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Numerical Solutions to Optimal Portfolio Selection and Consumption Strategies under Stochastic Volatility

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1. Introduction

How to optimally allocate assets and optimally consume are extremely important and difficult topics in portfolio management [1–3]. These topics are important not only for theoretical consideration but also for applications in the financial industry. Early studies usually assumed the volatility of the risky asset to be a constant. However, in recent years, researchers found that volatility should be modeled as stochastic rather than deterministic [4–7]. This adds further complication to the problem. The optimal asset allocation and optimal consumption strategies are governed by the Hamilton–Jacobi–Bellman (HJB) equation. Due to the nonlinearity and inhomogeneity of this partial differential equation, no exact solution has been found. Furthermore, even numerical solutions are not available. In this paper, we present an accurate and efficient numerical method for solving this equation and generate the first set of accurate numerical solutions for this problem.

Due to the importance of portfolio selection under stochastic volatilities, several important theoretical works have been carried out, and exact solutions have been obtained under certain special settings, such as no consumption [8–10], complete markets which means that the stock movement and the volatility movement are either perfectly correlated or perfectly anticorrelated [9–12], or when investors have unit elasticity of intertemporal substitution of consumption [13].

In this paper, we consider this optimal stochastic control problem under a general setting: stochastic volatility, incomplete markets, finite investment horizons, and CRRA utility. Our numerical method combines a three-level Crank–Nicolson scheme and Richardson’s extrapolation technique. The Crank–Nicolson scheme has second-order accuracy in terms of discretization error, and Richardson’s extrapolation technique further improves the accuracy. We verify that our numerical method is accurate and efficient.
This paper is organized as follows. In Section 2, we describe the model for financial market, the stochastic control optimization procedure, and the governing HJB equation for the optimal asset allocation and consumption strategies. In Section 3, we present our numerical method for solving the HJB equation. In Section 4, we verify the accuracy and the efficiency of our numerical method and present accurate numerical solutions for the optimal asset allocation strategy and the optimal consumption strategy. In the last section, we present our conclusions.

2. Financial Market and Stochastic Control

We consider a market consisting of one riskless asset $B_t$, whose price is governed by

$$dB_t = rB_t dt,$$

with a constant risk-free interest rate $r$ and a risky asset $S_t$ modeled as

$$dS_t = S_t \left[ \mu(v_t) + \sigma(v_t) dW^v_t \right].$$

In (2), $\mu(v_t)$ and $\sigma(v_t)$ are the return and the stochastic volatility of the stock price $S_t$, respectively. $v_t = \sigma^2_t$ is the stochastic variance of $S_t$. Empirical studies show presence of 2 Complexity

A\textsuperscript{2} Complexity

Here, $dW^v_t$ and $dW^S_t$ are the increments of the Wiener processes under a probability $P$. The correlation between $dW^v_t$ and $dW^S_t$ is $\rho$, namely, $\text{Corr}((dv_t/v_t), (dS_t/S_t)) = \rho dt$. We assume $\rho$ is a constant. In (3), $\theta$ is the long-run average variance (i.e., as $t$ tends to infinity, the expected value of $v_t$ tends to $\theta$), $\kappa$ is the rate at which $v_t$ reverts to $\theta$, and $\xi$ is the volatility of the stock variance $v_t$. The parameters $\kappa$, $\theta$, $\xi$ are positive constants and need to satisfy the Feller condition, $2k\theta > \xi^2$, to ensure that $v_t$ is strictly positive. The risk premia is defined as

$$A = \frac{\mu_t - r}{\sigma_t^2} = \frac{\mu_t - r}{v_t}.$$

Following [1, 5, 15–17], we assume $A$ is a constant. This means the stock excess return is proportional to the stock variance.

Consider an investor who has an initial wealth $w_0$ and needs to determine strategies for asset allocation and consumption over an investment horizon $[0, T]$. Let $w_t$ be the investor’s wealth at time $t$. The strategies consist of an asset allocation rate $\phi_t$ and a consumption rate $c_t$, which mean he/she allocates $\phi_t w_t$ to the risky asset and $(1 - \phi_t) w_t$ to the riskless asset at time $t$ and consumes $c_t dt$ over the time interval $[t, t + dt]$. Thus, under the strategies $\phi_t$ and $c_t$, the wealth process is governed by

$$dw_t = \frac{\phi_t w_t}{S_t} dS_t + (1 - \phi_t) w_t r dt - c_t dt.$$

The goal is to maximize the expected utilities over the investment horizon, namely,

$$\sup_{\phi_t, c_t} E \left[ \int_0^T ae^{-\beta t} u_1(c_t) dt + (1 - a)e^{-\beta T} u_2(w_T) \right].$$

In (6), $\phi_t$ and $c_t$ are control variables for this optimization problem. $E$ is the expectation operator under the probability $P$. $\beta$ is the subjective discount rate, namely, the time preference of the investor. The larger $\beta$ is, the more weight the investor puts on the present than on the future. The parameter $a$ determines the relative importance between intertemporal consumption and the terminal wealth. $u_1(\cdot)$ and $u_2(\cdot)$ are the investor’s utility functions which measure the investor’s degree of satisfaction with the outcomes from intertemporal consumption and terminal wealth, respectively.

CRRA utility functions have been widely adopted for modeling investors’ behavior. Therefore, we adopt the CRRA utility function for $u_1(\cdot)$ and $u_2(\cdot)$:

$$u_1(c_t) = \frac{a_t c_t^{1-\gamma}}{1 - \gamma}, \quad \text{for } \gamma \neq 1,$$

$$u_2(w_T) = \frac{a_w w_T^{1-\gamma}}{1 - \gamma}, \quad \text{for } \gamma \neq 1,$$

$$u_1(c_t) = a_t \log(c_t), \quad \text{for } \gamma = 1,$$

$$u_2(w_T) = a_w \log(w_T), \quad \text{for } \gamma = 1,$$

where $\gamma$, $a_t$, and $a_w$ are positive constants. Since $u_1(\cdot)$ and $u_2(\cdot)$ stand for the intertemporal consumption utility and the terminal wealth utility of the same investor, we use the same $\gamma$ in $u_1(\cdot)$ and $u_2(\cdot)$. However, $a_t$ and $a_w$ can be different since $c$ and $w$ have different dimensions.

Let $V(t, w, v)$ be the value function of problem (6), which is given by

$$V(t, w_t, v_t) = \sup_{\phi_t, c_t} E \left[ \int_t^T ae^{-\beta t} u_1(c_t) dt + (1 - a)e^{-\beta T} u_2(w_T) | \mathcal{F}_t \right],$$

where $\mathcal{F}_T$ is the filtration associated to the stochastic processes in this problem. The terminal condition is obtained by setting $t = T$ in (8):

$$V(T, w_T, v_T) = (1 - a)e^{-\beta T} u_2(w_T).$$

Based on the HJB dynamic programming procedure, $V$ is governed by

$$0 = \sup_{\phi_x} \left[ ae^{-\beta t} u_1(c) + V_t + (rw + \phi w Av - c) V_w ight. + \left. \kappa (\theta - \nu) V_v + \frac{1}{2} \phi^2 w^2 V_{ww} + \phi w \rho \xi V_{ww} + \frac{1}{2} \xi^2 V_{VV} \right],$$

(10)
with the optimal strategies $\varphi^*$ and $c^*$ determined by

$$\varphi^* = -\frac{AV_w + \rho V_{wv}}{wV_{ww}}, \quad (11)$$

$$c^* = \left(\frac{V_w}{a,ae^{-\beta t}}\right)^{(1/\gamma)}. \quad (12)$$

After substituting expressions (11) and (12) into (10), one obtains an equation for the value function $V$:

$$\frac{Y}{1-Y} \left(1 \cdot e^{-\frac{\beta}{\gamma} T}\right)^{(1/\gamma)} V^{(1-\gamma)^-\gamma}_w + r w V_w + V_t + \kappa(\theta - v) V_v,$$

$$\frac{1}{2} \xi v^2 V_{ww} - \frac{1}{2} \left(\frac{AV_w + \rho V_{wv}}{V_{ww}}\right)^2 = 0. \quad (13)$$

Based on the terminal condition and the scaling property of (13), it is reasonable to guess that

$$V(\tau, w, v) = e^{-\beta(\tau - t)} a w^{1-\gamma} \left(\frac{1}{1 - \gamma}ight) f(\tau, v)^\gamma, \quad (14)$$

where $\tau = T - t$, (13) becomes

$$0 = -f_v + \frac{1}{2} \xi v^2 f_{vv} + \left(\frac{\kappa(\theta - v) + \frac{1 - \gamma}{\gamma} A \rho \xi}{\gamma} f_v\right), \quad (15)$$

with

$$f(0, v) = (1 - a)^{(1/\gamma)}, \quad (16)$$

and (11) and (12) become

$$\varphi^* = \frac{A}{\gamma} + \rho \xi f_v / f, \quad (17)$$

$$c^* = \left(\frac{a a_c}{a_w}\right)^{(1/\gamma)} f^{1-\gamma}. \quad (18)$$

Equation (15) is a nonlinear and inhomogeneous partial differential equation. Since no closed-form solution is available for this equation, numerical computation plays a critical role for studying this important practical problem in modern finance. However, there are even no numerical solutions available in the literature.

### 3. Numerical Method

In this section, we develop a numerical method for solving (15). For the sake of conciseness of our expressions, we rewrite (15) as

$$-f_v + a_1 v f_{vv} + (a_2 v + a_3) f_v + a_4 v f_v^2 + (a_5 v + a_6) f_v^3,$$

$$+ a_7 = 0, \quad (19)$$

with the initial condition $f(0, v) = (1 - a)^{(1/\gamma)}$, where

$$a_1 = \frac{1}{2} \xi,$$

$$a_2 = -\frac{1 - \gamma}{\gamma} A \rho \xi,$$

$$a_3 = \kappa \theta,$$

$$a_4 = \frac{1}{2} (1 - \gamma) \xi^2 (1 - \rho^2),$$

$$a_5 = \frac{1 - \gamma}{2 \gamma^2} A^2,$$

$$a_6 = \frac{(1 - \gamma) r}{\gamma} - \frac{\beta}{\gamma},$$

$$a_7 = \left(\frac{a a_c}{a_w}\right)^{(1/\gamma)}. \quad (20)$$

#### 3.1. Crank–Nicolson Scheme and Richardson’s Extrapolation.

We use a three-level Crank–Nicolson scheme (see [18–21]) of second-order accuracy to solve the nonlinear and inhomogeneous partial differential equation given by (19) and use Richardson’s extrapolation technique for further improving accuracy. Numerically, one can only solve (19) over a finite domain $v \in [0, v_{\text{max}}]$. Since the boundary conditions at $v = 0$ and at $v = v_{\text{max}}$ are not known, we use one-sided difference method at these two numerical boundaries. Step sizes $\Delta \tau$ and $\Delta v$ are used to discretize $\tau$ and $v$, respectively. Thus, $\tau = n \Delta \tau$ and $v = m \Delta v$. We adopt the standard notation $f^n_{m} = f(n \Delta \tau, m \Delta v)$.

The three-level Crank–Nicolson scheme involves the levels $n - 1, n$, and $n + 1$. It is straightforward to discretize all linear terms in (19) with second-order errors, namely,

$$f_v^n = \frac{f_{m+1} - f_{m-1}}{2 \Delta v} + O(\Delta v^2),$$

$$f_v^n = \frac{1}{2} \left(\frac{f_{m+1} - f_{m-1}}{2 \Delta v} + \frac{f_{m+1}^{n+1} - f_{m-1}^{n+1}}{2 \Delta v}\right) + O(\Delta v^2),$$

$$f_v^n = \frac{1}{2} \left(\frac{f_{m+1}^{n+1} - 2 f_{m+1}^{n+1} + f_{m-1}^{n+1}}{\Delta v^2} + f_{m+1}^{n+1} - 2 f_{m+1}^{n+1} + f_{m-1}^{n+1}\right) + O(\Delta v^2).$$

(21)
The nonlinear term $f^2_v/f$ has two factors $f_v/f$ and $f_v$. We discretize the factor $f_v/f$ at level $n$ and approximate the factor $f_v$ as an average between $f_v$ at level $n - 1$ and that at level $n + 1$, namely,

\[
\left( \frac{f^2_v}{f} \right)_m = \left( \frac{f_v}{f} \right)_m \left[ ((f_v)_m^n + (f_v)_{m-1}^{n-1}) + O(\Delta t^2) \right] \\
= \frac{f_{m+1} - f_{m-1}}{4\Delta v f_m^n} \left(\frac{f_{m+1}^{n+1} - f_{m+1}^{n-1} + f_{m+1}^{n+1} - f_{m-1}^{n-1}}{2\Delta v}\right) + O(\Delta t^2) + O(\Delta v^2).
\]

(22)

This discretization scheme leads to a set of linear equations. Based on the expressions given by (21) and (22), equation (19) can be discretized as

\[
e_1(m) f_{m+1}^{n+1} + e_2(m) f_m^{n+1} + e_3(m) f_{m-1}^{n+1} = e_4(m) + O(\Delta t^2) + O(\Delta v^2),
\]

(23)

for $0 < m < M$ and $n \geq 2$, where $M$ is the maximal value of $m$ and

\[
e_1(m) = \frac{a_1 m}{\Delta v} - \frac{\lambda(m)}{2\Delta v},
\]

\[
e_2(m) = -\frac{a_1 m}{\Delta v} - \frac{1}{\Delta t} + a_3 m \Delta v + a_6,
\]

\[
e_3(m) = \frac{a_1 m}{\Delta v} + \frac{\lambda(m)}{2\Delta v},
\]

\[
e_4(m) = -\frac{1}{\Delta t} f_m^{n+1} - 2\alpha_a^{(n+1)} a_7 - \frac{a_4 m}{\Delta v} \left( f_{m+1}^{n-1} - 2 f_m^{n-1} + f_{m-1}^{n-1} \right)
\]

\[-\frac{\lambda(m)}{2\Delta v} \left( f_{m+1}^{n-1} - f_{m-1}^{n-1} \right) - (a_3 m \Delta v + a_6) f_{m+1}^{n-1},
\]

(24)

with

\[
\lambda(m) = a_2 m \Delta v + a_3 + \frac{a_4 m (f_{m+1}^{n-1} - f_{m-1}^{n-1})}{2 f_m^n}.
\]

(25)

Since (23) is not applicable to the boundaries at $m = 0$ and $m = M$, we used one-sided difference technique to discretize (19) and obtained the boundary equations in the following. It is straightforward to show that, at $m = 0$, we have

\[
f_v(0, \tau) = \frac{1}{4\Delta v} \left( -3 f_0^{n+1} + 4 f_1^{n+1} - f_2^{n+1} - 3 f_0^{n-1} + 4 f_1^{n-1} - f_2^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2),
\]

\[
f_{vv}(0, \tau) = \frac{1}{2\Delta v^2} \left( 2 f_0^{n+1} - 5 f_1^{n+1} + 4 f_2^{n+1} - f_3^{n+1} + 2 f_0^{n-1} - 5 f_1^{n-1} + 4 f_2^{n-1} - f_3^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2),
\]

(26)

\[
f^2_v(f_0^n, \tau) = -\frac{3 f_0^n + 4 f_1^n - f_2^n}{8\Delta v^2 f_0^n} \left( -3 f_0^{n+1} + 4 f_1^{n+1} - f_2^{n+1} - 3 f_0^{n-1} + 4 f_1^{n-1} - f_2^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2),
\]

and at $m = M$, we have

\[
f_v(\nu_{\text{max}}, \tau) = \frac{1}{4\Delta v} \left( 3 f_M^{n+1} - 4 f_{M-1}^{n+1} + f_{M-2}^{n+1} - 3 f_M^{n-1} + 4 f_{M-1}^{n-1} + f_{M-2}^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2),
\]

\[
f_{vv}(\nu_{\text{max}}, \tau) = \frac{1}{2\Delta v^2} \left( 2 f_M^{n+1} - 5 f_{M-1}^{n+1} + 4 f_{M-2}^{n+1} - f_{M-3}^{n+1} + 2 f_M^{n-1} - 5 f_{M-1}^{n-1} + 4 f_{M-2}^{n-1} - f_{M-3}^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2),
\]

(27)

\[
f^2_v(\nu_{\text{max}}, \tau) = \frac{3 f_M^n - 4 f_{M-1}^n + f_{M-2}^n}{8\Delta v^2 f_M^n} \left( 3 f_M^{n+1} - 4 f_{M-1}^{n+1} + f_{M-2}^{n+1} + 3 f_M^{n-1} - 4 f_{M-1}^{n-1} + f_{M-2}^{n-1} \right) + O(\Delta t^2) + O(\Delta v^2).
\]

By substituting these expressions into (19), we have

\[
d_1(0) f_0^{n+1} + d_2(0) f_1^{n+1} + d_3(0) f_2^{n+1} + d_4(0) f_3^{n+1} = d_5(0) + O(\Delta t^2) + O(\Delta v^2),
\]

(28)

\[
d_4(M) f_{M-3}^{n+1} + d_3(M) f_{M-2}^{n+1} + d_2(M) f_{M-1}^{n+1} + d_1(M) f_M^{n+1} = d_5(M) + O(\Delta t^2) + O(\Delta v^2),
\]

(29)
where

\[ \begin{align*}
    d_1(0) &= -\frac{3\lambda(0)}{2\Delta v} - \frac{1}{\Delta \tau} + a_6, \\
    d_2(0) &= -\frac{2\lambda(0)}{\Delta v}, \\
    d_3(0) &= -\frac{\lambda(0)}{2\Delta v}, \\
    d_4(0) &= 0, \\
    d_5(0) &= -\frac{1}{\Delta \tau} f_0^{n-1} - 2a_1^M + \frac{\lambda(0)}{2\Delta v} \left( -3f_0^{n-1} + 4f_1^{n-1} - f_2^{n-1} \right) - a_6 f_0^{n-1}, \\
    d_1(M) &= \frac{2a_1 M}{\Delta v} + \frac{3\lambda(M)}{2\Delta v} - \frac{1}{\Delta \tau} + a_5 M \Delta v + a_6, \\
    d_2(M) &= -\frac{5a_1 M}{\Delta v} - \frac{2\lambda(M)}{\Delta v}, \\
    d_3(M) &= \frac{4a_1 M}{\Delta v} + \frac{\lambda(M)}{2\Delta v}, \\
    d_4(M) &= -\frac{a_1 M}{\Delta v}, \\
    d_5(M) &= -\frac{1}{\Delta \tau} f_M^{n-1} - 2a(M) a_7 - \frac{a_1 M}{\Delta v} \left( 2f_M^{n-1} - 5f_{M-1}^{n-1} + 4f_{M-2}^{n-1} - f_{M-3}^{n-1} \right) \\
    &\quad - \frac{\lambda(M)}{2\Delta v} \left( 3f_M^{n-1} - 4f_{M-1}^{n-1} + f_{M-2}^{n-1} \right) - (a_2 M \Delta v + a_6) f_M^{n-1},
\end{align*} \]

with

\[ \begin{align*}
    \lambda(0) &= a_3, \\
    \lambda(M) &= a_2 M \Delta v + a_3 + \frac{a_4 M (3f_M^n - 4f_{M-1}^n + f_{M-2}^n)}{2f_M^n},
\end{align*} \]

From (23), (28), and (29), the numerical solution of (19) for \( n \geq 2 \) is determined by the following system of linear equations:

\[ \begin{bmatrix}
    d_1(0) & d_2(0) & d_3(0) & d_4(0) & \vdots & \vdots & \vdots \\
    e_1(1) & e_2(1) & e_3(1) & \vdots & \vdots & \vdots & \vdots \\
    e_4(2) & e_5(2) & e_6(2) & \vdots & \vdots & \vdots & \vdots \\
    \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
    e_{1}(M-1) & e_{2}(M-1) & e_{3}(M-1) & \vdots & \vdots & \vdots & \vdots \\
    d_{4}(M) & d_{3}(M) & d_{2}(M) & d_{1}(M) & \vdots & \vdots & \vdots \\
\end{bmatrix}
\begin{bmatrix}
    f_0^{n-1} \\
    f_1^{n-1} \\
    f_2^{n-1} \\
    \vdots \\
    f_{M-1}^{n-1} \\
\end{bmatrix} =
\begin{bmatrix}
    d_5(0) \\
    e_4(1) \\
    e_4(2) \\
    \vdots \\
    e_4(M-1) \\
\end{bmatrix}. \]
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After eliminating \( d_4(0), d_4(0), d_4(M), \) and \( d_4(M) \), (33) can be transformed into the following tridiagonal matrix form for \( n \geq 2 \):

\[
\begin{bmatrix}
ed_2(0) & e_3(0) \\
e_1(1) & e_2(1) & e_3(1) \\
e_1(2) & e_2(2) & e_3(2) \\
\vdots & \vdots & \vdots \\
e_1(M-1) & e_2(M-1) & e_3(M-1) \\
e_1(M) & e_2(M) & e_3(M) \\
\end{bmatrix}
\begin{bmatrix}
f_0^{n+1} \\
f_1^{n+1} \\
f_2^{n+1} \\
\vdots \\
f_{M-1}^{n+1} \\
f_M^{n+1} \\
\end{bmatrix} =
\begin{bmatrix}
e_4(0) \\
e_4(1) \\
e_4(2) \\
\vdots \\
e_4(M-1) \\
e_4(M) \\
\end{bmatrix}, \tag{34}
\]

where

\[
e_2(0) = d_1(0) - \frac{e_3(2)d_1(0) - e_2(2)d_4(0)}{e_3(2)e_1(1)},
\]

\[
e_3(0) = d_2(0) - \frac{d_4(0)}{e_3(2)}e_1(2) - \frac{e_3(2)d_1(0) - e_2(2)d_4(0)}{e_3(2)e_1(1)},
\]

\[
e_4(0) = d_5(0) - \frac{d_4(0)}{e_3(2)}e_4(2) - \frac{e_3(2)d_1(0) - e_2(2)d_4(0)}{e_3(2)e_1(1)},
\]

\[
e_1(M) = d_2(M) - \frac{d_4(M)}{e_1(M-2)}e_3(M-2) - \frac{e_1(M-2)d_3(M) - e_2(M-2)d_4(M)}{e_1(M-2)e_1(M-1)}e_2(M-1),
\]

\[
e_2(M) = d_1(M) - \frac{e_1(M-2)d_3(M) - e_2(M-2)d_4(M)}{e_1(M-2)e_1(M-1)}e_3(M-1),
\]

\[
e_4(M) = d_5(M) - \frac{d_4(M)}{e_1(M-2)}e_4(M-2) - \frac{e_1(M-2)d_3(M) - e_2(M-2)d_4(M)}{e_1(M-2)e_1(M-1)}e_4(M-1),
\]

The method given by (21) and (22) is a two-step method, namely, \( f^{n+1} \) depends on \( f^n \) and \( f^{n-1} \). At the zeroth step, \( f^0 \) is given by initial condition (16), namely, \( f_0^m = (1-a)^{0.5} \), for \( 0 \leq m \leq M \). We now determine \( f^1 \), the solution at the first step. Performing Taylor expansion on \( f(\Delta \tau, v) \) at \( \tau = 0 \) gives

\[
f(\Delta \tau, v) = f(0, v) + f_v(0, v)\Delta \tau + \frac{1}{2}f_{vv}(0, v)\Delta \tau^2 + \frac{1}{6}f_{vvv}(0, v)\Delta \tau^3 + O(\Delta \tau^4), \tag{36}
\]

where \( f(0, v) \) is given by (16) and \( f_v(0, v), f_{vv}(0, v), \) and \( f_{vvv}(0, v) \) can be determined analytically from (19):
The details of derivations for $f_v(0, v)$, $f_{\tau v}(0, v)$, and $f_{\tau\tau v}(0, v)$ are given in Appendix A. From (36), $f_m^n$ is given by

$$f_m^1 = f_m^0 + f_v(0, m\Delta v)\Delta\tau + \frac{1}{2} f_{\tau v}(0, m\Delta v)\Delta\tau^2 + \frac{1}{6} f_{\tau\tau v}(0, m\Delta v)\Delta\tau^3,$$

with an error of $O(\Delta\tau^4)$.

Knowing $f$, the numerical solutions of optimal portfolio and consumption rules can be obtained from (17) and (18):

$$\varphi_m^n = \frac{A}{\gamma} + \rho\xi \frac{f_v^n}{f_m^n},$$

$$\frac{c_m^n}{w} = \left(\frac{a\alpha}{a_w}\right)^{(1/\gamma)} \left(f_m^n\right)^{-1},$$

for $0 \leq m \leq M$, where $f_m^0$ is given by (34) and $(f_m)^n$ is given by

$$f_m^n = \begin{cases} -3f_m^0 + 4f_m^n - f_m^{n-1}, & \text{for } m = 0, \\ f_m^{n+1} - f_m^{n-1}, & \text{for } 0 < m < M, \\ 3f_m^n - 4f_{M-1}^n + f_{M-2}^n, & \text{for } m = M. \end{cases}$$

In summary, our numerical solutions for $f_m^0$ and $f_m^1$ are determined by (16) and (38), respectively, and the numerical solutions for $f_m^n$ with $n \geq 2$ are determined by (34). The numerical solution of $f$ obtained by the three-level Crank–Nicolson scheme has an accuracy of $O(\Delta\tau^3) + O(\Delta v^2)$.

### 3.2. Performing Richardson’s Extrapolation

To further improve the accuracy of the numerical method, we apply Richardson’s extrapolation technique to $f$. We will choose $\Delta v$ proportional to $\Delta\tau$. Let $f_{m,n,m,\Delta\tau}$ represent $f_m^n$ obtained by (34) with a step size $\Delta\tau$. Then,

$$f_{m,n,m,\Delta\tau} = f_{\text{exact}}(\tau, v) + C_1\Delta\tau^2 + C_2\Delta\tau^3 + O(\Delta\tau^4),$$

where $f_{\text{exact}}$ is the exact value. We perform two computations with the step sizes $\Delta\tau$ and $\Delta\tau/2$, respectively. Then, we have the following two equations:

$$f_{2m,n,2\Delta\tau} = f_{\text{exact}}(\tau, v) + C_1(\Delta\tau^2) + C_2(\Delta\tau^3) + O(\Delta\tau^4).$$

From (43) and (44), we solve $f_{\text{exact}}$ and obtain an expression based on Richardson’s extrapolation technique:

$$f_{\text{expl}}(n\Delta\tau, m\Delta v) = \frac{4}{3} f_{2m,n,2\Delta\tau} - \frac{1}{3} f_{m,n,m,\Delta\tau} = f_{\text{exact}} + O(\Delta\tau^2).$$

After substituting $f_{\text{expl}}$ into (39) and (40), we obtain the expressions for $\varphi^*$ and $c^*/w$ with an accuracy of $O(\Delta\tau^2)$:

$$\varphi_{\text{expl}}^* = \frac{A}{\gamma} + \rho\xi \frac{f_{\text{expl}}^*}{f_{\text{expl}}},$$

$$\frac{c_{\text{expl}}^*}{w} = \left(\frac{a\alpha}{a_w}\right)^{(1/\gamma)} \left(f_{\text{expl}}^*\right)^{-1},$$

where $f_{\text{expl}}$ is given by (45) and $(f_{\text{expl}})^n$ is given by

$$\left(f_{\text{expl}}^n\right) = \begin{cases} -9(f_{\text{expl}}^n) + 16(f_{\text{expl}}^n)_{m-1} - 8(f_{\text{expl}}^n)_{m+2} + (f_{\text{expl}}^n)_{m+4}, & \text{for } m \leq 1, \\ \frac{1}{6}\Delta v \left[9(f_{\text{expl}}^n)_{m-2} - 4(f_{\text{expl}}^n)_{m-1} + 4(f_{\text{expl}}^n)_{m+1} - (f_{\text{expl}}^n)_{m+2}, \right. & \text{for } 1 < m < M - 1, \\ \frac{1}{6}\Delta v \left[9(f_{\text{expl}}^n)_{m-2} - 16(f_{\text{expl}}^n)_{m-1} + 8(f_{\text{expl}}^n)_{m-2} - (f_{\text{expl}}^n)_{m-4}, \right. & \text{for } m \geq M - 1. \end{cases}$$

For the purpose of giving a quick understanding of our method, Figure 1 presents a flowchart of the algorithm for solving (19). We also summarize the procedure in words in the following for obtaining the numerical solutions of $f$, $\varphi^*$, $c^*$, $f_{\text{expl}}$, $\varphi_{\text{expl}}^*$, and $c_{\text{expl}}^*$. Here, we choose $\Delta v = \Delta\tau$.

(i) Step 1: initialize $f$ by initial condition (16), namely, $f_m^0 = (1 - \alpha)^{(1/\gamma)}$, for $0 \leq m \leq M$.

(ii) Step 2: initialize $f_m^1$ by (38) for $0 \leq m \leq M$.

(iii) Step 3: for $n > 2$, knowing $f_m^{n-1}$ and $f_m^n$, for $0 \leq m \leq M$, $f_m^n$ can be determined from (34), which is in a tridiagonal form and can be easily and efficiently solved. $f_m^n$ has an accuracy of $O(\Delta\tau^2)$.

(iv) Step 4: to obtain $\varphi^*$ and $c^*$, we substitute $f_m^n$ from Steps 1–3 into (39) and (40). This provides the
Algorithm for solving equation (19)

Start

Set \((\Delta_t, \Delta v, N, M)\). Input all parameters

\(f_{\text{course}} = \) three-level Crank–Nicolson method \((\Delta_t, \Delta v, N, M)\)

To perform extrapolation?

No

Yes

\(f_{\text{fin}} = \) three-level Crank–Nicolson method \((\Delta_t/2, \Delta v/2, 2N, 2M)\)

Apply Richardson’s extrapolation technique on \(f_{\text{course}}\) and \(f_{\text{fin}}\) to obtain the third-order-accuracy solution \(f_{\text{extpl}}\), see equation (45)

Output \(f_{\text{num}} = f_{\text{course}}\)

Output \(f_{\text{extpl}}\)

End

Details in three-level Crank–Nicolson method

Input \((\Delta_t', \Delta v', N', M')\)

Initialize step-1 solution \((n = 0)\) by \(f_{n0}^0 = (1 - \alpha)^n\) for \(0 \leq m \leq M'\)

Initialize step-2 solution \((n = 1)\) \(f_{n1}^1\) by formula equation (38) for \(0 \leq m \leq M'\)

Perform three-level Crank–Nicolson method for \(2 \leq n \leq N'\):

① Determine the equations for boundary points \(f_{n0}^0\) and \(f_{n0}^1\) by one-side difference, see equations (28) and (29)

② Determine the equations for interior points \(f_{n}^0\) for \(0 < m < M'\) by central difference and technique Equation (22), see equation (23)

③ Combine equations in ① and ② and obtain the solution \(f_{n}^0\) for \(0 \leq m \leq M'\) by solving a tridiagonal matrix, see equation (24)

Combine equations in ① and ② and obtain the solution \(f_{n}^0\) for \(0 \leq m \leq M'\) by solving a tridiagonal matrix, see equation (24)

\(n = N'\)

Repeat with \(n = n + 1\)

Return solution \(f_{N'}^N\)

\(\Delta t\) and \(\Delta v\) are step sizes for time and space. \(N'\) and \(M'\) are the total number of grid points in \(t\) and \(v\) directions

Figure 1: Flowchart of the algorithm.

4. Validation Study of the Numerical Method

Equation (19) is an inhomogeneous equation. However, since the inhomogeneous term \(a^{(1/2)}\alpha\) affects neither the stability nor the accuracy of the three-level Crank–Nicolson method, it is sufficient to conduct validation studies for the corresponding homogeneous equation, namely, for the case of \(\alpha = 0\). Let \(\tilde{f}\) be the solution of the homogeneous equation of (19), namely, the case of \(\alpha = 0\). Then, \(\tilde{f}\) satisfies

\[-(\tilde{f})_t + a_1 v (\tilde{f})_v + (a_2 v + a_3) (\tilde{f})_v + a_4 v (\tilde{f})_v = 0\]  \((49)\)

with the initial condition \(\tilde{f}(0, v) = 1\). Following the procedure outlined in [10], the exact solution for \(\tilde{f}\) can be obtained. After expressing \(\tilde{f}(r, v)\) as

\[\tilde{f}(r, v) = e^{h_1(r)v + h_2(r)}\]  \((50)\)

from (49), \(h_1(r)\) and \(h_2(r)\) are governed by

\[h_1'(r) - (a_3 + a_4)h_1(r) - a_5 = 0, \quad \text{with } h_1(0) = 0,\]

\[h_2'(r) - a_3 h_1(r) - a_6 = 0, \quad \text{with } h_2(0) = 0,\]  \((51)\)

and the solutions are
Numerical solutions for the instantaneous volatility of S&P 500 index options, we examine the Options Exchange Volatility Index, a popular measure of the volatility of S&P 500 index options.

Since wealth $w$ does not appear in (19), (17), and (18), its value is irrelevant in our study. For the remaining set of parameters $t$ and $v$, we consider $T \leq 100$. Based on the historical records of the Chicago Board Options Exchange Volatility Index, a popular measure of the implied volatility of S&P 500 index options, we examine the numerical solutions for the instantaneous volatility $\sigma_i = \sqrt{\nu_i}$ in the interval $[0.1, 0.8]$ (to eliminate possible influence from the numerical boundary, the authors choose $\nu_{i,\text{max}} = 2$ in their numerical computations). Since wealth $w$ does not appear in (19), (17), and (18), its value is irrelevant in our study.
parameters, we vary only one of the parameters at a time and keep other parameters at their benchmark values as shown in Table 1. Extensive sets are given in Table 5.

By choosing the step size $\Delta \tau = 0.01$ and $\Delta \nu = 0.01$, the proposed algorithm is conducted, and the relative errors are recorded both before and after performing the extrapolation technique. In Tables 6 and 7, we show the maximum relative errors of the proposed algorithm before and after performing the extrapolation technique, respectively, in the domain $0 \leq \tau \leq 100$ and $0 \leq \sqrt{\nu} = \sigma \leq 0.8$. It can be found that the extrapolation technique does improve one-order accuracy for the ten sets of parameters in Table 5.

By taking half of the step size above, namely, choosing $\Delta \tau = 0.005$ and $\Delta \nu = 0.005$, the proposed algorithm is...
Table 5: Values for the parameters $\kappa, \theta, \xi, \rho, A, r, \beta, \gamma, a_c$, and $a_w$.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$\kappa$</th>
<th>$\theta$</th>
<th>$\xi$</th>
<th>$\rho$</th>
<th>$A$</th>
<th>$r$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$a_c$</th>
<th>$a_w$</th>
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</thead>
<tbody>
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<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 2</td>
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<td>0.08</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 3</td>
<td>1.6048</td>
<td>0.0464</td>
<td>0.6</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 4</td>
<td>1.6048</td>
<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
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<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 6</td>
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<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 7</td>
<td>1.6048</td>
<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 8</td>
<td>1.6048</td>
<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Set 9</td>
<td>1.6048</td>
<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
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<td>1</td>
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<td>Set 10</td>
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<td>0.0464</td>
<td>0.3796</td>
<td>-76.70%</td>
<td>1.55</td>
<td>1%</td>
<td>0.06</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6: Maximum relative error for $\tilde{f}_{\text{num}}$ and $\tilde{\rho}_{\text{num}}$ with $\Delta \tau = 0.01$ and $\Delta \nu = 0.01$.

<table>
<thead>
<tr>
<th>Set</th>
<th>$\tilde{f}_{\text{num}}$</th>
<th>$\tilde{\rho}_{\text{num}}$</th>
</tr>
</thead>
<tbody>
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<td>$5.8 \times 10^{-6}$</td>
<td>$3.9 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 2</td>
<td>$3.6 \times 10^{-6}$</td>
<td>$2.7 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 3</td>
<td>$3.6 \times 10^{-6}$</td>
<td>$3.9 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 4</td>
<td>$4.0 \times 10^{-6}$</td>
<td>$1.8 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 5</td>
<td>$2.4 \times 10^{-6}$</td>
<td>$2.0 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 6</td>
<td>$4.0 \times 10^{-6}$</td>
<td>$2.8 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 7</td>
<td>$4.2 \times 10^{-6}$</td>
<td>$2.9 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 8</td>
<td>$2.1 \times 10^{-6}$</td>
<td>$1.4 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 9</td>
<td>$3.8 \times 10^{-6}$</td>
<td>$2.7 \times 10^{-6}$</td>
</tr>
<tr>
<td>Set 10</td>
<td>$3.8 \times 10^{-6}$</td>
<td>$2.7 \times 10^{-6}$</td>
</tr>
</tbody>
</table>

Table 7: Maximum relative error for $\tilde{f}_{\text{expl}}$ and $\tilde{\rho}_{\text{expl}}$ with $\Delta \tau = 0.01$ and $\Delta \nu = 0.01$.

<table>
<thead>
<tr>
<th>Set</th>
<th>$\tilde{f}_{\text{expl}}$</th>
<th>$\tilde{\rho}_{\text{expl}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1</td>
<td>$1.2 \times 10^{-7}$</td>
<td>$9.3 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 2</td>
<td>$5.0 \times 10^{-8}$</td>
<td>$4.3 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 3</td>
<td>$9.5 \times 10^{-8}$</td>
<td>$5.9 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 4</td>
<td>$5.9 \times 10^{-8}$</td>
<td>$3.1 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 5</td>
<td>$3.3 \times 10^{-8}$</td>
<td>$3.1 \times 10^{-8}$</td>
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<tr>
<td>Set 6</td>
<td>$5.6 \times 10^{-8}$</td>
<td>$4.5 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 7</td>
<td>$5.8 \times 10^{-8}$</td>
<td>$4.7 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 8</td>
<td>$2.5 \times 10^{-8}$</td>
<td>$2.02 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 9</td>
<td>$5.4 \times 10^{-8}$</td>
<td>$4.4 \times 10^{-8}$</td>
</tr>
<tr>
<td>Set 10</td>
<td>$5.4 \times 10^{-8}$</td>
<td>$4.4 \times 10^{-8}$</td>
</tr>
</tbody>
</table>

Table 8: Maximum relative error for $\tilde{f}_{\text{num}}$ and $\tilde{\rho}_{\text{num}}$ with $\Delta \tau = 0.005$ and $\Delta \nu = 0.005$.

<table>
<thead>
<tr>
<th>Set</th>
<th>$\tilde{f}_{\text{num}}$</th>
<th>$\tilde{\rho}_{\text{num}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1</td>
<td>$1.4 \times 10^{-6}$</td>
<td>$9.7 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 2</td>
<td>$9.1 \times 10^{-7}$</td>
<td>$6.7 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 3</td>
<td>$9.0 \times 10^{-7}$</td>
<td>$9.8 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 4</td>
<td>$1.0 \times 10^{-6}$</td>
<td>$4.6 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 5</td>
<td>$6.0 \times 10^{-7}$</td>
<td>$5.0 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 6</td>
<td>$10.0 \times 10^{-7}$</td>
<td>$6.9 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 7</td>
<td>$1.0 \times 10^{-6}$</td>
<td>$7.2 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 8</td>
<td>$5.1 \times 10^{-7}$</td>
<td>$3.5 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 9</td>
<td>$9.6 \times 10^{-7}$</td>
<td>$6.7 \times 10^{-7}$</td>
</tr>
<tr>
<td>Set 10</td>
<td>$9.6 \times 10^{-7}$</td>
<td>$6.7 \times 10^{-7}$</td>
</tr>
</tbody>
</table>
conducted, and the relative errors are recorded both before and after performing the extrapolation technique. In Tables 8 and 9, we show the maximum relative errors of the proposed algorithm before and after performing the extrapolation technique, respectively, in the domain $0 \leq \tau \leq 100$ and $0 \leq \sqrt{\nu} = \sigma \leq 0.8$. Tables 6–9 show that the proposed algorithm before and after performing the extrapolation technique has second-order accuracy and third-order accuracy, respectively, for the extensive sets of parameters.

4.3. Evidence for Stability and Convergence. To provide the evidence for stability, we calculate the maximum relative errors of $\tilde{f}_{\text{num}}$ for $\Delta \tau = \Delta \nu = 0.04, 0.02, 0.01, 0.005, 0.0025$, respectively. The results are shown in Figure 2. One can see that, as the step size goes to zero, the maximum relative errors tend to zero, which numerically verifies the stability of the proposed algorithm.

To provide the evidence for convergence, let $e(\Delta \tau, \Delta \nu)$ be the maximum relative error; then, the convergence order is given by

$$\text{convergence order} = \log_2 \left( \frac{e(\Delta \tau, \Delta \nu)}{e((\Delta \tau)/2, (\Delta \nu)/2)} \right).$$  \hspace{1cm} (56)

In Table 10, the maximum relative errors and convergence orders of $\tilde{f}_{\text{num}}$ for different values of $\Delta \tau$ and $\Delta \nu$ are given. It shows that the convergence orders are always equal to 2.0 as $\Delta \tau$ and $\Delta \nu$ go to zero, which numerically verifies the convergence of the proposed algorithm.

Table 9: Maximum relative error for $\tilde{f}_{\text{expl}}$ and $\tilde{\varphi}_{\text{expl}}$ with $\Delta \tau = 0.005$ and $\Delta \nu = 0.005$.

<table>
<thead>
<tr>
<th>Set</th>
<th>$\tilde{f}_{\text{expl}}$</th>
<th>$\tilde{\varphi}_{\text{expl}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set 1</td>
<td>1.6×10^{-8}</td>
<td>1.2×10^{-8}</td>
</tr>
<tr>
<td>Set 2</td>
<td>6.4×10^{-9}</td>
<td>7.5×10^{-9}</td>
</tr>
<tr>
<td>Set 3</td>
<td>2.1×10^{-8}</td>
<td>7.6×10^{-9}</td>
</tr>
<tr>
<td>Set 4</td>
<td>7.6×10^{-8}</td>
<td>4.0×10^{-9}</td>
</tr>
<tr>
<td>Set 5</td>
<td>4.2×10^{-9}</td>
<td>4.0×10^{-9}</td>
</tr>
<tr>
<td>Set 6</td>
<td>7.1×10^{-9}</td>
<td>5.8×10^{-9}</td>
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<td>6.0×10^{-9}</td>
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<td>Set 9</td>
<td>6.9×10^{-9}</td>
<td>5.6×10^{-9}</td>
</tr>
<tr>
<td>Set 10</td>
<td>6.9×10^{-9}</td>
<td>5.6×10^{-9}</td>
</tr>
</tbody>
</table>

Table 10: Maximum relative errors and convergence orders of $\tilde{f}_{\text{num}}$ in the domain $0 \leq \tau \leq 100$ and $0 \leq \sqrt{\nu} = \sigma \leq 0.8$.

<table>
<thead>
<tr>
<th>$\Delta \tau$</th>
<th>$\Delta \nu$</th>
<th>Maximum relative errors</th>
<th>Convergence order</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.02</td>
<td>0.02</td>
<td>1.53×10^{-5}</td>
<td>2.0</td>
</tr>
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<td>0.01</td>
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<td>3.83×10^{-6}</td>
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<td>0.005</td>
<td>0.005</td>
<td>9.58×10^{-7}</td>
<td>2.0</td>
</tr>
<tr>
<td>0.0025</td>
<td>0.0025</td>
<td>2.40×10^{-7}</td>
<td>2.0</td>
</tr>
</tbody>
</table>
4.4. Numerical Results for $\alpha \neq 0$. We have confirmed the accuracy of our numerical solutions for $\alpha = 0$. This guarantees that our numerical solution $f_{\text{expl}}$ for $\alpha \neq 0$ will also have an accuracy of $O(\Delta \tau^3)$. In Tables 11–13, we present the numerical solutions of $f_{\text{expl}}$, $\varphi^*_{\text{expl}}$, and $c^*_{\text{expl}}/\omega$ for $\alpha = 0.1, 0.5, 0.9$ with step sizes $\Delta \tau = \Delta \nu = 0.001$. In Tables 14 and 15, we show the results for $\gamma = 1$ and 10 with $\alpha = 0.5$ and $\Delta \tau = \Delta \nu = 0.001$. All other parameter values in Tables 11–15 are the same as the ones in Table 1. All digits shown in Tables 11–15 are exact, in the sense that they do not change when we further refine the values of $\Delta \tau$ and $\Delta \nu$.

**Table 11**: Numerical solutions for $f, \varphi^*$, and $c^*/\omega$ after performing Richardson’s extrapolation. Here, $\alpha = 0.1$ and $\Delta \tau = \Delta \nu = 0.001$. Other parameter values are the same as those in Table 1.

<table>
<thead>
<tr>
<th>$\tau$</th>
<th>$\sigma$</th>
<th>$f_{\text{expl}}$</th>
<th>$\varphi^*_{\text{expl}}$</th>
<th>$c^*_{\text{expl}}/\omega$</th>
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data for optimal asset allocation and consumption strategies.

5. Conclusion

In this paper, we study the portfolio selection problem in a general setting under CRRA utility functions: stochastic volatility, incomplete markets, finite investment horizons, and consumption choice. To the best of our knowledge, no explicit solution or numerical result is available in the literature for this setting. We present an accurate and efficient numerical method for optimal asset allocation and optimal consumption strategies. The optimal strategies are based on a solution to a nonlinear and inhomogeneous partial differential equation which is derived from the portfolio selection problem. A three-level Crank–Nicolson finite difference scheme, which has second-order accuracy, is used to determine numerical solutions. In addition, we have used a technique to deal with the nonlinear term, which is one of our main contributions. We believe that the technique to deal with the nonlinear term could be applied to other similar numerical problems. The Crank–Nicolson algorithm also has been extended to third-order accuracy by performing Richardson’s extrapolation. Some experiments are conducted to verify the performance of the proposed algorithm. Based on this algorithm, we present the first set of accurate numerical solutions of optimal strategies. Since the portfolio selection problem under stochastic volatility is an important issue in modern finance, the proposed algorithm will be useful for further theoretical research and for applications in the financial industry.

Appendix

A. Derivations for \( f_\tau(0, v), f_{\tau\tau}(0, v), \) and \( f_{\tau\tau\tau}(0, v) \)

From (19), we obtain

\[
f_\tau = a_1 v f_{vv} + (a_2 v + a_3) f_v + a_4 v \frac{f^2}{f} + (a_5 v + a_6) f + a^{(1/v)}_7 a_7.
\]

(A.1)

By taking the derivative of (A.1) with respect to \( \tau \), we obtain

\[
f_{\tau\tau} = a_1 v f_{\tau v} + (a_2 v + a_3) f_{\tau v} + a_4 v \frac{2 f_v f_{vv}}{f^2} - a_4 v \frac{f^2}{f^2} \frac{f^2}{f} + (a_5 v + a_6) f_{\tau}.
\]

(A.2)
By taking the derivative of (A.2) with respect to τ, we obtain
\[
f_{\tau \tau \tau} = a_1 v f_{\tau \nu \nu} \tau + (a_2 v + a_3) f_{\nu \tau \tau} + a_4 v \frac{2 f_{\tau \tau \tau}}{f} + a_5 v \frac{2 f_{\tau \nu \nu}}{f}
- 4a_4 v \frac{f_{\tau \tau \tau}}{f} f_{\tau \nu} + 2a_4 v \frac{f_{\tau \tau \tau}}{f^2} f_{\tau \nu} - a_4 v \frac{2 f_{\tau \nu \nu}}{f}
+ (a_3 + a_6) f_{\tau \tau}.
\] (A.3)

By setting τ = 0 in (A.1) and using the initial condition
\[
f_0 (0, v) = (a_5 + a_6) f_0 (0, v) + \alpha^{(1/\rho)} a_7.
\] (A.4)

By setting τ = 0 in (A.2) and using the initial condition
\[
f_0 (0, v) = (a_1 v + a_6) f_0 (0, v) + \alpha^{(1/\rho)} a_7.
\] (A.5)

By setting τ = 0 in (A.3) and using the initial condition
\[
f_0 (0, v) = (1 - \alpha)^{(1/\rho)} a_7.
\] (A.6)

B. HARA Utility Setting

In this appendix, the portfolio selection problem under HARA utility setting is considered. We would like to show that the proposed method could also be applied to this problem under HARA utility setting.

We assume that HARA utility functions \( u_1 (\cdot) \) and \( u_2 (\cdot) \) are used for consumption utility and terminal wealth utility, respectively:
\[
u_1 (c_t) = \frac{c_t (1 - \gamma)}{\gamma} \left( \frac{c_t}{1 - \gamma} + b_c \right)^\gamma,
\] (B.1)
\[
u_2 (w_T) = \frac{a_w (1 - \gamma)}{\gamma} \left( \frac{w_T}{1 - \gamma} + b_w \right)^\gamma.
\]
The market setting and investors’ objective are the same as before which are given by (2)–(6). Following the procedure in this paper, the value function satisfies the following equation:
\[
0 = \frac{(1 - \gamma)^2}{\gamma} \left( a_w e^{-\beta} \right)^{(1/\gamma)p-1} v_T \left( w_T \right)^{(1-\gamma)p-1} + ((1 - \gamma)b_c + rw) V_w
+ V_t + \kappa (\theta - v) V_t + \frac{1}{2} \xi^2 v V_{vv} - \frac{1}{2} \frac{A V_w + \rho V_{ww}}{V_{ww}} + \frac{\rho V_{ww}}{w V_{ww}}
\] (B.2)
and optimal strategies are given by
\[
\phi^* = -\left( AV_w + \rho V_{ww} \right) w V_{ww} - \rho V_{ww}
+ \frac{\rho V_{ww}}{w V_{ww}}.
\] (B.3)
\[
c^* = (1 - \gamma) \left( \frac{V_w}{\alpha_a \alpha_e \beta} \right)^{(1/\gamma)-1} - b_c.
\] (B.4)

Based on the terminal condition and the scaling property of this problem, a reasonable trial solution form for \( V \) is assumed:
\[
V (\tau, w, v) = e^{-\beta (1-\gamma) a_w (1 - \gamma) \left( \frac{w}{1 - \gamma} + g (\tau) \right) ^\gamma} f (\tau, v) \left( 1 - \gamma \right),
\] (B.5)
where \( g (\tau) \) and \( f (\tau, v) \) need to be determined and \( \tau = T - t \).

The initial conditions of \( g \) and \( f \) are
\[
g (0) = b_w,
\] (B.6)
\[
f (0, v) = (1 - \alpha)^{(1/\gamma)}.
\]

To determine \( f \) and \( g \), we substitute expression (B.4) into (B.2) and obtain
\[
-f_{\tau} + \frac{1}{2} \xi^2 v f_{vv} + \left( \kappa (\theta - v) + \frac{\gamma}{1 - \gamma} Ap \xi v \right) f_{\nu},
\]
\[
\frac{1}{2} \frac{A^2 - 2 (1 - \gamma) v + \beta}{1 - \gamma} f + \left( \frac{a a_c}{a w} \right)^{(1/\gamma)} = 0.
\] (B.7)

By setting
\[
g (\tau) + r g (\tau) - b_c = 0,
\] (B.8)
equation (B.6) becomes an equation involving \( f \) only, namely,
\[
-f_{\tau} + \frac{1}{2} \xi^2 v f_{vv} + \left( \kappa (\theta - v) + \frac{\gamma}{1 - \gamma} Ap \xi v \right) f_{\nu},
\]
\[
\frac{1}{2} \frac{A^2 - 2 (1 - \gamma) v + \beta}{1 - \gamma} f + \left( \frac{a a_c}{a w} \right)^{(1/\gamma)} = 0.
\] (B.9)

Thus, we have achieved dimension reduction by removing \( w \) dependence in (B.2). The solution of \( g \) is obtained from (B.7) and (B.5):
\[
g (\tau) = b_w e^{-\tau r} + \frac{b_c}{r} (1 - e^{-\tau r}).
\] (B.10)
Equation (B.8) has the same form as (19), which could be solved numerically by applying the proposed algorithm the same as that in Section 3. Then, the optimal strategies could be obtained:

\[ \phi^* = \left(1 + \frac{1 - y}{w} g(r) \right) \left( \frac{A}{1 - y} + \rho \xi f \right), \]

\[ \hat{c}^* = \left( \frac{a \alpha}{a_w} \right)^{(1/1-y)} f^{-1} \frac{1 - y}{w} \left( \frac{a \alpha}{a_w} \right)^{(1/1-y)} g(r) f^{-1} - b \right). \]

(B.10)

**Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

**Acknowledgments**

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