

Derivative Pricing under Uncertain Market Conditions: An Integrated Stochastic Volatility and Jump Framework

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Abstract. With the increase in uncertainty of the modern financial market, so too has the problem of derivative pricing risen. Traditionally, the Black-Scholes model has been a solid theoretical model. However, it relies on idealized assumptions such as constant volatility and continuous asset price movements. In reality, financial markets do not always conform to this classical model; instead, they exhibit time-varying volatility, heavy-tailed return distributions, and sudden price changes. Therefore, the old derivative pricing models have obvious shortcomings. This paper introduces an integrated framework for derivative pricing under uncertain market conditions. By adding stochastic volatility and jump risks to the model, it better reflects fluctuations in asset prices than a traditional diffusion model. Based on the above analysis, the value of derivatives is closely linked to the distribution of future asset prices, and this distribution is determined by expected returns, fluctuations in volatility and tail risks. This framework contributes to existing derivative pricing literature by integrating two major sources of uncertainty that are often modeled separately. Furthermore, the model provides practical implications for risk management and derivative valuation, particularly during periods of growing market uncertainty.

Keywords: derivative pricing, stochastic volatility, jump diffusion, option pricing

1. Introduction

1.1. Background and motivation

Pricing derivatives is a core function of modern financial markets. Among all kinds of derivatives, options stand out for their value. They directly affect how the underlying asset changes over time, and thus precise pricing is both theoretically desired and practically difficult. Therefore, the construction of a stable-price system has been an old problem in financial engineering.

However, with the market growing complicated, the defects in traditional pricing methods have been exposed. Real-world financial data rarely meet the conditions for simplified models. Asset returns tend to show volatility clustering, fat tails, and abrupt jumps [1, 2]. This suggests that financial uncertainty cannot be assumed to follow a single normal distribution and is inherently multi-dimensional.

Accurate modeling of uncertainty is particularly important in market downturns. Since a derivative's price reflects expectations about the future distribution of the underlying asset, any error in predicting volatility or tail risk will result in widespread mispricing. Any effort to improve derivative valuation consequently depends on building models that can handle both ordinary market fluctuations and extreme movements.

The Black-Scholes model laid the groundwork for modern option pricing by developing a continuous-time stochastic framework grounded in risk-neutral valuation. It turned derivative pricing from a rough estimation exercise into a mathematically rigorous discipline. Even so, its reliance on constant volatility and continuous price paths means it falls short of observed market behavior.

These shortcomings spurred the search for richer models that bring in additional sources of uncertainty. Two strands of work have proved especially influential: stochastic volatility models, which let volatility itself evolve over time, and jump diffusion models, which account for sudden, discontinuous price moves. The limitation is that each approach addresses a different dimension of market uncertainty — neither, on its own, offers a unified treatment.

A gap therefore remains: existing integrated models still face limitations in estimation, computation, and the practical representation of time-varying volatility and extreme market events within a coherent pricing framework.

1.2. Limitations of existing pricing models

The Black-Scholes model ranks among the most consequential achievements in financial economics. By modeling asset prices as geometric Brownian motion, it delivers closed-form solutions for European option prices and lays the theoretical basis for risk-neutral valuation.

However, a large number of empirical studies have found that the main assumptions of the model are not in line with the actual behaviour of the market. The constant-volatility assumption fails to explain the clustering of risk and time-varying risk premia in real data. The model assumes normally distributed returns, but the actual return series frequently have extreme values that occur much more often than expected under a normal distribution.

Stochastic volatility models have been proposed to address the above problems. Rather than treating volatility as a fixed parameter, they model it as a stochastic process. Heston extended the model to add a diffusion process for the variance and considered fluctuations in market volatility [3]. These models better capture observed option market phenomena, such as volatility smiles and the term structure of implied volatility.

Where they fall short is that stochastic volatility models generally maintain the assumption of continuous price paths and are therefore not suitable for addressing sudden changes in the market.

Jump diffusion models take a different route. Merton extended the Black-Scholes model to include a Poisson process for jumps and thus accounted for discontinuous price changes [4]. This extension improves the model's ability to address extreme events and explains the heavy tails in return distributions. The trade-off is that the traditional jump model keeps volatility constant and thus fails to capture the time-varying nature of market uncertainty.

Accordingly, neither stochastic volatility nor jump diffusion models alone provide an adequate account of modern financial markets. Asset prices are very sensitive to fluctuations in volatility and will be unstable at times. This is precisely why people are trying to build an all-encompassing system that combines the two.

2. Literature review

2.1. Evolution of traditional derivative pricing models

The history of derivative pricing theory is intertwined with advances in stochastic process modeling. Before the time of quantitative methods, derivative valuation was based on relatively simple assumptions about market equilibrium and asset behaviour; although they were convenient, these were not very accurate reflections of reality.

The Black-Scholes model changed the landscape decisively. Black and Scholes constructed a continuous-time pricing framework that combined stochastic asset dynamics with the idea of risk-neutral valuation [5]. The key insight was that an option's price can be determined by the above four factors: the price of the underlying asset, volatility, interest rates and time to maturity. The model quickly became the standard against which other pricing approaches are measured for its theoretical elegance.

Soon after, the relevant studies found a discrepancy between the theoretical assumptions of the model and the reality of the market. Mandelbrot and Fama have shown that financial returns are not normally distributed and thus do not meet the assumption of stable return distribution [1, 2].

The volatility smile, where implied volatility is plotted against strike price, furnished further evidence that constant volatility does not hold in practice. At the given market price, different traders anticipate different levels of volatility for various strikes and maturities; thus, volatility will likely fluctuate over time and is not constant.

These empirical findings pushed researchers to look for more flexible frameworks, ones capable of accommodating additional sources of uncertainty.

2.2. Stochastic volatility models and dynamic risk representation

Among the extensions beyond Black-Scholes, stochastic volatility (SV) models stand out as one of the most significant models. Their essential contribution is a simple but powerful idea: volatility itself fluctuates over time in a random fashion, instead of remaining constant.

Heston proposed what is now one of the most popular SV models by introducing a separate variance process that is correlated with the asset price [3]. Therefore, volatility will change in response to fluctuations in the market and is more realistic than a constant-volatility benchmark.

Later work extended SV modeling using improved estimation techniques, alternative volatility specifications, or more efficient numerical pricing methods [6, 7]. These refinements have strengthened the empirical and computational performance of SV models in explaining observed option prices.

However, SV models are still unable to explain sudden and discontinuous changes in the market. They need to show an increasing level of uncertainty and should not drop suddenly due to a financial crisis. When prices jump suddenly during a crash, default or geopolitical shocks have occurred, etc., volatility changes alone are insufficient.

So, while stochastic volatility models mark a clear advance over the constant-volatility paradigm, they need to be supplemented with additional mechanisms to capture the full spectrum of market risk.

2.3. Jump diffusion models and extreme market events

Jump diffusion models arose from a different starting concern: the inability of purely continuous processes to explain why asset prices sometimes change discontinuously rather than continuously, from one level to another. The underlying intuition is straightforward — financial returns reflect both ordinary, day-to-day fluctuations and occasional, large-magnitude shocks.

Merton formalized this idea by adding a Poisson-driven jump component onto the Black-Scholes diffusion [4]. The resulting framework allows asset prices to make discontinuous leaps in response to sudden news or economic events, something a pure diffusion cannot do.

The advantages for derivative pricing are tangible. By admitting discrete price jumps, the model produces return distributions with fatter tails and does a better job of capturing downside tail risk. This matters a great deal for options, where extreme price realizations can dominate the payoff and therefore the fair price.

But there is a cost. Traditional jump diffusion models tend to keep the volatility of the diffusion component constant. However, constant diffusion volatility prevents these models from capturing time-varying market uncertainty.

2.4. Integration of stochastic volatility and jump processes

A natural response to the shortcomings of either approach pursued in isolation has been to bring them together. A growing body of recent work aims to nest both stochastic volatility and jump processes inside a single pricing framework. The motivation is hardly obscure: real financial markets exhibit gradual shifts in uncertainty and sudden price dislocations at the same time, and a model that sees only one of the two is necessarily incomplete.

Together, these fragments can offer a more complete picture of the development of asset prices. The stochastic volatility component has a slow change in market risk, and the jump component is due to a sudden increase in risk caused by unforeseen circumstances. At the same time, the return distribution generated by the two mechanisms is closer to the observed return distribution in the actual market, and the model's reproduction of the cross-section of option prices is improved.

Bates was the first to combine stochastic volatility and jumps, and he found that the joint model could fit the pattern of option-implied volatility better than models with only one feature [8]. Duffie, Pan and Singleton subsequently put forward a general affine jump-diffusion model to provide all-encompassing theoretical support for studying asset prices under multiple sources of risk [9].

Recently, some research has improved the numerical methods needed for practical application of integrated SV-jump models and expanded their application scope to real-world pricing [10]. However, many problems still exist: they have relatively high computational requirements, the jump parameters are difficult to estimate accurately, and it is challenging to distinguish a real jump from a large but temporary volatility spike [7, 11].

Despite the problems listed above, in recent years, a full-coverage approach has been taken in derivative pricing research to show the market under conditions of both continuous and intermittent uncertainty more accurately.

2.5. Research gap

Notwithstanding the considerable progress reviewed above, a meaningful gap in the literature persists. What remains less developed is a clear examination of how stochastic volatility and jump

risk jointly affect derivative valuation, particularly in terms of their distinct pricing mechanisms and implications for market risk.

The trade-offs are by now familiar. Black-Scholes delivers mathematical simplicity but leans on assumptions that empirical evidence repeatedly contradicts. Stochastic volatility models do a better job with the time-varying nature of uncertainty but tend to smooth over discontinuous price moves. Jump diffusion models take extreme events seriously but often revert to constant volatility for the diffusion background, sidestepping the problem they were meant to solve elsewhere.

In short, existing approaches tend to focus on a single source of uncertainty at a time, leaving their combined effects understudied. Yet actual markets are characterized by the coexistence of fluctuating volatility and sporadic shocks. Overlooking either element risks producing a skewed picture of the asset price distribution — and, by extension, bias derivative valuations.

This paper takes up the gap directly. It develops an integrated stochastic volatility and jump framework that brings dynamic volatility modeling and jump risk analysis within a unified framework, with the aim of offering a more complete account of how derivatives are priced. More concretely, the study stresses two channels: how shifts in the level of uncertainty affect pricing through stochastic volatility, and how the risk of extreme payoffs feeds into valuation through the jump component.

3. Theoretical foundation

3.1. Black-Scholes framework and continuous diffusion process

The Black-Scholes model provides the theoretical foundation for modern derivative pricing by establishing a continuous-time stochastic framework. The model assumes that the asset prices follow a geometric Brownian motion, and their returns are composed of a deterministic part and a random diffusion term.

The underlying asset price process is expressed as:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t \quad (1)$$

where S_t is the asset price at time t , μ is the expected return, σ is constant volatility, and W_t is a standard Brownian motion.

Under the risk-neutral valuation framework, derivative prices can be expressed as the discounted expected payoff:

$$V_t = e^{-r(T-t)} E^Q[\text{Payoff}(S_T)] \quad (2)$$

where V_t represents the derivative value, r represents the risk-free interest rate, and E^Q represents expectation under the risk-neutral probability measure.

The Black-Scholes framework establishes a mathematical relationship between asset price dynamics and derivative valuation. However, assuming a constant level of volatility may not show changes in the market. Therefore, a flexible model is required.

3.2. Stochastic volatility theory

Stochastic volatility theory extends the original derivative pricing model to allow volatility to change over time. Based on the above empirical evidence, it is assumed that changes in market uncertainty are not constant.

In a stochastic volatility framework, the asset price process becomes:

$$\frac{dS_t}{S_t} = \mu dt + \sqrt{v_t} dW_t^S \quad (3)$$

where v_t is the instantaneous variance of asset returns.

A widely used specification for the variance process is the Heston model:

$$dv_t = \kappa(\theta - v_t)dt + \xi\sqrt{v_t} dW_t^v \quad (4)$$

where κ is the speed of mean reversion, θ is the long-term variance level, and ξ is volatility of volatility.

Unlike the Black-Scholes model, this framework allows volatility to adjust according to changing market conditions. Since derivative prices depend strongly on future uncertainty, dynamic volatility provides a more realistic foundation for option valuation.

However, stochastic volatility models generally assume continuous asset price evolution. Consequently, they cannot fully explain sudden market disruptions and extreme price movements. This limitation motivates the incorporation of jump processes.

3.3. Jump process theory

Jump processes provide a mathematical framework to model a sudden increase in asset prices caused by unforeseen circumstances. Unlike Brownian motion, which generates continuous price changes, a jump process allows asset prices to experience sudden discontinuous movements with a certain probability.

A commonly used jump specification is the Poisson process:

$$N_t \sim \text{Poisson}(\lambda t) \quad (5)$$

where N_t represents the number of jump events and λ represents jump intensity.

The asset price process can therefore be extended as:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t + J_t dN_t \quad (6)$$

where J_t is the jump magnitude.

The jump component allows the model to capture a sudden change that cannot be explained by continuous diffusion. It is quite important because large price movements can significantly change derivative payoffs and risk exposure.

3.4. Integrated theoretical framework

The limitations of individual models indicate that neither stochastic volatility nor jump processes alone can fully represent modern financial markets. Actual asset prices are influenced by both gradual uncertainty changes and sudden market shocks.

Therefore, this study adopts an integrated stochastic volatility-jump framework. The underlying assumption is that asset returns consist of three components:

$$\text{Asset Return} = \text{Normal Diffusion} + \text{Stochastic Volatility} + \text{Jump Risk} \quad (7)$$

The diffusion component captures ordinary market movements, the stochastic volatility component captures changing uncertainty, and the jump component captures extreme events.

This framework provides the theoretical foundation for the model developed in the following section.

4. Model construction and mechanism analysis

4.1. Model assumptions

Based on the theoretical framework established above, this study adopts an integrated stochastic volatility and jump model to analyze derivative pricing under uncertain market conditions. The objective is to extend existing pricing theory by incorporating two important sources of uncertainty modeled separately: dynamic volatility risk and discontinuous jump risk.

The three basic assumptions of the proposed framework are: firstly, the price of an asset is a continuous-time stochastic process. However, not all sources of uncertainty in asset returns can be represented by a single diffusion process, as in the Black-Scholes model. Secondly, volatility is regarded as a stochastic variable. This assumption reflects the fact that market uncertainty varies over time in response to economic conditions, investor expectations, and information flows. Thirdly, extreme market events occur randomly and cause a sudden drop in asset prices. These are modeled through a jump process, and indicate a sudden change in the form of financial crisis or a substantial modification of policy and information.

Under these assumptions, asset price dynamics can be expressed as:

$$\text{Asset Price Change} = \text{Normal Diffusion} + \text{Stochastic Volatility} + \text{Jump Effect} \quad (8)$$

This structure is also more realistic in showing the financial market; that is to say, there are both continuous fluctuations and occasional extreme events that cause uncertainty.

4.2. Integrated stochastic volatility-jump asset price equation

The proposed asset price process extends the Black-Scholes framework by incorporating stochastic volatility and jump risks:

$$\frac{dS_t}{S_t} = \mu dt + \sqrt{v_t} dW_t^S + J_t dN_t \quad (9)$$

where S_t represents the underlying asset price, μ represents expected return, v_t represents stochastic variance, W_t^S represents Brownian motion, N_t represents the Poisson jump process, and J_t represents jump magnitude.

Compared with the Black-Scholes process:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t \quad (10)$$

the proposed framework introduces two additional sources of risk.

The first one is stochastic volatility. By replacing constant volatility σ with dynamic standard deviation $\sqrt{v_t}$, the model makes uncertainty levels change according to market conditions.

The second one is jump risk. The additional term $J_t dN_t$ captures sudden price movements which cannot be explained by continuous diffusion processes.

The volatility process follows:

$$dv_t = \kappa(\theta - v_t)dt + \xi\sqrt{v_t} dW_t^v \quad (11)$$

where volatility tends to return to a long-term equilibrium and continuously respond to market fluctuations.

The jump process follows:

$$N_t \sim \text{Poisson}(\lambda t) \quad (12)$$

where λ determines the expected frequency of extreme events.

Therefore, the integrated framework captures three different dimensions of market behavior: The term μdt represents the expected market return; $\sqrt{v_t} dW_t^S$ represents dynamic uncertainty arising from stochastic volatility; $J_t dN_t$ represents extreme market shocks and the resulting discontinuous price movements. This distinguishes ordinary return dynamics from time-varying volatility and jump risk.

4.3. Derivative pricing mechanism under the integrated model

After establishing the integrated stochastic volatility-jump asset price process under the physical measure P , derivative valuation is carried out under the equivalent risk-neutral measure Q . The expected return μ in the physical measure is replaced by the risk-free rate, and the compensation for jump risk is incorporated into the risk-neutral jump specification. Therefore, the asset price dynamics can be written as:

$$\frac{dS_t}{S_{t-}} = (r - \lambda^Q \kappa_j^Q)dt + \sqrt{v_t}dW_t^{S,Q} + J_t dN_t \quad (13)$$

where r is the risk-free interest rate, λ^Q is the risk-neutral jump intensity, and $\kappa_j^Q = E^Q[J_t]$ represents the expected jump size under Q . The compensating term $-\lambda^Q \kappa_j^Q$ ensures that the discounted asset price remains a martingale under the risk-neutral measure. In this specification, the change of measure may replace the jump intensity and the jump-size distribution. Thus, λ^Q and the distribution of J_t should not be interpreted as identical to their physical-measure counterparts.

The derivative value is obtained from the risk-neutral pricing relationship:

$$V_t = e^{-r(T-t)} E^Q[\text{Payoff}(S_T)] \quad (14)$$

Although this valuation principle remains consistent with the Black-Scholes framework, the proposed model fundamentally changes the distribution of future asset prices. In the traditional model, future asset prices are generated through a continuous, constant-volatility diffusion process, and as a result, the distribution of future outcome is relatively restrictive.

In contrast, the integrated framework generates a more flexible distribution by incorporating both dynamic uncertainty and discontinuous shocks. Market uncertainty and extreme price movements both shape future asset prices distribution. This is the expected payoff under the risk-neutral measure, and thus it will affect the current value.

The stochastic volatility component affects derivative prices by changing the spread of future asset returns. When volatility increases, the range of possible future asset prices becomes wider, thereby increasing the probability of extreme outcomes. Since option payoffs are nonlinear, a change in return dispersion directly affects option prices.

Meanwhile, the jump component changes the probability of large price movements. Unlike continuous fluctuations, jump events introduce additional probability mass into extreme regions of the return distribution. Therefore, options get more sensitive to the intensity and magnitude of jump.

The integrated framework provides a more realistic pricing mechanism. It recognizes that derivative values are determined not only by expected returns, but also by the entire distribution of future asset outcomes.

4.4. Impact mechanism of stochastic volatility

The stochastic volatility models assume that changes in market risk are random processes. As market conditions change, the volatility process adjusts accordingly, thereby altering the uncertainty

surrounding future asset prices.

The variance process $dv_t = \kappa(\theta - v_t)dt + \xi\sqrt{v_t} dW_t^v$ implies that volatility changes according to long-term market changes and random shocks. The mean-reversion feature implies that volatility will return to a certain level over time, and the stochastic component introduces fluctuations in uncertainty.

This mechanism improves derivative pricing in several ways.

First, stochastic volatility can better capture fluctuations in the market. During periods of heightened uncertainty, investors may demand higher risk premia, while market volatility may also increase. A model with constant volatility cannot show these changes.

Second, stochastic volatility helps explain observed option market phenomena. Assuming a constant volatility in the Black-Scholes model, the form of volatility is flat. However, the actual market data show that investors have different volatility expectations for the various payoff scenarios. Thus, dynamic volatility models provide a more flexible explanation.

Third, stochastic volatility affects derivative values as market uncertainty changes, which has important implications for risk management. For financial institutions managing large derivative portfolios, recognizing changes in volatility is particularly important when risk exposures increase substantially during periods of heightened market uncertainty.

Therefore, stochastic volatility improves the representation of continuous uncertainty in derivative pricing. However, it remains insufficient when markets experience sudden extreme events, and this motivates the introduction of jump risk.

4.5. Impact mechanism of jump risk

The jump component captures the influence of unexpected market shocks on derivative pricing. Unlike ordinary market fluctuations generated by Brownian motion, jump events represent sudden and discontinuous changes in asset prices.

The transmission mechanism can be described as: Extreme Event $\rightarrow$ Price Jump $\rightarrow$ Payoff Distribution Change $\rightarrow$ Derivative Price Adjustment.

The jump process:

$$N_t \sim \text{Poisson}(\lambda t) \quad (15)$$

determines the frequency of extreme events, while J_t determines the magnitude.

The importance of jump risk lies in the asymmetric effect of extreme price movements on derivative payoffs. For example, a sudden decline in the underlying asset price can substantially increase the value of put options. Such large downward movements are difficult to explain using continuous diffusion models alone.

By introducing jump risk, the proposed model assigns greater probability to extreme outcomes and therefore provides a richer and more flexible representation of return distributions. This is particularly important during crisis periods, when market movements are dominated by unexpected shocks.

From a risk management perspective, ignoring jump risk may lead to systematic underestimation of potential losses. In a continuous model, a derivative portfolio exposed to tail events may appear relatively stable, although its valuation can change sharply when extreme market movements occur.

Therefore, jump processes supplement stochastic volatility by capturing a different dimension of uncertainty. While stochastic volatility explains the evolution of market uncertainty, jump risk explains how rare but severe events influence asset prices.

4.6. Comparison with the Black-Scholes model

To evaluate the contribution of the proposed framework, it is useful to compare it with traditional derivative pricing models.

Table 1. Comparison of derivative pricing models

Model	Volatility Assumption	Jump Risk	Market Uncertainty Representation
Black-Scholes Model	Constant volatility	Not included	Limited
Stochastic Volatility Model	Dynamic volatility	Not included	Moderate
Jump Diffusion Model	Constant volatility	Included	Moderate
Integrated SV-Jump Model	Dynamic volatility	Included	Comprehensive

The comparison demonstrates that each previous model addresses only part of the complexity of financial markets.

The Black-Scholes model provides analytical simplicity and theoretical elegance, but cannot fully explain changing volatility or extreme price movements. Its assumption of constant volatility becomes restrictive under market uncertainty.

Stochastic volatility models improve on this limitation by introducing dynamic uncertainty. However, they generally assume continuous price movements and cannot fully capture sudden market disruptions.

Jump diffusion models successfully incorporate discontinuous price changes and improve the representation of extreme events. Nevertheless, traditional jump models maintain simplified volatility assumptions, limiting their ability to describe evolving market risk.

The proposed integrated stochastic volatility-jump framework combines the advantages of both approaches. By simultaneously modeling volatility dynamics and jump risks, it provides a more complete representation of asset price behavior.

Therefore, the contribution of this framework is providing a more realistic economic mechanism for understanding how different forms of uncertainty influence derivative values.

5. Conclusion

This paper puts forward an integrated framework that brings together stochastic volatility and jump processes to examine derivative pricing in the presence of market uncertainty. The starting point is a set of well-known shortcomings in conventional pricing models — most notably the Black-Scholes formulation, which rests on constant volatility and continuous price paths. While Black-Scholes undeniably provides the theoretical backbone of modern option pricing, a substantial body of evidence has accumulated showing that real markets behave quite differently: volatility shifts over time, and extreme events occur with a frequency that smooth diffusions cannot accommodate.

To confront these issues head-on, the study embeds both a stochastic volatility process and a Poisson jump component within a single pricing structure. The resulting model is built on the recognition that asset price dynamics are shaped by more than one kind of uncertainty — ordinary day-to-day fluctuations, evolving volatility conditions, and abrupt market shocks each play a role, and a model that overlooks any of them tells an incomplete story.

The analysis shows that letting volatility evolve over time improves derivative valuation in a tangible way. It yields a more faithful picture of shifting market conditions and helps make sense of observed option market regularities such as the volatility smile. At the same time, the jump component picks up where continuous diffusion models leave off: it captures the tail events and abnormal price movements, strengthening the model's grip on downside risk.

Where this study departs from much of the existing literature is in bringing together two dimensions of financial uncertainty that are more often studied separately. It offers a fuller account of how volatility dynamics and extreme events jointly shape derivative values: not one or the other, but both operating at once.

On the practical side, the framework carries implications for investors, financial institutions, and risk managers alike. Building both volatility uncertainty and jump risk into the machinery of valuation and risk assessment provides a broader basis for evaluating derivatives, and the gains are likely to be largest precisely during periods of financial stress.

The integrated specification entails higher computational costs and more demanding parameter estimation. Future work could push the approach further by drawing on machine learning methods, incorporate stochastic interest rates and liquidity risk, and pursue empirical calibration against high-frequency financial data.

Taken as a whole, the study makes the case that derivative pricing models which weave together stochastic volatility and jump processes offer a more realistic lens through which to view modern financial markets. By capturing both the gradual drift of uncertainty and the sudden ruptures that punctuate it, the proposed framework contributes to a richer understanding of how derivatives are valued under conditions of genuine uncertainty.

References

- [1] Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36(4), 394–419. <https://doi.org/10.1086/294632>
- [2] Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1), 34–105. <https://doi.org/10.1086/294743>
- [3] Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The Review of Financial Studies*, 6(2), 327–343. <https://doi.org/10.1093/rfs/6.2.327>
- [4] Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, 3(1–2), 125–144. [https://doi.org/10.1016/0304-405X\(76\)90022-2](https://doi.org/10.1016/0304-405X(76)90022-2)
- [5] Black, F., & Scholes, M. S. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3), 637–654. <https://doi.org/10.1086/260062>
- [6] Christoffersen, P., Jacobs, K., & Mimouni, K. (2010). Volatility dynamics for the S&P500: Evidence from realized volatility, daily returns, and option prices. *The Review of Financial Studies*, 23(8), 3141–3189. <https://doi.org/10.1093/rfs/hhq032>
- [7] Broadie, M., & Kaya, Ö. (2006). Exact simulation of stochastic volatility and other affine jump diffusion processes. *Operations Research*, 54(2), 217–231. <https://doi.org/10.1287/opre.1050.0247>
- [8] Bates, D. S. (1996). Jumps and stochastic volatility: Exchange rate processes implicit in Deutsche Mark options. *The Review of Financial Studies*, 9(1), 69–107. <https://doi.org/10.1093/rfs/9.1.69>
- [9] Duffie, D., Pan, J., & Singleton, K. (2000). Transform analysis and asset pricing for affine jump-diffusions. *Econometrica*, 68(6), 1343–1376. <https://doi.org/10.1111/1468-0262.00164>

- [10] Creel, M., & Kristensen, D. (2015). ABC of SV: Limited information likelihood inference in stochastic volatility jump-diffusion models. *Journal of Empirical Finance*, 31, 85–108. <https://doi.org/10.1016/j.jempfin.2015.01.002>
- [11] Laurent, S., & Shi, S. (2020). Volatility estimation and jump detection for drift–diffusion processes. *Journal of Econometrics*, 217(2), 259–290. <https://doi.org/10.1016/j.jeconom.2019.12.004>