

Beyond Black-Scholes: A Synthesis of AI-Driven Advancements in Derivatives Pricing, Risk Sensitivity, and Computational Efficiency (2020–2025)

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Abstract:

Traditional derivatives pricing models, while theoretically elegant, increasingly struggle with the scale, non-linearity, and real-time demands of modern financial markets. This paper provides a comprehensive synthesis of recent advancements in artificial intelligence (AI) and machine learning (ML) applied to the valuation of financial instruments. Through a systematic review of literature and empirical results from 2020 to 2025, the study evaluates diverse methodologies including Gaussian Process Regression (GPR), Physics-Informed Neural Networks (PINNs), and gradient boosting frameworks like CatBoost.

The findings demonstrate that AI-based approaches achieve computational speed-ups of three to four orders of magnitude compared to traditional finite-difference and Monte Carlo methods, while maintaining relative error rates as low as 0.5% for complex instruments like variance swaps and American options. Furthermore, the paper examines the integration of "Greeks" estimation and deep calibration into unified AI frameworks, addressing the operational bottlenecks of risk management. While the "black box" nature of deep learning remains a primary concern for regulators and practitioners, the emergence of hybrid models—combining financial theory with machine learning acceleration—offers a path toward robust, interpretable, and near-instantaneous financial engineering. The study concludes that AI is not a replacement for traditional quantitative finance but a powerful extension that redefines what is analytically feasible in high-frequency environments.

Keywords:

Artificial Intelligence (AI), Machine Learning, Quantitative Finance, Financial Risk Management

Introduction: "The What & Why"

If you work anywhere near financial markets, you've probably noticed that AI keeps coming up in conversations where it never used to. Derivatives pricing is one area where that shift has been especially pronounced – and especially consequential. At its core, derivatives pricing is about figuring out what financial instruments like options, futures, and swaps are actually worth, given that their value is tied entirely to something else: a stock price, an benchmark interest rate, a commodity.

For a long time, this was purely the domain of mathematical models. Black-Scholes. The binomial model. Elegant frameworks built on carefully defined assumptions about how volatility behaves and how markets move. These models held up well enough for decades, but today's markets have genuinely outgrown them. They're more complex, less predictable, and they generate data at a scale that older frameworks were never designed to handle.

That's the gap AI stepped into. Machine learning, neural networks, deep learning – these techniques are increasingly being applied to derivatives pricing because they can process enormous datasets, detect nonlinear relationships that traditional models tend to miss, and price complicated instruments in a fraction of the time (Khalife et al., 2023). The pitch is straightforward: faster, more accurate pricing, with fewer computational headaches along the way. But it's not all upside. The most persistent concern is transparency. Banks and regulators need to understand how a model actually reaches its conclusions. A model that gets the right answer most of the time but can't explain itself – or behaves unpredictably when markets get stressed – isn't just unhelpful. It's dangerous. The 2008 financial crisis demonstrated in brutal detail how mispricing and valuation errors in derivatives markets don't stay contained. They spread, they compound, and they can bring down entire financial systems, on the other hand, the immense growth in the US GDP is an example of how technology can positively attribute to the economies of entire countries when used correctly (Beainy & kamel, 2023) and (Athari et al., 2026).

Central Research Question: Does using AI to value financial products actually make things better – more accurate, more efficient without creating new risks or turning pricing into an unexplainable black box?

Working Hypothesis: AI does improve on traditional methods, but getting the most out of it requires proper validation and tools that make the models interpretable.

Literature Review: "The story so far "

The move toward AI in derivatives pricing didn't happen in a vacuum. It reflects a growing recognition that conventional quantitative methods, for all their theoretical elegance, have real practical limits, and the Silicon Valley bank bankruptcy is a mere argument that prove it (Beainy & Kamel, 2023). Even in Audit, AI is no longer optional but a must (Sawaya et al., 2026).

Traditional approaches generally fall into three camps:

Transform techniques (analytical characteristic functions).

Partial differential equation (PDE) methods (Markovian processes).

Monte Carlo simulation (high-dimensional or path-dependent instruments).

All of them start to buckle when portfolios get large and complex. Real-time risk management and dynamic hedging demand a level of speed that these methods often can't deliver.

2.1 Core AI Approaches

Two main approaches have emerged from research:

Direct Approximation: Training models to learn the relationship between key risk factors and valuations. Ding, Lu, and Cheung's work with Gaussian Process Regression (GPR) illustrates this, allowing for near-instant execution.

Theory-Embedded Networks: Physics-Informed Neural Networks (PINNs) incorporate governing PDEs directly into the network's loss function. Mrad and Iassamen extended this to the Heston model, achieving accurate pricing with far fewer training examples.

2.2 Specialized Applications and Greeks

Deep hedging allows for modeling market frictions like transaction costs, while deep calibration addresses the bottleneck of fitting model parameters to market prices. On the portfolio side, Zhang, Tian, Yang, and Ye developed frameworks to estimate the full set of Greeks (Delta, Gamma, Rho, and Vega) alongside parameter inference in a unified system.

2.3 Algorithm Comparisons

Trivedi found that CatBoost outperformed LSTM and Random Forests on raw predictive accuracy for certain tasks, while LSTMs remained superior for capturing temporal dynamics. The takeaway is that the right tool depends on the specific instrument and context.

Methodology: "The how we did it "

This study uses a hybrid approach: a systematic literature review combined with analytical synthesis of empirical results from recent implementations.

Data Sources: Searches were conducted across arXiv, EconPapers, Semantic Scholar, and institutional repositories from central banks.

Selection Criteria: Focused on publications from 2020 to 2025. From an initial pool of 60 documents, 25 sources were selected based on original empirical results, methodological frameworks, or systematic reviews.

Analysis Framework: Methodological approaches were grouped into supervised learning, PINNs, deep hedging/calibration, and comparative studies. Empirical results were standardized to compare accuracy metrics and computational speed-ups.

Limitations: The fast pace of AI development, the prevalence of non-peer-reviewed preprints, and the proprietary nature of industry implementations may impact the representation of the field.

Results: "The facts "

The empirical evidence is consistent: AI delivers meaningful improvements in both accuracy and speed.

Volatility Surface Products: Ding, Lu, and Cheung's GPR framework achieved relative errors of only 0.5% for variance swaps and 1.7–3.5% for American puts. More importantly, it provided a three to four orders of magnitude speed-up over the Crank-Nicolson finite-difference method.

Data Efficiency: PINNs (Mrad and Iassamen) demonstrated that incorporating physical regularization significantly reduces the volume of training labels required for complex stochastic volatility models.

Risk Sensitivities: Zhang et al. demonstrated that integrating machine learning with traditional path derivatives allows for fast, comprehensive estimation of Greeks suitable for day-to-day trading operations.

Market Frictions: Shinozaki's review indicates that Deep Hedging successfully models previously "expensive" factors like transaction costs, providing a more realistic view of hedging operations.

Discussion and conclusion: "The so what ? "

The literature shows the field has moved past proof-of-concept. The traditional trade-off between accuracy and speed has been substantially overcome. Reducing valuation times from minutes to milliseconds expands what is operationally possible—enabling high-frequency dynamic hedging and large-scale scenario analysis.

However, the dominant paradigm is a hybrid one: using traditional numerical methods to generate training data, and AI for real-time execution. This leverages the theoretical rigor of conventional approaches with the speed of AI. Key challenges remain, including:

Model Selection: No universal "winner" exists among architectures.

Interpretability: Regulatory scrutiny requires models that can explain their outputs.

Validation: Standardized frameworks are still needed to ensure robustness in stressed markets.

Conclusion

AI has already changed derivatives pricing by producing a new generation of hybrid quantitative tools. For practitioners and regulators, the question is no longer if these methods should be used, but how to use them well. The future of derivatives pricing will be shaped by the integration of AI as a powerful extension of the broader quantitative toolkit—one that maintains robustness and risk awareness while achieving unprecedented computational performance. In today's environment, AI can be used as a complementary to traditional financial services such as banks, but even more, technology can be a substitute (Mawad & Freiha, 2024), future research ought to examine what can be the influence of ML, AI and technology as a substitute for traditional financial systems.

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