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Applying 2025 Nobel Economic Insights to Actuarial Practice in Health Insurance

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Title

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Abstract

While technological disruption often dominates discussions of innovation, sustainable growth in healthcare fundamentally relies on the institutional mechanisms that facilitate the adoption of new knowledge. This paper applies the groundbreaking insights of the 2025 Nobel Prize in Economic Sciences, awarded to Joel Mokyr, Philippe Aghion, and Peter Howitt, to the Australian Private Health Insurance (PHI) sector. Innovation is reframed not merely as novelty, but as the reduction of friction between clinical knowledge and systemic implementation. Growth is conceptualised as an endogenous process, driven by internal institutional mechanisms rather than external technological shocks. In PHI, these mechanisms operate through pricing, benefit design, and risk pooling.

Using preventative care programs as a case study, the paper illustrates how incremental, non-drastic innovations are absorbed and scaled within the PHI system. Actuaries are identified as key mediators of this process, managing uncertainty, aligning incentives, and preserving the stability required for innovations to mature. A simulation model quantifies these dynamics to demonstrate how marginal institutional improvements cumulate into significant long-term gains. The model also shows how actuarial decisions determine whether an innovation contributes to sustainable growth or systemic strain.

By bridging economic theory with practical modelling, the paper provides a coherent framework for analysing institutional adoption. It positions actuaries not as passive responders to innovation, but as active catalysts who enable measurable and durable improvements in healthcare systems.

1. Introduction

The Australian private health insurance (PHI) sector is facing growing pressure on its long-term sustainability. For decades, the industry has largely responded to rising healthcare costs by adjusting prices, rather than influencing the underlying drivers of those costs. As chronic disease burdens rise and premium growth approaches the limits of household affordability, this approach is becoming increasingly difficult to sustain.

At the same time, clinical knowledge continues to expand rapidly, accelerated by developments such as AI-assisted drug discovery and genomic medicine. Yet this expansion has not translated into lower claims trajectories. Many interventions with clear clinical value remain underutilised or slow to scale. This is not simply a neutral wait-and-see dynamic, but reflects the practical barriers that shape how new treatments are adopted in real-world settings.

To remain sustainable, the sector must move beyond historical projections and engage more directly with the institutional factors that determine whether clinical innovation translates into system-level impact.

Innovation and economic growth have long been central to economic, political, and corporate discourse. Yet despite decades of research, a persistent conceptual gap remains between the creation of new knowledge and its systemic adoption. The 2025 Nobel Prize in Economics, awarded to Joel Mokyr, Philippe Aghion, and Peter Howitt, addresses this gap by clarifying the mechanisms through which innovation-driven growth occurs (The Royal Swedish Academy of Sciences, 2025)

Mokyr's seminal work emphasises that the economic value of knowledge lies not in its mere existence, but in its absorption into institutions and productive systems. Complementing this, Aghion and Howitt's theory of endogenous growth demonstrates that long run trajectories emerge from successive, quality-improving innovations. These are propelled by internal incentives and constrained by the threat of obsolescence rather than external technological shocks (Aghion & Howitt, 1990) Collectively, these contributions reveal that growth is not an automatic consequence of discovery. Instead, the impact of innovation depends fundamentally on the institutional mechanisms that translate nascent knowledge into sustained use.

The Australian Private Health Insurance (PHI) sector provides a consequential setting for these principles. Public discourse frequently equates healthcare innovation with new drugs, medical devices, or artificial intelligence (Tulane University School of Public Health, 2024). While these developments are important, focusing only on technology obscures the decisive role of institutions in converting knowledge into measurable outcomes. PHI does not create new medicines or conduct clinical trials; its influence lies in shaping how innovations are financed, priced, and delivered.

This paper addresses a fundamental research question:

How does innovation translate into sustainable system-level growth within PHI, and what role do actuaries play in facilitating that process?

Addressing this question requires bridging conceptual theory, practical implementation, and quantitative modelling. The subsequent analysis is organized into five sections. Section Two defines innovation and endogenous growth in operational terms. Section Three maps these concepts onto the PHI landscape, identifying the specific institutional levers that drive growth. Section Four illustrates these dynamics through a case study of preventative care programs. Section Five introduces a quantitative framework to simulate how actuarial interventions impact economic outcomes. By situating PHI within the context of recent Nobel Prize winning theory, this paper provides a rigorous framework that combines bridges theory with practical actuarial insight.

2. Innovation and Endogenous Growth

While "innovation" and "growth" are widely used terms in both economics and healthcare policy, their meanings are often implicit, imprecise, or misaligned with institutional realities. Before mapping these concepts to Private Health Insurance (PHI), an operational definition is required to align theoretical insights with systemic functions.

2.1 Innovation: From Novelty to Adoption

Innovation is frequently equated with novelty: the introduction of new technologies, products, or methods. In healthcare, this framing often prioritises clinical breakthroughs such as pharmaceuticals, medical devices, or artificial intelligence. (Tulane, 2024) While these developments are significant, defining innovation solely by novelty is analytically incomplete.

Many clinically effective interventions fail to produce system-level impact because they remain confined to pilot programs, face uncertain funding, or conflict with existing reimbursement and regulatory structures. (Actuaries Institute, 2025) Research on hospitals adopting new surgical technologies, for example, shows that even where clinical effectiveness is well established, organisational factors such as team learning, workflow adaptation, and embedded routines can determine whether an innovation becomes integrated into everyday practice or stalls in early use (Edmondson et al., 2001, p. 685). Conversely, modest changes to care pathways, payment arrangements, or administrative processes can generate substantial improvements at scale, despite little technical novelty. The decisive factor is whether knowledge can be adopted reliably and consistently.

This observation motivates a critical distinction. Invention and innovation are not synonymous. Invention refers to the creation of new ideas, techniques, or technologies. Innovation refers to the successful embedding of those ideas into economic and institutional practice. An invention may demonstrate technical feasibility yet remain economically inert if it cannot be financed, integrated, or sustained. Innovation, by contrast, is revealed through diffusion, durability, and use. To illustrate how new knowledge translates into system-level impact, it is useful to represent this distinction as a simple process:

Figure 1: From knowledge to system impact

As illustrated in Figure 1, the economic value of knowledge does not arise at the point of discovery, but through its successful adoption and integration into practice. At each stage, there are points where this translation can stall, preventing new ideas from generating measurable system-level impact.

Understanding why these breakdowns occur, and what enables knowledge to be reliably absorbed and scaled, is central to long-run economic growth.

Joel Mokyr's historical analysis of long-run economic growth illustrates why the distinction between invention and innovation matters. Many societies generated significant inventions long before the Industrial Revolution, yet experienced little sustained improvement in productivity or living standards (Mokyr, 2005). What changed was not invention alone, but the emergence of systems capable of absorbing, explaining, refining, and recombining knowledge over time. Central to this process is the difference between propositional knowledge, or "knowing that," and prescriptive knowledge, or "knowing how." Propositional knowledge explains why techniques work, enabling learning and adaptation. Without it, innovations remain fragile, difficult to transfer, and hard to scale.

Mokyr further differentiates between macro-inventions, which are major conceptual breakthroughs, and micro-inventions, which consist of incremental refinements and organisational improvements. Long-run growth is driven primarily by micro-inventions, as they embed new ideas into routine practice. Knowledge alone is insufficient for sustained growth; institutions must be capable of absorbing, adapting, and recombining that knowledge. Cultural openness, scientific explanation, and institutional flexibility jointly determine whether innovations diffuse or stagnate.

These insights converge on a central economic mechanism: access costs. (Mokyr, 2005) Innovation fails not because knowledge does not exist, but because financial, institutional, behavioural, or informational costs of adoption are too high. From this perspective, innovation is less about creating new ideas than about lowering the barriers that prevent existing knowledge from being used consistently and at scale. Accordingly, this paper adopts the following operational definition:

Innovation is a sustained reduction in friction between knowledge and adoption.

In PHI, this definition is essential. Insurers do not invent technologies; their influence lies in shaping whether existing knowledge can be funded, priced, and embedded into the system.

2.2 Endogenous Growth: The Dynamics of Creative Destruction

Traditional economic models often treat growth as exogenous, a byproduct of external technological shocks. Aghion and Howitt's model of creative destruction rejects this passive view, formalising growth as an internally generated, stochastic process (Aghion & Howitt, 1990). Successive quality-improving innovations are driven by competition for temporary monopoly rents, making long-run growth endogenous to the system's incentives.

At the core of this model is creative destruction. Growth does not proceed smoothly but through discrete improvements. Each successful innovation raises productivity by improving an existing product or process. The innovator gains temporary monopoly power, capturing rents, while the previous incumbent's technology becomes obsolete. Creation and destruction are therefore inseparable features of the growth process. To illustrate how these dynamics translate into a cumulative growth process, it is useful to represent endogenous growth as a reinforcing cycle:

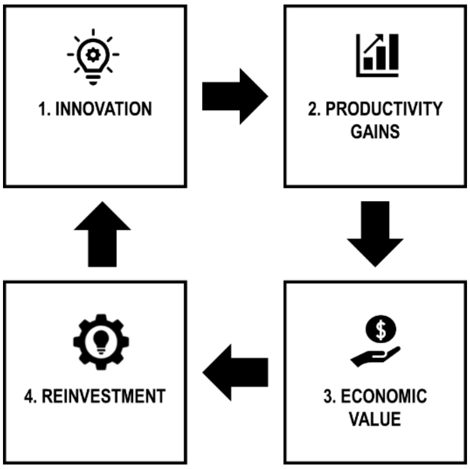


Figure 2: The endogenous growth cycle

As illustrated in Figure 2, growth emerges through a self-reinforcing cycle. Innovations improve productivity, generating economic value that can be reinvested into further innovation. This cumulative process underpins sustained improvements over time, rather than one-off gains.

Investing in innovation involves trade-offs across time. Expectations of future innovation can reduce current profits by shortening the duration of monopoly rents and increasing future costs, a phenomenon known as the “business-stealing” effect. Strong expectations of future innovation can dampen current investment, potentially producing cycles or stagnation. Growth is not automatic; it depends on how institutions manage incentives over time.

Institutions play a central role as active shapers of growth trajectories. Some degree of market power is necessary to incentivise innovation, yet unregulated competition can generate inefficiencies. Knowledge spillovers may leave private investment too low, while business-stealing effects can produce excessive or misdirected innovation. Sustained growth therefore requires institutional arrangements that balance these opposing forces.

Translated into the PHI environment, endogenous growth can be defined as follows:

Growth in PHI is endogenous when the system actively generates and absorbs knowledge-enhancing innovations.

Under this definition, growth is not simply an increase in revenue or membership. It reflects sustained improvements in system performance, such as better health outcomes per unit of expenditure (Porter, 2010, p. 2477) and stronger long-term financial sustainability. These gains arise through successive quality improvements in care models, contracts, and risk assessment practices.

2.3 Linking Innovation and Growth

Innovation and endogenous growth are inseparable within an institutional framework. When friction between knowledge and adoption is reduced, the system accumulates capability and resilience over time. In PHI, growth depends on successful adoption: even high-quality clinical discoveries remain economically inert if pricing models or benefit designs misalign incentives.

This linkage establishes the foundation for the remainder of the paper. Having defined innovation and growth in institutional terms, it becomes clear that Mokyr’s emphasis on reducing access costs is precisely the mechanism through which the PHI system can foster quality-improving innovations. These access costs represent the financial, institutional, behavioural or informational barriers to adoption described by Aghion and Howitt. In practice, these barriers emerge through decisions such as how premiums are set, which services are funded, and how provider incentives are structured, each of which can either facilitate or impede the adoption of new models of care.

By systematically lowering these frictions, actuaries enable the continuous embedding of new knowledge. This process transforms inert discovery into the engine of endogenous growth. The following sections examine how actuarial mechanisms transmit this new knowledge into system-level outcomes, demonstrating how incremental innovations accumulate into sustainable growth.

3. Actuarial Levers of Endogenous Growth

This section applies innovation and growth concepts to Private Health Insurance (PHI). PHI is often seen as a passive financing layer that sits downstream of medical innovation. In practice, it actively mediates growth through actuarial judgement. Actuaries translate clinical uncertainty and stochastic variation into pricing, benefit design, and risk-pooling decisions, determining which innovations are absorbed, marginalised, or rejected. These choices shape whether innovations survive initial adoption and contribute to long-term system performance.

3.1 The Actuary as a Transmission Mechanism for Innovation

Innovations, whether clinical, digital, or organisational, must pass through institutional filters before they affect system-level outcomes. These filters are defined by actuarial decisions. By setting prices, designing benefits, and managing risk pools, actuaries determine which innovations are funded, scaled, or constrained. This role makes actuaries the key transmission mechanism between discovery and measurable growth.

The constraints they navigate are rarely technological. Relevant medical knowledge often already exists, but adoption depends on institutional compatibility. By aligning incentives, managing risk, and structuring financial decisions, actuaries convert potential innovation into system-level improvements. Without this mediation, even highly promising innovations may remain economically inert.

3.2 Actuarial Levers of Endogenous Growth in PHI

Within PHI, endogenous growth operates through three interrelated institutional levers: pricing, benefit design, and risk pooling. Each corresponds to an access cost in the sense described by Mokyr, and each is shaped by actuarial decisions that determine how the system responds to new information. Together, these levers define the institutional capacity to absorb uncertainty and enable cumulative learning.

In practice, these levers are not applied in isolation, but through a series of trade-offs. Actuarial decisions frequently involve balancing short-term financial stability against long-term system performance, or managing uncertainty in ways that either enable or constrain the adoption of new models of care. These trade-offs determine whether the mechanisms of endogenous growth are realised or suppressed.

3.2.1 Pricing: Absorbing or Rejecting Uncertainty

Pricing is often framed as a technical exercise involving the estimation of expected claims, regulatory compliance, and margin setting. From an endogenous growth perspective, pricing plays a deeper role by determining whether uncertainty is absorbed by the system or rejected.

When a new intervention is introduced, such as a preventative care program or a digital monitoring solution, the institutional question is whether it can be funded at scale under conditions of incomplete information. Premium levels, risk margins, and sustainability constraints jointly shape the adoption path of the innovation. These factors determine whether a new method diffuses across the membership, remains confined to lower-risk or higher-income segments, or destabilises the risk pool to the point of withdrawal.

Mispricing raises access costs even when solvency is maintained. Under-pricing leads to short-term volatility that undermines institutional confidence, while over-pricing suppresses uptake and stalls learning. In both cases, innovation fails to translate into sustained growth.

Pricing therefore functions as a learning mechanism within the institution: repeated success in absorbing uncertainty enables cumulative improvement, while repeated failure blocks the endogenous growth process. This mechanism acts as a quality ladder (Boldrin & Levine, 2009). allowing the insurance system to tolerate short-term volatility in exchange for structural long-run improvements.

3.2.2 Benefit Design: Translating Knowledge into Action

If pricing determines whether uncertainty is tolerated, benefit design determines whether knowledge becomes operational. Clinical guidelines, trial results, and expert consensus represent propositional knowledge. On their own, they do not alter behaviour. They must be translated into concrete institutional rules governing eligibility, reimbursement structures, waiting periods, and caps, limits, or exclusions.

Each design choice embeds assumptions about behavioural response, moral hazard, selection effects, and long-term cost trajectories. Benefit design therefore acts as a translation layer between knowledge and action.

From an institutional standpoint, compatibility is critical. Some innovations improve average outcomes but increase variance, while others reduce variance without materially improving means. The former may be clinically impressive yet institutionally destabilising. The latter may appear incremental but prove transformative when deployed at scale. This dynamic explains why healthcare innovation often appears slow. The constraint is not technical feasibility, but alignment with existing institutional structures. (Greenhalgh et al., 2017) Effective benefit design lowers these barriers, reducing access costs and enabling innovation to reach the scale where compounding returns begin.

3.2.3 Risk Pooling: Enabling Intertemporal Learning

Endogenous growth requires time for learning and benefits to be realised. Many healthcare innovations involve high upfront costs, delayed returns, and uncertain long-run effects. The ability of PHI to pool risk across individuals and over time is therefore central to adoption.

Actuarial decisions relating to product mix, membership retention, and capital buffers directly affect the system's capacity to absorb early losses and sustain experimentation. When intertemporal risk pooling is weak, innovations with delayed benefits are systematically rejected, even when their long-run value is substantial. Growth breaks down when learning cannot be sustained long enough for benefits to materialise.

3.3 System-Level Implications and Transition

This framework establishes that endogenous growth in Private Health Insurance emerges through actuarial mediation of uncertainty. Pricing determines whether uncertainty is absorbed or excluded. Benefit design translates clinical knowledge into operational rules. Risk pooling provides the temporal stability required for learning to occur. Together, these mechanisms determine whether innovation becomes embedded in the system or remains economically inert.

Growth therefore depends not only on the existence of medical innovation, but on the institutional capacity to absorb and sustain it. When actuarial structures align incentives, manage volatility, and support intertemporal learning, incremental innovations accumulate into measurable improvements in system performance. Conversely, when uncertainty is mispriced, incentives are misaligned, or risk pooling is insufficient, adoption stalls and endogenous growth breaks down.

This perspective reframes actuarial practice as a structural component of the growth process rather than a purely technical or defensive function. Actuarial decisions shape the conditions under which innovation can diffuse, scale, and generate long-term value. The following sections operationalize this framework, first through a practical case study and then via a formal simulation model, illustrating how actuarial decisions influence the long-run growth trajectory of the insurance system.

4. Practical Example: Preventative Care Programs in Private Health Insurance

The abstract mechanisms of institutional mediation become most visible when examined through a concrete application. Preventative care programs, particularly those targeting chronic disease, offer a clear illustration of how innovation, actuarial mediation, and endogenous growth interact within the insurance environment. These programs serve as a test case for the theory that growth is a function of institutional absorption rather than mere clinical discovery.

Preventative interventions are rarely radical technological breakthroughs. They typically extend existing clinical knowledge through incremental, data-enabled improvements. Despite their limited technical novelty, they can materially alter long-run cost trajectories and health outcomes. Their success in a private insurance setting depends less on medical innovation and more on institutional design by lowering access costs of the intervention through superior pricing, benefit structures, and risk management.

4.1 The Innovation: A Digital Lifestyle Intervention for Type 2 Diabetes

To ground the theory, consider a representative preventative care innovation: a digital Diabetes Prevention Program (DPP) targeting members with pre-diabetes. This DPP, while not a novel clinical discovery, represents an innovation in delivery, combining remote biometric monitoring, personalized digital coaching, and predictive behavioral nudges.

As per Mokyr’s insights, the propositional knowledge underpinning this intervention (e.g., nutritional science, behavioral psychology) is well-established. The critical challenge, therefore, lies in reducing the access costs associated with converting this theoretical knowledge into prescriptive knowledge that members consistently apply in their daily lives.

The Clinical Evidence Base

The Diabetes Prevention Program Outcomes Study (DPPOS) (2015) demonstrates that participants who avoid disease progression experience approximately 28% fewer microvascular complications. For the actuary, this efficacy is not a "step function" but a long-term decay of risk. By preventing the transition from pre-diabetes to Type 2 diabetes, the insurer is effectively managing the drift of the individual claims trajectory of the member.

The Economic Friction

The institutional hurdle is the asymmetry of cash flows. The program requires a substantial upfront investment in "actuarial rails" including IT integration, data privacy frameworks and clinical monitoring. These costs are certain and immediate. Conversely, the financial benefits are delayed, stochastic and contingent on member adherence.

Without actuarial mediation, this asymmetry leads to innovation rejection, which is the natural immune response of the system to short-term margin volatility. The decisive factor is not whether the program works clinically, but whether the PHI framework can internalise these access costs and bridge the learning phase.

4.2 Pricing and Risk Adjustment: Funding Innovation Under Uncertainty

The first institutional hurdle to adopting an innovation like the Diabetes Prevention Program (DPP) is pricing. The insurer must determine how the program can be integrated without destabilising the risk pool or compromising financial stability.

To anchor this scenario, the model's logic is informed by established digital health benchmarks for the DPP. For example, an institutional access cost of $200 per member per year serves as a representative friction point, weighed against a projected claims offset of $1,000 per member by Year 5. Applying an initial enrolment projection of 30% for the eligible cohort would further illustrate the deliberate actuarial 'margin of safety' used to account for behavioural friction within our structural assumptions.

The Actuary as Governor

Actuaries must translate these uncertain and delayed savings into present-day pricing structures. This requires discounting future benefits, modelling partial uptake and allowing for significant model uncertainty. In effect, the actuary determines the institutional cost of the "learning phase" required for the DPP to mature.

If premiums are increased too sharply to cover the $200 access cost, participation in the diabetes intervention may fall and the projected health benefits will not materialise. Conversely, if premiums are not adjusted to reflect the upfront investment, early losses may undermine financial sustainability. Pricing therefore acts as a filter. It determines whether the uncertainty of the DPP is absorbed by the system or rejected at the gate.

A calibrated pricing approach allows the insurance system to tolerate short-term volatility in exchange for structural long-run improvements, effectively governing entry into the institutional quality (Boldrin & Levine, 2009) ladder. An overly restrictive filter, driven by a 12-month margin focus, leaves clinically effective knowledge outside the system. By correctly pricing the intervention, the actuary is not just balancing a budget; they are permitting the system to learn and evolve.

4.3 Benefit Design and Incentive Alignment: From Evidence to Behaviour

Even if pricing permits the program to exist, benefit design determines whether members actually adopt it. For the Diabetes Prevention Program, this lever defines the rules of participation. Key considerations include whether enrolment is voluntary or automatic, the calibration of financial incentives such as subsidised wearable devices and the management of adverse selection risks.

Managing the Selection Hurdle

Benefit design is the tool used to manage the participation asymmetry of innovation. In a diabetes intervention, if the program attracts only those members with advanced complications, short-term claims costs will rise without the benefit of prevention. Conversely, if enrolment is skewed towards low-risk cohorts who would not have progressed to chronic disease regardless of the intervention, the program may fail to generate a meaningful reduction in the total claims pool. Actuaries must, therefore, simulate how incentive structures, such as premium discounts for program adherence, influence uptake and claims trajectories among high-risk cohorts, thereby managing selection bias.

Behavioural Engineering

Benefit design translates clinical evidence into human behaviour. For the diabetes program, it embeds assumptions about how a member will respond to digital nudges or coaching. Within an endogenous growth framework, poor design acts as institutional friction that raises adoption costs. A complex referral process for a digital platform can stifle participation regardless of the clinical merit.

Effective design lowers these barriers and enables innovation to reach the scale where compounding returns begin. By aligning individual member interests with the long-term sustainability of the risk pool, the actuary ensures that the prescriptive knowledge of diabetes management is actually put into practice.

4.4 Risk Pooling and Intertemporal Stability: Carrying the Learning Phase

Preventative programs like the Diabetes Prevention Program (DPP) rarely generate immediate financial returns. Their benefits emerge gradually, often over several years. The ability of Private Health Insurance (PHI) to pool risk across individuals and over time is therefore central to their survival.

Cross-Subsidisation and the DPP

Early-stage costs, such as the initial platform setup and coaching for the DPP, must be absorbed through cross-subsidisation, capital buffers and stable retention assumptions. Within the Australian community-rated environment, younger and healthier members implicitly subsidise the early losses of these programs. In turn, older cohorts or those at high risk realise the clinical and financial benefits at a later stage.

The Financial Bridge

Actuarial assumptions regarding lapses, demographic shifts and capital adequacy determine whether this intertemporal transfer is feasible. If projected long-term claims reductions from the DPP cannot justify the immediate $200 per-member expenditure, the program lacks the financial stability required to mature.

Without sufficient intertemporal stability, interventions may be terminated prematurely, even when they are welfare-improving in the long run. Many healthcare innovations fail for this reason. They do not fail because they lack clinical merit, but because the system cannot sustain the learning phase required for their value to emerge. The actuary’s role is to ensure the "learning phase" is protected, allowing the program to transition from an experimental cost to a structural asset.

4.5 Cumulative, Non-Disruptive Growth in Action

This example demonstrates how non-drastic innovation functions within the Australian insurance context. Rather than making current treatments obsolete, the DPP builds incrementally on existing chronic disease protocols. Its goal is to reduce systemic friction by helping patients align their daily behaviour with long-term health goals. This is a process that stabilises rather than disrupts the insurance pool.

The Feedback Loop of Institutional Learning

The impact of such interventions is cumulative. While initial results may be modest, the system gradually experiences lower long-term claims growth and superior health outcomes. These gains are powered by institutional learning. As data on patient adherence flows back into actuarial models, the insurer can refine pricing and benefit designs with higher precision. This increased accuracy reduces the access costs for the next wave of innovation, such as a heart health or mental wellbeing program.

Resilience through Incrementalism

In this framework, growth does not depend on a single, unpredictable medical breakthrough. Instead, it emerges from the repeated, successful adoption of small improvements. By encoding these successes into the actuarial framework, the insurer creates a path for endogenous growth. This path is resilient to the volatility of clinical trials or sudden technological shifts.

4.6 Synthesis: The Actuarial Conversion of Knowledge

The Diabetes Prevention Program could exist indefinitely as a pilot study or research initiative without ever transforming the broader system. What converts a clinical experiment into endogenous growth is institutionalisation: the formal integration of that knowledge into pricing, benefit design and risk pooling.

Actuaries are the primary agents of this conversion. By mediating uncertainty and aligning financial incentives, they translate isolated clinical knowledge into financially sustainable, system-level improvement.

This case illustrates the core claim of this paper. In Private Health Insurance, growth is not driven by innovation alone. It depends on the institutional mechanisms that allow innovation to scale, persist and compound. The transition from evidence to institutional embedding marks the point at which the insurance system begins to learn. The following section formalises these dynamics through a 10-year simulation model, making this process of endogenous growth observable and testable.

5. Illustrative Simulation: The Opportunity Cost of Actuarial Caution

To quantify the strategic impact of proactive actuarial mediation and formalise the theoretical arguments presented, we introduce a stochastic 10-year comparative regime simulation. The model assumes initial annualised claims of $500 million and examines the divergence between two contrasting management philosophies over a decade. This model, distinct from a conventional claims inflation forecast, is designed to illustrate how an actuary's philosophical stance towards innovation, ranging from passive acceptance to active institutional shaping, fundamentally alters the long-term structural path of healthcare system costs. By subjecting two contrasting management philosophies to identical stochastic claims environments, we make the trade-offs of institutional design observable, testable, and ultimately, priceable.

Defining the Two Regimes

The simulation pits a Passive Management Regime against an Active Innovation Portfolio.

- In the **Passive Regime**, the actuary treats innovation as an external clinical shock. Pricing is reactive, and the primary focus is on 12-month margin protection. Programs requiring material upfront investment are typically rejected or heavily discounted due to their immediate impact on financial results and capital margins. Consequently, the system remains on its original inflation trajectory, absorbing external shocks without altering its underlying cost structure.

- In the **Active Regime**, the actuary treats innovation as an internal quality ladder. The unit economics of the Diabetes Prevention Program (DPP), as calibrated in Section 4, are scaled across a broader portfolio of interventions. This regime assumes that the insurer actively invests in the institutional rails required to lower access costs over time.

Beyond the Point Estimate

By subjecting both regimes to the same stochastic claims environment, we can observe more than just the expected savings. We can observe the structural resilience of the fund. We test whether the perceived safety of the passive approach is actually a long-term solvency risk. Conversely, we examine whether the volatility of the active approach is the necessary price of endogenous growth. This model makes the trade-offs of institutional design observable, testable and, ultimately, priceable.

The central trade-off is between short-term financial caution and long-term system improvement. The Passive Regime preserves near-term margins but leaves the underlying claims process unchanged. The Innovation-Aware Regime accepts temporary investment and volatility in exchange for a lower drift path, reduced uncertainty, and stronger long-run affordability. The simulation makes this trade-off observable by showing how the same clinical opportunity produces different cost trajectories depending on the actuarial stance taken.

5.1 The Mathematical Engine: Endogenous Parameter Mediation

Aggregate claims expenditure (C_t)is modelled as a time-inhomogeneous Geometric Brownian Motion:

$$C_{t+dt} = C_t \exp\left[(\mu(t) - \frac{1}{2}\sigma(t)^2)dt + \sigma(t)dW_t\right]$$

This formulation captures two core actuarial realities: the multiplicative nature of medical cost inflation and the compounding of uncertainty over time.

Endogenising the Parameters

The key refinement in this model is that the drift $\mu(t)$and volatility $\sigma(t)$are no longer treated as purely external constants. Instead, they become endogenous functions of actuarial intervention and the level of prescriptive knowledge

Each innovation, such as the Diabetes Prevention Program, gradually lowers the underlying inflation trend through prevention and care coordination. Simultaneously, improved monitoring and feedback loops reduce volatility by increasing system predictability. In this model, the actuary is not merely a passive observer of a random walk. They are actively "shaping the drift" of the claims process.

The parameter assumptions used in this simulation are stylised but grounded in industry-relevant ranges. The baseline drift and volatility (μ = 5.0%, σ = 10%) reflect typical private health insurance claims inflation and uncertainty observed in practice. The magnitude and timing of intervention effects are informed by the case study in Section 4 and comparable preventative health programs, which demonstrate gradual reductions in cost growth and variability over multi-year implementation periods. While simplified, these assumptions are intended to capture the directional impact of actuarial intervention rather than provide precise forecasts.

Figure 3 illustrates the causal chain in the simulation: how actuarial decisions influence parameter dynamics, which in turn shape the trajectory of claims over time.

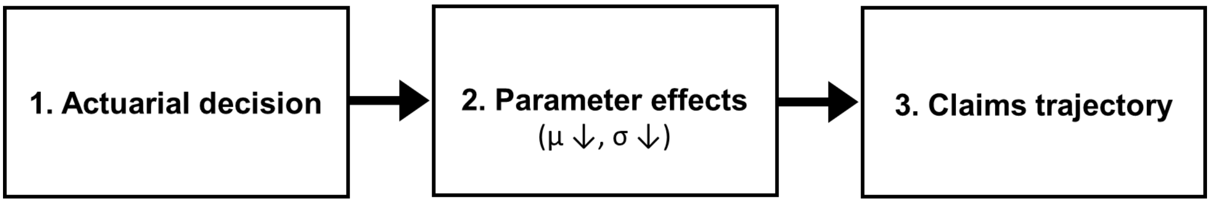


Figure 3: Linking actuarial decisions to claims outcomes

As shown, proactive actuarial mediation alters both the expected growth rate and uncertainty of claims, demonstrating how institutional decisions translate into long-term structural outcomes.

Implementation and Learning Ramps

These effects are applied with realistic implementation ramps of two to three years. This produces a smooth and credible "bending of the cost curve" rather than an abrupt or unrealistic collapse. By incorporating cumulative learning effects, the model reflects the reality that the second and third innovations in a portfolio are cheaper and more effective to implement than the first.

5.2 Scenario Design: Passive Acceptance vs Active Mediation

The simulation contrasts two actuarial approaches confronting the same clinical and technological opportunities. These scenarios illustrate the difference between managing a static pool and cultivating a learning system.

1. The Traditional Regime (Passive Payer)

In this scenario, the actuary adopts a philosophical stance where inflation and uncertainty are viewed as external forces. Their primary role is to observe these forces and ensure adequate provisioning.

Under this regime, the parameters $\mu = 5.0\%$ and $\sigma = 10\%$.are held constant throughout the 10-year period. Programs requiring material upfront investment are typically rejected or heavily discounted because of their immediate impact on financial results and capital margins. Consequently, the system remains on its original inflation trajectory, absorbing external shocks without altering its underlying cost structure.

2. The Innovation-Aware Regime (Actively Mediated)

In this scenario, the actuary believes they can deliberately influence the parameters of the claims process. Targeted investments in health innovation are treated as structural capital rather than mere expenses. The mechanism for growth is the introduction of successive innovations with configurable timing and learning effects. This model includes two specific interventions:

- **Year 1 (Preventative and Triage):** A $50 million investment in a platform-wide intervention. This gradually reduces drift and volatility by over a two-year ramp period.
- **Year 5 (Chronic Disease Management):** A $30 million investment in targeted care coordination. The lower cost reflects the reuse of established data infrastructure and actuarial capability built during the first phase. This further reduces drift and volatility over a 3-year ramp-up period, benefiting from the institutional learning established by the first innovation.

Structural Constraints and Resilience

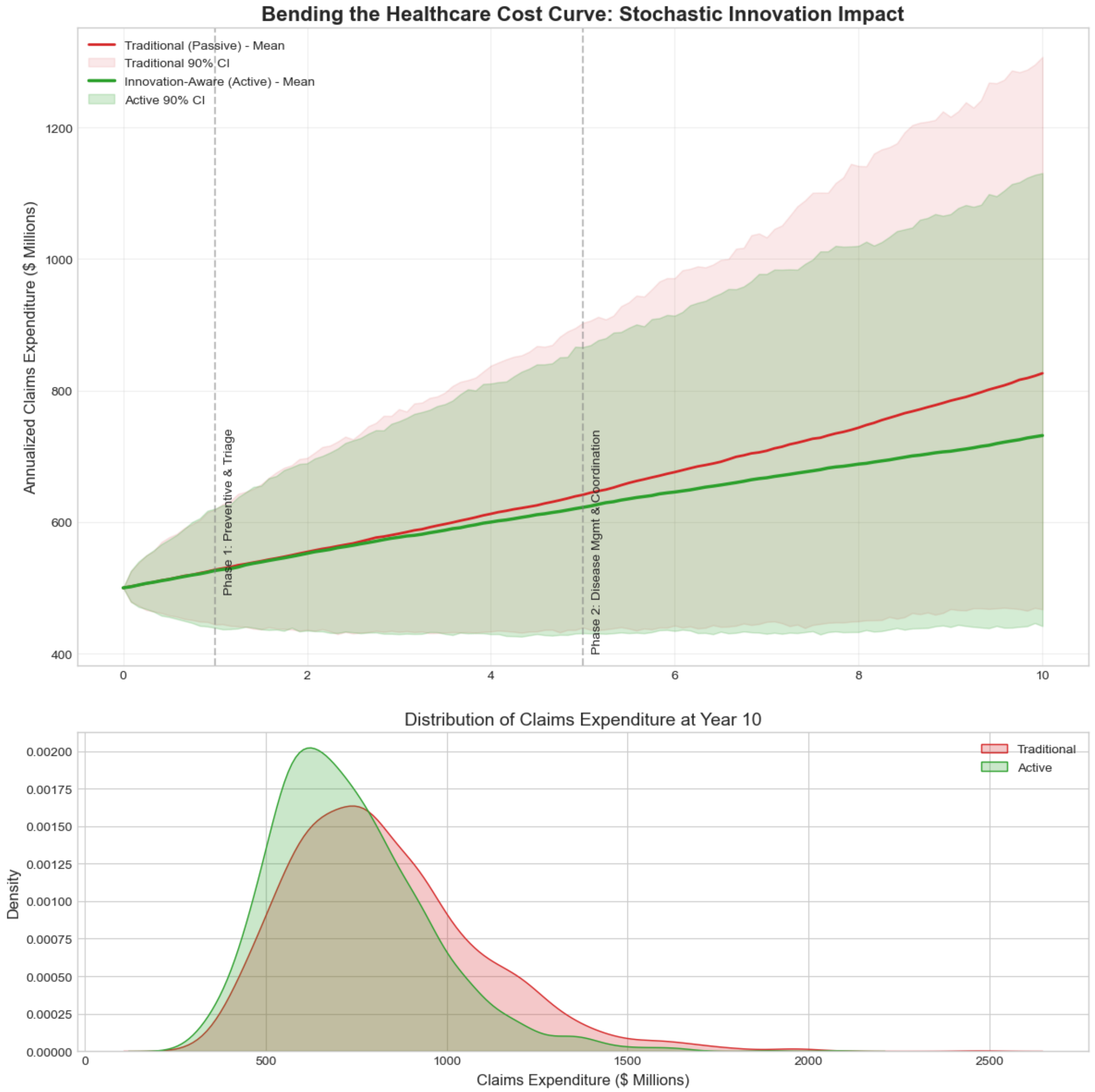
To ensure the simulation remains grounded in reality, parameter floors are enforced at $(\mu \geq 1.5\%, \sigma \geq 5\%)$These constraints reflect persistent demographic, utilisation and technological pressures that cannot be fully eliminated through management alone. Furthermore, the model incorporates a selection bias factor, acknowledging that the initial uptake of an innovation might be skewed towards certain member cohorts, potentially reducing its aggregate effectiveness until institutional learning mitigates this effect.

5.3 Simulation Results and Discussion

The simulation, incorporating stochastic innovation effects and selection bias, provides compelling evidence for the long-term benefits of an actively mediated approach to innovation. The results clearly demonstrate that while the Traditional (Passive) regime experiences a steady increase in claims expenditure, the Innovation-Aware (Active) regime successfully bends the cost curve, leading to significant savings over the 10-year horizon.

Key Simulation Metrics:

Metric	Traditional (Passive)	Innovation-Aware (Active)
Mean Claims at Year 10	$826.19m	$731.58m
Cumulative Cost (10yr)	$6.49b	$6.28b
Reduction in Year 10 Claims	N/A	11.45%
Volatility (90% CI Spread) at Year 10	$839.74m	$688.65m
Net Present Value of Innovation Strategy (applying 4% discount rate)	N/A	$210.61m



Years 0 to 3: Investment and Ramp Phase

Both paths initially track closely. The Innovation-Aware scenario absorbs the first $50 million investment while the clinical and operational effects are still emerging. During this period, total expenditure is temporarily higher. However, the underlying claims growth rate has already begun to slow. This represents the "learning phase" where the insurer pays for the creation of new prescriptive knowledge.

Years 3 to 6: Divergence Phase

As the first intervention reaches maturity and the second program begins, the trajectories separate. The Innovation-Aware curve continues to rise but at a visibly slower rate. The system begins to realise the compounding benefits of reduced drift. Because the second intervention is cheaper to implement, the "investment hump" is less pronounced, and the net savings begin to accumulate more rapidly.

Years 6 to 10: Structural Advantage Phase

The cumulative effect of lower drift and reduced volatility becomes clear. By Year 10, mean claims expenditure in the Innovation-Aware scenario is approximately 11% lower than the Traditional path. Crucially, the confidence bands are also narrower. This reflects improved predictability and a reduced need for extreme capital buffers against volatility.

The Cumulative Outcome

On a cumulative 10-year basis, including the $80 million of targeted investments, the Innovation-Aware strategy delivers net savings of approximately $210 million. The $210 million in net savings represents more than a 2.5× return on our innovation capital. More importantly, by Year 10 the strategy structurally lowers the annual claims run-rate by over 11% relative to the passive trajectory, helping secure long-term affordability. This advantage does not emerge from one-time effects or lucky clinical breaks. Instead, it is the result of structural change. The actuary has successfully converted short-term capital into long-term systemic health, demonstrating that the "cost" of innovation is actually an investment in the sustainability of the risk pool.

5.4 Interpretation: Why Apparent Caution Can Become Strategic Risk

This simulation challenges the conventional definition of actuarial prudence. A decision that appears financially conservative in a single year, such as avoiding upfront investment, locks the organisation into a steeper long term cost trajectory. Over time, this approach becomes both more expensive and more risky.

Actuarial mediation reframes the actuary’s role. Instead of passively measuring healthcare cost inflation, the actuary actively shapes its trajectory. By influencing the parameters governing claims growth, the actuary moves from reporting costs to governing system affordability.

The visible learning dividend, reflected in lower costs and more efficient deployment of subsequent innovations, highlights a deeper organisational dynamic. Insurers that invest in actuarial capability and infrastructure become progressively more effective at improving system efficiency.

In an environment of sustained medical cost pressure, the highest value actuarial function is no longer limited to measuring the cost of disease with precision. It is to design, price, and enable systems that reduce the cost of producing health.

6. Conclusion

6.1 Limitations

Several limitations should be acknowledged. The modelling framework is intentionally simplified, abstracting from member-level heterogeneity, regulatory constraints, and detailed behavioural responses. This improves transparency and interpretability but limits predictive specificity. The numerical illustrations also rely on hypothetical parameters rather than empirical PHI data, as the simulation is intended to illustrate structural dynamics rather than forecast realised outcomes. In addition, innovation adoption is represented implicitly through changes in growth parameters, whereas in practice adoption is shaped by complex behavioural, organisational, and regulatory factors.

These limitations define the scope of the analysis. The framework is designed to clarify mechanisms and relationships, providing a conceptual and quantitative illustration of how institutional mediation can shape system trajectories.

6.2 Final Remarks

This paper has argued that growth in private health insurance systems is not driven solely by external forces such as demographics, medical breakthroughs, or macroeconomic conditions. It also emerges from within the system itself, through the institutional mechanisms that determine how knowledge is adopted and sustained in practice. Drawing on the insights of Mokyr, Aghion, and Howitt, innovation is therefore understood not simply as invention, but as the sustained reduction of friction between knowledge and its implementation.

This perspective helps explain a persistent paradox in healthcare. Many interventions demonstrate clear clinical efficacy yet fail to produce meaningful system-level impact. The constraint is rarely the absence of knowledge. More often it is the presence of access costs and institutional frictions that prevent adoption.

Within PHI systems, actuarial functions play a central role in reducing these frictions. Pricing, benefit design, and risk pooling allow uncertainty to be carried across populations and across time, enabling new interventions to be introduced without destabilising financial sustainability. In doing so, actuarial mediation allows incremental improvements to accumulate into durable system level change.

The simulation framework illustrates how these dynamics compound over time. Small differences in growth trajectories, once sustained, produce material long-term differences in claims costs. The significance of innovation therefore lies less in dramatic one off breakthroughs than in gradual shifts in system behaviour that alter the long run cost path.

Viewed through this lens, actuarial practice becomes part of the growth process itself. By translating uncertainty into sustainable financial pathways, actuaries help determine whether innovation remains theoretical or becomes embedded in the long-term evolution of the system. Sustainable growth in private health insurance therefore depends not only on medical progress, but on the institutional capacity to absorb and sustain innovation.

Translating these insights into practice, several implications emerge for actuaries and insurers. Investing in data infrastructure and feedback systems enables more precise measurement of outcomes and reduces uncertainty around innovation adoption. A calibrated approach to innovation risk, balancing short-term caution with long-term system benefits, can prevent structural cost escalation. Embedding actuarial judgement into product and benefit design ensures that pricing, coverage, and risk-pooling decisions actively facilitate the diffusion of high-value interventions. Finally, recognising the compounding effect of successive innovations encourages proactive management, as each successful intervention lowers access costs and improves the effectiveness of future initiatives.

Appendix

The following Python code was used to generate the simulation results presented in Section 5.

```
import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

# Set seed for reproducibility

np.random.seed(42)

# ---------------------------------------------------------

# Parameters

# ---------------------------------------------------------

C0 = 500_000_000  # Initial claims pool ($500M)

time_horizon = 10

steps_per_year = 12

dt = 1.0 / steps_per_year

n_steps = int(time_horizon * steps_per_year)

time = np.linspace(0, time_horizon, n_steps + 1)

num_simulations = 2000  # Increased for better distribution

# Base parameters (Traditional Regime)

mu_base = 0.05

sigma_base = 0.10

# Innovation parameters (Active Regime)

# We model innovation as a stochastic process

innovations = [

    {

        'name': 'Phase 1: Preventive & Triage',
```

```
        'start_year': 1.0,

        'mu_red_mean': 0.015,

        'mu_red_std': 0.005,  # Stochasticity in success

        'sig_red_mean': 0.015,

        'sig_red_std': 0.005,

        'ramp': 2.0,

        'cost': 50_000_000,

        'prob_success': 0.9,  # 90% chance of being effective

        'selection_bias_factor': 0.8  # Initial effectiveness reduced by selection bias

    },

    {

        'name': 'Phase 2: Disease Mgmt & Coordination',

        'start_year': 5.0,

        'mu_red_mean': 0.010,

        'mu_red_std': 0.003,

        'sig_red_mean': 0.010,

        'sig_red_std': 0.003,

        'ramp': 3.0,

        'cost': 30_000_000,

        'prob_success': 0.85,

        'selection_bias_factor': 0.9  # Better targeting due to learning

    }

]

mu_floor = 0.015

sigma_floor = 0.05

# ---------------------------------------------------------

# Simulation Engine

# ---------------------------------------------------------

def simulate_regime(is_active=False):
```

```
# Initialize claims array: (num_simulations, n_steps + 1)
claims = np.zeros((num_simulations, n_steps + 1))
claims[:, 0] = C0
# Shared shocks for fair comparison
shocks = np.random.normal(0, np.sqrt(dt), (num_simulations, n_steps))
# For Active Regime, we need to handle stochastic innovation per simulation
if is_active:
    # Pre-calculate innovation impacts for each simulation
    # This addresses the "deterministic innovation" criticism
    sim_mu_red = []
    sim_sig_red = []
    sim_success = []
    for inn in innovations:
        # Success/Failure
        success = np.random.binomial(1, inn['prob_success'], num_simulations)
        # Magnitude of reduction (Normal distribution, clipped at 0)
        mu_red = np.maximum(0, np.random.normal(inn['mu_red_mean'], inn['mu_red_std'], num_simulations))
        sig_red = np.maximum(0, np.random.normal(inn['sig_red_mean'], inn['sig_red_std'], num_simulations))
        sim_mu_red.append(mu_red * success * inn['selection_bias_factor'])
        sim_sig_red.append(sig_red * success * inn['selection_bias_factor'])
        sim_success.append(success)
    # Iterate through time steps
    for t_idx in range(n_steps):
        t = t_idx * dt
        # Calculate current mu and sigma for each simulation
        current_mu = np.full(num_simulations, mu_base)
        current_sig = np.full(num_simulations, sigma_base)
        for i, inn in enumerate(innovations):
            if t >= inn['start_year']:
```

```
                    # Linear ramp-up

                    strength = min(1.0, (t - inn['start_year']) / inn['ramp'])

                    current_mu -= sim_mu_red[i] * strength

                    current_sig -= sim_sig_red[i] * strength

                # Apply floors

                current_mu = np.maximum(mu_floor, current_mu)

                current_sig = np.maximum(sigma_floor, current_sig)

                # GBM step

                drift = (current_mu - 0.5 * current_sig**2) * dt

                diffusion = current_sig * shocks[:, t_idx]

                claims[:, t_idx + 1] = claims[:, t_idx] * np.exp(drift + diffusion)

        else:

            # Traditional Regime: Constant parameters

            for t_idx in range(n_steps):

                drift = (mu_base - 0.5 * sigma_base**2) * dt

                diffusion = sigma_base * shocks[:, t_idx]

                claims[:, t_idx + 1] = claims[:, t_idx] * np.exp(drift + diffusion)

        return claims

    # Run simulations

    claims_trad = simulate_regime(is_active=False)

    claims_active = simulate_regime(is_active=True)

    # --------------------------------------------------------

    # Analysis & Visualization

    # --------------------------------------------------------

    # Metrics

    mean_trad = claims_trad.mean(axis=0) / 1e6

    mean_active = claims_active.mean(axis=0) / 1e6

    ci_trad_low, ci_trad_high = np.percentile(claims_trad, [5, 95], axis=0) / 1e6

    ci_active_low, ci_active_high = np.percentile(claims_active, [5, 95], axis=0) / 1e6
```

```
# Cumulative Expenditure ($B)
total_invest = sum(inn['cost'] for inn in innovations)
cum_trad = np.trapz(mean_trad * 1e6, time) / 1e9
cum_active = (np.trapz(mean_active * 1e6, time) + total_invest) / 1e9
net_savings = cum_trad - cum_active
# Plotting
plt.style.use('seaborn-v0_8-whitegrid')
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 12), gridspec_kw={'height_ratios': [2, 1]})
# Top Plot: Claims Trajectories
ax1.plot(time, mean_trad, color='#d62728', label='Traditional (Passive) - Mean', linewidth=2)
ax1.fill_between(time, ci_trad_low, ci_trad_high, color='#d62728', alpha=0.1, label='Traditional 90% CI')
ax1.plot(time, mean_active, color='#2ca02c', label='Innovation-Aware (Active) - Mean', linewidth=2.5)
ax1.fill_between(time, ci_active_low, ci_active_high, color='#2ca02c', alpha=0.2, label='Active 90% CI')
# Annotations for innovations
for inn in innovations:
    ax1.axvline(inn['start_year'], color='gray', linestyle='--', alpha=0.5)
    ax1.text(inn['start_year']+0.1, mean_trad.max()*0.9, inn['name'], rotation=90, verticalalignment='top', fontsize=10)
ax1.set_title('Bending the Healthcare Cost Curve: Stochastic Innovation Impact', fontsize=16, fontweight='bold')
ax1.set_ylabel('Annualized Claims Expenditure ($ Millions)', fontsize=12)
ax1.legend(loc='upper left')
ax1.grid(True, alpha=0.3)
# Bottom Plot: Distribution of Outcomes at Year 10
sns.kdeplot(claims_trad[:, -1] / 1e6, ax=ax2, color='#d62728', fill=True, label='Traditional')
sns.kdeplot(claims_active[:, -1] / 1e6, ax=ax2, color='#2ca02c', fill=True, label='Active')
ax2.set_title('Distribution of Claims Expenditure at Year 10', fontsize=14)
ax2.set_xlabel('Claims Expenditure ($ Millions)', fontsize=12)
ax2.set_ylabel('Density', fontsize=12)
ax2.legend()
```

```
plt.tight_layout()

plt.savefig('improved_innovation_simulation.png', dpi=300)

# Print results for integration

print(f"--- Simulation Results ---")

print(f"Traditional Mean Year 10: ${mean_trad[-1]:.2f}M")

print(f"Active Mean Year 10: ${mean_active[-1]:.2f}M")

print(f"Reduction in Year 10 Claims: {((mean_trad[-1] - mean_active[-1]) / mean_trad[-1] * 100):.2f}%")

print(f"Cumulative Traditional Cost (10yr): ${cum_trad:.2f}B")

print(f"Cumulative Active Cost (10yr, incl. invest): ${cum_active:.2f}B")

print(f"Net Present Value of Innovation Strategy: ${net_savings*1000:.2f}M")

print(f"Active Regime Volatility (Year 10): ${(ci_active_high[-1] - ci_active_low[-1]):.2f}M")

print(f"Traditional Regime Volatility (Year 10): ${(ci_trad_high[-1] - ci_trad_low[-1]):.2f}M")print(metrics)
```

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