

All this becomes even more complex when fairness objectives conflict with strict actuarial soundness. By design, insurance pools risk. For centuries, this risk pooling was partly social - the young subsidised the old, the healthy

helped cover the sick, and mutual benefit justified cross-subsidies that pure actuarial fairness would not support. As machine learning sharpens risk segmentation to micro-levels, these natural pooling effects weaken. Without guardrails, ultra-personalised pricing can splinter the solidarity that makes insurance a viable social safety net. By enforcing goals like demographic parity or equalised odds, fairness-aware algorithms reintroduce intentional cross-subsidies, so risk pricing doesn't fragment society into tiny pockets of people who can't get coverage at all.

The hardest frontier is explainability. Fairness corrections, especially those involving adversarial training or post-processing score shifts, can be opaque. A policyholder may ask why they pay more than a neighbour with the same driving record - and the true answer may involve statistical dependencies or constraints that are not easy to translate into a one-sentence explanation. Regulators increasingly demand that insurers show not only that their models are fair on paper but that individual decisions can be justified in plain language. This often means insurers must choose between sophisticated black-box algorithms and simpler, interpretable models that satisfy both accuracy and fairness goals without losing the customer's trust.

A critical tension is that enforcing fairness constraints often means accepting some loss in predictive accuracy. If a protected trait is strongly correlated with actual risk, then suppressing it or its proxies will reduce a model's statistical precision. This trade-off can be visualized using an accuracy-fairness Pareto frontier, which shows that for every point of fairness gain there may be an opportunity cost in underwriting precision or profit margin. Smart modelling can sometimes find 'sweet spots' where large fairness improvements cost very little in accuracy, but not always. In the insurance context, this balancing act is real: achieving demographic parity for gender, for example, may lead to implicit cross-subsidization between groups, as famously happened when the EU banned gender-based pricing for auto insurance. Actuarially,

young male drivers pose higher risk on average, but the law imposed unisex rates - the result was that lower-risk female drivers partly subsidized higher-risk male drivers, with a modest impact on the overall loss ratio that insurers simply absorbed or offset with other rating factors.

In practice, insurers manage this trade-off by tuning a hyperparameter - often denoted λ - that weighs the importance of fairness relative to raw predictive accuracy during training. This multi-objective optimization produces a family of models, allowing the company to select a point on the curve that meets its risk appetite, regulatory requirements, and ethical standards. Scenario testing helps communicate to executives and regulators what level of fairness constraint is operationally sustainable without destabilizing premiums, profit, or market share.

These theoretical principles find powerful illustration in real-world use cases. In health insurance, fairness is vital for both legal compliance and moral legitimacy. A striking example shows how hidden bias can persist even when models appear neutral. A health risk prediction algorithm used in the US to allocate patients to high-risk care programs relied on healthcare spending as a proxy for medical need. Because Black patients historically incurred lower healthcare costs due to barriers to access, the algorithm consistently underpredicted their true health risk. As a result, sicker Black patients were flagged as lower priority than equally ill white patients - an insidious case of disparate impact. The solution was to redesign the model to predict health status directly instead of using spending as a flawed stand-in, demonstrating how a thoughtful pre-processing fix can improve fairness without major loss of utility.

In health underwriting, insurers often use only approved medical and lifestyle data while excluding genetic information to comply with anti-discrimination rules. But fairness gaps can still arise if correlated variables leak sensitive signals. For instance, if a model learns to assign higher premiums to certain ethnic groups because of correlated lifestyle or

location factors, a post-processing step may be required to adjust the predicted prices downward to align with the risk expected for the average population. Similar logic applies to fraud detection: fairness-aware insurers use metrics like equalized odds to ensure that fraud flagging systems do not unfairly target claims from elderly, disabled, or minority customers at higher rates than warranted by the evidence.

Auto insurance provides another high-profile context where fairness concerns have triggered regulatory and public pushback. Investigative journalism by ProPublica revealed that in some US states, minority neighbourhoods were charged up to 30% higher auto premiums than white neighbourhoods with equivalent accident risk. This pattern stemmed from the use of factors like ZIP codes, credit history, and homeownership - which correlate strongly with race and wealth. In response, states like California and Illinois reviewed rating models and restricted the use of certain high-bias inputs. Some states have gone further: Colorado's SB 21-169 prohibits insurers from using external consumer data and predictive models in ways that result in unfair discrimination in any line of insurance. Insurers operating there must conduct bias testing, monitor their models for disparate impact, and demonstrate that tools like telematics or credit-based scores do not produce unjustifiable group disparities. This creates practical governance requirements: companies must test for bias, adjust models if disparities arise, and maintain a documented framework for monitoring fairness.

Life insurance, too, is navigating the frontier of fairness-aware AI. In 2019, the New York Department of Financial Services issued landmark guidance making it clear that any predictive model used for underwriting must be transparent and free of proxy bias. If a life insurer uses unusual data - say, magazine subscriptions or shopping habits - to infer mortality risk, they must prove there is a sound causal link to life expectancy, not just a spurious correlation that echoes racial or socio-economic differences. This

has forced many life insurers to strengthen model governance, routinely testing whether accelerated underwriting approvals or preferred rate offers are equitably distributed when controlling for actual health status. Many have added explicit in-processing constraints - such as training models to equalize mean scores across groups - and post-processing adjustments to align acceptance rates. Similar fairness checks now extend into fraud detection and marketing. For example, if a fraud detection model flags claims from a certain neighbourhood disproportionately, the company may retrain the system, exclude location as an input, or deploy adversarial debiasing to break any hidden link.

Yet building such fairness into operational reality remains challenging. Insurers must navigate conflicting laws - often forbidden from using protected traits directly yet needing data on those same traits to test for hidden bias. Data availability is also limited, as insurers seldom collect race or ethnicity for legal and privacy reasons. Some use external census overlays or ZIP code proxies to run fairness simulations, but these imperfect workarounds raise concerns of their own. Explaining fairness-adjusted model decisions to regulators and customers in clear, non-technical language adds another layer of complexity. Moreover, fairness monitoring cannot be a one-time exercise: models can drift as social or economic conditions shift. Firms are building new model risk management regimes that blend actuarial, data science, compliance, and even ethical oversight. They face tough operational trade-offs: fairness constraints may lead to adverse selection if high-risk customers cluster in underpriced segments, potentially destabilizing books of business.

Despite these hurdles, the trend toward more transparent, bias-aware insurance is accelerating. Forward-thinking insurers recognize that embracing fairness is not just about avoiding fines or reputational damage - it is about earning trust in a world where customers expect algorithms to be accountable, not inscrutable. By investing in fairness metrics, robust governance,

explainable AI, and continuous bias detection, insurers can transform machine learning from a black box into a tool for equitable risk protection, ensuring that the promise of insurance - pooling risk to protect the vulnerable - is upheld, not undermined, by the data-driven future.

Building a Resilient Society

Insurance plays a vital role in building resilient societies. By pooling and redistributing risk, it ensures that when disaster strikes - whether it's a car crash, an unexpected medical bill, or a home destroyed by flooding - no single person is left to shoulder the full burden alone. But as the world faces rising uncertainty - from global economic shocks to the intensifying impacts of climate change - the fairness of how insurance prices that risk has become more critical than ever. In this high-stakes landscape, ensuring that premiums are both technically sound and ethically defensible is no longer optional: it is fundamental to the sustainability of insurance itself as a social safety net.

Regulators and policymakers around the world are now responding decisively to this challenge, rebalancing the equation between actuarial precision and social fairness. The European Union's Gender Directive forced all EU insurers to abandon gender as a risk factor, pushing companies to adjust models and accept intentional cross-subsidisation: young women's auto insurance premiums rose slightly, young men's fell, and the result was a fairer, unisex market by law. In the United States, Colorado's SB 21-169 breaks new ground by explicitly banning insurers from using algorithms or external data that result in unfair discrimination - even indirectly - and requiring companies to test, monitor and prove that their models treat protected groups equitably.

In practice, embedding this fairness into the daily business of pricing requires insurers to rethink every step of the process. It begins with robust ethical frameworks: many insurers now have formal fairness or ethics committees - cross-functional teams bringing together actuaries, underwriters, data scientists, legal

and compliance experts, and sometimes external advisors to scrutinise models and flag risks of unfair bias before they ever reach the market. These frameworks codify what "fair" means for the company: for example, committing that no protected group will pay a systematically higher profit margin than another, or that certain sensitive attributes will never be used in rating - directly or by proxy. Documentation is vital too. Increasingly, leading firms maintain clear audit trails showing how fairness was tested, what metrics were used, what interventions were applied to mitigate bias, and how ongoing monitoring is built into the life of the model.

In South Africa, multiple overlapping regulations are raising the bar too. The Financial Sector Conduct Authority's (FSCA) Treating Customers Fairly (TCF) framework - soon to be reinforced by the upcoming Conduct of Financial Institutions (CoFI) Act - requires that insurers demonstrate transparent, justifiable premiums, fair value over the life of the policy, and clear explanations for any increases. The new Conduct Standard on Loyalty Pricing tightens this by ensuring long-term customers do not face unjustified renewal penalties or opaque loadings. Together, these rules directly challenge hidden pricing practices that exploit inertia or target vulnerable policyholders with higher margins over time.

At the same time, the Promotion of Equality and Prevention of Unfair Discrimination Act (PEPUDA) makes it unlawful to discriminate unfairly in providing financial services - so if rating factors systematically disadvantage protected groups, insurers must justify them or risk legal challenge. And the Financial Advisory and Intermediary Services (FAIS) Act places a parallel duty on brokers and intermediaries: they must ensure that the products they recommend are appropriate, fairly priced, and genuinely in the client's best interest - adding another gatekeeper for ethical pricing.

Yet alongside these conduct and equality rules comes the Protection of Personal Information Act (POPIA), which rightly protects customer privacy but complicates fairness testing. Without explicit data on protected attributes

like race or religion, it is far harder to detect indirect bias or proxy discrimination. This creates a tension: robust bias checks often need data that POPIA restricts. Many insurers try to bridge this by using proxy simulations, census overlays, or aggregated trends - but these workarounds are imperfect, raising ethical and statistical questions about how reliably they flag hidden unfairness.

Globally, new frameworks like the EU's upcoming AI Act will push this even further - categorising insurance pricing as a high-risk AI use case that must be fully documented, bias-tested, and explainable to regulators and customers. In practice, insurers everywhere will be forced to prove that machine learning models are not only accurate but demonstrably fair and lawful.

Actuaries and data scientists now use fairness metrics alongside traditional accuracy measures. A pricing model might be judged not just on how well its loss predictions align with claims data, but also on demographic parity (do approval rates match across groups?), equalised odds (are misclassification rates balanced?), or measures of individual fairness (do similar people receive similar outcomes?). Tools like "remove and replace" help test for hidden proxies: if dropping an input like area or credit score drastically shifts predicted premiums for a vulnerable group, that's a red flag that the factor may be acting as a stand-in for race or poverty.

All of this is pushing the profession to innovate. Actuaries are not only technical modelers but guardians of insurance's social contract. They translate new fairness rules into pricing practice. They challenge hidden assumptions, smooth sharp premium changes that could unfairly shock loyal customers and communicate the trade-offs of fairness constraints to executives and boards. Many lead scenario testing: if unemployment spikes or climate events increase, does the model respond in ways that remain consistent with TCF? Should an insurer accept some cross-subsidy - for example, capping rate increases for pensioners funded by small surcharges on lower-risk groups - to maintain social trust and market stability? And if a fairness constraint

slightly reduces pure predictive power, is that cost acceptable to avoid reputational or regulatory damage?

Beyond technical checks, practical solutions are emerging to rebuild trust. Insurers now send more transparent premium breakdowns, showing drivers exactly how their price was calculated and how to reduce it. Some let customers experiment with variables online - "what if I install an alarm or drive fewer miles?" - putting control back in policyholders' hands. Some push for simpler, clearer products: fewer exclusions, straightforward excesses, and no fine-print traps that surprise people when claims arise. Others experiment with community rating or value-based pricing: ensuring that historically underserved segments are not just profitable for the insurer but actually receive reasonable coverage for their premium.

Regulators themselves are shifting from passive oversight to proactive checks. Many now use industry data to run disparity tests, looking for patterns of unexplained premium gaps that could point to indirect discrimination. Globally, new laws like the EU's upcoming AI Act will likely push these expectations further - requiring insurers to demonstrate not only that algorithms work but that they work fairly and transparently.

In the end, insurance pricing that ignores fairness is a short-term gain but a long-term risk. In a time when climate extremes, global shocks and social fragmentation threaten shared resilience, fair pricing is more than an ethical box-tick - it is the foundation of insurance's promise to protect people against life's worst surprises. As regulators tighten standards and customers expect transparency, the insurers and actuaries who lead on fairness will not just comply they will help rebuild trust in insurance as a force for collective security and shared prosperity in an uncertain world.

CONCLUSION _

Fair pricing is more than a compliance requirement - it is a test of whether the insurance profession can balance sound risk-based pricing with fairness in a deeply

unequal society. For South Africa's market, this means not only refining models and metrics but asking harder questions: Are we explaining premiums clearly? Are we detecting hidden bias where data proxies hide structural inequality? Are we using regulation, technology and professional judgment to protect the most exposed households rather than pricing them out?

Fair pricing will always involve trade-offs - between predictive accuracy, capital sustainability, and solidarity - but these trade-offs must be intentional and transparent. Ultimately, this is not just about models or regulation; it is about whether insurance can continue to serve as a credible social safety net as economic and climate risks grow.

For actuaries, underwriters and regulators alike, this challenge is real- but so is the opportunity: to lead the conversation, test assumptions, and ensure that the promise of insurance remains true: shared risk, shared security, and resilience for all.

Questions to Consider

As South Africa grapples with structural inequality, climate shocks, and shifting regulation, the insurance profession must keep asking hard questions:

- How can insurance become more inclusive in highly unequal societies like South Africa?
- Can we design insurance products that actively mitigate inequality, rather than just reflect it?
- What alternatives exist beyond simply lowering premiums - can product design, partnerships or technology expand affordability?
- Can we design insurance products that actively mitigate inequality, rather than just reflect it?
- How can we ensure that innovations like telematics do not introduce new forms of exclusion or bias?
- Should insurers value actuarial fairness over social fairness – or find a better balance?
- Are we in a cycle where inequality leads to low insurance penetration, which

leads to worse outcomes, which deepen inequality?

- Do insurers have a responsibility to influence public policy for more equitable growth - on infrastructure, healthcare, or education?

These questions are not easy - but asking them is part of what will keep insurance relevant and trusted in a world facing growing shocks and persistent inequality.

The views expressed in this article are the author's own and do not necessarily reflect the views of their employer or any affiliated institutions. 

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NATIONAL HEALTH INSURANCE (NHIS) – A look at key drivers and considerations based on the experiences of Zambia and Tanzania

by Taonaziso Chowa

Universal health coverage

Global movement towards UHC - Universal health coverage is an important part of the Sustainable Development Goals (SDGs). SDG 3.8 aims to “achieve universal health coverage, including financial risk protection, access to quality essential health care services, and access to safe, effective, quality, and affordable essential medicines and vaccines for all.” In addition, the SDG 1 call to “end poverty in all its forms everywhere” could be in peril without UHC given that out-of-pocket health spending pushes people into, or further into, poverty. UHC has found backing from the UN in September 2023. <https://datatopics.worldbank.org/universal-health-coverage/> and <https://blogs.worldbank.org/en/voices/scaling-affordable-health-insurance-same-dish-many-different-recipes>

Health is an investment, not an expense - Affordable accessible health care can unlock human capital and economic dividends for countries. But latest World Bank estimates show that, 41 countries – many of them low income and middle-income countries- will face stagnation or contraction of government spending over the next five years. Governments in low-income countries spend less than 2% of GDP on health, and governments in lower middle-income countries spend less than 3%. In addition to the shrinking of the overall size of government budgets, the share going to health is also decreasing.



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Demographics and disease profile are changing and put pressure on health systems. Globally, fertility has fallen significantly from an average of 5 births per woman in 1950 to 2.3 per woman in 2021. Populations are also aging worldwide: people aged 65 and older now outnumber children under 5. By 2050, 1.5 billion people will be 65 and older. Non-communicable diseases (NCDs) are on the rise, accounting for 41 million deaths each year (74% of all deaths globally), with more than three quarters of NCD deaths occurring in low and middle-income countries. Climate change is also a critical contributor to the burden of NCDs through factors such as air pollution, heat stress, and extreme weather events.

The World Bank Group in April 2024 announced an ambitious plan to support countries in delivering quality, affordable health services to 1.5 billion people by 2030 focused on three core elements:

1. Expanding focus from maternal and child health to include coverage throughout a person's lifetime, including non-communicable diseases.
2. Expanding operations to hard-to-reach areas, including remote villages, cities, and countries (through interface with a health-care worker via an in-person visit or telehealth).
3. Working with governments to cut unnecessary fees and other financial barriers to health care.

In this article, I takes an inquisitive view to the growing drive for national health insurance schemes (NHIS) in Africa. Looking at the experience of Tanzania and Zambia, this article present some key considerations by reviewing the mandates of NHIS, various risks and the observed inequalities towards the informal sector. Suggestions for NHIS coexistence with the private life and health insurance mechanisms and its future sustainability are also presented.

Mandate of the NHI or State Healthcare

The mandates for the NHIS has largely ben based on the following four reasons.

1. Protecting the nation's health – universal coverage and provision of health cover to every citizen of the nation.
2. Subsidising the poor – extending health cover to those who may otherwise not afford to pay for is through some cross-subsidy/solidarity model or free rider indigencies.
3. Balancing the budget – Healthcare provision is part of State expenditure and the NHIS enables provision to be done through specific health charges.
4. Following social, culture or other political promises – political ethics, constitutional provisions and general ethos as a way to foster national cohesion through

non-discrimination in health provision especially among the vulnerable groups (children and the elderly)

Summary of risks in NHIS

The Tanzania NHIF levies 15% of contributions received at the administration fees while Zambia's NHIMA has administration charges at 10% of the collected premiums. The post COVID-19 era has laid bare the susceptibility of the NHIS to the theoretically common actuarial and financial risks as well as emerging risks summarised below.



Table 1: Summary of NHIS Risks

Insurance risks	Adverse morbidity developments – , outbreaks, epidemics, pandemics and hospitalisation	Current morbidity mix – Non-communicable diseases (NCDs), other chronic ailments and the spread of conditions being experienced	Demographic mix of current and future members, longevity
Contributions risks	Contributions levels	Lapse and non-renewal (with open rejoining)	Contributions mix of new entrants
Claims risks	Future benefit/claims inflation	Benefit size/structure (without limits)	Future expense levels (and inflation)
Market risk	Investment yields	interest rate risk	Exchange rate fluctuations in case of foreign treatment
Operational risks	Claims fraud and inappropriate billing	Poor decision making	Service provider mix between private and public
Credit Risks	Employer/employee default	Covenant risk counterparty risk	SLAs
Reputational risks	Lack of engagement and Poor governance	poor communication to members	Inequality and stakeholder conflicts
Liquidity Risks	Funding and solvency,	Inadequate contributions	Initial strain and lack of government support

Emerging NHIS risks have manifested more from patient choice, overutilization and medical service provider overservicing. While choice fosters competition, unregulated freedom can result in negative outcomes, such as overutilization of high-end facilities, distortion of the hierarchical referral system or marginalization of rural providers. The text below gives some brief descriptions into these emerging risks.

Choice risk – Private Preference

There is general patient preference for private medical services over the public ones given a choice. The adverse to this results in diseconomies for certain public hospital services. This could be tamed through managed care and co-payments.

Choice risk – Overservicing by facilities

There is a temptation by private health facility ecosystem to tick all the boxes of the set benefit structure through internal referrals as long as the procedure is covered thereby

increasing the average patient walk through cost.

Choice risk – Overservicing by medical professionals

This creates the risk and cost of inappropriate practice to the public within the Private Medical services provision.

Overservicing in its forms above has led to serious dilemmas on; How do to balance customer experience, minimising medical negligence (underservicing) and the profit motive. The profit motive manifest itself through overutilisation whereby the “Incentives in the market promote overutilization. In particular fee-for-service means that the more services practitioners provide, the greater their income, which creates a perverse incentive for profit maximising individuals or groups”

Exclusion and inequality

Current design of the NHIS is meant to cover for the formally employed through compulsion based on the set percentage of basic shared equally between employer and

employee. Considering Tanzania's NHIF with a contribution rate set at 5% of basic (with already an approval to migrate to gross) and Zambia's NHIMA at 2% and also seeking a gross based contributions. The biggest huddle has been on how to foster health insurance inclusion without adverse selection among the informal and rural people who make up the majority of the population, being over 60% for both Tanzania and Zambia. The most reflective tariff on the informal sector that better captures their ability to pay has been an elusive target with questions being brought afore on equity and affordability.

In Tanzania the informally employed are to subscribe for the basic package or comprehensive and pay for the set premiums while in Zambia the informal sector obtain access to the NHIMA comprehensive package at two entry points at k30 per

month per family or k60 if taxed income assessment points to higher income. Zambia's NHIS is also mandates to onboard all retirees and also selected indigents who are free riders. Inequality has arising mainly from the fact that there is a significant portion of the formal sector whose salaries around the minimum wage which translates to about a quarter of the NAE usually pay far less than the set minimum premium for the NHIS. Also disparities in health service standards across the country, especially when comparing rural and urban and the choice for private health services means that the rural populace may be paying for a non-existent choice.

The analysis of the formal vs informal contribution rates are analysed based on the national average earnings (NAE) concept for Tanzania and Zambia and dollarised the figures for ease of comparison as shown below.

Table 2: NHIS Burden on informal sector

Tanzania NHIF						
National average earnings	0.25NAE	0.5NAE	NAE	2NAE	3NAE	4NAE
Basic salary USD	46.17	92.34	184.68	369.36	554.04	738.73
Employer contribution @3%	1.39	2.77	5.54	11.08	16.62	22.16
Employee contribution @3%	1.39	2.77	5.54	11.08	16.62	22.16
Total	2.77	5.54	11.08	22.16	33.24	44.32
Ngorongoro Afya - 1	Family of five	4.59				
Serengeti Afya - 2	Family of five	5.23				
Unemployed burden 1	331%	166%	83%	41%	28%	21%
Unemployed burden 2	378%	189%	94%	47%	31%	24%
Zambia NHIMA						
National average earnings	0.25NAE	0.5NAE	NAE	2NAE	3NAE	4NAE
Basic salary USD	76.00	152.00	304.00	608.00	912.00	1,216.0
Employer contribution @1%	0.76	1.52	3.04	6.08	9.12	12.16
Employee contribution @1%	0.76	1.52	3.04	6.08	9.12	12.16
Total	1.52	3.04	6.08	12.16	18.24	24.32
Family @30	Family of Six	1.22				
Family @60 income assessed	Family of Six	2.45				
Unemployed burden @30	161%	81%	40%	20%	13%	10%
Unemployed burden @60	322%	161%	81%	40%	27%	20%

The table on the previous page shows that, in its current state, the Tanzania NHIF is quite exclusive with its average packages requiring contribution rates of around the NAE value. The Ngorongoro family package contribution is at around at 83% of the NAE, while Serengeti package sits at 95% and leaves a significant portion of the population uncovered. It is important to note that the Tanzania NHIF does offer two levels of largely primary health packages below Ngorongoro and another two packages on either side of Serengeti, which somewhat might be an indicator of an over tired package setup with some bands not easy to differentiate the packages.

The current state of the Zambia NHIMA, though still at formative stages shows some attempt towards making health care affordable. The minimum informal sector contribution of ZMW30 (\$1.22) is around 40% of NAE while the assessed income contribution of double the minimum is about 80% of NAE. Where the unemployed burden exceeds 200% in the table above, it points to a scenario whereby the informal sector contribution rate is more than double the one paid by the lower bands of those in formal employment. Despite possible inequalities arising from the lowly paid formal sector, Zambia's NHIMA may appear to be more affordable than the Tanzania NHIF. The simple analysis above of the rates based on the national average earnings (NAE) concept reveals that failure to achieve UHC is going to be more difficult for Tanzania than Zambia, despite both

institutions failing on the mandate for UHC and equity. Furthermore, the NHIS in Tanzania and Zambia have failed to create a fully national pool and hence failed to fully benefit from the 'healthy' of the nation.

Coexistence of the NHIS and the private health funders

Co-existence of the NHIS with the private health insurance refers to the harmonious integration and functioning of the NHIS alongside existing healthcare financing mechanisms, such as private health insurance, donor-supported programs, employer-based schemes, and out-of-pocket payment systems. Coexistence ensures that the NHIS does not disrupt or duplicate existing services but rather complements them to enhance healthcare delivery and financial protection. Private health insurance has been presented to play some cataclysmic roles to the environment with the NHIS as optional or compulsory complement or as an alternative to the NHIS.

Insurance may be a more affordable option for employers who opt out. Self insurance can be the only option to access medical services due to invalidity Incentives for self-provision – Additional Medical Expenses Tax Credit (AMTC) is a rebate which, in itself, is non-refundable, but which is used to reduce the normal tax a person pays and medical scheme fees tax credit (MTC) in South Africa.



Coverage for Remaining Risks

The leaving out of the informal sector and other consequential risks faced by individuals mean that with good products mappings and innovations. The table below presents some of the options for private life and health insurance sector could still be relevant to play in the economy even after the advent of the NHIS.

Table 3: Complementary and Alternative Insurance to NHIS

Product	Scope	Target
Microinsurance	Basic Health Cover	The informal sector
Hospital cash plan	Easing financial burden during hospitalisation of family member	Both current NHIS members and the excluded
Critical illnesses	All NCDs and other Chronic illnesses	For the excluded or limited benefits under NHIS
Income protection	Include waiver of NHIS premiums or other insurances	Both current NHIS members and the excluded
long-term care	Care for the elderly with accommodation and basic health services	Current members of the NHIS active and retired
Medical refund accounts	Pooled savings or contingent funded to refund medical expenses incurred by employees/members	Excluded employers and affinity groups e.g. traders associations and other
Life insurance	Funeral grant beyond the principal member	Both current NHIS members and the excluded

The future of NHIS

Creating a NHIS of the future hinges more on making it as universal as possible and having every resident of a country come on board requires some integrated IT system. A sustainable NHIS may start with full funding of the basic health care and set an affordable premium from the beginning. Tired Benefit structure for NHIS in line with member NAE or total employer average reaching a set NAE threshold or apply the minimum contributions for the informal sector to formal sector as well. Overservicing co-payment penalties that follow the average walk-through cost and using it to determine retrospectively rated co-payment bands. Making the NHIS supportive of the government health care system may mean continuous monitoring of patient traffic back to the public hospitals through managed care clinics at public hospitals for the high cost ailments. A more equitable approach to determining the

informal sector contributions could be based on means tested contributions based on affordability. The NHIS need not cloud the space to allow for co-existence with the private life and health insurance product innovations. 🚫

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OPTIMAL MECHANISM DESIGN FOR
CLAIMS SETTLEMENT EFFICIENCY:

A Game-Theoretic Analysis

by Yoboua Angoua



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Optimal Mechanism Design for Claims Settlement Efficiency: A Game-Theoretic Analysis

Yoboua ANGOUA

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1 Introduction

In Côte d'Ivoire, third-party liability insurance is mandatory for all motor vehicles on public roads. This requirement makes motor insurance one of the population's primary interactions with the insurance industry—either as clients or as victims.

To improve the post-accident experience, Ivorian insurers introduced the *Indemnisation Rapide de l'Assuré* (IRA) mechanism in 2012. Designed to streamline the settlement of material damage claims for accidents involving two vehicles, the IRA aimed to foster trust within the industry and among clients.

However, by 2021, a seminar organized by the Ivorian Insurance Association (ASACI) revealed the system's operational failures. Insurers reported significant delays, administrative burdens, and disputes over inter-insurer payments. These issues led to a backlog of over 6,000 unsettled claims and contributed to growing customer dissatisfaction.

Instead of promoting insurance adoption, negative experiences with mandatory insurance have become a barrier to wider market development. Given the low insurance penetration in Côte d'Ivoire and the CIMA zone, enhancing the claims settlement mechanism is critical for the industry's credibility and growth.

This article uses economic modeling, game theory, and mechanism design to:

- Analyze the inefficiencies of the current IRA mechanism;
- Propose a theoretical model for insurer interactions;
- Introduce a new mechanism to improve settlement outcomes;
- Illustrate findings through real-world data applications.

The proposed structure includes: a modeling framework, game-theoretic analysis, new mechanism design, empirical application using market data, and concluding remarks.

2 Description of the Ivorian Mechanism and Key Problems

The current Ivorian IRA mechanism operates on a process involving both the non-labile and liable insurers, requiring prior approval before client compensation. While designed to enhance inter-insurer trust and streamline settlements, the system has become inefficient and costly to operate.

The mechanism introduces several layers of transaction costs:

- Verification costs for the liable insurer (validating liability and coverage);
- Recovery costs for the non-labile insurer (claim filing and follow-up).

These steps significantly delay settlements for victims, especially in the absence of digital systems and effective governance. Moreover, penalties for non-compliance are seldom enforced due to the administrative burden of proof and collection.

To understand these inefficiencies, we adopt a game-theoretic modeling approach in which insurers are rational agents seeking to maximize profit. We examine whether current rules incentivize investment in claims processing systems and cooperation between insurers.

Using simple cost-benefit expressions and payoff matrices, we formalize each insurer's decision to:

1. Cooperate by promptly processing and reimbursing claims;
2. Defect by delaying or ignoring recourse requests.

Our model shows that under the current IRA framework, liable insurers have no financial incentive to invest in reducing delays. Improvements by one insurer are ineffective unless mirrored by others, resembling a classic Prisoner's Dilemma. Thus, unilateral improvements do not lead to increased client satisfaction or profitability, and delays persist market-wide.

This modeling framework serves as a foundation for the game-theoretical analysis in the next section.

3 Theoretical Framework of Recourse and Transactions

3.1 Framework Overview

We analyze motor liability claims involving two vehicles under the IRA agreement. For each claim c , we define $\{Cost_c, Responsible_c, NonResponsible_c\}$, with $Cost_c$ the indemnity, $Responsible_c$ the at-fault insurer, and $NonResponsible_c$ the insurer of the victim.

- MS_i : market share of insurer i
- PQ_i : portfolio quality, with $\sum PQ_i = 1$
- NB_{Claims} : total number of claims in period T

Assumptions:

- Claims and cost variables are i.i.d.
- $\mathbb{P}(NonResponsible_c = i) = MS_i$
- $\mathbb{P}(Responsible_c = i) = \frac{MS_i \cdot PQ_i}{\sum MS_j \cdot PQ_j}$

Definition:

Given the previous assumptions and notations, for each insurer i over period T , we define:

- $NB_{i \rightarrow k}$: number of claims where $Responsible_c = i$, $NonResponsible_c = k$
- $NB_{AtFault_i} = \sum_k NB_{i \rightarrow k}$
- $NB_{nonAtFault_i} = \sum_k NB_{k \rightarrow i}$
- $Recoveries_{i \rightarrow k} = \sum Cost_c \cdot \mathbb{1}_{\{i=Responsible_c, k=NonResponsible_c\}}$
- $PaidbyOther_Recoveries_i = \sum_k Recoveries_{k \rightarrow i}$
- $PaidToOther_Recoveries_i = \sum_k Recoveries_{i \rightarrow k}$
- $Balance_i = PaidbyOther_Recoveries_i - PaidToOther_Recoveries_i$

3.2 Expected Payments and Balances

Here below the mains results derived from the assumptions and the definitions:

Result 3.1

$$E[NB_{i \rightarrow k}] = NB_{Claims} \cdot MS_k \cdot \frac{MS_i \cdot PQ_i}{\sum MS_j \cdot PQ_j}$$

Result 3.2

$$E[Balance_i] = NB_{Claims} \cdot M_{market} \cdot MS_i \cdot \left(1 - \frac{PQ_i}{\sum MS_j \cdot PQ_j}\right)$$

We can thus introduce the following quality index:

$$QualityIndex_i = \frac{PQ_i}{\sum MS_j \cdot PQ_j}$$

If this index is greater than 1, insurer i has a relatively poor portfolio quality and will have to pay more claims to the market than it will receive.

3.3 Economics and Decision making within IRA

Under the IRA agreement, insurers receiving at-fault claims must (i) verify liability and coverage, and (ii) compensate the non-liaible insurer within 60 days, or face penalties. We define below the concepts to model the decision making process an agent maximizing its profits.

Management cost

Let CU_i be the unit management cost and λ_i the proportion of timely settled at-fault claims. Then, the management cost is:

$$R_i = CU_i \cdot \lambda_i \cdot NB_{AtFault_i}$$

Satisfaction and Reputation Effects

Non-liaible insurers benefit from timely settlements by liaible insurers via client retention. Let $Goodwill_i$ be the expected unit gain per satisfied client and $NB_{nonAtFault'_i} = \sum_k \lambda_k \cdot NB_{k \rightarrow i}$ the number of such clients. Additionally, a collective market reputation bonus ($GoodWillBonus$) is shared proportionally to the lowest λ_k . The total benefit is:

$$B_i = Goodwill_i \cdot NB_{nonAtFault'_i} + \min_k(\lambda_k) \cdot \frac{1}{I} \cdot GoodWillBonus$$

Penalty

If not all claims are settled on time, insurer i pays a penalty P_i :

$$P_i = (1 - \lambda_i) \cdot p \cdot \sum_{k=1}^I Recoveries_{i \rightarrow k}$$

With p , penalty rate expressed as a percentage of the unit cost per file not processed on time defined within the IRA Convention (e.g: $p = 10\%$)

Net Management Balance

Generally, for each insurer i , at the end of period T , on average, the balance of management costs related to its efforts, penalties to pay, and positive externalities derived from management efforts of other insurers is expressed as follows:

$$ManagementBalance_i = -R_i - P_i + B_i$$

Using macro indicators:

$$\begin{aligned}
E[R_i] &= CU_i \cdot \lambda_i \cdot NB_{Claims} \cdot \frac{MS_i \cdot PQ_i}{\sum_l MS_l \cdot PQ_l} \\
E[P_i] &= (1 - \lambda_i) \cdot p \cdot M_{market} \cdot NB_{Claims} \cdot \frac{MS_i \cdot PQ_i}{\sum_l MS_l \cdot PQ_l} \\
E[B_i] &= Goodwill_i \cdot NB_{Claims} \cdot MS_i \cdot \sum_k \frac{\lambda_k \cdot MS_k \cdot PQ_k}{\sum_l MS_l \cdot PQ_l} + \min_k(\lambda_k) \cdot \frac{1}{I} \cdot GoodWillBonus
\end{aligned}$$

Thus:

$$E[\text{ManagementBalance}_i] = -E[R_i] - E[P_i] + E[B_i]$$

4 Application of Game Theory to the IRA Agreement Framework

4.1 Decision Framework and Game Theory

To analyze the decision-making mechanisms within the framework of the IRA agreement, and without loss of generality, we assume that only two companies operate in the automobile liability insurance market and participate in the agreement.

Using the notations from the theoretical framework, companies A and B have the following characteristics:

- $\{MS_A, PQ_A\}$ and $\{MS_B, PQ_B\}$: the parameters of *market share* and *portfolio quality*, respectively for insurers A and B ,
- $\{CU_A, GoodWill_A\}$ and $\{CU_B, GoodWill_B\}$: the unit management costs per received claim and unit satisfaction benefits per claim sent and processed on time, respectively for insurers A and B .

At the end of period T , considering that the insurers have respectively committed the necessary resources to settle proportions λ_A and λ_B of reported claims, the expected management and externality balances of claims are:

$$\begin{aligned}
E[\text{ManagementBalance}_A] &= -\left(CU_A \cdot \lambda_A + (1 - \lambda_A) \cdot p \cdot M_{market}\right) \cdot NB_{Claims} \cdot \frac{MS_A \cdot PQ_A}{\sum_{l \in \{A, B\}} MS_l \cdot PQ_l} \\
&\quad + GoodWill_A \cdot NB_{Claims} \cdot MS_A \cdot \frac{\sum_{k \in \{A, B\}} \lambda_k \cdot MS_k \cdot PQ_k}{\sum_{l \in \{A, B\}} MS_l \cdot PQ_l} \\
&\quad + \frac{1}{2} \cdot \min(\lambda_A, \lambda_B) \cdot GoodWillBonus
\end{aligned}$$

To simplify further, we assume the companies have two decision levels: settle all claims received on time ($\lambda = 1$) or do not settle them ($\lambda = 0$) within the deadlines set by the agreement. The payoff matrix of this mechanism is as presents in table 1.

4.2 Analysis of Decisions by Players A and B

We begin by analyzing, using simple characteristic examples, the choices made by insurers A and B in the context of the current game by assigning numerical values to the various parameters.

We analyze the interactions between the different decisions of the two insurers and identify the resulting decision levers. To do this, considering the symmetric nature of the payoff matrix and previous notations, we will analyze—conditional on the choice made by Insurer B —the conditions under which the decision $\lambda_A = 1$, i.e., settling claims in a timely manner, maximizes Insurer A 's gain.

If Insurer B decides not to settle claims in a timely manner, i.e., $\lambda_B = 0$: Then Insurer A will opt for $\lambda_A = 1$ provided that:

	$\lambda_B = 1$	$\lambda_B = 0$
$\lambda_A = 1$	$ \begin{aligned} & -CU_A \cdot E[\text{NBAtFault}_A] + E[\text{NBnonAtFault}_A] \cdot \text{GoodWill}_A \\ & \quad + \frac{1}{2} \cdot \text{GoodWillBonus} \quad ; \\ & -CU_B \cdot E[\text{NBAtFault}_B] + E[\text{NBnonAtFault}_B] \cdot \text{GoodWill}_B \\ & \quad + \frac{1}{2} \cdot \text{GoodWillBonus} \end{aligned} $	$ \begin{aligned} & -CU_A \cdot E[\text{NBAtFault}_A] \quad ; \\ & -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_B] \\ & + E[\text{NBnonAtFault}_B] \cdot \text{GoodWill}_B \end{aligned} $
$\lambda_A = 0$	$ \begin{aligned} & -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_A] \\ & + E[\text{NBnonAtFault}_A] \cdot \text{GoodWill}_A \quad ; \\ & -CU_B \cdot E[\text{NBAtFault}_B] \end{aligned} $	$ \begin{aligned} & -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_A] \quad ; \\ & -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_B] \end{aligned} $

Table 1: Payoff matrix depending on λ_A and λ_B

$$\begin{aligned}
& -CU_A \cdot E[\text{NBAtFault}_A] > -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_A], \\
& \Leftrightarrow CU_A < p \cdot M_{\text{market}}. \quad (\text{Condition 1})
\end{aligned}$$

If Insurer B decides to settle claims in a timely manner, i.e., $\lambda_B = 1$: Then Insurer A will choose $\lambda_A = 1$ provided that:

$$\begin{aligned}
& -CU_A \cdot E[\text{NBAtFault}_A] + E[\text{NBnonAtFault}_A] \cdot \text{Goodwill}_A + \frac{1}{2} \cdot E[\text{GoodWillBonus}] \\
& > -p \cdot M_{\text{market}} \cdot E[\text{NBAtFault}_A] + E[\text{NBnonAtFault}_A] \cdot \text{Goodwill}_A, \\
& \Leftrightarrow CU_A < p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_A]} \quad (\text{Condition 2})
\end{aligned}$$

Thus, from *Condition 1* and *Condition 2*, the decisions and Nash equilibria arising from the current game depend on the relative values of:

- (CU_A) compared to $p \cdot M_{\text{market}}$ and $p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_A]}$,
- and (CU_B) compared to $p \cdot M_{\text{market}}$ and $p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_B]}$.

For example, suppose that $CU_A < p \cdot M_{\text{market}}$ and $CU_B > p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_B]}$: this places us in the upper-left corner of Figure 1. In this case:

- If Insurer B chooses $\lambda_B = 0$: from *Condition 1*, Insurer A chooses $\lambda_A = 1$.
- If Insurer B chooses $\lambda_B = 1$: since $CU_A < p \cdot M_{\text{market}} < p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_B]}$, then from *Condition 2*, Insurer A still chooses $\lambda_A = 1$.

Hence, regardless of B's choice, we anticipate that A chooses $\lambda_A = 1$. Assuming A chooses $\lambda_A = 1$ and given that

$$CU_B > p \cdot M_{\text{market}} + \frac{\text{GoodWillBonus}}{2 \cdot E[\text{NBnonAtFault}_B]},$$

then, by symmetry of the problem and based on *Condition 2*, B chooses $\lambda_B = 0$ as it maximizes its gain.

We thus find that in our example, the Nash equilibrium corresponds to Insurer A choosing to settle claims in a timely manner, while Insurer B decides not to.

By proceeding with the same iterative analysis, we obtain the various Nash equilibria summarized in Figure 1.

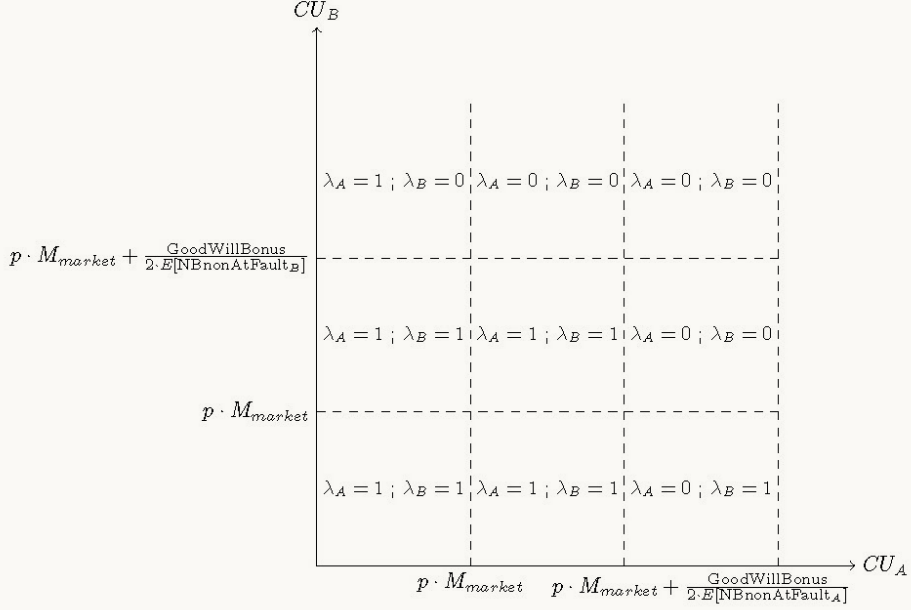


Figure 1: Diagram of Decision

4.3 Analysis of Equilibria Induced by the IRA Convention

The IRA convention has the following core limitations:

- Compliance with settlement deadlines yields no direct benefit to the insurer.
- Reputation losses from non-compliance affect the entire industry, not individual insurers. <

As illustrated by the duopoly model, these features lead to equilibria driven solely by insurers' unit costs of handling at-fault claims (see *Condition 1* and *Condition 2*).

We can the sum up as follow the main findings :

- **Low Unit Cost:** If the unit cost is below the penalty, insurers always choose to settle claims to avoid the sanction. Conversely, when the penalty is null or lacks credibility, no insurer is incentivized to comply.
- **High Unit Cost:** If the unit cost exceeds a certain upper threshold, insurers systematically opt not to settle claims, regardless of the opponent's actions.
- **Intermediate Unit Cost:** When costs fall between the above thresholds, strategic interaction matters:
 - If the competitor's cost is below a critical value (depending on GoodwillBonus and the number of at-fault claims), both settle claims on time.
 - If the competitor's cost is above that value, neither does.

This interdependence reveals a structural weakness in the IRA convention: it requires insurers to infer each other's cost structures.

- **Investment Disincentives:** Under the current framework, there is no economic rationale for insurers to invest in reducing their settlement costs.

4.4 Proposal for an Alternative Mechanism: No Prior Agreement

Description of the Mechanism

Building on the limitations identified in the analysis of the current IRA convention, we propose and analyze the impact of two key changes:

1. **Elimination of prior agreement from the liable insurer:** The non-liable insurer independently determines liability for its own policyholders, based on a set of standardized and transparent rules established by the convention, and proceeds to settle claims accordingly.
2. **Systematic recovery via inter-insurer compensation:** Recourse between insurers is automated and guaranteed through a centralized mechanism.

What are the expected benefits of these modifications?

First, by removing the need for prior agreement, the non-liable insurer assumes full responsibility for the satisfaction of its own policyholders. As a result, it is directly incentivized to ensure prompt and fair claim settlements.

Second, unlike the previous system, where failure to act affected the collective image of the industry, under this revised mechanism, reputational consequences are borne individually. An insurer that fails to meet service expectations damages its own reputation rather than that of the entire market.

In the following sections, we analyze the consequences of these changes on insurers' decision-making.

Payoff Function and Matrix in the Absence of Prior Approval

When prior approval is eliminated, claim management costs fall entirely on the non-liable insurer. In this framework, the components of the payoff function under a duopoly evolve as follows:

- Resource expenditure for management: $R_i = CU_i \cdot \lambda_i \cdot NBnonAtFault_i$
- Benefit from client satisfaction: $B_i = GoodWill_i \cdot \lambda_i \cdot NBnonAtFault_i$
- Economic consequences of client dissatisfaction: $P_i = Badwill_i \cdot (1 - \lambda_i) \cdot NBnonAtFault_i$

The payoff function then becomes:

$$E[ManagementBalance_A] = \left(\lambda_A \cdot Goodwill_A - (\lambda_A \cdot CU_A + (1 - \lambda_A) \cdot BadWill_A) \right) \cdot E[NBnonAtFault_A]$$

Unlike the current IRA scheme with prior approval, the proposed new mechanism makes each actor's payoff independent of their competitor's decisions.

The payoff matrix for settlement decisions ($\lambda_i = 1$) versus non-settlement ($\lambda_i = 0$) takes the following form (see Table 2):

	$\lambda_B = 1$	$\lambda_B = 0$
$\lambda_A = 1$	$(-CU_A + Goodwill_A) \cdot E[NBnonAtFault_A]$; $(-CU_B + Goodwill_B) \cdot E[NBnonAtFault_B]$	$(-CU_A + Goodwill_A) \cdot E[NBnonAtFault_A]$; $-Badwill_B \cdot E[NBnonAtFault_B]$
$\lambda_A = 0$	$-Badwill_A \cdot E[NBnonAtFault_A]$; $(-CU_B + Goodwill_B) \cdot E[NBnonAtFault_B]$	$-Badwill_A \cdot E[NBnonAtFault_A]$; $-Badwill_B \cdot E[NBnonAtFault_B]$

Table 2: Payoff matrix as a function of λ_A and λ_B

Player Decisions and Nash Equilibrium

With the modified game structure, the payoff maximization for Insurer A depends on the relative values of $(-CU_A + Goodwill_A)$ versus $(-Badwill_A)$, regardless of Insurer B's choice.

If $(-CU_A + Goodwill_A) > (-Badwill_A)$, Insurer A will choose $\lambda_A = 1$ and settle non-at-fault claims promptly.

Generally:

- The term $(-CU_A + Goodwill_A)$, representing the net unit benefit from client satisfaction (goodwill minus processing cost), is positive
- The term $(-Badwill_A)$, representing the unit cost of client dissatisfaction, is typically negative

Thus, payoff maximization leads to a unique Nash equilibrium: $(\lambda_A = 1, \lambda_B = 1)$, which is also Pareto optimal.

Advantages of the Mechanism Without Prior Agreement

This mechanism offers several advantages:

- It resolves the conflict between profit motives and timely claim settlement.
- It simplifies decision-making, as each insurer acts independently, without anticipating competitors' costs or strategies.
- It eliminates the need for costly oversight and sanctions.
- It naturally incentivizes insurers to improve operational efficiency, as payoffs decline with higher unit costs.

As a result, the mechanism promotes timely compensation for non-liable claimants and encourages insurers to exceed the 60-day settlement deadline by fostering competition in claim-handling speed.

Implementation Conditions for the Mechanism Without Prior Agreement

Effective implementation requires clear, standardized rules for liability determination by the non-liable insurer to minimize disputes and eliminate the need for prior agreement.

The earlier model assumes minimal delay between settlement and recovery. This is best achieved via a clearinghouse-type system ensuring systematic and timely recourse.

However, combining systematic recourse with this mechanism may create moral hazard: the non-liable insurer, incentivized to satisfy clients without bearing full claim costs, may be less strict on controlling expenses, leading to inflationary drift harmful to both insurers and policyholders.

A suitable solution is flat-rate recovery. In the numerical section, we introduce a method for estimating flat-rate values using Ivorian data and assess their impact on inter-company balances.

5 Data Application

Using 14,354 claims from 20 insurers, we were able to estimate the main parameters of the models:

- MS_i : Estimated via OLS to minimize $\|E[NB_{nonAtFault_i}] - \text{Observed}\|$.
- PQ_i : Estimated via Lagrangian optimization.

Furthermore, using the Fletcher & Reeves (1964) gradient procedure, we estimated the flat-rate amount for exercising recourse that minimizes the gap between the observed real balances and those obtained with a flat-rate recourse.

An assessment of the pertinence of the modeling is given, by the closeness, between:

- the observed balance for each insurance `Solde_reel`
- the theoretic balance `solde_theorique` computed from result 3.2
- the balanced derived from a flat-rate recourse estimated earlier: `Solde_Forfait_Mean`

As we can see, with the graphic 2, the application of the modeling on real data, provides promising results.

6 Conclusion

Motor third-party liability insurance often shapes users' first impressions of the insurance industry. Delays in claim settlements can erode trust and limit growth beyond mandatory coverage. This study analyzed the 2012 rapid indemnification mechanism (IRA) through a game-theoretic lens.

Key features of the current mechanism include:

- A non-liable insurer interacting with the victim, creating opacity in the claim process;
- The liable insurer bearing the settlement burden without direct benefit;

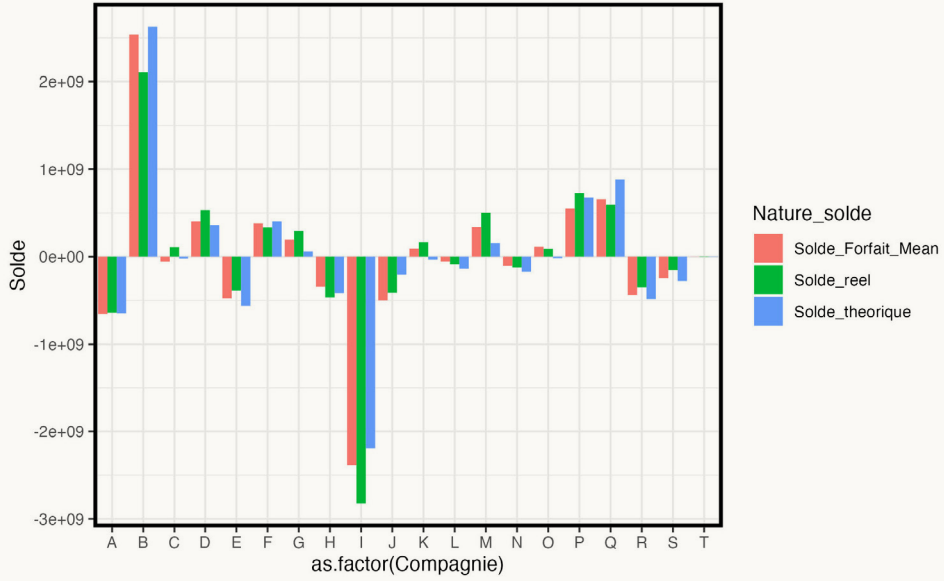


Figure 2: Flat-Rate vs. Actual Cost Balances Across Insurers

- A reputational benefit shared only if all insurers meet deadlines—creating collective interdependence.

This creates a non-cooperative game where individual incentives conflict with collective efficiency. Timely settlements are only rational when penalties are credible and unit costs are low. Otherwise, insurers have limited motivation to invest in efficiency improvements like digitalization.

We propose an alternative mechanism based on:

- Settling claims without prior agreement from the liable insurer;
- Using flat-rate recourse.

This would:

- Align individual and collective interests;
- Eliminate costly enforcement mechanisms;
- Incentivize cost reduction and faster settlements;
- Maintain balanced inter-insurer recoveries.

However, future work is needed. Game-theoretic predictions may diverge from actual behavior, calling for economic experiments. Simulations could also refine the flat-rate's impact and account for delayed recourse costs and variable marginal costs.