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# ON EUROPEAN OPTION PRICING UNDER PARTIAL INFORMATION 

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#### Abstract

We consider a European option pricing problem under a partial information market, i.e., only the security's price can be observed, the rate of return and the noise source in the market cannot be observed. To make the problem tractable, we focus on gap option which is a generalized form of the classical European option. By using the stochastic analysis and filtering technique, we derive a Black-Scholes formula for gap option pricing with dividends under partial information. Finally, we apply filtering technique to solve a utility maximization problem under partial information through transforming the problem under partial information into the classical problem.


Keywords: option pricing; European option; partial information; backward stochastic differential equation

MSC 2010: 93E11, 60H10, 91B24

## 1. INTRODUCTION

Option pricing is one of the most important problems which has been widely studied. The Black-Scholes-Merton model [2], [15] for valuing European call and put options on an investment asset was published in 1973. It assumes the volatility of the asset is a constant and the price of the asset changes smoothly with no jumps. Since neither of these conditions is satisfied for exchange rates, individual stocks or stock indices, and no empirical evidence in financial industry shows that the geometric Brownian motion is suitable, one major extension of the Black-Scholes option pricing model is to overcome the drawbacks of the model. One renowned model is the well-known constant elasticity of variance (for short, CEV) diffusion

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model. This model was initially studied by Cox [3]. Then, Cox and Ross [4] designed and developed it to incorporate the negative correlation between underlying asset price change and volatility change. The CEV diffusion has been applied to exotic options as well as standard options by many researchers. However, it is found in Ballestra and Pacelli [1] that the CEV model does not offer a correct description of equity prices, whereas Emanuel and Macbeth [7] state that the CEV model with stationary parameters does not appear to be able to explain the mispricing of call options by the Black-Scholes model. Therefore, many researchers study the option pricing problem from other perspectives. We refer interested readers to Duffie [5], Karatzas [8], [9] and Merton [16] for detailed reviews of the option pricing and its extensions.

The common feature of previous studies for the option pricing problem is that they all assume investors can observe the drift process and the Brownian motion appearing in the stochastic differential equation for the security prices. However, it is more realistic to assume that investors have only partial information since prices and interest rates are published and available to the public, but drifts and paths of Brownian motions are merely mathematical tools for model creation, but certainly not observable. Therefore, we shall call this situation the case of partial information to distinguish it from the case of full information.

Under partial information, the utility maximization problem was for the first time considered by Lakner [10]. Later, Lakner [11] discussed the optimal trading strategy problem with partial information. Recently, Wu and Wang [18] studied an option pricing problem under partial information by using the convex analysis and the backward stochastic differential equation techniques. To our best knowledge, there are no studies to present a general result for European-type option pricing problem under partial information.

To fill this research gap, we study the gap option pricing problem with dividends under partial information, using stochastic analysis and filtering techniques. We find that the European-type option pricing problem is tractable. By using filtering technique, we derive a Black-Scholes formula for the gap option pricing problem with dividends under partial information. Further, we solve a utility maximization problem under partial information through transforming the problem under partial information into the classical problem by using the filtering technique.

## 2. Model formulation

Let $\left(\Omega, \mathcal{F}, \mathcal{F}_{t}, \mathbb{P}\right)$ be a complete probability space, where $t \in[0, T]$. We consider a market which consists of one risky and one risk-free asset with price processes $S_{t}$
and $B_{t}$, respectively. The price process $B_{t}$ of risk-free asset satisfies

$$
\begin{gather*}
\mathrm{d} B_{t}=r_{t} B_{t} \mathrm{~d} t \quad \text { if } \quad B_{t}>0  \tag{1}\\
\mathrm{~d} B_{t}=-R_{t} B_{t} \mathrm{~d} t \quad \text { if } B_{t}<0, \tag{2}
\end{gather*}
$$

with an initial condition $B_{0}=b_{0}$ where $b_{0}$ is a constant, $r_{t}$ and $R_{t}$ are the lending and borrowing interest rates at time $t$, respectively. The dynamics of the stock's price process $S_{t}$ is determined by the stochastic differential equations

$$
\begin{equation*}
\mathrm{d} S_{t}=\mu_{t} S_{t} \mathrm{~d} t+\sigma_{t} S_{t} \mathrm{~d} W_{t}, \quad S_{0}=s_{0}>0 \tag{3}
\end{equation*}
$$

where $s_{0}$ is a constant, $\mu_{t}$ and $\sigma_{t}$ are the expected return and the volatility rate at time $t$, respectively. Since the expected return of the stock $\mu_{t}$ may not be observed directly, we suppose that it could be described as

$$
\mathrm{d} \mu_{t}=a \mu_{t} \mathrm{~d} t+b \mathrm{~d} W_{t}+c \mathrm{~d} V_{t}, \quad \mu_{0}=\eta
$$

where $\left\{W_{t}\right\}_{t \geqslant 0}$ and $\left\{V_{t}\right\}_{t \geqslant 0}$ are independent 1-dimensional Brownian motions on the space $\left(\Omega, \mathcal{F}, \mathcal{F}_{t}, \mathbb{P}\right)$. Further, we assume that $a, b$ and $c$ are constants, $r_{t}, R_{t}$, and $\sigma_{t}$ are deterministic bounded functions and $\sigma_{t}$ has a bounded inverse function.

Note that $\mu_{t}$ should be driven by another Wiener process which is different from the Wiener process $W$. Since $\mu_{t}$ is the expected return of the stock and $S_{t}$ is driven by $W_{t}$, Wiener process $W$ should affect both $\mu_{t}$ and $S_{t}$. Thus, we assume that $\mu_{t}$ is driven by both $W_{t}$ and $V_{t}$.

For investors, both the stock price and the interest rate are published and available. However, drifts and all information of white noises $\left\{W_{t}\right\}_{t \geqslant 0}$ and $\left\{V_{t}\right\}_{t \geqslant 0}$ are certainly not observable. Thus we let

$$
\mathcal{F}_{t}:=\sigma\left\{W_{s}, V_{s} ; 0 \leqslant s \leqslant t\right\}, \quad \mathcal{G}_{t}:=\sigma\left\{S_{u} ; 0 \leqslant u \leqslant t\right\}
$$

and suppose that $S_{t}$ is $\mathcal{G}_{t}$-adapted and both $\left\{W_{t}\right\}_{t \geqslant 0}$ and $\left\{V_{t}\right\}_{t \geqslant 0}$ are $\mathcal{F}$-adapted. Since drifts and all information of white noises are not observable, only $\mathcal{G}_{t}$-adapted processes are observable. Further, the decisions of investors mainly depend on the information of $\mathcal{G}_{t}$. Therefore, in order to get some ideas of the nature of partial information, we assume that only $\mathcal{G}_{t}$-adapted processes are observable, which implies investors cannot directly observe the drift process $\left\{\mu_{t}\right\}_{t \geqslant 0}$.

We assume that $X_{t}$ represents the wealth of an agent at time $t$ and the initial wealth $X_{0}=x_{0}>0$ is a deterministic constant. Further, we define a trading strategy $\pi_{t}$ for an agent acting in the market, i.e., the amount of money invested in the stock at time $t$, where $\pi_{t}$ is a measurable, $\mathcal{G}_{t}$-adapted process such that
$E\left[\int_{0}^{T} \pi_{t}^{2} \mathrm{~d} t\right]<\infty$. The negative values of both $\pi_{t}$ and $X_{t}-\pi_{t}$ are allowed, which indicates that the stock can be sold out and the agent could get a loan from a bank, respectively. We denote the dividend rate at time $t$ by $d\left(t, S_{t}\right)$ where dividends of stock are assumed to be paid continuously and $d\left(t, S_{t}\right)$ is a bounded function.

Under the above assumptions, the wealth process $\left\{X_{t} ; t \in[0, T]\right\}$ is assumed to evolve according to the dynamics

$$
\mathrm{d} X_{t}=\left[r_{t}\left(X_{t}-\pi_{t}\right)^{+}+\left(\mu_{t}+d\left(t, S_{t}\right)\right) \pi_{t}-R_{t}\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} W_{t}, \quad X_{0}=x_{0}
$$

which is equivalent to
$\mathrm{d} X_{t}=\left[r_{t} X_{t}+\left(\mu_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} W_{t}, \quad X_{0}=x_{0}$,
where $x^{-}=(|x|-x) / 2, x^{+}=(|x|+x) / 2$, for all $x \in \mathbb{R}$. The explanation for the wealth process $X_{t}$ is that, for any time $t$, if investors buy a stock with their own capital, i.e., $\pi_{t} \leqslant X_{t}$, then investors can get revenue from both the stock and the riskless asset, i.e., $r_{t}\left(X_{t}-\pi_{t}\right)^{+}+\left(\mu_{t}+d\left(t, S_{t}\right)\right) \pi_{t}$; otherwise, investors can buy stocks with borrowed money, i.e., $\pi_{t} \geqslant X_{t}$, then investors should pay for the cost of borrowed money, i.e., $R_{t}\left(X_{t}-\pi_{t}\right)^{-}$, and get revenue from the stock, i.e., $\left(\mu_{t}+d\left(t, S_{t}\right)\right) \pi_{t}$.

Gap option is one of the most widely used options in the real world. For a striking price $K$ and a predetermined price $\xi$ which is a constant and irrelevant to $K$, the investor who has a gap call option can get $S_{t}-\xi$ when stock price is higher than $K$ at time $T$. Otherwise, there is no revenue for investors. The situation of a gap put option is in the opposite. The value of gap option at expire time $T$ is defined as

$$
V(T)= \begin{cases}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}}, & \text { call option }, \\ \left(\xi-S_{T}\right) I_{\left\{S_{T} \leqslant K\right\}}, & \text { put option. }\end{cases}
$$

To derive the price of a gap option in the next section, the following lemma will be employed.

Lemma 2.1. Consider a continuous system variable $x_{t} \in \mathbb{R}$ and a continuously observable variable $Z_{t} \in \mathbb{R}$ which satisfy

$$
\left\{\begin{array}{l}
\mathrm{d} x_{t}=F(t) x_{t} \mathrm{~d} t+G(t) \mathrm{d} W_{t}+C(t) \mathrm{d} U_{t}, \\
\mathrm{~d} Z_{t}=x_{t} Z_{t} \mathrm{~d} t+D(t) Z_{t} \mathrm{~d} W_{t} \quad \forall t \in[0, T]
\end{array}\right.
$$

where $F(t), G(t), C(t), D(t), D^{-1}(t) \in \mathbb{R}$ are bounded, $\left\{U_{t}\right\}_{0 \leqslant t \leqslant T}$ and $\left\{W_{t}\right\}_{0 \leqslant t \leqslant T}$ are two independent 1-dimensional Brownian motions. If $E x_{0}^{4}<\infty, x_{0}$ and $Z_{0}$ are independent of the Wiener processes $U$ and $W$, and the conditional distribution
$P\left(x_{0} \leqslant x \mid Z_{0}\right)$ is Gaussian, $N\left(\widehat{x}_{0}, \Pi_{0}\right)$, where $\mathcal{Z}_{t}:=\sigma\left\{Z_{u} ; 0 \leqslant u \leqslant t\right\}$, then the solution of the filtering problem $\widehat{x}_{t}=E\left[x_{t} \mid \mathcal{Z}_{t}\right]$ satisfies the equations

$$
\left\{\begin{array}{l}
\mathrm{d} \widehat{x}_{t}=F(t) \widehat{x}_{t} \mathrm{~d} t+\frac{G(t) D(t)+\Pi_{t}}{D^{2}(t)}\left(\frac{\mathrm{d} Z_{t}}{Z_{t}}-\widehat{x}_{t} \mathrm{~d} t\right), \\
\widehat{x}_{0}=E\left[x_{0}\right] \quad \forall t \in[0, T]
\end{array}\right.
$$

where $\Pi_{t}=E\left[\left(x_{t}-\widehat{x}_{t}\right)^{2} \mid \mathcal{Z}_{t}\right]$ satisfies the Ricatti equation

$$
\left\{\begin{array}{l}
\frac{\mathrm{d} \Pi_{t}}{\mathrm{~d} t}=-\frac{\Pi_{t}^{2}}{D^{2}(t)}+2\left(F(t)-\frac{G(t)}{D(t)}\right) \Pi_{t}+C^{2}(t) \\
\Pi_{0}=E\left[\left(x_{0}-\widehat{x}_{0}\right)^{2}\right] \quad \forall t \in[0, T]
\end{array}\right.
$$

Proof. The proof is analogous to that of Theorem 12.2 in [13]. So we omit it here.

## 3. Gap option pricing under partial information

To derive the price of a gap option, we first should discuss whether the contingent claim replication is possible. For an arbitrary contingent claim $\zeta$, we consider the backward stochastic differential equation (for short, BSDE)
(4) $\left\{\begin{array}{l}\mathrm{d} X_{t}=\left[r_{t} X_{t}+\left(\mu_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} W_{t}, \\ X_{T}=\zeta,\end{array}\right.$
where $\zeta$ is an arbitrary $F_{T}$-measurable process such that $E\left|\zeta^{2}\right|<\infty$. Let $Z_{t}=\sigma_{t} \pi_{t}$ and
(5) $h\left(t, X_{t}, Z_{t}\right)=r_{t} X_{t}+\left(\mu_{t}+d\left(t, S_{t}\right)-r_{t}\right) \sigma_{t}^{-1} Z_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\sigma_{t}^{-1} Z_{t}\right)^{-}$,
then

$$
\left\{\begin{array}{l}
\mathrm{d} X_{t}=h\left(t, X_{t}, Z_{t}\right) \mathrm{d} t+Z_{t} \mathrm{~d} W_{t}  \tag{6}\\
X_{T}=\zeta
\end{array}\right.
$$

Lemma 3.1. For any $\zeta$, the $\operatorname{BSDE}$ (6) admits a unique adapted solution $(X(\cdot), Z(\cdot))$.

Proof. By Theorem 4.1 of [14], we have that (6) admits a unique adapted solution if there exists a constant $L$ which satisfies the inequalities

$$
\left\{\begin{array}{l}
\left|h\left(t, X_{t}, Z_{t}\right)-h\left(t, \bar{X}_{t}, \bar{Z}_{t}\right)\right| \leqslant L\left(\left|X_{t}-\bar{X}_{t}\right|+\left|Z_{t}-\bar{Z}_{t}\right|\right)  \tag{7}\\
|h(t, 0,0)| \leqslant L, \quad t \in[0, T]
\end{array}\right.
$$

It follows from (5) that

$$
\begin{aligned}
\mid h\left(t, X_{t}, Z_{t}\right) & -h\left(t, \bar{X}_{t}, \bar{Z}_{t}\right)|=| r_{t}\left(X_{t}-\bar{X}_{t}\right)+\left(\mu_{t}+d\left(t, S_{t}\right)-r_{t}\right) \sigma_{t}^{-1}\left(Z_{t}-\bar{Z}_{t}\right) \\
& -\left(R_{t}-r_{t}\right)\left(\left(X_{t}-\sigma_{t}^{-1} Z_{t}\right)^{-}-\left(\bar{X}_{t}-\sigma_{t}^{-1} \bar{Z}_{t}\right)^{-}\right) \mid \\
= & \left\lvert\, \frac{1}{2}\left(R_{t}+r_{t}\right)\left(X_{t}-\bar{X}_{t}\right)+\left(\mu_{t}+d\left(t, S_{t}\right)-\frac{1}{2}\left(R_{t}+r_{t}\right)\right) \sigma_{t}^{-1}\left(Z_{t}-\bar{Z}_{t}\right)\right. \\
& \left.-\frac{1}{2}\left(R_{t}-r_{t}\right)\left(\left|X_{t}-\sigma_{t}^{-1} Z_{t}\right|-\left|\bar{X}_{t}-\sigma_{t}^{-1} \bar{Z}_{t}\right|\right) \right\rvert\, \\
\leqslant & \left|\frac{1}{2}\left(R_{t}+r_{t}\right)\left(X_{t}-\bar{X}_{t}\right)+\left(\mu_{t}+d\left(t, S_{t}\right)-\frac{1}{2}\left(R_{t}+r_{t}\right)\right) \sigma_{t}^{-1}\left(Z_{t}-\bar{Z}_{t}\right)\right| \\
& +\frac{1}{2}\left|\left(R_{t}-r_{t}\right)\right|\left|\left(X_{t}-\bar{X}_{t}\right)+\sigma_{t}^{-1}\left(Z_{t}-\bar{Z}_{t}\right)\right| \\
\leqslant & \frac{1}{2}\left(\left|\left(R_{t}+r_{t}\right)\right|+\left|\left(R_{t}-r_{t}\right)\right|\right)\left|X_{t}-\bar{X}_{t}\right|+\left|\sigma_{t}^{-1}\right|\left(\mid \mu_{t}+d\left(t, S_{t}\right)\right. \\
& \left.\left.-\frac{1}{2}\left(R_{t}+r_{t}\right)\left|+\frac{1}{2}\right|\left(R_{t}-r_{t}\right) \right\rvert\,\right)\left|Z_{t}-\bar{Z}_{t}\right| \\
\leqslant & R_{t}\left|X_{t}-\bar{X}_{t}\right|+\left|\sigma_{t}^{-1}\right|\left(\left|\mu_{t}\right|+d\left(t, S_{t}\right)+R_{t}\right)\left|Z_{t}-\bar{Z}_{t}\right|
\end{aligned}
$$

and

$$
|h(t, 0,0)|=0
$$

Let $L=\max \left\{R_{t},\left|\sigma_{t}^{-1}\right|\left(\left|\mu_{t}\right|+d\left(t, S_{t}\right)+R_{t}\right)\right\}$. Since $\sigma_{t}^{-1}, \mu_{t}$ and $d\left(t, S_{t}\right)$ are bounded and $\lambda, \psi$ are constants, (7) holds. Therefore, BSDE (6) admits a unique adapted solution $(X(\cdot), Z(\cdot))$. This completes the proof.

Lemma 3.1 implies that $\operatorname{BSDE}(4)$ has a unique adapted solution $(X(\cdot), \sigma(\cdot) \eta(\cdot))$. As $\sigma_{t}$ is a deterministic bounded function, $(X(\cdot), \eta(\cdot))$ also is an adapted solution. Since the contingent claim $\zeta$ is arbitrary, the market is complete and the price of the gap call option satisfies the BSDE
(8) $\left\{\begin{array}{l}\mathrm{d} X_{t}=\left[r_{t} X_{t}+\left(\mu_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} W_{t}, \\ X_{T}=\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} .\end{array}\right.$

Since neither $\left\{W_{t}\right\}_{t \in[0, T]}$ nor $\left\{V_{t}\right\}_{t \in[0, T]}$ are observable, we cannot observe $\left\{\mu_{t}\right\}_{t \in[0, T]}$ directly. However, we could employ the filtering technique to observe $\left\{\mu_{t}\right\}_{t \in[0, T]}$ through the information of $\left\{S_{t}\right\}_{t \in[0, T]}$. Then we have the following result.

Theorem 3.1. Under partial information, the price process of a gap call option $\left\{X_{t} ; t \in[0, T]\right\}$ is

$$
X_{t}=\operatorname{ess} \sup \left\{X_{t}^{\delta} ; r_{t} \leqslant \delta_{t} \leqslant R_{t}\right\}
$$

where

$$
X_{t}^{\delta}=E_{Q}\left[\exp \left\{-\int_{t}^{T} \delta_{s} \mathrm{~d} s\right\}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right]
$$

and $\mathbb{Q}$ is a risk neutral probability measure which satisfies

$$
\frac{\mathrm{dQ}}{\mathrm{dP}}=\exp \left\{\int_{0}^{T}-\frac{\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}\right)^{2}}{2 \sigma_{t}^{2}} \mathrm{~d} t-\int_{0}^{T} \frac{\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}}{\sigma_{t}} \mathrm{~d} \bar{W}_{t}\right\}
$$

and

$$
\bar{W}_{t}=W_{t}+\int_{0}^{t} \frac{\mu_{s}-\widehat{\mu}_{s}}{\sigma_{s}} \mathrm{~d} s
$$

Proof. Let

$$
\widehat{\mu}_{t}=E\left[\mu_{t} \mid \mathcal{G}_{t}\right], \quad \gamma_{t}=E\left[\left(\mu_{t}-\widehat{\mu}_{t}\right)^{2} \mid \mathcal{G}_{t}\right] .
$$

By Theorem 7.17 of [12], there exists a standard Brownian motion $\left\{\bar{W}_{t}\right\}_{t \in[0, T]}$ on the space $\left(\Omega, \mathcal{G}, \mathcal{G}_{t}, \mathbb{P}\right)$ which satisfies

$$
\begin{equation*}
\mathrm{d} S_{t}=\widehat{\mu}_{t} S_{t} \mathrm{~d} t+\sigma_{t} S_{t} \mathrm{~d} \bar{W}_{t} \tag{9}
\end{equation*}
$$

From Lemma 2.1 we have

$$
\left\{\begin{array}{l}
\mathrm{d} \widehat{\mu}_{t}=a \widehat{\mu}_{t} \mathrm{~d} t+\frac{b \sigma_{t}+\gamma_{t}}{\sigma_{t}^{2}}\left(\frac{\mathrm{~d} S_{t}}{S_{t}}-\widehat{\mu}_{t} \mathrm{~d} t\right)  \tag{10}\\
\widehat{\mu}_{0}=E\left[\mu_{0}\right] \quad \forall t \in[0, T]
\end{array}\right.
$$

and $\gamma_{t}$ is the unique solution of the Riccati equation

$$
\left\{\begin{array}{c}
\frac{\mathrm{d} \gamma_{t}}{\mathrm{~d} t}=2 a \gamma_{t}+b^{2}+c^{2}-\left(b+\frac{\gamma_{t}}{\sigma_{t}}\right)^{2}  \tag{11}\\
\gamma_{0}=E\left[\left(\mu_{0}-\widehat{\mu}_{0}\right)^{2}\right] \quad \forall t \in[0, T]
\end{array}\right.
$$

Solving (11), we have

$$
\begin{equation*}
\gamma_{t}=\frac{\beta_{1}-L \beta_{2} \exp \left(\left(\beta_{2}-\beta_{1}\right) \sigma_{t}^{-2} t\right)}{1-L \exp \left(\left(\beta_{2}-\beta_{1}\right) \sigma_{t}^{-2} t\right)} \tag{12}
\end{equation*}
$$

where

$$
\begin{aligned}
\beta_{1} & =\left(a-\frac{b}{\sigma_{t}}\right) \sigma_{t}^{2}-\sigma_{t} \sqrt{\left(a-\frac{b}{\sigma_{t}}\right) \sigma_{t}^{2}+c^{2}} \\
\beta_{2} & =\left(a-\frac{b}{\sigma_{t}}\right) \sigma_{t}^{2}+\sigma_{t} \sqrt{\left(a-\frac{b}{\sigma_{t}}\right) \sigma_{t}^{2}+c^{2}} \\
L & =\frac{\gamma_{0}-\beta_{1}}{\gamma_{0}-\beta_{2}}
\end{aligned}
$$

It follows from (10) and (12) that

$$
\widehat{\mu}_{t}=\widehat{\mu}_{0} \mathrm{e}^{a t}+\int_{0}^{t} \mathrm{e}^{a(t-s)}\left(b+\frac{\gamma_{s}}{\sigma_{s}}\right) \mathrm{d} \bar{W}_{s}
$$

By (1), (8), and (9), the price of a gap call option satisfies

$$
\left\{\begin{array}{l}
\mathrm{d} X_{t}=\left[r_{t} X_{t}+\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} \bar{W}_{t} \\
X_{T}=\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}}
\end{array}\right.
$$

Let

$$
\begin{gathered}
Y_{t}=\sigma_{t} \pi_{t}, \quad \theta_{t}=\sigma_{t}^{-1}\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right) \\
b(t, X, Y)=-\left[r_{t} X_{t}+\theta_{t} Y_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right]
\end{gathered}
$$

Then we have

$$
\left\{\begin{array}{l}
-\mathrm{d} X_{t}=-\left[r_{t} X_{t}+\theta_{t} Y_{t}-\left(R_{t}-r_{t}\right)\left(X_{t}-\pi_{t}\right)^{-}\right] \mathrm{d} t-Y_{t} \mathrm{~d} \bar{W}_{t}  \tag{13}\\
X_{T}=\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \quad \forall t \in[0, T]
\end{array}\right.
$$

Since (13) is a nonlinear BSDE, by using the method of variational formulation of the price system in [6], we have

$$
\begin{equation*}
b\left(t, X_{t}, Y_{t}\right)=\sup \left\{b^{\delta}\left(t, X_{t}, Y_{t}\right) ; r_{t} \leqslant \delta_{t} \leqslant R_{t}\right\} \tag{14}
\end{equation*}
$$

where

$$
b^{\delta}\left(t, X_{t}, Y_{t}\right)=-\delta_{t} X_{t}-\theta_{t} Y_{t}-\frac{r_{t}-\delta_{t}}{\sigma_{t}} Y_{t}=-\delta_{t} X_{t}-\sigma_{t}^{-1}\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}\right) Y_{t}
$$

By Proposition 3.6 and the BSDE comparison theorem in [6], the solution of $\operatorname{BSDE}$ (13) is

$$
\begin{equation*}
X_{t}=\operatorname{ess} \sup \left\{X_{t}^{\delta} ; r_{t} \leqslant \delta_{t} \leqslant R_{t}\right\} \tag{15}
\end{equation*}
$$

where $X_{t}^{\delta}$ satisfies the equation

$$
\left\{\begin{array}{l}
-\mathrm{d} X_{t}^{\delta}=-\left[\delta_{t} X_{t}^{\delta}+\sigma_{t}^{-1}\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}\right) Y_{t}^{\delta}\right] \mathrm{d} t-Y_{t}^{\delta} \mathrm{d} \bar{W}_{t},  \tag{16}\\
X_{T}^{\delta}=\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \quad \forall t \in[0, T] .
\end{array}\right.
$$

The adjoint process of (16) is

$$
\left\{\begin{array}{l}
\mathrm{d} \Gamma_{s}^{t}=-\Gamma_{s}^{t}\left[\delta_{s} \mathrm{~d} s+\sigma_{s}^{-1}\left(\widehat{\mu}_{s}+d\left(t, S_{s}\right)-\delta_{s}\right) \mathrm{d} \bar{W}_{s}\right], \\
\Gamma_{t}^{t}=1 \quad \forall s \in[t, T] .
\end{array}\right.
$$

Thus

$$
\Gamma_{s}^{t}=\exp \left\{\int_{t}^{s}-\delta_{v}-\frac{\left(\widehat{\mu}_{v}+d\left(v, S_{v}\right)-\delta_{v}\right)^{2}}{2 \sigma_{v}^{2}} \mathrm{~d} v-\int_{t}^{s} \frac{\widehat{\mu}_{v}+d\left(v, S_{v}\right)-\delta_{v}}{\sigma_{v}} \mathrm{~d} \bar{W}_{v}\right\} .
$$

Further, we have
(17) $X_{t}^{\delta}=E\left[\Gamma_{T}^{t} X_{T}^{\delta} \mid \mathcal{G}_{t}\right]=E\left[\exp \left\{\int_{t}^{T}-\delta_{s}-\frac{\left(\widehat{\mu}_{s}+d\left(s, S_{s}\right)-\delta_{s}\right)^{2}}{2 \sigma_{s}^{2}} \mathrm{~d} s\right.\right.$

$$
\left.\left.-\int_{t}^{T} \frac{\widehat{\mu}_{s}+d\left(s, S_{s}\right)-\delta_{s}}{\sigma_{s}} \mathrm{~d} \bar{W}_{s}\right\}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right] .
$$

Since $d\left(t, S_{t}\right), \delta_{t}, \sigma_{t}$ and $\sigma_{t}^{-1}$ are bounded, it is easy to verify that $\widehat{\mu}_{t}$ is a Gaussian process and satisfies

$$
\sup _{0 \leqslant t \leqslant T} E \widehat{\mu}_{t}<\infty, \sup _{0 \leqslant t \leqslant T} E \widehat{\mu}_{t}^{2}<\infty, \quad \sup _{0 \leqslant t \leqslant T} D \widehat{\mu}_{t}<\infty .
$$

Further, we have

$$
E\left[\exp \left\{\int_{0}^{T}-\frac{\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}\right)^{2}}{2 \sigma_{t}^{2}} \mathrm{~d} t-\int_{0}^{T} \frac{\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}}{\sigma_{t}} \mathrm{~d} \bar{W}_{t}\right\}\right]=1 .
$$

It follows from the Girsanov theorem (see, for example, Theorem 8.26 of [17]) that

$$
\frac{\mathrm{d} \mathbb{Q}}{\mathrm{dP}}=\exp \left\{\int_{0}^{T}-\frac{\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}\right)^{2}}{2 \sigma_{t}^{2}} \mathrm{~d} t-\int_{0}^{T} \frac{\widehat{\mu}_{t}+d\left(t, S_{t}\right)-\delta_{t}}{\sigma_{t}} \mathrm{~d} \bar{W}_{t}\right\}
$$

where $\mathbb{Q}$ is a risk neutral probability measure, and

$$
\begin{equation*}
\widehat{W}_{t}=\bar{W}_{t}+\int_{0}^{t} \frac{\widehat{\mu}_{s}+d\left(t, S_{s}\right)-\delta_{s}}{\sigma_{s}} \mathrm{~d} s \tag{18}
\end{equation*}
$$

is a standard Brownian motion under the probability measure $\mathbb{Q}$. From (9) and (16), we have

$$
\mathrm{d} S_{t}=\left(\delta_{t}-d\left(t, S_{t}\right)\right) S_{t} \mathrm{~d} t+\sigma_{t} S_{t} \mathrm{~d} \widehat{W}_{t},
$$

which is equivalent to

$$
S_{T}=S_{t} \exp \left\{\left[\delta_{t}-d\left(t, S_{t}\right)-\frac{1}{2} \sigma_{t}^{2}\right](T-t)+\sigma_{t}\left(\widehat{W}_{T}-\widehat{W}_{t}\right)\right\},
$$

and then

$$
\left\{\begin{array}{l}
-\mathrm{d} X_{t}^{\delta}=-\left[\delta_{t} X_{t}^{\delta}\right] \mathrm{d} t-Y_{t}^{\delta} \mathrm{d} \widehat{W}_{t} \\
X_{T}^{\delta}=\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}}
\end{array}\right.
$$

The adjoint process of the above BSDE is

$$
\left\{\begin{array}{l}
\mathrm{d} \Gamma_{s}^{t}=-\Gamma_{s}^{t} \delta_{s} \mathrm{~d} s, \\
\Gamma_{t}^{t}=1 \quad \forall s \in[t, T] .
\end{array}\right.
$$

This gives

$$
\Gamma_{s}^{t}=\exp \left\{\int_{t}^{s}-\delta_{v} \mathrm{~d} v\right\}
$$

Then we have

$$
\begin{equation*}
X_{t}^{\delta}=E_{Q}\left[\Gamma_{T}^{t} X_{T}^{\delta} \mid \mathcal{G}_{t}\right]=E_{Q}\left[\exp \left\{-\int_{t}^{T} \delta_{s} \mathrm{~d} s\right\}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right] . \tag{19}
\end{equation*}
$$

This completes the proof.

Corollary 3.1. When all parameters are constants, the price of a gap call option with dividends under partial information is

$$
X_{t}=\mathrm{e}^{-d(T-t)} S_{t} N\left(d_{1}^{R}\left(S_{t}\right)\right)-\xi \mathrm{e}^{-R(T-t)} N\left(d_{0}^{R}\left(S_{t}\right)\right),
$$

where $d\left(t, S_{t}\right)=d, \delta_{t}=\delta, \sigma_{t}=\sigma$ are constants and

$$
\begin{aligned}
d_{0}^{\delta}\left(S_{t}\right) & =\frac{1}{\sigma \sqrt{T-t}} \ln \left(\frac{S_{t}}{K \mathrm{e}^{-(\delta-d)(T-t)}}\right)-\frac{1}{2} \sigma \sqrt{T-t}, \\
d_{1}^{\delta}\left(S_{t}\right) & =d_{0}^{\delta}\left(S_{t}\right)+\sigma \sqrt{T-t}, \\
\left\{S_{T}>K\right\} & =\left\{-\frac{\widehat{W}_{T}-\widehat{W}_{t}}{\sqrt{T-t}}<d_{0}^{\delta}\left(S_{t}\right)\right\}, \\
N(x) & =\frac{1}{\sqrt{2 \pi}} \int_{-\infty}^{x} \mathrm{e}^{-z^{2} / 2} \mathrm{~d} z .
\end{aligned}
$$

Proof. From (19), we have

$$
\begin{aligned}
X_{t}^{\delta}= & E_{\mathbb{Q}}\left[\exp \left\{-\int_{t}^{T} \delta \mathrm{~d} s\right\}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right] \\
= & E_{\mathbb{Q}}\left[\exp \{-\delta(T-t)\}\left(S_{T}-\xi\right) I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right] \\
= & E_{\mathbb{Q}}\left[\mathrm{e}^{-\delta(T-t)} S_{T} I_{\left\{S_{T}>K\right\}} \mid \mathcal{G}_{t}\right]-\xi \mathrm{e}^{-\delta(T-t)} E_{\mathbb{Q}}\left[I_{\left\{S_{T}>K\right\}}\right] \\
= & -\xi \mathrm{e}^{-\delta(T-t)} \mathbb{Q}\left(I_{\left\{S_{T}>K\right\}}\right)+\mathrm{e}^{-d(T-t)} S_{t} E_{\mathbb{Q}}\left[\mathrm{e}^{\sigma\left(\widehat{W}_{T}-\widehat{W}_{t}\right)-1 / 2 \sigma^{2}(T-t)} I_{\left\{S_{T}>K\right\}}\right] \\
= & -\xi \mathrm{e}^{-\delta(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right) \\
& +\mathrm{e}^{-d(T-t)} S_{t} \int_{-\infty}^{\infty} \mathrm{e}^{-\sigma \sqrt{T-t x-1 / 2 \sigma^{2}(T-t)} I_{\left\{x<d_{0}^{\beta}\left(S_{t}\right)\right\}} \frac{1}{\sqrt{2 \pi}} \mathrm{e}^{-x^{2} / 2} \mathrm{~d} x} \\
= & -\xi \mathrm{e}^{-\delta(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right)+\mathrm{e}^{-d(T-t)} S_{t} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2 \pi}} \mathrm{e}^{-1 / 2\left(x+\sigma \sqrt{T-t)^{2}} I_{\left\{x<d_{0}^{\beta}\left(S_{t}\right)\right\}} \mathrm{d} x\right.} \\
= & -\xi \mathrm{e}^{-\delta(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right)+\mathrm{e}^{-d(T-t)} S_{t} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2 \pi}} \mathrm{e}^{-1 / 2 y^{2}} I_{\left\{y<d_{1}^{\beta}\left(S_{t}\right)\right\}} \mathrm{d} y \\
= & -\xi \mathrm{e}^{-\delta(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right)+\mathrm{e}^{-d(T-t)} S_{t} \int_{-\infty}^{d_{1}^{\beta}\left(S_{t}\right)} \frac{1}{\sqrt{2 \pi}} \mathrm{e}^{-1 / 2 y^{2}} \mathrm{~d} y \\
= & \mathrm{e}^{-d(T-t)} S_{t} N\left(d_{1}^{\delta}\left(S_{t}\right)\right)-\xi \mathrm{e}^{-\delta(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right)
\end{aligned}
$$

and

$$
\begin{equation*}
\frac{\partial X_{t}^{\delta}}{\partial \delta}=\xi(T-t) \mathrm{e}^{-(\delta-\alpha)(T-t)} N\left(d_{0}^{\delta}\left(S_{t}\right)\right)>0 \tag{20}
\end{equation*}
$$

which implies that $X_{t}^{\delta}$ increases with respect to $\delta$. By (15) and (20), the option price at time $t$ is

$$
\begin{equation*}
X_{t}=\mathrm{e}^{-d(T-t)} S_{t} N\left(d_{1}^{R}\left(S_{t}\right)\right)-\xi \mathrm{e}^{-R(T-t)} N\left(d_{0}^{R}\left(S_{t}\right)\right) \tag{21}
\end{equation*}
$$

This completes the proof.
If $d=0$ and $R_{t}=r_{t}=r$, then (21) reduces to the classical gap call option pricing formula, i.e.,

$$
X_{t}=S_{t} N\left(d_{1}\left(S_{t}\right)\right)-\xi \mathrm{e}^{-r(T-t)} N\left(d_{0}\left(S_{t}\right)\right)
$$

where

$$
\begin{aligned}
d_{0}\left(S_{t}\right)= & \frac{1}{\sigma \sqrt{T-t}}\left\{\ln \frac{S_{t}}{K}+\left(r-\frac{1}{2} \sigma^{2}\right)(T-t)\right\} \\
& d_{1}\left(S_{t}\right)=d_{0}\left(S_{t}\right)+\sigma \sqrt{T-t}
\end{aligned}
$$

In the same way, we can get the gap put option pricing formula under partial information either.

## 4. Optimal trading strategy under partial information

In this section, we consider the optimal trading strategy under partial information. Let $x_{0}$ be the initial wealth at time 0 of an agent. The investor wants to select a portfolio in order to maximize the expected utility on the finite time interval $[0, T]$.

Definition 4.1. A trading strategy $\pi=\left\{\pi(t)=\left(\pi_{1}(t), \ldots, \pi_{N}(t)\right) ; 0 \leqslant t \leqslant T\right\}$ is an $N$-dimensional, measurable, $\mathcal{G}$-adapted process such that

$$
E \int_{0}^{T} \pi_{t}^{2} \mathrm{~d} t<\infty
$$

where $\mathcal{G}$ is the augmented filtration generated by the price process $S_{t}$.
Definition 4.2. A trading strategy $\pi$ is called admissible if $X_{t}^{x_{0}, \pi} \geqslant 0$, a.s. $t \in[0, T]$.

Definition 4.3. A function $U:[0, \infty) \rightarrow \mathcal{R} \cup\{-\infty\}$ is called a utility function if it is continuous, strictly increasing, strictly concave on its domain, continuously differentiable on $[0, \infty)$ with derivative function $U^{\prime}(\cdot)$ satisfying the relation $\lim _{x \rightarrow \infty} U^{\prime}(x)=0$.

Our optimization problem is to maximize the expected utility from the terminal wealth, i.e.,

$$
\begin{equation*}
\max _{\left\{\pi_{t}\right\}_{0 \leqslant t \leqslant T}} E\left[U\left(X_{T}^{x_{0}, \pi}\right)\right] \tag{22}
\end{equation*}
$$

over all admissible trading strategies. To find an optimal solution for the above problem, we can use both the information of the stock price and the optimal estimation of $\mu_{t}$ which was obtained by using the filtering technique.

From the preceding section, we have

$$
\left\{\begin{array}{l}
\mathrm{d} X_{t}^{x_{0}, \pi}=\left[r_{t} X_{t}^{x_{0}, \pi}+\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}\right.  \tag{23}\\
\left.\quad \quad-\left(R_{t}-r_{t}\right)\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)^{-}\right] \mathrm{d} t+\sigma_{t} \pi_{t} \mathrm{~d} \bar{W}_{t} \\
\mathrm{~d} S_{t}=\widehat{\mu}_{t} S_{t} \mathrm{~d} t+\sigma_{t} S_{t} \mathrm{~d} \bar{W}_{t} \\
\mathrm{~d} \widehat{\mu}_{t}=a \widehat{\mu}_{t} \mathrm{~d} t+\frac{b \sigma_{t}+\gamma_{t}}{\sigma_{t}} \mathrm{~d} \bar{W}_{t} \quad \forall t \in[0, T]
\end{array}\right.
$$

where $\left\{\bar{W}_{t}\right\}_{t \in[0, T]}$ and $\left\{\widehat{\mu}_{t}\right\}_{t \in[0, T]}$ are observable.
In an uncertain market, besides the expected profit, investors focus more on risk or potential loss. In view of this, we consider the Constant Relative Risk Aversion (CRRA) utility function which is defined as

$$
U(x)= \begin{cases}\frac{1}{\nu} x^{\nu} & \text { if } \nu<0 \\ \ln x & \text { if } \nu=0\end{cases}
$$

First, we consider the case of $\nu<0$, then the utility function is

$$
\begin{equation*}
U(x)=\frac{1}{\nu} x^{\nu} . \tag{24}
\end{equation*}
$$

By using the Itô formula, we have

$$
\begin{align*}
E\left(\frac{1}{\nu}\left(X_{T}^{x_{0}, \pi}\right)^{\nu}\right)= & \frac{1}{\nu} x^{\nu}+\frac{1}{2} E \int_{0}^{T}(\nu-1)\left(X_{t}^{x_{0}, \pi}\right)^{\nu-2} \sigma_{t}^{2} \pi_{t}^{2} \mathrm{~d} t  \tag{25}\\
& +E \int_{0}^{T}\left(X_{t}^{x_{0}, \pi}\right)^{\nu-1}\left[r_{t} X_{t}^{x_{0}, \pi}+\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right) \pi_{t}\right. \\
& \left.-\left(R_{t}-r_{t}\right)\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)^{-}\right] \mathrm{d} t \\
= & \frac{1}{\nu} x^{\nu}+E \int_{0}^{T}\left(X_{t}^{x_{0}, \pi}\right)^{\nu} r_{t} \mathrm{~d} t \\
& -E \int_{0}^{T} \frac{1}{\left(X_{t}^{x_{0}, \pi}\right)^{2-\nu}}\left[X _ { t } ^ { x _ { 0 } , \pi } \left[\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right) \pi_{t}\right.\right. \\
& \left.\left.+\left(R_{t}-r_{t}\right)\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)^{-}\right]+\frac{1}{2}(1-\nu) \sigma_{t}^{2} \pi_{t}^{2}\right] \mathrm{d} t .
\end{align*}
$$

Theorem 4.1. Under partial information, the optimal trading strategy for (22) and (24) is

$$
\pi_{t}=\frac{X_{t}^{x_{0}, \pi}}{\sigma_{t}^{2}(\nu-1)}\left[\left(r_{t}-\mu_{t}-d\left(t, S_{t}\right)\right)+\left(R_{t}-r_{t}\right) \frac{1-\operatorname{sgn}\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)}{2}\right],
$$

where $\operatorname{sgn}(\cdot)$ is the sign function.
Proof. In order to maximize the expected utility from the terminal wealth, we should maximize (25), i.e., minimize the following term:

$$
M\left(\pi_{t}\right):=X_{t}^{x_{0}, \pi}\left[\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right) \pi_{t}+\left(R_{t}-r_{t}\right)\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)^{-}\right]+\frac{1}{2}(1-\nu) \sigma_{t}^{2} \pi_{t}^{2}
$$

Let $\mathrm{d} M\left(\pi_{t}\right) / \mathrm{d} \pi_{t}=0$. Then we have

$$
X_{t}^{x_{0}, \pi}\left[\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right)+\left(R_{t}-r_{t}\right) \frac{1-\operatorname{sgn}\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)}{2}\right]+(1-\nu) \sigma_{t}^{2} \pi_{t}=0
$$

which implies

$$
\pi_{t}=\frac{X_{t}^{x_{0}, \pi}}{\sigma_{t}^{2}(\nu-1)}\left[\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right)+\left(R_{t}-r_{t}\right) \frac{1-\operatorname{sgn}\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)}{2}\right]
$$

This completes the proof.

Corollary 4.1. If both the borrowing and lending interest rates are identical, then the optimal trading strategy under partial information is

$$
\pi_{t}=\frac{X_{t}^{x_{0}, \pi}}{\sigma_{t}^{2}(\nu-1)}\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right) .
$$

Next, we consider the case of $\nu=0$. In this case, the utility function is also called the logarithmic utility function, i.e.,

$$
\begin{equation*}
U(x)=\ln x . \tag{26}
\end{equation*}
$$

By using the Itô formula, we have

$$
\begin{aligned}
E\left(\ln \left(X_{T}^{x_{0}, \pi}\right)\right)= & \ln x_{0}+E \int_{0}^{T} r_{t} \mathrm{~d} t-E \int_{0}^{T} \frac{1}{\left(X_{t}^{x_{0}, \pi}\right)^{2}}\left[X _ { t } ^ { x _ { 0 } , \pi } \left[\left(r_{t}-\widehat{\mu}_{t}-d\left(t, S_{t}\right)\right) \pi_{t}\right.\right. \\
& \left.\left.+\left(R_{t}-r_{t}\right)\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)^{-}\right]+\frac{1}{2} \sigma_{t}^{2} \pi_{t}^{2}\right] \mathrm{d} t
\end{aligned}
$$

Corollary 4.2. Under partial information, the optimal trading strategy for (22) and (26) is

$$
\pi_{t}=\frac{X_{t}^{x_{0}, \pi}}{\sigma_{t}^{2}}\left[\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right)-\left(R_{t}-r_{t}\right) \frac{1-\operatorname{sgn}\left(X_{t}^{x_{0}, \pi}-\pi_{t}\right)}{2}\right]
$$

where $\operatorname{sgn}(\cdot)$ is the sign function. If both the borrowing and lending interest rates are identical, then the optimal trading strategy under partial information is

$$
\pi_{t}=\frac{X_{t}^{x_{0}, \pi}}{\sigma_{t}^{2}}\left(\widehat{\mu}_{t}+d\left(t, S_{t}\right)-r_{t}\right)
$$

Proof. The proof is analogous to that of Theorem 4.1. So we omit it here.
For both utility functions, the optimal trading strategies heavily depend on the filtered estimation of $\mu_{t}$, i.e., $\widehat{\mu}_{t}$. Therefore, in the sequel, we compare the difference of the optimal expected utility between full information and partial information. To make the problem easy to analyze, we assume that all parameters are constant and both the borrowing and lending interest rates are identical, i.e., $r_{t}=R_{t}=r, \sigma_{t}=\sigma$, and $d\left(t, S_{t}\right)=0$. The terminal wealth under full information is given as

$$
\mathrm{d} \widetilde{X}_{t}^{x_{0}, \pi}=\left[r \widetilde{X}_{t}^{x_{0}, \pi}+\left(\mu_{t}-r\right) \pi_{t}\right] \mathrm{d} t+\sigma \pi_{t} \mathrm{~d} W_{t},
$$

and the optimal trading strategy is

$$
\pi_{t}=\frac{\widetilde{X}_{t}^{x_{0}, \pi}}{\sigma^{2}}\left(\mu_{t}-r\right) .
$$

Therefore, the optimal terminal wealth under full information is

$$
\mathrm{d} \widetilde{X}_{t}^{x_{0}}=\left[r+\frac{\left(\mu_{t}-r\right)^{2}}{\sigma^{2}}\right] \widetilde{X}_{t}^{x_{0}} \mathrm{~d} t+\frac{\mu_{t}-r}{\sigma} \widetilde{X}_{t}^{x_{0}} \mathrm{~d} W_{t} .
$$

Similarly, the optimal terminal wealth under partial information is

$$
\mathrm{d} X_{t}^{x_{0}}=\left[r+\frac{\left(\widehat{\mu}_{t}-r\right)^{2}}{\sigma^{2}}\right] X_{t}^{x_{0}} \mathrm{~d} t+\frac{\widehat{\mu}_{t}-r}{\sigma} X_{t}^{x_{0}} \mathrm{~d} \bar{W}_{t} .
$$

Under the logarithmic utility function, the difference of the optimal expected utility between full information and partial information is

$$
\begin{equation*}
\left|E \ln \left(\widetilde{X}_{T}^{x_{0}}\right)-E \ln \left(X_{T}^{x_{0}}\right)\right|=\frac{1}{2 \sigma^{2}}\left|E \int_{0}^{T}\left(\mu_{s}-r\right)^{2} \mathrm{~d} s-E \int_{0}^{T}\left(\widehat{\mu}_{s}-r\right)^{2} \mathrm{~d} s\right| . \tag{27}
\end{equation*}
$$

For $\mu_{t}$, the unique solution of $\operatorname{SDE}(3)$ is

$$
\begin{equation*}
\mu_{t}=\eta \mathrm{e}^{a t}+\int_{0}^{t} b \mathrm{e}^{a(t-s)} \mathrm{d} W_{s}+\int_{0}^{t} c \mathrm{e}^{a(t-s)} \mathrm{d} V_{s} \tag{28}
\end{equation*}
$$

It is easy to verify that $\mu_{t}$ is Gaussian on the space $\left(\Omega, \mathcal{F}, \mathcal{F}_{t}, \mathbb{P}\right)$. Then we have $E \mu_{t}=\widehat{\mu}_{0} \mathrm{e}^{a t}$ and

$$
E \mu_{t}^{2}=\left(\gamma_{0}+\widehat{\mu}_{0}^{2}\right) \mathrm{e}^{2 a t}+\int_{0}^{t}\left(b^{2}+c^{2}\right) \mathrm{e}^{2 a(t-s)} \mathrm{d} s
$$

where $\widehat{\mu}_{0}=E\left(\mu_{0}\right)=E(\eta)$ and $\gamma_{0}=E\left[\left(\mu_{0}-\widehat{\mu}_{0}\right)^{2}\right]=E\left[\left(\mu_{0}-E\left(\mu_{0}\right)^{2}\right]\right.$.
For $\widehat{\mu}_{t}$, it follows from (9) and (10) that

$$
\mathrm{d} \widehat{\mu}_{t}=a \widehat{\mu}_{t} \mathrm{~d} t+\frac{b \sigma+\gamma_{t}}{\sigma} \mathrm{~d} \bar{W}_{t},
$$

which implies that

$$
\begin{equation*}
\widehat{\mu}_{t}=\widehat{\mu}_{0} \mathrm{e}^{a t}+\int_{0}^{t}\left(b+\frac{\gamma_{s}}{\sigma}\right) \mathrm{e}^{a(t-s)} \mathrm{d} \bar{W}_{s} . \tag{29}
\end{equation*}
$$

Then, from (11) and (18), we have

$$
\begin{align*}
\widehat{\mu}_{t}=\widehat{\mu}_{0} \mathrm{e}^{\int_{0}^{t} a-\sigma^{-1}\left(b+\gamma_{s} / \sigma\right) \mathrm{d} s} & +\int_{0}^{t} \frac{r}{\sigma}\left(b+\frac{\gamma_{s}}{\sigma}\right) \mathrm{e}^{\int_{s}^{t} a-\sigma^{-1}\left(b+\gamma_{v} / \sigma\right) \mathrm{d} v} \mathrm{~d} s  \tag{30}\\
& +\int_{0}^{t}\left(b+\frac{\gamma_{s}}{\sigma}\right) \mathrm{e}^{\mathrm{e}_{s}^{t} a-\sigma^{-1}\left(b+\gamma_{v} / \sigma\right) \mathrm{d} v} \mathrm{~d} \widehat{W}_{s}
\end{align*}
$$

where

$$
\begin{gathered}
\gamma_{t}=\frac{\beta_{1}-\beta_{2} L \mathrm{e}^{\left(\beta_{2}-\beta_{1}\right) t / \sigma^{2}}}{1-L \mathrm{e}^{\left(\beta_{2}-\beta_{1}\right) t / \sigma^{2}}}, \quad \beta_{1}=\sigma\left(a \sigma-b-\sqrt{a \sigma^{2}-b \sigma+c^{2}}\right), \\
\beta_{2}=\sigma\left(a \sigma-b+\sqrt{a \sigma^{2}-b \sigma+c^{2}}\right), \\
L=\frac{\gamma_{0}-\beta_{1}}{\gamma_{0}-\beta_{2}} \text { and } \bar{W}_{t}=W_{t}+\int_{0}^{t} \frac{\mu_{s}-\widehat{\mu}_{s}}{\sigma} \mathrm{~d} s=\widehat{W}_{t}-\int_{0}^{t} \frac{\widehat{\mu}_{s}-r}{\sigma} \mathrm{~d} s .
\end{gathered}
$$

By (28) and (30), the difference of the optimal expected utility between full information and partial information (27) can be further written as

$$
\begin{aligned}
\left|E \ln \left(\widetilde{X}_{T}^{x_{0}}\right)-E \ln \left(X_{T}^{x_{0}}\right)\right|= & \left.\frac{1}{8 a^{2} \sigma^{2}} \right\rvert\,\left(b^{2}+c^{2}+2 a \gamma_{0}\right)\left(\mathrm{e}^{2 a T}-1\right)-2 a\left(b^{2}+c^{2}\right) T \\
& \left.-4 a^{2} \int_{0}^{T} \int_{0}^{s}\left(b+\frac{\gamma_{s}}{\sigma}\right)^{2} \mathrm{e}^{2 a(s-v)} \mathrm{d} v \mathrm{~d} s \right\rvert\,
\end{aligned}
$$

Obviously, the difference is decreasing with respect to both $\sigma$ and $\gamma_{0}$.

## 5. Conclusions

This paper addresses a gap option pricing problem with dividends under partial information. Since investors could not observe complete information in financial markets, it is more realistic to consider how to price financial derivatives under partial information. By using the filtering technique, a Black-Scholes formula for pricing a gap option is derived. Although we only focus on the gap option, this method could be applied to other European-type options. In the last part of this paper, we solve a utility maximization problem of an investor who wants to maximize the expected utility from the terminal value of his portfolio on the finite time interval $[0, T]$ under partial information. By using the filtering technique, the problem under partial information can be transformed into the classical problem.

Future studies can go one step further by adapting the proposed method to the valuation of American-type options. Moreover, it would be more interesting to generalize the model to discuss the portfolio selection problem under partial information.

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