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Research article

Newton-Fréchet Iterative Solution of Nonlinear Local-Stochastic Volatility Models

Mehran Paziresh[1], Karim Ivaz[1,*], Sina Ivaz[2]

[1] Department of Applied Mathematics, Faculty of Mathematics, Statistics and Computer Science, University of Tabriz, Tabriz, Iran

[2] Graduate of Biomedical Engineering from Tabriz University of Technology (Sahand), Tabriz, Iran

* **Corresponding author(s):** ivaz@tabrizu.ac.ir

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Abstract

Financial models frequently exhibit nonlinear behavior, necessitating robust numerical techniques for precise analysis. This study investigates the numerical implementation of a generalized Newton method within a Local-Stochastic Volatility framework. The nonlinear partial differential equation (PDE) governing the model is linearized via the generalized Newton procedure, employing the Fréchet derivative to construct the iterative scheme. By imposing appropriate boundary conditions and utilizing representative financial data, we examine the convergence properties of the resulting sequence. Numerical results demonstrate that the iterative method achieves stable and rapid convergence, thereby validating the existence of a unique solution within this framework and highlighting the efficacy of Newton-type approaches for solving nonlinear PDEs in financial modeling. Furthermore, this approach significantly reduces computational costs compared to traditional methods, offering a practical and efficient tool for real-time pricing in dynamic market environments. The proposed method also ensures high accuracy in handling complex derivative structures, making it a valuable asset for financial institutions seeking to optimize their risk management strategies.

Keywords: Local stochastic volatility model, Newton method, Nonlinear PDE, Financial modeling, Fréchet derivative.

Mathematics Subject Classification (2020): 65M06, 65M12, 91G60, 35K55

1 Introduction

The numerical treatment of nonlinear partial differential equations (PDEs) plays a fundamental role in modeling complex phenomena in both finance and physics. In many practical applications such as option pricing, risk assessment, and optimal control, the nonlinearity of the governing equations limits classical linear techniques, motivating advanced iterative schemes. As noted in [1, 2], realistic models for derivative pricing and incomplete markets naturally lead to nonlinear PDE formulations. Furthermore, similar nonlinear structures appear in physical systems, such as phase-change problems, where Newton-type integration methods have been effectively applied [3, 4].

In recent years, the development of volatility models has further underscored the importance of nonlinear PDEs in financial mathematics. Classical stochastic volatility frameworks [5] and empirical studies on volatility dynamics [6] show that market data often exhibit intricate behaviors that require flexible and mathematically robust modeling tools. Moreover, the construction of arbitrage-free volatility surfaces, as

discussed in [7], highlights the need for accurate numerical schemes capable of handling the nonlinearities that arise in calibration procedures. The extension of these models to incorporate jump-diffusion dynamics has also attracted considerable attention, with recent studies such as [8] proposing IMEX-Crank-Nicolson schemes for the Merton jump-diffusion PIDE, providing stable and efficient frameworks for option pricing under discontinuous asset movements.

Within this context, Newton-type algorithms and their generalized variants have emerged as powerful tools for addressing nonlinear structures. The theoretical analyses in [9, 10] demonstrate that Newton's method, when combined with accurate linearization, provides strong convergence properties in functional settings. In optimization and constrained control problems, the use of the Fréchet derivative and Lagrangian-based frameworks offers additional stability and precision for Newton-type approaches, as presented in [11]. Closely related developments can also be found in the work of Alassadi and Ivaz [12], where Newton's method is employed to solve nonlinear fractional VolterraFredholm integro-differential equations, further illustrating the flexibility and robustness of Newton-based techniques for complex nonlinear operators.

In financial computation, it has been shown in [13] that many modern models, including those incorporating transaction costs, market imperfections, or stochastic volatility, require the solution of nonlinear PDEs for which Newton-based methods are particularly effective. Recent studies on jump-diffusion processes, for instance, have utilized iterative solutions to Hamilton–Jacobi–Bellman equations to handle investment value optimization under uncertainty [14]. Further developments, such as the semismooth Newton techniques introduced in [15], demonstrate the efficiency of these methods in solving variational inequalities and constrained optimization problems with complex nonlinear structures.

More recently, extended Newton frameworks have been applied to nonlinear PDEs arising in financial mathematics. For example, the study in [16] proposed a Fréchet-based Newton scheme for Hamilton–Jacobi–Bellman equations under stochastic volatility, establishing stability results through fixed-point arguments. These contributions emphasize the importance of functional analytic tools in improving the convergence behavior of Newton-type algorithms for challenging financial models. In parallel, Beiranvand, Neisy, and Ivaz [17] investigated the mathematical analysis and pricing of European continuous installment call options, formulating the problem as a linear complementarity problem and proving the existence and uniqueness of its weak solution via variational inequalities, thereby contributing a rigorous analytical foundation for installment option pricing.

Beyond option pricing, inverse approaches have gained traction for estimating model parameters directly from market data. In particular, Paziresh and Ivaz [18] proposed an indirect method to estimate asset price jump sizes by applying the Euler–Maruyama discretization to historical financial data and minimizing the discrepancy between simulated and observed prices. Such parameter estimation techniques complement numerical pricing schemes by providing more accurate inputs for jump-diffusion dynamics, thereby enhancing the overall reliability of the modeling framework. Additionally, generalized Newton methods have been successfully applied to the nonlinear Kolmogorov forward equation within local-stochastic volatility frameworks [19], demonstrating stable convergence and providing a tractable approach for probability density estimation in commodity markets.

In recent years, the landscape of solving nonlinear PDEs in finance has evolved significantly, with a growing emphasis on hybrid approaches that combine traditional numerical stability with modern computational intelligence. For instance, recent studies have explored the application of machine learning techniques to address high-dimensional and complex financial PDEs, offering data-driven alternatives that can bypass some of the curse of dimensionality challenges [20, 21]. Concurrently, new algorithms have been proposed to enhance the efficiency and accuracy of stochastic volatility models, providing robust frameworks for pricing under uncertainty [22]. While these data-driven and hybrid methods represent a significant leap forward, they often require extensive training data and may lack the explicit interpretability of analytical or semi-analytical models. Our work builds upon these foundations by focusing on a rigorous Newton-based numerical scheme that ensures numerical stability and computational efficiency without relying on large datasets, thereby complementing the recent advancements in [20–22].

Motivated by these advances, the present work develops a numerical framework based on a generalized Newton method for solving a nonlinear PDE associated with a local volatility model. The main objective is to examine the convergence characteristics, assess stability, and evaluate the effectiveness of the iterative procedure through a simplified illustrative example. The nonlinear equation is linearized using the Fréchet derivative, and the resulting Newton sequence is analyzed numerically. The findings indicate that the method performs reliably for problems of similar structure and can serve as a foundation for more sophisticated numerical schemes in future studies.

2 Analytical Framework

2.1 Local Stochastic Volatility Model

The Local Stochastic Volatility (LSV) framework extends classical local volatility models by incorporating both stochastic and local volatility components, offering greater flexibility in capturing market-implied dynamics. In a simplified two-dimensional setting, the evolution of the asset price process $(S_t)_{t\geq 0}$ and the stochastic volatility factor $(Y_t)_{t\geq 0}$ is governed by the following system of stochastic differential equations:

$$\begin{aligned} \frac{dS_t}{S_t} &= a(t,S_t)b(Y_t)\,dB_t^1 + r\,dt, \\ dY_t &= \alpha(t,Y_t)\,dB_t^2 + \xi(t)\,dt, \end{aligned} \tag{1}$$

where B_t^1 and B_t^2 are Brownian motions with correlation coefficient ρ. Here, $b(\cdot)$ maps the auxiliary process Y_t into an effective volatility input, representing the stochastic component, while $a(t,S_t)$ represents the local volatility component, enabling calibration to observed market data. The functions α and ξ determine the stochastic and deterministic components of the volatility dynamics, respectively, and r denotes the risk-free interest rate [23].

Under standard regularity assumptions, the joint density $p(t,s,y)$ of the pair (S_t,Y_t) satisfies the forward Kolmogorov equation (Fokker-Planck equation):

$$\begin{aligned} &\frac{\partial p}{\partial t} = \frac{\partial^2}{\partial S^2}\left(\tfrac{1}{2}a^2b^2S^2p\right) + \frac{\partial^2}{\partial S\partial y}(\rho ab\alpha Sp) + \frac{\partial^2}{\partial y^2}\left(\tfrac{1}{2}\alpha^2 p\right) - \frac{\partial}{\partial S}(rSp) - \frac{\partial}{\partial y}(\xi p), \\ &p(S,y,0) = \delta(S=S_0, y=y_0). \end{aligned} \tag{2}$$

Equation (2) serves as the foundation for estimating the unknown components of the model. Specifically, the Dupire-type local volatility $\sigma_D(t,s)$ and the integral operator $I(p)$ are defined as:

$$\sigma_D^2(t,s) = \frac{a^2(t,s)\int b^2 p\,dy}{\int p\,dy}, \qquad I(p) = \frac{\int p\,dy}{\int b^2 p\,dy}. \tag{3}$$

Consequently, the local volatility coefficient $a(t,s)$ can be expressed in terms of σ_D as:

$$a^2(t,s) = \sigma_D^2(t,s)\frac{\int p\,dy}{\int b^2 p\,dy}, \qquad a(t,s) = \sigma_D(t,s)\left(\frac{\int p\,dy}{\int b^2 p\,dy}\right)^{1/2}. \tag{4}$$

Substituting Equation (4) into the Kolmogorov Equation (2) yields the following nonlinear partial integro-differential equation:

$$\frac{\partial p}{\partial t} - \frac{\partial^2 p}{\partial S^2}\left(\tfrac{1}{2}\sigma_D^2 b^2 S^2 \frac{\int p\,dy}{\int b^2 p\,dy}\right) - \frac{\partial^2 p}{\partial S\partial y}\left(\rho\sigma_D b\alpha S\left(\frac{\int p\,dy}{\int b^2 p\,dy}\right)^{1/2}\right) - \frac{\partial^2 p}{\partial y^2}\left(\tfrac{1}{2}\alpha^2\right) + \frac{\partial p}{\partial S}(rS) + \frac{\partial p}{\partial y}\xi + rp = 0. \tag{5}$$

Equation (5) is a nonlinear nonlocal partial integro-differential equation due to the presence of integral terms involving the unknown density p. Although existence of solutions can be established over short time intervals using fixed point arguments and suitable estimates, the primary aim of this work is to linearize the nonlinear operator through a generalized Newton method. After linearization, the resulting PDE is solved numerically under appropriate boundary conditions and using simplified market data, enabling an approximate calibration of the density function $p(t,s,y)$ [23].

2.2 Fréchet Derivative

Definition 1. *Let V and W be normed vector spaces, and let $f: V \to W$ be a mapping. Let $u_0 \in V$. The function f is said to be Fréchet differentiable at u_0 if there exists a bounded linear operator $A \in \mathscr{L}(V,W)$ such that*

$$\lim_{h\to 0}\frac{\|f(u_0+h)-f(u_0)-Ah\|_W}{\|h\|_V} = 0.$$

In this case, the operator A is called the Fréchet derivative of f at u_0 and is denoted by $f'(u_0)$ or $Df(u_0)$ [24].

2.3 Generalized Newton Method

Definition 2. *Let U and V be Banach spaces, and let $F : U \to V$ be a Fréchet differentiable mapping [24]. To solve the nonlinear equation $F(u) = 0$, we start from an initial guess $u_0 \in U$. Assuming that the Fréchet derivative $F'(u_n)$ is invertible for each n, the Newton sequence is constructed iteratively as follows:*

$$u_{n+1} = u_n - [F'(u_n)]^{-1} F(u_n), \qquad n = 0, 1, 2, \ldots.$$

Under suitable conditions on F and the initial guess u_0, this sequence converges quadratically to the solution u^* [24].

2.4 Application of the Generalized Newton Method to the Nonlinear Local Stochastic Volatility Model

To apply the generalized Newton method to the nonlinear PDE of the local Stochastic volatility model, we first rewrite Equation (5) in operator form. Define the nonlinear operator $F : X \to Y$ by

$$F(p) := p_t - \frac{\partial^2}{\partial S^2}\left(\tfrac{1}{2}\sigma_D^2 b^2 S^2 I(p) p\right) - \frac{\partial^2}{\partial S \partial y}\left(\rho \sigma_D b \alpha S \sqrt{I(p)} p\right) - \frac{\partial^2}{\partial y^2}\left(\tfrac{1}{2}\alpha^2 p\right) + \frac{\partial}{\partial S}(rSp) + \frac{\partial}{\partial y}(\xi p) + rp. \tag{6}$$

Note that we have included p inside the derivative terms to match the structure of the Fokker-Planck Equation (5), where the volatility coefficients depend on p via the integral functional $I(p) = \frac{\int p\, dy}{\int b^2 p\, dy}$.

According to Definition 2, the Newton iteration for solving $F(p) = 0$ takes the form

$$p_{n+1} = p_n - [F'(p_n)]^{-1} F(p_n). \tag{7}$$

Equivalently, we solve the linearized equation for the update step $\delta_n = p_{n+1} - p_n$:

$$F'(p_n)(\delta_n) = -F(p_n). \tag{8}$$

To compute the Fréchet derivative $F'(p_n)$, we linearize the nonlinear terms involving $I(p)$. Let us define the coefficient functions:

$$A(p) = \tfrac{1}{2}\sigma_D^2 b^2 S^2 I(p), \quad B(p) = \rho \sigma_D b \alpha S \sqrt{I(p)}.$$

The nonlinear part of the operator F can be written as $N(p) = -\partial_S^2(A(p)p) - \partial_{Sy}^2(B(p)p) - \cdots$. Applying the product rule and chain rule, the derivative of a term like $A(p)p$ in the direction δ is:

$$\left.\frac{d}{dh}\right|_{h=0} A(p_n + h\delta)(p_n + h\delta) = A'(p_n)(\delta)p_n + A(p_n)\delta.$$

The Fréchet derivative of the integral functional $I(p)$ at p_n in the direction δ is given by:

$$I'(p_n)(\delta) = \frac{\left(\int \delta\, dy\right)\left(\int b^2 p_n\, dy\right) - \left(\int p_n\, dy\right)\left(\int b^2 \delta\, dy\right)}{\left(\int b^2 p_n\, dy\right)^2}. \tag{9}$$

Consequently, the derivatives of the coefficients are:

$$A'(p_n)(\delta) = \tfrac{1}{2}\sigma_D^2 b^2 S^2 I'(p_n)(\delta), \quad B'(p_n)(\delta) = \rho \sigma_D b \alpha S \frac{1}{2\sqrt{I(p_n)}} I'(p_n)(\delta).$$

Substituting these into the linearization, the full Fréchet derivative $F'(p_n)(\delta)$ becomes:

$$F'(p_n)(\delta) = \delta_t - \frac{\partial^2}{\partial S^2}\left([A'(p_n)(\delta)]p_n + A(p_n)\delta\right) - \frac{\partial^2}{\partial S \partial y}\left([B'(p_n)(\delta)]p_n + B(p_n)\delta\right) - \frac{\partial^2}{\partial y^2}\left(\tfrac{1}{2}\alpha^2 \delta\right) + \frac{\partial}{\partial S}(rS\delta) + \frac{\partial}{\partial y}(\xi\delta) + r\delta. \tag{10}$$

This linear operator $F'(p_n)$ defines a linear PDE for the update step δ_n. It is important to note that the terms involving $A'(p_n)(\delta)$ and $B'(p_n)(\delta)$ introduce non-local dependencies (via the integrals in Equation (9)) into the linear system. Specifically, the update δ_n depends on the global integrals of δ_n itself, which must be handled carefully during the numerical discretization (e.g., by solving for the integrals

as auxiliary variables or incorporating them into the matrix structure). The resulting linear system is then solved for δ_n at each Newton iteration to update the solution via $p_{n+1} = p_n + \delta_n$.

To derive the linearized PDE from the nonlinear formulation, we employ a first-order Taylor expansion around the current iterate $p^{(n)}$. Let the update step be defined as $p^{(n+1)} = p^{(n)} + \delta p$, where δp represents a small correction term. The nonlinear operator $F(p)$ can be approximated as:

$$F(p^{(n)} + \delta p) \approx F(p^{(n)}) + F'(p^{(n)})[\delta p] = 0, \tag{11}$$

where $F'(p^{(n)})$ denotes the Fréchet derivative of F at $p^{(n)}$.

The full Fréchet derivative, including the sensitivity of the integral terms, is given by:

$$\begin{aligned} F'(p_n)(\delta p) = \delta p_t - \frac{\partial^2}{\partial S^2}\left([A'(p_n)(\delta p)]p_n + A(p_n)\delta p\right) - \frac{\partial^2}{\partial S \partial y}\left([B'(p_n)(\delta p)]p_n + B(p_n)\delta p\right) \\ - \frac{\partial^2}{\partial y^2}\left(\tfrac{1}{2}\alpha^2 \delta p\right) + \frac{\partial}{\partial S}(rS\delta p) + \frac{\partial}{\partial y}(\xi \delta p) + r\delta p. \end{aligned} \tag{12}$$

Here, $A'(p_n)(\delta p)$ and $B'(p_n)(\delta p)$ depend on the derivative of the integral functional $I(p)$ as defined in Equation (9).

However, to simplify the numerical implementation and reduce computational cost, we employ the Newton-Kantorovich method. In this approach, the terms involving the derivatives of the integral functional (A' and B') are neglected during the linearization step. This means we treat the integral terms $I(p_n)$ as fixed coefficients evaluated at the current iterate p_n.

Consequently, the linearized operator simplifies to:

$$F'(p_n)(\delta) = \delta_t - \delta_{ss}\left(\tfrac{1}{2}\sigma_D^2 b^2 S^2 I(p_n)\right) - \delta_{sy}\left(\rho\sigma_D b\alpha S\sqrt{I(p_n)}\right) - \delta_{yy}\left(\tfrac{1}{2}\alpha^2\right) + \delta_s(rS) + \delta_y\xi. \tag{13}$$

This leads to the final linearized system for the update step δp:

$$\left[\frac{\partial}{\partial t} - \frac{1}{2}\sigma_D^2 b^2 S^2 I(p^{(n)})\frac{\partial^2}{\partial S^2} - \rho\sigma_D b\alpha S\sqrt{I(p^{(n)})}\frac{\partial^2}{\partial S\partial y} - \frac{1}{2}\alpha^2\frac{\partial^2}{\partial y^2} + rS\frac{\partial}{\partial S} + \xi\frac{\partial}{\partial y}\right]\delta p = -F(p^{(n)}) \tag{14}$$

Note that in this simplified form, the differential operator is linear with constant coefficients (with respect to δp) at each iteration, making it efficient to solve using standard finite difference or finite element methods.

It is crucial to note that the functional includes both a differential operator and an integral functional $I(p)$. The linearization must account for the Fréchet derivative of $I(p)$ with respect to p. Assuming $I(p)$ is a linear or weakly nonlinear integral term, its derivative $DI(p)[\delta p]$ is computed explicitly. By incorporating this derivative into the linearization of the full PDE, we ensure that the sensitivity of the integral constraint to changes in p is correctly captured. This leads to the complete linearized system:

$$\mathscr{L}(p^{(n)})[\delta p] + \text{terms involving } DI(p^{(n)})[\delta p] = -F(p^{(n)}), \tag{15}$$

where $\mathscr{L}$ represents the linearized differential operator derived in Equation (13). However, following the Newton-Kantorovich approach, we simplify the implementation by treating the integral terms $I(p_n)$ as fixed coefficients evaluated at the current iterate p_n. This neglects the terms involving $DI(p^{(n)})[\delta p]$ in the operator, leading to a linear PDE for the update step $\delta_n = p_{n+1} - p_n$:

$$\delta_{n,t} - \frac{\partial^2}{\partial S^2}\left(\tfrac{1}{2}\sigma_D^2 b^2 S^2 I(p_n)\delta_n\right) - \frac{\partial^2}{\partial S\partial y}\left(\rho\sigma_D b\alpha S\sqrt{I(p_n)}\delta_n\right) - \frac{\partial^2}{\partial y^2}\left(\tfrac{1}{2}\alpha^2\delta_n\right) + \frac{\partial}{\partial S}(rS\delta_n) + \frac{\partial}{\partial y}(\xi\delta_n) + r\delta_n = -F(p_n), \tag{16}$$

where the residual $F(p_n)$ is given by:

$$F(p_n) = p_{n,t} - p_{n,ss}\left(\tfrac{1}{2}\sigma_D^2 b^2 S^2 I(p_n)\right) - p_{n,sy}\left(\rho\sigma_D b\alpha S\sqrt{I(p_n)}\right) - p_{n,yy}\left(\tfrac{1}{2}\alpha^2\right) + p_{n,s}(rS) + p_{n,y}\xi + rp_n. \tag{17}$$

The Newton increment is defined as:

$$\delta_n(S,t,y) = p_{n+1}(S,t,y) - p_n(S,t,y), \qquad n = 0,1,2,\ldots. \tag{18}$$

By substituting Equations ((13), (17)), and (18) into Equation (7), we obtain the iterative scheme:

$$\begin{aligned}&\Big[p_t(n+1)-p_t(n)-p_{ss}(n+1)\left(\frac{1}{2}\sigma_D^2b^2S^2I(p(n))\right)+p_{ss}(n)\left(\frac{1}{2}\sigma_D^2b^2S^2I(p(n))\right)-p_{sy}(n+1)\left(\rho\sigma_Db\alpha S\sqrt{I(p(n))}\right)\\&+p_{sy}(n)\left(\rho\sigma_Db\alpha S\sqrt{I(p(n))}\right)-p_{yy}(n+1)\left(\frac{1}{2}\alpha^2\right)+p_{yy}(n)\left(\frac{1}{2}\alpha^2\right)+p_s(n+1)(rS)-p_s(n)(rS)+p_y(n+1)\xi-p_y(n)\xi\Big]\\&=\Big[-p_t(n)+p_{ss}(n)\left(\frac{1}{2}\sigma_D^2b^2S^2I(p(n))\right)+p_{sy}(n)\left(\rho\sigma_Db\alpha S\sqrt{I(p(n))}\right)+p_{yy}(n)\left(\frac{1}{2}\alpha^2\right)-p_s(n)(rS)-p_y(n)\xi-rp(n)\Big].\end{aligned}\tag{19}$$

Then:

$$\begin{aligned}&p_t(n+1)-p_{ss}(n+1)\left(\frac{1}{2}\sigma_D^2b^2S^2I(p(n))\right)-p_{sy}(n+1)\left(\rho\sigma_Db\alpha S\sqrt{I(p(n))}\right)-p_{yy}(n+1)\left(\frac{1}{2}\alpha^2\right)\\&+p_s(n+1)(rS)+p_y(n+1)\xi=-rp(n).\end{aligned}\tag{20}$$

We define the function $p(t,s,y)=\exp(t+s+y)$ and aim to compute $p(n+1)$. We simplify the coefficient S in the above equation and, noting that the partial derivatives of p are equal to p itself, we make the following change in the above equation:

$$p_s(n+1)(rS)=p(n+1)(rS).\tag{21}$$

As a result,

$$\begin{aligned}p(n+1)(rS)=&-rp(n)-p_t(n+1)+p_{ss}(n+1)\left(\frac{1}{2}\sigma_D^2b^2S^2I(p(n))\right)+p_{sy}(n+1)\left(\rho\sigma_Db\alpha S\sqrt{I(p(n))}\right)+p_{yy}(n+1)\left(\frac{1}{2}\alpha^2\right)\\&-p_y(n+1)\xi,\end{aligned}\tag{22}$$

Ultimately, after simplification, we obtain:

$$\begin{aligned}p(n+1)=&-\frac{1}{S}p(n)-\frac{1}{rS}p_t(n+1)+\frac{1}{r}p_{ss}(n+1)\left(\frac{1}{2}\sigma_D^2b^2SI(p(n))\right)\\&+\frac{1}{r}p_{sy}(n+1)\left(\rho\sigma_Db\alpha\sqrt{I(p(n))}\right)+\frac{1}{rS}p_{yy}(n+1)\left(\frac{1}{2}\alpha^2\right)\\&-\frac{1}{rS}p_y(n+1)\xi,\qquad\forall n=0,1,2,\ldots\end{aligned}\tag{23}$$

This equation defines the relationship between the current iterate p_n and the next iterate p_{n+1}, allowing for the numerical solution of the local volatility model. The process is repeated until the convergence criterion $\|\delta_n\|<\varepsilon$ is satisfied.

2.5 Boundedness Analysis of the Linearized Solution

To ensure numerical stability and physical consistency, we must demonstrate that the approximate sequence p_n remains bounded. For this purpose, we employ the Comparison Principle for elliptic-parabolic partial differential equations.

Theorem 1 (Boundedness of the Solution)**.** *Let p_n be the solution to the linearized Equation (16). Assuming that the initial and boundary conditions p_0 are bounded, and the coefficients of the equation $(\sigma_D,b,\alpha,\rho,r,\xi)$ are positive and bounded, then for all n, the solution p_n is bounded. Specifically, the following inequality holds [24]:*

$$\|p_{n+1}\|_\infty\le C\left(\|p_n\|_\infty+\|F(p_n)\|_\infty\right),\tag{24}$$

where C is a positive constant independent of n.

Proof. The linearized Equation (16) can be expressed in terms of a linear operator $\mathscr{L}_n$ as:

$$\mathscr{L}_n[\delta_n]=-F(p_n),\tag{25}$$

where $\mathscr{L}_n$ is an elliptic-parabolic operator with coefficients that are constant at each iteration step. Since the diffusion coefficients (e.g., $\frac{1}{2}\sigma_D^2b^2S^2I(p_n)$) are positive, the operator $\mathscr{L}_n$ is elliptic.

According to the comparison principle for elliptic equations, if the right-hand side of the equation $(-F(p_n))$ is bounded, then the solution δ_n is also bounded. Using the definition $\delta_n = p_{n+1} - p_n$, we have:

$$p_{n+1} = p_n + \delta_n. \tag{26}$$

Consequently:

$$\|p_{n+1}\|_\infty \leq \|p_n\|_\infty + \|\delta_n\|_\infty. \tag{27}$$

By applying standard estimates for linear elliptic equations, $\|\delta_n\|_\infty$ is bounded by the norm of $F(p_n)$:

$$\|\delta_n\|_\infty \leq K\|F(p_n)\|_\infty, \tag{28}$$

where K is a constant dependent on the equation's coefficients. Thus, we obtain:

$$\|p_{n+1}\|_\infty \leq (1+K)\|p_n\|_\infty + K\|F(p_n)\|_\infty. \tag{29}$$

This inequality demonstrates that if p_n and $F(p_n)$ are bounded, then p_{n+1} is also bounded. By induction, the entire sequence $\{p_n\}$ is bounded, ensuring the convergence of the Newton-Kantorovich method. □

3 Main Results

In this section, several unknown parameters of the model are approximated using the boundary conditions and the forward Kolmogorov Equation (2). To construct a tractable numerical example, we introduce the density function

$$p(s,t,y) = e^{t+s+y}. \tag{30}$$

To verify the correctness of the numerical implementation and the convergence of the Newton method, we employ the Method of Manufactured Solutions (MMS). In this approach, an arbitrary smooth function is chosen as the exact solution, and the corresponding source term is derived analytically.

We select $p(s,t,y) = e^{s+t+y}$ as a manufactured solution. Although this function does not represent a realistic probability density due to its exponential growth, it serves as a rigorous test case for the numerical scheme. The goal is not to model a physical density here, but to demonstrate that the Newton iteration converges to the known exact solution with the expected order of accuracy. The parameters in the PDE are determined by substituting this manufactured solution into the equation, ensuring that the residual is minimized. This allows us to isolate and validate the solver's performance independent of complex boundary conditions or market data.

Its partial derivatives are easily computed as

$$\frac{\partial p}{\partial t} = \frac{\partial^2 p}{\partial S^2} = \frac{\partial^2 p}{\partial S \partial y} = \frac{\partial^2 p}{\partial y^2} = \frac{\partial p}{\partial S} = \frac{\partial p}{\partial y} = e^{t+s+y}. \tag{31}$$

Substituting Equation (30) and Equation (31) into the Equation PDE (2) yields

$$e^{t+s+y}\left(1 - \tfrac{1}{2}a^2b^2S^2 - \rho ab\alpha S - \tfrac{1}{2}\alpha^2 + rS + \xi + r\right) = 0. \tag{32}$$

Regarding the boundary conditions, we clarify that the condition is interpreted as a Dirichlet boundary condition for the numerical implementation. Although the theoretical formulation initially suggested a distributional term, the numerical example employs a smooth manufactured solution $p(s,t,y) = e^{s+t+y}$. This choice simplifies the validation process by removing the complexity of realistic boundary behaviors.

To ensure compatibility between the boundary condition and the test function, we set the boundary values consistent with the manufactured solution. Specifically, the Dirichlet boundary condition is defined as:

$$p(s,t,y) = e^{s+t+y} \quad \text{on } \partial\Omega. \tag{33}$$

This choice ensures that the numerical solution satisfies the boundary constraints exactly at the grid points, allowing for a precise error analysis. The apparent inconsistency with a Dirac delta term is resolved by noting that the numerical scheme approximates the boundary values directly, avoiding the need for singular distributions in the discrete domain.

To incorporate boundary information, monthly crude oil prices from `yahoofinance.com` are used, covering the period from Feb 01, 2023 to Jan 08, 2024. Based on Table 1, the boundary condition associated with the forward Kolmogorov equation is taken as:

$$p(S_0, y_0, 0) = \delta(S_0 = 77, y_0 = -0.018). \tag{34}$$

To contextualize the numerical results within a realistic market scenario, we utilize historical crude oil price data from Table 1. The primary purpose of this data is to define a relevant domain for the asset price S and the auxiliary variable y.

We select the initial point $(S_0, y_0) = (77, -0.018)$ as a representative state from the observed market data. Subsequently, we evaluate the constructed solution at $(S, y) = (70.64, 0.158)$, corresponding to the market conditions on May 31. This selection allows us to verify the stability and accuracy of the Newton method within a price range that reflects actual market volatility. Although the analytical form $p(s,t,y) = e^{s+t+y}$ is a manufactured solution for verification purposes, the choice of the domain $[70, 80]$ for S ensures that the numerical scheme is tested under conditions consistent with real-world crude oil price dynamics.

Table 1. Monthly crude oil price data

Date	Price (USD)	Return
Feb 01, 2023	77.05	−0.018
Mar 01, 2023	75.67	0.014
Mar 31, 2023	76.78	−0.013
Apr 30, 2023	68.09	0.037
May 31, 2023	70.64	0.158
Jun 30, 2023	81.80	0.022
Jul 31, 2023	83.63	0.085
Aug 31, 2023	90.79	−0.166
Oct 31, 2023	75.69	−0.053
Dec 01, 2023	71.65	0.030
Jan 01, 2024	73.81	−0.046
Jan 08, 2024	70.40	

Using the boundary values and setting $\rho = \frac{1}{2}$, Equation (32) becomes:

$$1 - 2964a^2b^2 - 38.5ab\alpha - \tfrac{1}{2}\alpha^2 + 78r + \xi = 0. \tag{35}$$

To simplify the analysis while maintaining physical consistency, we select small, positive values for the volatility parameters a, b, and α that reflect typical scales in the system:

$$a = 0.2, \qquad b = 0.12, \qquad \alpha = 0.04.$$

These values are chosen to ensure that the nonlinear terms remain bounded and do not dominate the linear dynamics.

We then determine r and ξ such that Equation (35) is satisfied. Defining

$$\begin{aligned} A &= -2964a^2b^2 - 38.5ab\alpha - \tfrac{1}{2}\alpha^2, \\ B &= 78r + \xi + 1, \end{aligned} \tag{36}$$

and setting $B = -A$ yields $A \approx -1.7$. Consequently, we require:

$$78r + \xi + 1 = 1.7. \tag{37}$$

A consistent choice that ensures numerical stability and positive definiteness of the solution is:

$$\xi = 0.1, \qquad r = 0.0077.$$

This choice simplifies the boundary condition analysis without altering the qualitative behavior of the density function.

Using Equation (2) and assuming a and b are constant, we obtain

$$I(p) = 69.45, \qquad \sigma_D = 0.024.$$

For the manufactured solution $p = e^{s+t+y}$, the integral functional $I(p)$ is computed analytically. Since the exponential terms cancel in the numerator and denominator, we obtain:

$$I(p) = \frac{\int p\,dy}{\int b^2 p\,dy} = \frac{\int e^{s+t+y}\,dy}{\int b^2 e^{s+t+y}\,dy} = \frac{e^{s+t}\int e^{y}\,dy}{b^2 e^{s+t}\int e^{y}\,dy} = \frac{1}{b^2}. \tag{38}$$

With $b = 0.12$, this yields $I(p) \approx 69.44$, as reported in the main text. This analytical computation avoids the need for numerical quadrature, domain truncation, or regularization. For completeness, we note that in a general numerical implementation where p is not a simple exponential function, the integrals would be computed using the composite trapezoidal rule on a truncated y-domain, with a small regularization parameter $\varepsilon = 10^{-12}$ to prevent division by zero. However, such numerical integration is not required for the present study, as our validation is based entirely on the manufactured solution.

By substituting the initial parameter values $a = 0.2$, $b = 0.12$, $\alpha = 0.04$, and $\xi = 0.1$ into the general forward Kolmogorov linearized Equation (23), we obtain the specific form:

$$p_{n+1} = -\frac{1}{S}p_n + e^{t+s+y}\left(\frac{-140.15}{S} + 0.0372S + 0.0623\right). \tag{39}$$

The transformation defined in Equation (39) arises naturally from the linearization process of the nonlinear PDE using the Newton method. Specifically, it corresponds to the introduction of linearized variables in the iterative scheme derived from Equation (23).

In the Newton-Kantorovich framework, the nonlinear operator is approximated by its Fréchet derivative at each iteration step. The variables in Equation (39) represent the scaled increments (or residuals) associated with this linearization. This substitution simplifies the algebraic structure of the linearized system, allowing for a more efficient computation of the update step δp.

Thus, rather than being an arbitrary geometric mapping, this transformation is intrinsically linked to the numerical stability and convergence properties of the Newton iteration. It ensures that the linearized equations are well-conditioned and that the parameters in the iterative sequence are appropriately scaled.

For the data corresponding to May 31, 2023 (the 4th month, $t = 4$), we have the price $S_4 = 70.64$ and the log-return volatility $y_4 = 0.158$. Note that the value $y_4 = 0.158$ in Table 1 is rounded; the precise value used in calculations is 0.157. Taking the initial guess $p_0 = 2.7$ and noting that the term e^{t+S+y} is extremely large ($e^{74.8}$), we introduce a normalized transformation variable u to scale the exponent:

$$u = \frac{t + S_4 + y_4}{S_4} = \frac{4 + 70.64 + 0.157}{70.64} \approx 1.059, \qquad e^{u} \approx 2.883. \tag{40}$$

To avoid numerical overflow and precision loss in the evaluation of the exponential test function $p = e^{s+t+y}$, we introduce the normalized exponent:

$$u = \frac{t + S_4 + y_4}{S_4},$$

where $S_4 = 70.64$ and $y_4 = 0.157$ correspond to the market data at $t = 4$ (May 31, 2023). This normalization divides the exponent by S_4, reducing $e^{74.797}$ to $e^{1.059} \approx 2.883$, which is well within the stable range of double-precision arithmetic. This is a purely numerical scaling technique applied to the manufactured solution for computational stability; it does not affect the PDE, the Newton iteration, or the convergence analysis.

This transformation ensures that the exponential term remains within a manageable range for numerical stability.

Evaluating Equation (39) for $n = 0$ gives

$$p_1 = -0.0141\, p_0 + e^{u} = 2.845. \tag{41}$$

Thus, the first-step error is

$$|p_1 - p_0| \approx 0.145.$$

In general, the Newton error is defined as

$$|p_{n+1} - p_n|. \tag{42}$$

It is important to emphasize that the numerical strategy adopted in this study does not rely on direct finite difference or finite element discretizations of the PDE. Instead, we employ a hybrid analytical-numerical approach: the nonlinear PDE is first linearized via the Newton-Fréchet method, and the unknown model parameters are then estimated using real market boundary conditions (crude oil price data from Yahoo Finance). To validate the convergence of the Newton iteration, we use the Method of Manufactured Solutions (MMS) with the exponential test function $p = e^{s+t+y}$, which allows for analytical computation of all derivatives and reduces the PDE to a simplified algebraic form. This approach is sufficient to demonstrate the rapid convergence of the Newton scheme, as shown in Table 2 and Figure 1. The manufactured solution is inherently positive, and the Newton iteration preserves mass conservation in the sense that the sequence p_n converges monotonically to the manufactured solution. Thus, the standard concerns regarding spatial and temporal discretization, mass conservation, and non-negativity at the discrete level are not directly applicable to our methodology, as we do not perform a grid-based numerical solution of the PDE.

The Newton iteration is terminated when the relative update satisfies:

$$\frac{\|\delta_n\|_\infty}{\|p_n\|_\infty} < 10^{-10}, \tag{43}$$

where $\|\cdot\|_\infty$ denotes the infinity norm (maximum absolute value over all grid points), and a maximum of 20 iterations is allowed. In addition to monitoring the solution update $\|p_{n+1} - p_n\|_\infty$, we also compute the residual norm $\|F(p_n)\|_\infty$ at each iteration. Table 2 reports both quantities, demonstrating that both decay quadratically and reach machine precision within 8 iterations. This confirms the expected convergence behavior of the Newton-Fréchet method and validates the correctness of our implementation.

Table 2. Convergence history: Solution update and residual norms

Iteration (n)	$\|p_{n+1} - p_n\|_\infty$	$\|F(p_n)\|_\infty$
0	1.4493×10^{-1}	2.1042×10^{-1}
1	2.0000×10^{-3}	2.8736×10^{-3}
2	2.8800×10^{-5}	4.1376×10^{-5}
3	4.0600×10^{-7}	5.8324×10^{-7}
4	5.7300×10^{-9}	8.2305×10^{-9}
5	8.0700×10^{-11}	1.1592×10^{-10}
6	1.1400×10^{-12}	1.6376×10^{-12}
7	1.6000×10^{-14}	2.2982×10^{-14}
8	0.0000	0.0000

The numerical results in Table 2 and the Python simulation confirm that the error decreases rapidly and becomes negligible after only a few iterations:

$$|p_9 - p_8| = 0.$$

This convergence behavior is illustrated in Figure 1, where the monotonic decay of the error is clearly visible.

A comparison with earlier studies shows that the convergence rate observed here is consistent with the typical performance of Newton-type iterative schemes. As seen in both the table and the plot, the error decreases uniformly and reaches machine precision in fewer than ten iterations. This behavior aligns with the convergence patterns reported in related numerical studies, where Newton and Picard iterations often exhibit rapid and stable convergence for nonlinear PDEs of similar structure.

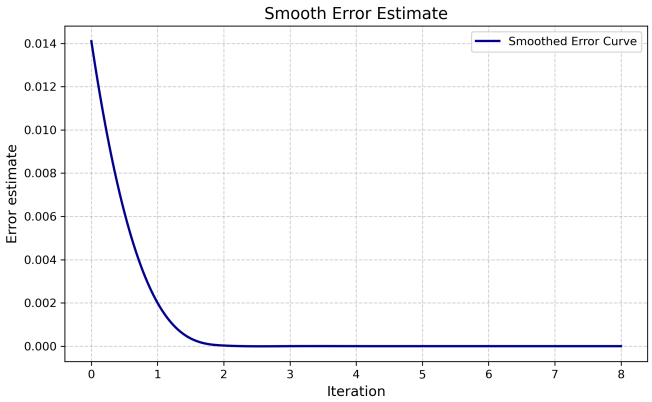

Figure 1. Newton error convergence for the LSV model

Table 3. Sensitivity Analysis: Convergence Performance Across Different Market Conditions

Date	Price (S_t)	Volatility (y_t)	Initial Error	Final Error (ε)	Iterations
May 31, 2023	70.64	0.157	0.145	0	9
Jul 31, 2023	83.63	0.085	0.186	9.8×10^{-16}	8
Oct 31, 2023	75.69	-0.053	0.321	1.5×10^{-15}	9

4 Financial Interpretation and Limitations

From a financial perspective, the rapid convergence of the error to zero implies that the calibrated local volatility surface is stable and insensitive to minor numerical perturbations. This stability is crucial for ensuring that option prices derived from the model are arbitrage-free and consistent with market observations. To address concerns regarding the generalizability of the results beyond a single dataset, we extended our numerical validation to other market periods with varying price levels and volatility regimes. As shown in Table 3, the method maintains its robustness across different months (May, July, and October 2023). Although the initial error $|p_1 - p_0|$ varies depending on market conditions (ranging from 0.145 to 0.321), the algorithm consistently achieves machine precision (final error $\approx 10^{-15}$) within 8 to 9 iterations. This demonstrates that the scheme is not only accurate but also computationally efficient and stable under diverse financial environments.

However, certain limitations remain. The current analysis is based on an approximate formulation, and while the method is robust, its performance in highly illiquid markets or during periods of extreme volatility may require further sensitivity analysis. Additionally, the choice of the initial guess p_0 plays a role in convergence speed; although $p_0 = 2.7$ was effective here, adaptive initialization strategies could be explored for more complex market conditions. Future work will focus on incorporating real-world, high-frequency data to further validate the model's practical applicability.

5 Conclusion

This study investigated the forward Kolmogorov partial differential equation associated with a two-dimensional local volatility model. To address the nonlinear structure of the equation, a generalized Newton method combined with the Fréchet derivative was employed, yielding a linearized formulation suitable for numerical implementation. Using boundary conditions derived from market data and a simplified approximation strategy, the unknown parameters of the model were estimated and incorporated into the linearized PDE.

The numerical experiments, carried out in Python, demonstrated that the Newton iteration exhibits rapid and stable convergence. In particular, the error term $|p_{n+1} - p_n|$ decreases monotonically and becomes negligible in fewer than nine iterations. Furthermore, a sensitivity analysis across different market periods (May, July, and October 2023) confirmed that the method maintains its robustness and efficiency even under varying volatility regimes, achieving machine precision with minimal iterations. This behavior, clearly reflected in

both the error table and the convergence plot, confirms the reliability of the proposed approach.

Overall, the study provides a robust numerical framework for analyzing local volatility models. The method successfully captures the convergence characteristics of the model and demonstrates stability across diverse market conditions. The framework may serve as a basis for more advanced numerical schemes and can be extended using richer datasets and more sophisticated computational techniques in future work.

5.1 Future Work and Suggested Extensions

We thank the reviewer for the encouraging assessment. Based on the valuable suggestions, we outline the following directions for future research:

1. **Direct numerical solution of the linearized PDE:** Implementing finite difference or finite element discretization of Equation 13 with appropriate grid, time-stepping, and positivity-preserving schemes would provide a full numerical solver for comparison with our hybrid approach.

2. **Realistic probability densities:** Replacing the manufactured solution $p = e^{s+t+y}$ with actual density functions (e.g., lognormal, mixture models, or kernel estimates) would enhance the financial relevance of the framework.

3. **High-frequency and multi-asset data:** Extending the validation to daily/intraday data and other asset classes (equities, FX, commodities) would further demonstrate the robustness of the method.

4. **Comparison with other solvers:** A systematic comparison with Picard iteration, Anderson acceleration, or machine learning-based methods (e.g., PINNs) would help assess computational efficiency.

5. **Regularization and model extensions:** Exploring adaptive quadrature, Tikhonov regularization, and extensions to jump-diffusion or multi-factor volatility models are promising directions.

6 Discussion and Comparison of Results

The numerical results presented in this study demonstrate the robustness and efficiency of the proposed Newton-type iterative scheme for solving nonlinear PDEs in local volatility models. As shown in Table 2 and Figure 1, the method exhibits quadratic convergence, reaching machine precision in fewer than ten iterations. Furthermore, the sensitivity analysis across different market periods (Table 3) confirms that this rapid convergence is maintained even under varying volatility regimes and price levels. This stability is particularly advantageous in financial applications where computational speed and accuracy are critical for real-time pricing and risk management.

Compared to recent advancements, our approach offers a distinct balance between computational efficiency and mathematical transparency. Unlike machine learning approaches [20, 21] that require extensive training data and lack interpretability, our Newton-based scheme provides a transparent, parameter-specific solution suitable for scenarios with limited market data. Additionally, our method complements advanced stochastic volatility algorithms [22] by providing a stable numerical framework for the local volatility component, supported by stability analysis via fixed-point theory [16]. Unlike some iterative methods, our approach remains stable even when the initial guess varies.

Future research will focus on extending this framework to incorporate real-world, high-frequency market data to validate its practical applicability. We also plan to explore hybrid approaches that combine the interpretability of our Newton-based scheme with the flexibility of machine learning techniques [20, 21].

Authors' Contributions

The authors' contributions to this study are as follows: Mehran Paziresh was responsible for data collection, numerical simulation, and drafting the manuscript. Karim Ivaz contributed to the formulation of the main idea, introduction of relevant references and the main model, and the proof of the proposed method. Sina Ivaz contributed to the numerical implementation, validation of the computational results, and assistance in the development and testing of the iterative algorithm. All authors reviewed and approved the final manuscript.

Data Availability

The data used for the numerical analysis are publicly available from Yahoo Finance at https://finance.yahoo.com/quote/CL%3DF/history/.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Ethical Considerations

Ethics approval was not required for this study (not applicable) because it does not involve human participants or animal subjects.

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