

*FinM 345/Stat 390 Stochastic Calculus,  
Autumn 2009*

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**Master of Science in Financial Mathematics Program  
University of Chicago**

**Lecture 10 (from Chicago)**

**Stochastic-Volatility, Jump-Diffusions: American Option  
Pricing and Optimal Portfolios**

*6:30-9:30 pm, 30 November 2009 at Kent 120 in Chicago*

*7:30-10:30 pm, 30 November 2009 at UBS Stamford*

*7:30-10:30 am, 01 December 2009 at Spring in Singapore*

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## *FinM 345 Stochastic Calculus:*

### **10. Stochastic-Volatility, Jump-Diffusion (SVJD): American Option Pricing and Optimal Portfolios:**

#### **• 10.1. SVJD American Option Pricing**

#### **\* 10.1.0. SVJD American Option Pricing Outline:**

1. Stochastic-Volatility Jump-Diffusion Model.
2. American Put Option Pricing.
3. *Heuristic Quadratic Approximation* for American Put Option.
4. American Option *Linear Complementarity Problem* Finite Differences.
5. Computation and Comparison of Methods.
6. Checking Approximation with Market Data.
7. Conclusions.

### \* 10.1.1. Stochastic-Volatility Jump-Diffusion (SVJD) SDE

[Hanson and Yan (ACC2007), invited talk in honor of I. Karatzas, *Stochastic Theory and Control in Finance*]: Assume asset price  $S^{(\text{rn})}(t)$ , under a risk-neutral probability, follows a jump-diffusion process and conditional variance  $V(t)$  follows the Heston (1993) square-root mean-reverting diffusion:

$$dS^{(\text{rn})}(t) = S^{(\text{rn})}(t)((r_0 - \lambda_0 \bar{\nu})dt + \sqrt{V(t)}dW_s(t)) + dCP_s(t, S^{(\text{rn})}(t)\nu(Q)), \quad (10.1)$$

where the compound Poisson jump process is

$$CP_s(t, S(t)\nu(Q)) = \sum_{j=1}^{P(t)} S(T_j^-)\nu(Q_j) \text{ and}$$

$$dV(t) = \kappa_v(\theta_v - V(t))dt + \sigma_v\sqrt{V(t)}dW_v(t), \quad (10.2)$$

where  $V(t) \geq \varepsilon_v > 0$ . Here,  $r_0$  = risk-free interest rate;  $W_s(t)$  and  $W_v(t)$  satisfy  $\text{Corr}[dW_s(t), dW_v(t)] = \rho_v(t)dt$ ;  $P(t)$  has intensity  $\lambda_0$ ;  $\nu(Q)$  = Poisson jump-amplitude;  $Q = \ln(\nu(Q) + 1)$  is the amplitude mark process.

### \* 10.1.2. Log-Uniform Jump-Diffusion Model

[Hanson and Westman (ACC2002)]:

$$\phi_Q(q) = \frac{1}{b-a} \begin{cases} 1, & a \leq q \leq b \\ 0, & \text{else} \end{cases}, \quad a < 0 < b,$$

where  $\mu_j \equiv E_Q[Q] = 0.5(b+a)$  is the mark mean;  
 $\sigma_j^2 \equiv \text{Var}_Q[Q] = (b-a)^2/12$  is the mark variance; and the  
jump-amplitude mean is

$$\bar{\nu} \equiv E[\nu(Q)] \equiv E[e^Q - 1] = (e^b - e^a)/(b-a) - 1.$$

**Finite jump-amplitudes and fat tail realism  $\implies$**

- **NYSE *circuit breakers*** limit extreme jumps since 1988-9;
- **In optimal portfolio problem, finite-support distributions allow realistic borrowing and short-selling** [Hanson and Zhu (Sethi2006)].
- **Uniformly distributed extreme tails.**

### \* 10.1.3 American Put Option Pricing:

*{Note: American CALL option on non-dividend stock, it is not optimal to exercise before maturity; so American call price is equal to corresponding European call price, at least in the case of diffusions.}*

- **American Put Option Price:**

$$P^{(A)}(s, v, t; K, T) = \sup_{\hat{\tau}} \left[ E^{(rn)} \left[ e^{-r_0(\hat{\tau}-t)} \max[K - S(\hat{\tau}), 0] \mid S(t) = s, V(t) = v \right] \right]$$

on the domain  $\mathcal{D}_{s,t} = \{(s, t) \mid [0, \infty) \times [0, T]\}$ , where  $K$  is the strike price,  $T$  is the maturity date,  $\mathcal{T}(t, T)$  are a set of random stopping times  $\hat{\tau} \in \mathcal{T}(t, T)$  (*on the Snell envelope, Karatzas (1988) and K & Shreve (1998)*) satisfying  $t < \hat{\tau} \leq T$ .

- **Early Exercise Feature:** The American option can be exercised at any time  $\hat{\tau} \in [0, T]$ , unlike the European option.

- Hence, there exists a **Critical Curve**  $s = S^*(t)$ , a free boundary, in the  $(s, t)$ -plane, separating the domain  $\mathcal{D}_{s,t}$  into two regions:
  - **Continuation Region**  $\mathcal{C}$ , where it is optimal to hold the option, i.e., if  $s > S^*(t)$ , then  $P^{(A)}(s, v, t; K, T) > \max[K - s, 0]$ . Here,  $P^{(A)}$  will have the same description as the European price  $P^{(E)}$ .
  - **Exercise Region**  $\mathcal{E}$ , where it is optimal to exercise the option, i.e., if  $s \leq S^*(t)$ , then  $P^{(A)}(s, v, t; K, T) = \max[K - s, 0]$ .

- The **American put option price** satisfies a **partial integro-differential equation (PIDE)** similar to that of the **European option price**, recalling that  $S(t) = s$  and  $V(t) = v$ , so let  $P_t^{(A)}(s, v, t; K, T) = P_t^{(A)}(s, v, t)$ , then

$$\begin{aligned}
0 &= P_t^{(A)}(s, v, t) + \mathcal{A} \left[ P^{(A)} \right] (s, v, t) \\
&\equiv P_t^{(A)} + (r_0 - \lambda_0 \bar{\nu}) s P_s^{(A)} + \kappa_v (\theta_v - v) P_v^{(A)} - r_0 P^{(A)} \\
&\quad + 0.5 \left( v s^2 P_{ss}^{(A)} + 2 \rho_v \sigma_v v s P_{sv}^{(A)} + \sigma_v^2 v P_{vv}^{(A)} \right) \\
&\quad + \lambda_0 \int_{-\infty}^{\infty} \left( P^{(A)}(s e^q, v, t) - P^{(A)}(s, v, t) \right) \phi_Q(q) dq,
\end{aligned} \tag{10.3}$$

for  $(s, t) \in \mathcal{C}$  and defining the **backward operator**  $\mathcal{A}$ .

- **American put option** pricing problem as **free boundary problem**:

$$0 = P_t^{(A)}(s, v, t) + \mathcal{A}[P^{(A)}](s, v, t) \quad (10.4)$$

for  $(s, t) \in \mathcal{C} \equiv [S^*(t), \infty) \times [0, T]$ ;

$$0 > P_t^{(A)}(s, v, t) + \mathcal{A}[P^{(A)}](s, v, t) \quad (10.5)$$

for  $(s, t) \in \mathcal{E} \equiv [0, S^*(t)] \times [0, T]$ . where **critical stock price**  $S^*(t)$  is not known *a priori* as a function of time, **called the free boundary**.



- **Conditions in the Continuation Region  $\mathcal{C}$ :**

- European put terminal condition limit:

$$\lim_{t \rightarrow T} P^{(A)}(s, v, t; K, T) = \max[K - s, 0],$$

- Zero stock price limit of option:

$$\lim_{s \rightarrow 0} P^{(A)}(s, v, t; K, T) = K,$$

- Infinite stock price limit of option:

$$\lim_{s \rightarrow \infty} P^{(A)}(s, v, t; K, T) = 0,$$

- **Critical option value limit:**

$$\lim_{s \rightarrow S^*(t)} P^{(A)}(s, v, t; K, T) = K - S^*(t),$$

- **Critical tangency/smooth contact limit in addition:**

$$\lim_{s \rightarrow S^*(t)} \frac{\partial P^{(A)}}{\partial s}(s, v, t; K, T) = -1.$$

## \* 10.1.4 Heuristic Quadratic Approximation for American Put Options:

- **Heuristic Quadratic Approximation [MacMillan (1986)] Key Insight:** if the PIDE applies to American options  $P^{(A)}$  as well as European options  $P^{(E)}$  in the continuation region, it also **applies to the American option optimal exercise premium**,

$$\varepsilon^{(P)}(s, v, t; K, T) \equiv P^{(A)}(s, v, t; K, T) - P^{(E)}(s, v, t; K, T),$$

where  $P^{(E)}$  is given by Fourier inverse in [Yan and Hanson (2006), also Lecture 9].

- **Change in Time:** Assuming

$$\varepsilon^{(P)}(s, v, t; K, T) \simeq G(t)Y(s, v, G(t))$$

and choosing  $G(t) = 1 - e^{-r_0(T-t)}$  as a new time variable such that  $\varepsilon^{(P)} = 0$  when  $G = 0$  at  $t = T$ .

- After dropping the term  $rg(1-g)Y_g$  with  $G(t) = g$  since the quadratic  $g(1-g) \leq 0.25$  on  $[0,1]$ , making  $G(t)$  a parameter instead of variable, then the *quadratic approximation* of the PIDE for  $Y(s, v, g)$  is

$$\begin{aligned}
0 = & +(r_0 - \lambda_0 \bar{\nu}) s Y_s - \frac{r_0}{G(t)} Y + \kappa_v (\theta_v - v) Y_v \\
& + 0.5 v s^2 Y_{ss} + \rho_v \sigma_v v s Y_{sv} + 0.5 \sigma_v^2 v Y_{vv} \\
& + \lambda_0 \int_{-\infty}^{\infty} (Y(se^q, v, G(t)) - Y(s, v, G(t))) \phi_Q(q) dq,
\end{aligned} \tag{10.6}$$

with **quadratic approximation boundary conditions:**

$$\begin{aligned}
\lim_{s \rightarrow \infty} Y(s, v, G(t)) &= 0, \\
\lim_{s \rightarrow S^*} Y(s, v, G(t)) &= \left( K - S^* - P^{(E)}(S^*, v, t) \right) / G, \\
\lim_{s \rightarrow S^*} Y_s(s, v, G(t)) &= \left( -1 - P_s^{(E)}(S^*, v, t) \right) / G.
\end{aligned} \tag{10.7}$$

- By **constant-volatility jump-diffusion (CVJD)** ad hoc approach [Bates (1996)] reformulated, we assume that the dependence on the volatility variable  $v$  is weak and replace  $v$  by the **constant time averaged quasi-deterministic approximation of  $V(t)$** :

$$\overline{\overline{V}} \equiv \frac{1}{T} \int_0^T \overline{V}(t) dt = \theta_v + (V(0) - \theta_v) (1 - e^{-\kappa_v T}) / (\kappa_v T), \quad (10.8)$$

assuming constant  $\{\kappa_v, \theta_v\}$ . The PIDE (10.6) for  $Y(s, v, g)$  becomes the **linear constant coefficient OIDE** for  $Y(s, v, g) \rightarrow \hat{Y}(s)$ , with argument suppressed parameters  $G$  and  $\overline{\overline{V}}$ ,

$$\begin{aligned} 0 = & +(r_0 - \lambda_0 \overline{\nu}) s \hat{Y}'(s) - \frac{r}{G} \hat{Y}(s) + 0.5 \overline{\overline{V}} s^2 \hat{Y}''(s) \\ & + \lambda_0 \int_{-\infty}^{\infty} \left( \hat{Y}(s e^q) - \hat{Y}(s) \right) \phi_Q(q) dq. \end{aligned} \quad (10.9)$$

- **Solution to the linear OIDE (10.9) has the power form:**

$$\hat{Y}(s) = c_1 s^{A_1} + c_2 s^{A_2}, \quad (10.10)$$

where  $c_1 = 0$  because positive root  $A_1$  is excluded by the vanishing boundary condition in (10.7) on  $Y$  for large  $s$ .

- Substituting power form (10.10) and the **uniform distribution** into (10.9) for  $\hat{Y}(s)$ ,

$$0 = \bar{\bar{V}} A_2^2 / 2 + \left( r_0 - \lambda_0 \bar{\nu} - \bar{\bar{V}} / 2 \right) A_2 - r_0 / G + \lambda \left( (e^{bA_2} - e^{aA_2}) / ((b - a) A_2) - 1 \right), \quad (10.11)$$

which is a **nearly-quadratic nonlinear equation for values of interest.**

- The last two boundary conditions in (10.7) give the equations satisfied by  $S^*(t)$  and  $c_2$ . Then  $S^* = S^*(t)$  can be calculated by fixed point iteration method with the expression:

$$S^* = \frac{A_2 \left( K - P^{(E)} \left( S^*, \bar{\bar{V}}, t; K, T \right) \right)}{A_2 - 1 - P_S^{(E)} \left( S^*, \bar{\bar{V}}, t; K, T \right)} \quad (10.12)$$

and

$$c_2 = \frac{K - S^* - P^{(E)} \left( S^*, \bar{\bar{V}}, t; K, T \right)}{G \cdot (S^*)^{A_2}}.$$

### \* 10.1.5 Linear Complementarity Problem (LCP) Finite Differences for American Put Options:

- **Free boundary problem** is transferred to **partial integro-differential complementarity problem (PIDCP)** formulated as follows

$$\begin{aligned} P^{(A)}(s, v, t; K, T) - F(s) &\geq 0, \\ P_{\tau}^{(A)} - \mathcal{A}P^{(A)} &\geq 0, \end{aligned} \quad (10.13)$$

$$\left( P_{\tau}^{(A)} - \mathcal{A}P^{(A)} \right) (P^{(A)} - F) = 0,$$

where  $F(s) \equiv \max[K - s, 0]$  is the **put payoff function** and  $\tau \equiv T - t$  is the **time-to-go**.

- **Crank-Nicolson second-order numerical scheme** with discrete state backward operator  $L \simeq \mathcal{A}$ ,

$$P^{(A)}(S_i, V_j, T - \tau_k; K, T) \equiv U(S_i, V_j, \tau_k) \simeq U_{i,j}^{(k)},$$

$$U^{(k)} = \left[ U_{i,j}^{(k)} \right],$$

$$P_{\tau}^{(A)} \simeq \frac{U^{(k+1)} - U^{(k)}}{\Delta\tau},$$

$$\mathcal{A}P^{(A)} \simeq 0.5L (U^{(k+1)} + U^{(k)}).$$

- **Standard Linear Algebraic Definitions:** Let

$\hat{U}^{(k)} = \left[ \hat{U}_i^{(k)} \right]$ , the single subscripted version of 2D-array

$U^{(k)} = \left[ U_{i,j}^{(k)} \right]$ , with corresponding variables  $\hat{\mathbf{F}}, \hat{\mathbf{L}}, \hat{\mathbf{M}}$  and

$\hat{\mathbf{b}}^{(k)}$ , so  $\hat{\mathbf{M}} \equiv I - \frac{\Delta\tau}{2}\hat{\mathbf{L}}$  and  $\hat{\mathbf{b}}^{(k)} \equiv \left( I + \frac{\Delta\tau}{2}\hat{\mathbf{L}} \right) \hat{U}^{(k)}.$



- **Discretized LCP [Cottle et al. (1992); Wilmott et al. (1995, 1998)]:**

$$\begin{aligned}\widehat{\mathbf{U}}^{(k+1)} - \widehat{\mathbf{F}} &\geq 0, & \widehat{\mathbf{M}}\widehat{\mathbf{U}}^{(k+1)} - \widehat{\mathbf{b}}^{(k)} &\geq 0, \\ \left(\widehat{\mathbf{U}}^{(k+1)} - \widehat{\mathbf{F}}\right)^\top \left(\widehat{\mathbf{M}}\widehat{\mathbf{U}}^{(k+1)} - \widehat{\mathbf{b}}^{(k)}\right) &= 0,\end{aligned}\tag{10.14}$$

- **Projective Successive OverRelaxation (PSOR)** (PSOR  $\equiv$  Projected SOR algorithm, projected onto the max function) with **SOR acceleration parameter**  $\omega$  for LCP (10.14) by iterating  $\widetilde{U}_i^{(n+1)}$  for  $\widehat{U}_i^{(k+1)}$  until changes are sufficiently small:

$$\begin{aligned}\widetilde{U}_i^{(n+1)} = \max &\left( \widehat{F}_i, \widetilde{U}_i^{(n)} + \omega \widehat{M}_{i,i}^{-1} \left( \widehat{b}_i^{(k)} - \sum_{j < i} \widehat{M}_{i,j} \widetilde{U}_j^{(n+1)} \right. \right. \\ &\left. \left. - \sum_{j \geq i} \widehat{M}_{i,j} \widetilde{U}_j^{(n)} \right) \right),\end{aligned}$$

where the sum splitting over iterates is from SOR.

- **Full Boundary Conditions for  $U(s, v, \tau)$ :**

$$U(0, v, \tau) = F(0) \text{ for } v \geq 0 \text{ and } \tau \in [0, T],$$

$$U(s, v, \tau) \rightarrow 0 \text{ as } s \rightarrow \infty \text{ for } v \geq 0 \text{ and } \tau \in [0, T],$$

$$U(s, 0, \tau) = F(s) \text{ for } s \geq 0 \text{ and } \tau \in [0, T],$$

$$U_v(s, v, \tau) = 0 \text{ as } v \rightarrow \infty \text{ for } s \geq 0 \text{ and } \tau \in [0, T].$$

- **Initial Condition for  $U(s, v, \tau)$ :**

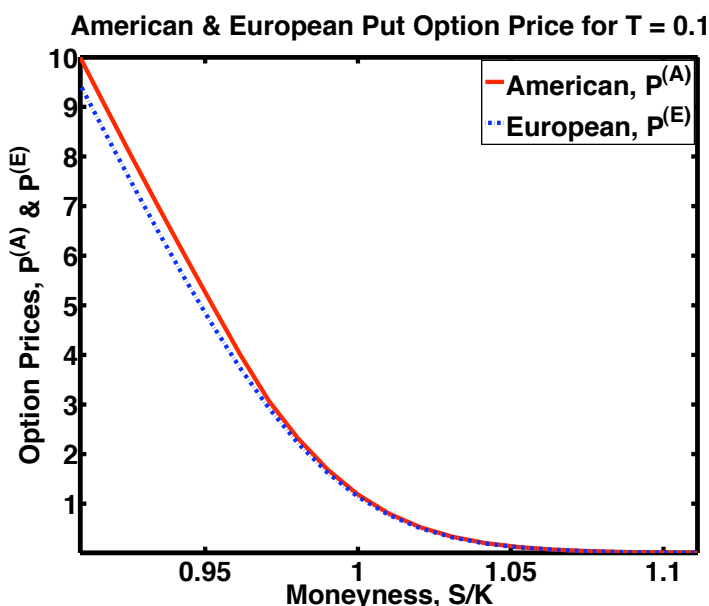
$$U(s, v, 0) = F(s) \text{ for } s \geq 0 \text{ and } v \geq 0.$$

- **Discretization of the PIDCP:** The first-order and second-order spatial derivatives and the cross-derivative term are all approximated with the **standard second-order accurate finite differences, using a nine-point computational molecule.**
- **Linear interpolation** is applied to the **jump integral** term and **quadratic extrapolation** of the solution is used for the **critical stock price  $S^*(t)$**  calculation, with comparable accuracy.

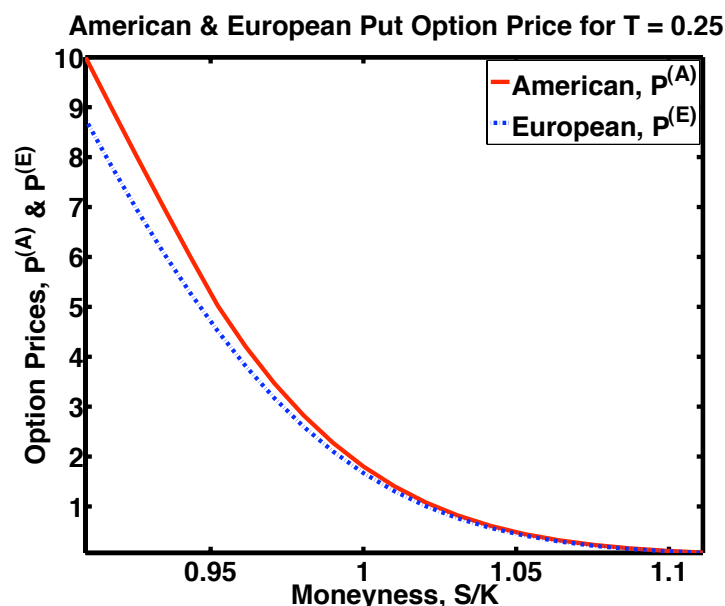
### \* 10.1.6 Computation and Comparison of Methods for American Put Options:

- The **Heuristic Quadratic Approximation** and **LCP/PSOR** approaches for American put option pricing are **implemented and compared**. All computations are done on a 2.40GHz Celeron<sup>(R)</sup> CPU. For the quadratic approximation analytic formula, one American put option price and critical stock price can be computed in about 7 seconds. The finite difference method can give a series of option prices for different stock prices and maturity for a specific strike price by one implementation. A single implementation, with  $51 \times 101 \times 51$  grids and acceleration parameter  $\omega = 1.35$ , takes 17 seconds.

- The American put option prices for **Parameters**:  
 $r_0 = 0.05$ ,  $S_0 = \$100$  ; the stochastic volatility part:  
 $V = 0.01$ ,  $\kappa_v = 10$ ,  $\theta_v = 0.012$ ,  $\sigma_v = 0.1$ ,  $\rho_v = -0.7$ ;  
and the uniform jump part:  $a = -0.10$ ,  $b = 0.20$  and  
 $\lambda_0 = 0.5$ .

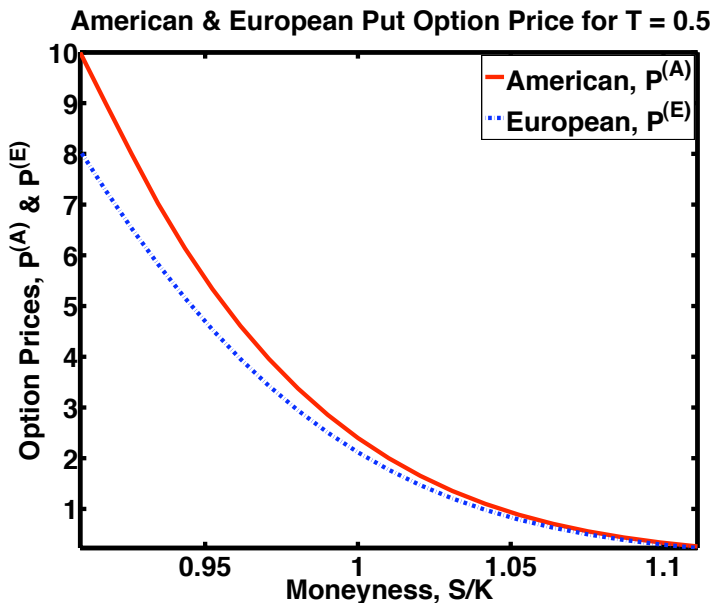


(a) American and European put option prices for  $T = 0.1$  years.

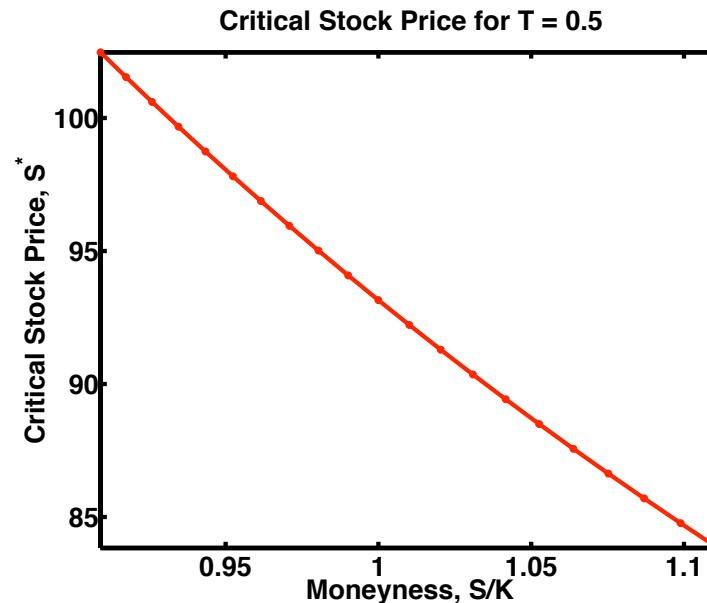


(b) American and European put option prices for  $T = 0.25$  years

Figure 10.1: The **heuristic quadratic approximation** gives SVJD-Uniform American  $P^{(A)} = P_{QA}^{(A)}$  compared to European  $P^{(E)}$  put option prices for  $T = 0.1$  ( $\simeq 5$  weeks) and  $0.25$  years (3 months), with averaged approximation of  $V(t)$ .

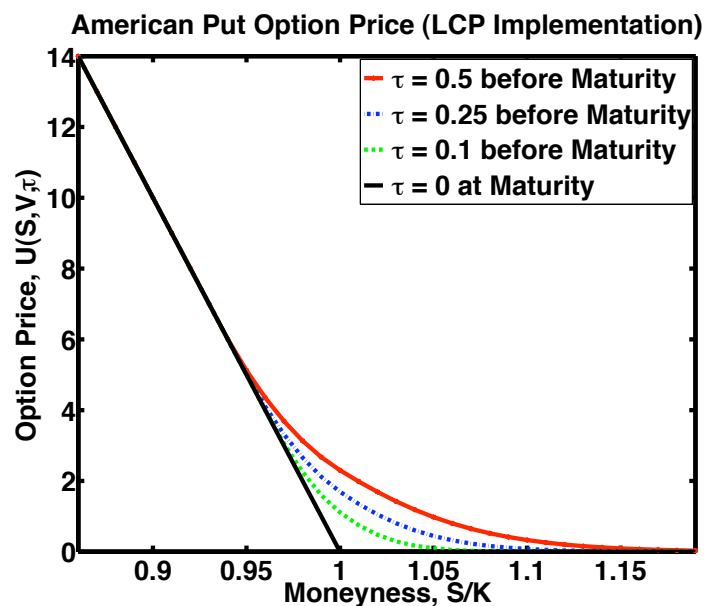


(a) American and European put option prices for  $T = 0.5$  years.

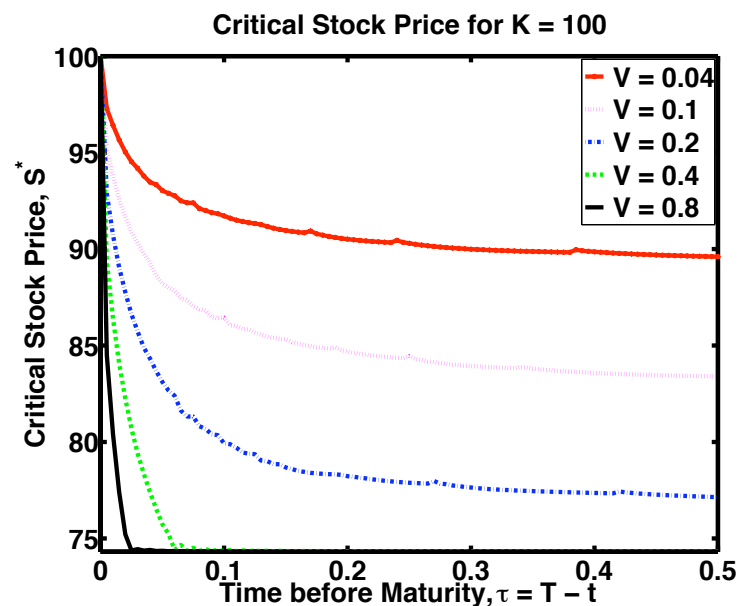


(b) Critical stock prices for  $T = 0.5$ .

Figure 10.2: The **heuristic quadratic approximation** gives SVJD-Uniform American  $P^{(A)} = P_{QA}^{(A)}$  compared European  $P^{(E)}$  put option prices and **critical stock prices** for  $T = 0.5$  years, with averaged approximation of  $V(t)$ .



(a) American put option prices by LCP.



(b) Critical stock prices for  $K = 100$ .

Figure 10.3: **PSOR finite difference implementation of LCP** gives SVJD-Uniform American put option prices  $U(S, V, \tau) = P_{LCP}^{(A)}$  and critical stock prices  $S^*(\tau; V)$  (using quadratic extrapolation approximations for smooth contact to the payoff function).



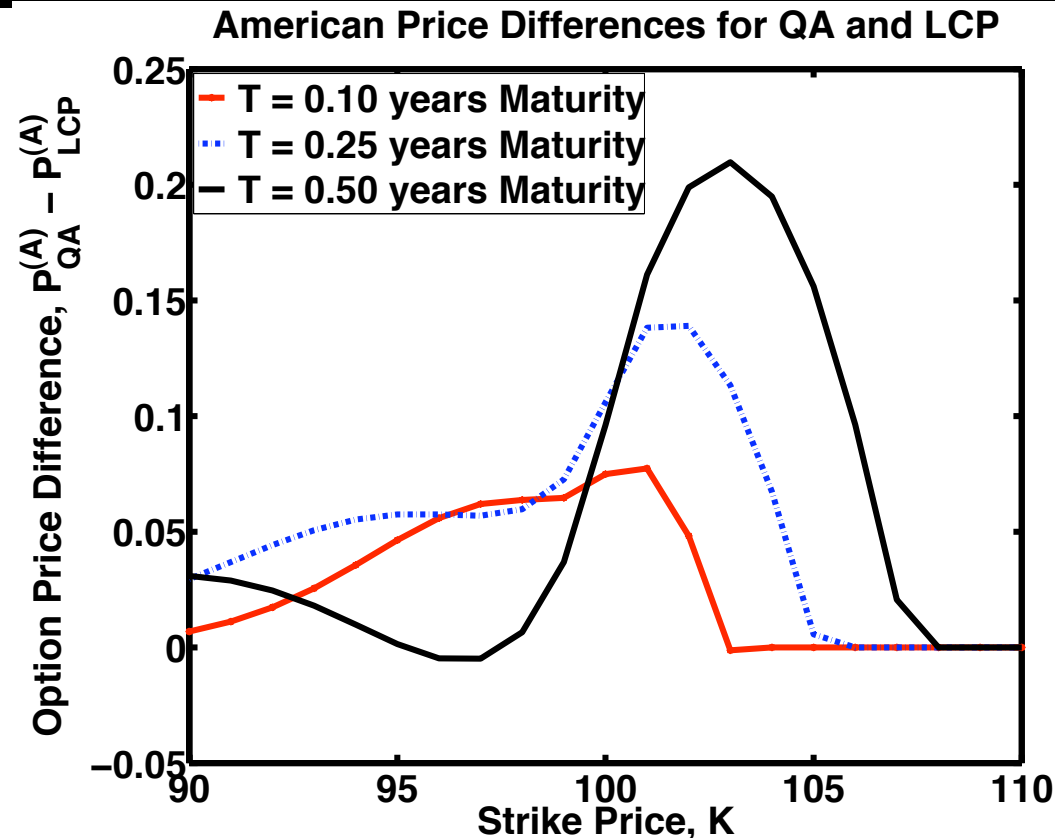


Figure 10.4: **Comparison of American put option prices evaluated by quadratic approximation (QA) and LCP finite difference (LCPFD) methods** when  $S = \$100$  and  $V = 0.01$  ( $\sqrt{V} = 0.1$ ). **Maximum price difference  $P_{QA}^{(A)} - P_{LCP}^{(A)} = \{\$0.08, \$0.14, \$0.21\}$  for  $T = \{0.1, 0.25, 0.5\}$  years, respectively, so QA is probably good for practical purposes.**

### \* 10.1.7 Checking Quadratic Approximation with Market Data:

- Choose same time **XEO (European options)** and **OEX (American options)** quotes on April 10, 2006 from CBOE. They are based on same underlying S&P 100 Index.
- Use XEO put option quotes to estimate parameter values of the European put option pricing for the quadratic approximation.
- Calculate American put option prices by quadratic approximation formula with estimated parameter values and compare the results with OEX quotes. Mean square error, **MSE = 0.137**, is obtained, showing good fit.

Table 1: **SVJD-Uniform Parameters Estimated** from XEO quotes on April 10, 2006

| Parameter  | Values |
|------------|--------|
| $\kappa_v$ | 10.62  |
| $\theta_v$ | 0.0136 |
| $\sigma_v$ | 0.175  |
| $\rho$     | -0.547 |
| $a$        | -0.140 |
| $b$        | 0.011  |
| $\lambda$  | 0.549  |
| $V$        | 0.0083 |
| MSE        | 0.195  |

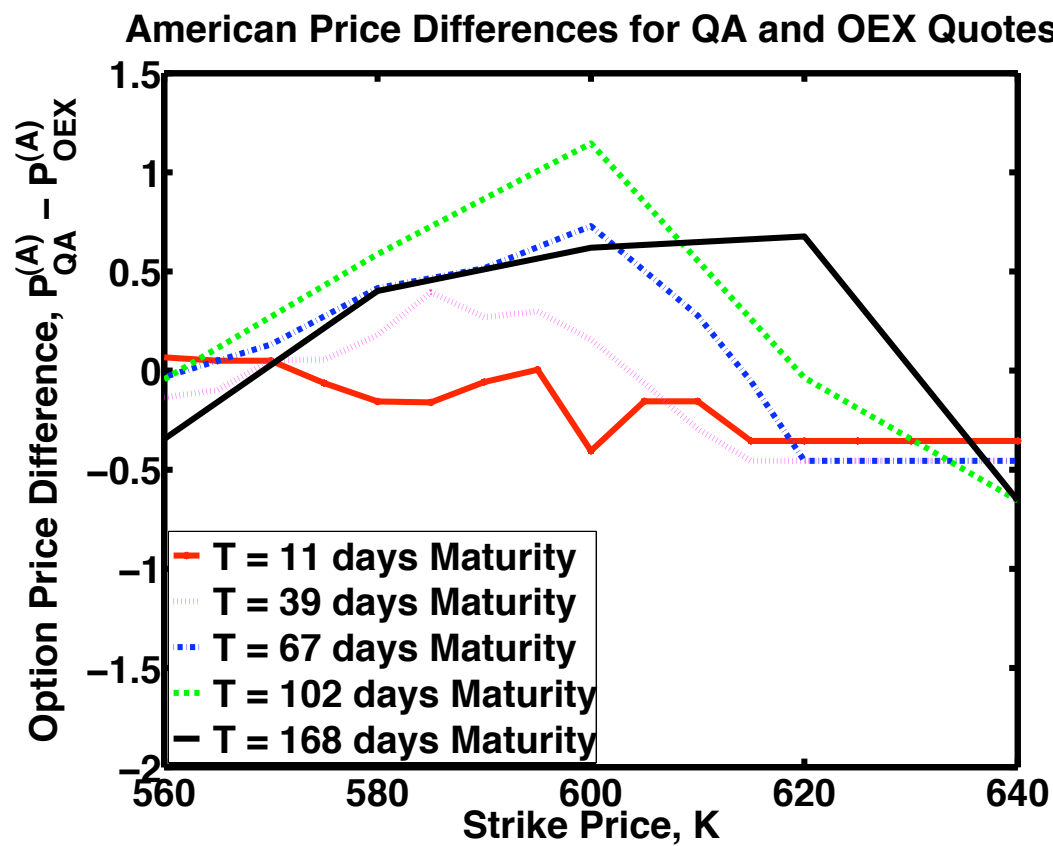


Figure 10.5: **American put option price differences between quadratic approximation (QA) and OEX (put) quotes**, when  $S = \$100$  and  $V = 0.01$  ( $\sqrt{V} = 0.1$ ). Maximum absolute price difference:  $P_{QA}^{(A)} - P_{OEX}^{(A)} = \{\$0.41, \$0.46, \$0.73, \$1.15, \$0.68\}$  for  $T = \{11, 39, 67, 102, 168\}$  days, respectively.

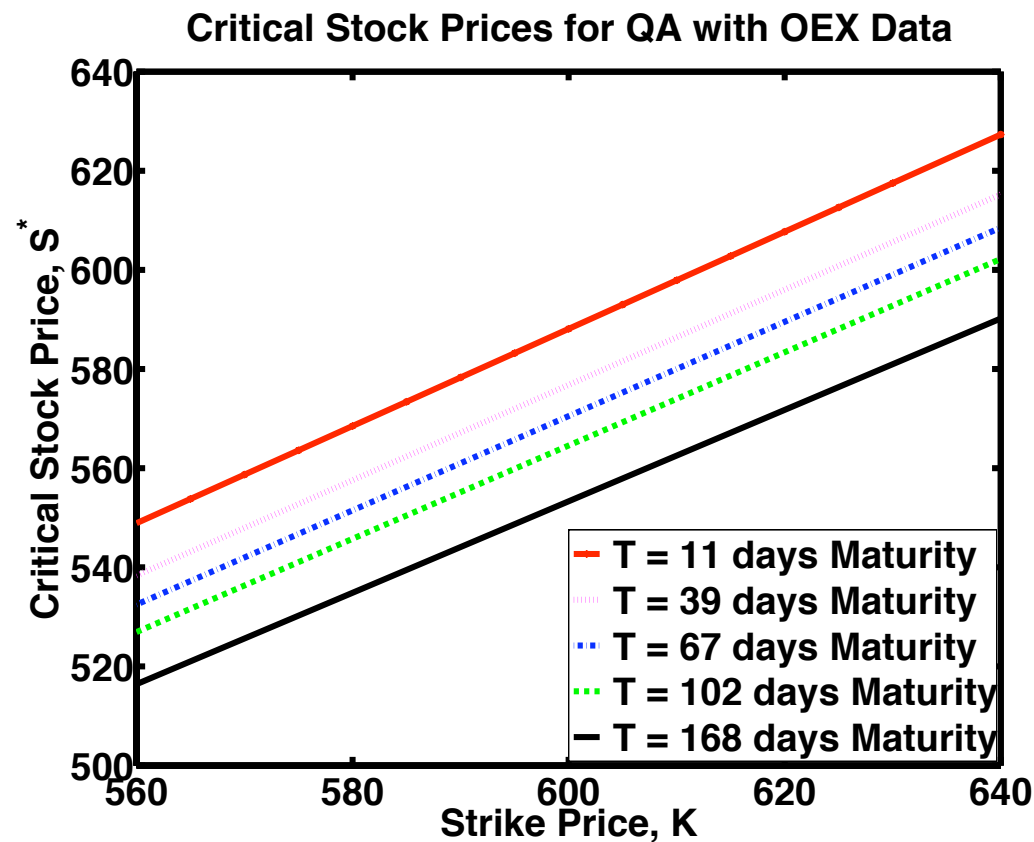


Figure 10.6: **Critical stock prices  $S^*$  using QA versus  $K$  with OEX quote data**, when  $S = \$100$  and  $V = 0.01$  ( $\sqrt{V} = 0.1$ ) for  $T = \{11, 39, 67, 102, 168\}$  days.

### \* 10.1.8 Conclusions for American Put Options:

- An **alternative stochastic-volatility jump-diffusion (SVJD)** stock model is proposed with square root mean reverting for stochastic-volatility **combined with log-uniform jump amplitudes**.
- The **heuristic quadratic approximation (QA)** and the **accurate LCP finite difference** scheme for American put option pricing **are compared**, with QA being good and fast for practical purposes.
- The QA results are also **checked against real market American option pricing data** OEX (with XEO for Euro. price base), yielding reasonable results considering the simplicity of QA.

## • 10.2. SVJD Optimal Portfolio and Consumption Problem

### \* 10.2.0. SVJD Optimal Portfolio and Consumption

#### Problem Outline:

1. Introduction.
2. Optimal Portfolio Problem and Underlying SVJD Model.
3. Portfolio Stochastic Dynamic Programming.
4. CRRA Canonical Solution to Optimal Portfolio Problem.
5. Computational Results.
6. Conclusions.

## \* 10.2.1. Introduction to SVJD Extension of Merton

### Portfolio Optimization Problem:

{Note: Some of the beginning of this part repeats somethings of the 10.1, first part of L10, but that is for completeness.}

- *Merton pioneered the optimal portfolio and consumption problem* for geometric diffusions used HARA (hyperbolic absolute risk-aversion) utility in his lifetime portfolio [Merton, RES (1969)] and general portfolio [Merton, JET (1971)] papers. However, there were some errors, in particular with bankruptcy boundary conditions and vanishing consumption.
- The optimal portfolio errors are thoroughly discussed in the collection of papers of Sethi's bankruptcy book (1997). See Sethi's introduction, [Karatzas et al., MOR (1986)] and [Sethi & Taksar, JET (1988)].



\* 10.2.2. Underlying Stochastic-Volatility, Jump-Diffusion (SVJD) Return Model: [*Hanson (BFS2008)*]

○ *Stock Price Linear Stochastic Differential Equation (SDE):*

$$dS(t) = S(t)(\mu_s(t)dt + \sqrt{V}(t)dG_s(t)) + dCP_s(t, S(t)\nu(Q)), \quad (10.15)$$

where the compound Poisson jump process is

$$CP_s(t, S(t)\nu(Q)) = \sum_{j=1}^{P(t)} S(T_j^-)\nu_s(Q_j),$$

and

- $S(t)$  = *stock price*,  $S(0) = S_0 > 0$ ;
- $\mu_s(t)$  = *expected rate of return* in absence of asset jumps;
- $V(t)$  = *stochastic variance* = (stochastic volatility)<sup>2</sup> = “ $\sigma_s^2(t)$ ”;

- $G_s(t)$  = *stock price diffusion process*, normally distributed such that  $\mathbf{E}[dG_s(t)] = 0$  and  $\mathbf{Var}[dG_s(t)] = dt$ , replacing  $dW_s(t)$  since wealth process  $W(t)$  has priority for symbol  $W$ ;
- $P_s(t)$  = *Poisson jump counting process*, Poisson distributed such that  $\mathbf{E}[dP_s(t)] = \lambda_s(t)dt = \mathbf{Var}[dP_s(t)]$ ;
- $\nu_s(v, t, q)$  = *Poisson jump-amplitude* with underlying *random mark variable*  $q = Q$ , selected for log-return so that  $Q = \ln(1 + \nu_s(v, t, Q))$ , such that  $\nu_s(v, t, q) > -1$ ;
- $T_k^-$  is the *pre-jump time* and  $Q_k$  is an independent and identically distributed (*IID*) *mark* realization at the  $k$ th jump;
- **Processes  $dG_s(t)$  and  $P_s(t) = P_s(t; Q)$  along with  $Q_k$  are independent**, except that  $Q_k$  is conditioned on a jump-event at  $T_k$ .

## ○ Stochastic-Volatility (Square-Root Diffusion) Model:

[CIR, Econometrica (1985); Heston, RFS (1993); FPS, book (2000)]

$$dV(t) = \kappa_v(t) (\theta_v(t) - V(t)) dt + \sigma_v(t) \sqrt{V(t)} dG_v(t), \quad (10.16)$$
with

- $V(t) \geq \min(V(t)) > 0^+, V(0) = V_0 \geq \min(V(t)) > 0^+;$
- *Log-rate*  $\kappa_v(t) > 0$ ; *reversion-level*  $\theta_v(t) > 0$ ; *volatility of volatility (variance)*  $\sigma_v(t) > 0$ ;
- $G_v(t)$  = *variance diffusion process*, normally distributed such that  $E[dG_v(t)] = 0$  and  $\text{Var}[dG_v(t)] = dt$ , with *correlation*  $\text{Corr}[dG_s(t), dG_v(t)] = \rho(t) dt$ ;
- Note: *SDE (10.16) is singular for transformations* as  $V(t) \rightarrow 0^+$  due to the square root, unlike SDE (10.1) for  $S(t)$  where the singularity is removable through the log transformation, but Itô-Taylor chain rule or simulation applications might not be valid unless
$$\Delta t \ll \sqrt{\min(V(t))} \ll 1.$$

○ *Double-Uniform Jump-Amplitude Q Mark Distribution:*

[*Zhu and Hanson, book chapter preprint (Sethi2006)*]

$$\begin{aligned}\Phi_Q(q; v, t) = & p_1(v, t) \frac{q - a(v, t)}{|a|(v, t)} I_{\{a(v, t) \leq q < 0\}} \\ & + \left( p_1(v, t) + p_2(v, t) \frac{q}{b(v, t)} \right) I_{\{0 \leq q < b(v, t)\}} \\ & + I_{\{b(v, t) \leq q < \infty\}}, \quad q \in [a(v, t), b(v, t)],\end{aligned}$$

where  $a(v, t) < 0 < b(v, t)$ ,  $p_1(v, t) + p_2(v, t) = 1$ ,

● *Mark Mean:*

$$\mu_j(v, t) \equiv \mathbb{E}_Q[Q] = (p_1(v, t)a(v, t) + p_2(v, t)b(v, t))/2;$$

● *Mark Variance:*  $\sigma_j^2(v, t) \equiv \text{Var}_Q[Q] =$

$$(p_1(v, t)a^2(v, t) + p_2(v, t)b^2(v, t))/3 - \mu_j^2(v, t);$$

● *More motivation: Double-uniform distribution unlinks the different extreme behaviors in crashes and rallies.*

○ **Wealth Portfolio with Bond, Stock and Consumption:**

- **Portfolio:** Riskless asset or *bond* at price  $B(t)$  and Risky asset or *stock* at price  $S(t)$  (10.15), with *instantaneous* portfolio change fractions  $U_b(t)$  and  $U_s(t)$ , respectively, such that

$$U_b(t) = 1 - U_s(t).$$

- **Exponential Bond Price Process:**

$$dB(t) = r(t)B(t)dt, \quad B(0) = B_0.$$

- **SVJD Portfolio Wealth Process  $W(t)$ , Less Consumption  $C(t)$  with Self-Financing  $\{dW/W = (1 - U_s)dB/B + U_s dS/S - Cdt/W\}$ :**

$$dW(t) = W(t) \left( r(t)dt + U_s(t) \left( (\mu_s(t) - r(t))dt + \sqrt{V(t)} dG_s(t) \right) + dCP_s(t, W(t)U_s(t)\nu(Q)) - C(t)dt, \right. \quad (10.17)$$

subject to constraints  $W(0) = W_0 > 0$ ,  $W(t) > 0$ ,  $v = V(t) > 0$ ,

$0 < C(t) \leq C_0^{(\max)}(v, t)W(t)$  and

$U_0^{(\min)}(v, t) \leq U_s(t) \leq U_0^{(\max)}(v, t)$ , while allowing extra shortselling ( $U_s(t) < 0$ ) and extra borrowing ( $U_b(t) < 0$ ).

**\* 10.2.3. SVJD Portfolio Optimal Objective — The Maximal, Expected Utilities of Final Wealth and Running Consumption:**

$$e^{-\bar{\beta}(t)} J^*(w, v, t) = \max_{\{u, c\}} \left[ \mathbb{E} \left[ e^{-\bar{\beta}(t_f)} \mathcal{U}_w(W(t_f)) + \int_t^{t_f} e^{-\bar{\beta}(\tau)} \mathcal{U}_c(C(\tau)) d\tau \right. \right. \\ \left. \left. \left| W(t) = w, V(t) = v, U_s(t) = u, C(t) = c \right] \right] \right]. \quad (10.18)$$

where

- **Cumulative Discount back to  $t = 0$ :**  $\bar{\beta}(t) = \int_0^t \beta(\tau) d\tau$ , where  $\beta(t)$  is the **instantaneous discount rate**. The  $t_f = T$  is the **final time**.
- **Consumption and Final Wealth Utility Functions:**  $\mathcal{U}_c(c)$  and  $\mathcal{U}_w(w)$  are bounded, strictly increasing and concave.
- **Variable Classes:** **State variables** are  $w$  and  $v$ , while **control variables** are  $u$  and  $c$ .
- **Final Condition:**  $J^*(w, v, t_f) = \mathcal{U}_w(w)$ .

○ *Absorbing Natural Boundary Condition:*

**Approaching bankruptcy as  $w \rightarrow 0^+$** , then, by the consumption constraint, as  $c \rightarrow 0^+$  and by the objective (10.18),

$$e^{-\bar{\beta}(t)} J^*(0^+, v, t) = \mathcal{U}_w(0^+) e^{-\bar{\beta}(t_f)} + \mathcal{U}_c(0^+) \int_t^{t_f} e^{-\bar{\beta}(s)} ds. \quad (10.19)$$

- This is the simple variant what Merton gave as a correction in his 1990 book for his 1971 optimal portfolio paper.
- However, [Karatzas, Lehoczky, Sethi and Shreve (KLASS) (1986) and [Sethi and Taksar (1988)] pointed out that it was necessary to enforce the non-negativity of wealth and consumption.

◦ *Derivation of Stochastic Dynamic Programming PIDE by Stochastic Calculus:*

Assume that the optimization and expectation of state and control stochastic processes can be decomposed into independent increments over nonoverlapping time intervals by **Bellman's Principle of Optimality** [Hanson (2007), Ch. 6 & Ex. 6.3] , so that

$$e^{-\bar{\beta}(t)} J^*(w, v, t) = \max_{\{U, C\}(t, t+\Delta t)} \left[ \mathbb{E}_{\{G, CP_Q\}(t, t+\Delta t)} \left[ \int_t^{t+\Delta t} e^{-\bar{\beta}(\tau)} \mathcal{U}_c(C(\tau)) d\tau + e^{-(\bar{\beta} + \Delta \bar{\beta})(t)} \cdot J^*((W + \Delta W)(t), (V + \Delta V)(t), t + \Delta t) \right] \right] \Bigg|_{W(t)=w, V(t)=v, U(t)=u, C(t)=c}. \quad (10.20)$$

Next, the limit is taken using the stochastic calculus.



As  $\Delta t \rightarrow 0^+$ , we simplify the state SΔE notation as

$\Delta W \triangleq \mu_w \Delta t + \sigma_w \Delta G_s + \nu_w \Delta P_s$ ,  $\nu_w = uw(\exp(Q) - 1)$  and

$\Delta V \triangleq \mu_v \Delta t + \hat{\sigma}_v \Delta G_v$ , while using  $J^* = J^*(w, v, t)$  and

conditional values, so

$$e^{-\bar{\beta}(t)} J^*(w, v, t) \triangleq \max_{\{u, c\}} \left[ e^{-\bar{\beta}(t)} \left( \mathcal{U}_c(c) \Delta t + J^* + \Delta t \left( -\beta(t) J^* \right. \right. \right. \\ \left. \left. \left. + J_t^* + J_w^* \mu_w + J_v^* \mu_v \right. \right. \right. \\ \left. \left. \left. + 0.5 J_{ww}^* \sigma_w^2 + \rho_w \sigma_w \hat{\sigma}_v J_{wv}^* + 0.5 J_{vv}^* \hat{\sigma}_v^2 \right. \right. \right. \\ \left. \left. \left. + \lambda_s \int_{\mathcal{Q}} dq \phi_Q(q) \right. \right. \right. \\ \left. \left. \left. \cdot (J^*(w + u(e^q - 1)w, v, t) - J^*(w, v, t)) \right) \right) \right]. \quad (10.21)$$

Cancellation of  $e^{-\bar{\beta}(t)} J^*(w, v, t)$  on both sides and  $\Delta t$ , yields

$$0 = \max_{\{u, c\}} \left[ \mathcal{U}_c(c) - \beta(t) J^* + J_t^* + J_w^* \mu_w + J_v^* \mu_v \right. \\ \left. + 0.5 J_{ww}^* \sigma_w^2 + \rho_w \sigma_w \hat{\sigma}_v J_{wv}^* + 0.5 J_{vv}^* \hat{\sigma}_v^2 \right. \\ \left. + \lambda_s(t) \int_{\mathcal{Q}} dq \phi_Q(q) (J^*(w + u(e^q - 1)w, v, t) - J^*(w, v, t)) \right]. \quad (10.22)$$

Next, we substitute for temporary coefficients and take the maximum (\*).

### \* 10.2.4. SVJD Portfolio Stochastic Dynamic Programming PIDE for Double-Uniform $Q$ s:

$$\begin{aligned}
 0 = & J_t^*(w, v, t) - \beta(t) J^*(w, v, t) + \mathcal{U}_c(c^*) - c^* J_w^*(w, v, t) \\
 & + (r(t) + (\mu_s(t) - r(t))u^*) w J_w^*(w, v, t) \\
 & + \kappa_v(t)(\theta_v(t) - v) J_v^*(w, v, t) + \frac{1}{2} v (u^*)^2 w^2 J_{ww}^*(w, v, t) \\
 & + \frac{1}{2} \sigma_v^2(t) v J_{vv}^*(w, v, t) + \rho_v(t) \sigma_v(t) v u^* w J_{wv}^*(w, v, t) \\
 & + \lambda_s(t) \left( \frac{p_1(v, t)}{|a|(v, t)} \int_{a(v, t)}^0 + \frac{p_2(v, t)}{b(v, t)} \int_0^{b(v, t)} \right) \\
 & \cdot \left( J^*(\underline{(1 + (e^q - 1)u^*)w}, v, t) - J^*(w, v, t) \right) dq,
 \end{aligned} \tag{10.23}$$

where  $u^* = u^*(w, v, t) \in [U_0^{(\min)}(v, t), U_0^{(\max)}(v, t)]$  and

$c^* = c^*(w, v, t) \in [0, C_0^{(\max)}(v, t)w]$  are the optimal controls, if they exist, while  $J_w^*(w, v, t)$  and  $J_{ww}^*(w, v, t)$  are the continuous partial derivatives with respect to wealth  $w$ . Note that  $(1 + (e^q - 1)u^*(w, v, t))w$  is a post-jump wealth argument.

### \* 10.2.5. Positivity of Wealth with Jump Distribution:

Since  $(1 + (e^q - 1)u^*(w, v, t))w$  is a wealth argument in (10.23), it must satisfy the wealth positivity condition, so

$$K(u, q) \equiv 1 + (e^q - 1)u > 0$$

on  $[a(v, t), b(v, t)]$  of the jump-amplitude density  $\phi_Q(q; v, t)$ .

**Lemma 10.1** *Bounds on Optimal Stock Fraction due to Positivity of Wealth Jump Argument:*

(a) If the support of  $\phi_Q(q; v, t)$  is the *finite* interval  $q \in [a(v, t), b(v, t)]$  with  $a(v, t) < 0 < b(v, t)$ , then  $u^*(w, v, t)$  is restricted by (10.23) to

$$\frac{-1}{\nu_s(v, t, b(v, t))} < u^*(w, v, t) < \frac{-1}{\nu_s(v, t, a(v, t))}, \quad (10.24)$$

where  $\nu_s(v, t, q) = \exp(q) - 1$ .

(b) If the support of  $\phi_Q(q; v, t)$  is fully *infinite*, i.e.,  $(-\infty, +\infty)$ , then  $u^*(w, v, t)$  is restricted by (10.23) to

$$0 < u^*(w, v, t) < 1. \quad (10.25)$$

○ *Remarks: Non-Negativity of Wealth and Jump Distribution:*

- Recall that  $u$  is the stock fraction, so that *short-selling and borrowing will be overly restricted in the infinite support case (10.25)* where  $a(v, t) \rightarrow -\infty$  and  $b(v, t) \rightarrow +\infty$ , *unlike the finite case (10.24)*, where  $-\infty < a(v, t) < 0 < b(v, t) < +\infty$ .
- So, unlike option pricing, *finite support of the mark density makes a big difference* in the optimal portfolio and consumption problem!
- Thus, it would *not be practical to use either normally or double-exponentially distributed marks in the optimal portfolio and consumption problem* with a bankruptcy condition.
- If  $[a_{\min}, b_{\max}] = [\min_t(a(v, t)), \max_t(b(v, t))]$ , then the overall  $u^*$  range for the S&P500 data used is

$$[u_{\min}, u_{\max}] = [-18, +12] \subset \left( \frac{-1}{(e^{b_{\max}} - 1)}, \frac{+1}{(1 - e^{a_{\min}})} \right).$$

- **Extreme tail ordering:**

$$\exp(-x^2) \ll |x|^N \exp(-|x|) \ll |x|^{-N} \ll 1, \quad |x| \gg 1, \quad N > 0.$$

## \* 10.2.6. Unconstrained Optimal or Regular Control

### Policies:

In absence of control constraints and in presence of sufficient differentiability, the dual policy, implicit critical conditions are

- **Regular Consumption**  $c^{(\text{reg})}(w, v, t)$  *{Implicitly}*:

$$\mathcal{U}'_c(c^{(\text{reg})}(w, v, t)) = J_w^*(w, v, t). \quad (10.26)$$

- **Regular Portfolio Fraction**  $u^{(\text{reg})}(w, v, t)$  *{Implicitly}*:

$$\begin{aligned} vw^2 J_{ww}^*(w, v, t) u^{(\text{reg})}(w, v, t) = & -(\mu_s(t) - r(t)) w J_w^*(w, v, t) \\ & - \rho \sigma_v(t) v w J_{wv}^*(w, v, t) \\ & - \lambda(t) w \left( \frac{p_1(v, t)}{|a|(v, t)} \int_{a(v, t)}^0 + \frac{p_2(v, t)}{b(v, t)} \int_0^{b(v, t)} \right) \\ & \cdot (e^q - 1) J_w^*(t, K(u^{(\text{reg})}(w, v, t), q) w) dq. \end{aligned} \quad (10.27)$$

## \* 10.2.6. CRRA Utilities Canonical Solution to Optimal Portfolio Problem:

- *Constant Relative Risk-Aversion (CRRA) Power Utilities:*

$$\mathcal{U}_c(x) = \mathcal{U}(x) = \mathcal{U}_w(x) = \begin{cases} x^\gamma / \gamma, & \gamma \neq 0 \\ \ln(x), & \gamma = 0 \end{cases}, \quad x \geq 0, \gamma < 1. \quad (10.28)$$

- $\Leftarrow$  *Relative Risk-Aversion (RRA):*

$RRA(x) \equiv -\mathcal{U}''(x) / (\mathcal{U}'(x)/x) = (1 - \gamma) > 0, \quad \gamma < 1,$   
i.e., negative of ratio of marginal to average change in  
marginal utility ( $\mathcal{U}'(x) > 0$  &  $\mathcal{U}''(x) < 0$ ) is a constant.

- *CRRA Canonical Separation of Variables:*

$$J^*(w, v, t) = \mathcal{U}(w) J_0(v, t), \quad J_0(v, t_f) = 1, \quad (10.29)$$

i.e., if valid, then wealth state dependence is known and  
only the time-variance dependent factor  $J_0(v, t)$  need be  
determined.

\* **10.2.6. Canonical Simplifications with CRRA Utilities:**

- ***Regular Consumption Control is Linear in Wealth:***

$c^{(\text{reg})}(w, v, t) = w \cdot c_0^{(\text{reg})}(v, t) \equiv w / J_0^{1/(1-\gamma)}(v, t), \quad (10.30)$   
 where  $c_0^{(\text{reg})}(v, t)$  is a wealth fraction, with optimal consumption,

$$c_0^*(v, t) = \max \left[ \min \left[ c_0^{(\text{reg})}(v, t), C_0^{(\text{max})}(v, t) \right], 0 \right]$$

per  $w$ .

- ***Regular Fraction Control is Independent of Wealth:***

$$u^{(\text{reg})}(w, v, t) \equiv u_0^{(\text{reg})}(v, t) = \frac{1}{(1-\gamma)v} \left( \mu_s(t) - r(t) + \frac{\rho \sigma_v(t) v J_{0,v}(v, t)}{J_0(v, t)} + \lambda_s(t) I_1 \left( u_0^{(\text{reg})}(v, t), v, t \right) \right), \quad (10.31)$$

where  $v > 0$ , in fixed point form, where

$$u^* = u_0^*(v, t) = \max \left[ \min \left[ u_0^{(\text{reg})}(v, t), U_0^{(\text{max})} \right], U_0^{(\text{max})} \right],$$

and

$$I_1(u, v, t) \equiv \left( \frac{p_1(v, t)}{|a|(v, t)} \int_{a(v, t)}^0 + \frac{p_2(v, t)}{b(v, t)} \int_0^{b(v, t)} \right) (e^q - 1) K^{\gamma-1}(u, q) dq.$$

**\* 10.2.7. CRRA Time-Variance Dependent Component in Formal “Bernoulli” PDE ( $\gamma \neq 0; \gamma < 1$ ):**

$$0 = J_{0,t}(v, t) + (1 - \gamma) \left( g_1 J_0 + g_2 J_0^{\frac{\gamma}{\gamma-1}} \right) (v, t) + g_3(v, t) J_{0,v}(v, t) + \frac{1}{2} \sigma_v^2(t) v J_{0,vv}(v, t), \quad (10.32)$$

where

- **Bernoulli Coefficients  $g_1(v, t)$ ,  $g_2(v, t)$ , and  $g_3(v, t)$ :**  
 $g_1(v, t) = g_1(v, t; u_0^*(v, t))$ ,  
 $g_2(v, t) = g_2\left(v, t; c_0^*(v, t), c_0^{(\text{reg})}(v, t)\right)$ , and  $g_3(v, t) = g_3(v, t; u_0^*(v, t))$ , introduce implicit nonlinear dependence on  $u_0^*(v, t)$ ,  $c_0^*(v, t)$  and  $c_0^{(\text{reg})}(v, t)$ , so iterations are required.
- **Formal (Implicit) Solution using Bernoulli transformation**,  $J_0(v, t) = \mathbf{y}^{1-\gamma}(\mathbf{v}, t)$ , improving iterations:

$$0 = y_t(v, t) + g_1(v, t)y(v, t) + g_4(v, t), \quad y(v, t_f) = 1,$$

$$J_0(v, t) = \left[ e^{\bar{g}_1(v, t, t_f)} + \int_t^{t_f} g_4(v, \tau) e^{\bar{g}_1(v, t, \tau)} d\tau \right]^{1-\gamma}. \quad (10.33)$$



Here,

$$g_1(v, t) \equiv \frac{1}{1 - \gamma} (-\beta(t) + \gamma (r(t) + (\mu_s(t) - r(t))u_0^*(v, t)) - \frac{1}{2}(1 - \gamma)v(u_0^*)^2(v, t) + \lambda_s(t) (I_2(u_0^*(v, t), v, t) - 1)) ,$$

$$\bar{g}_1(v, t, \tau) \equiv \int_t^\tau g_1(v, s) ds.$$

$$I_2(u, v, t) \equiv \left( \frac{p_1(v, t)}{|a|(v, t)} \int_{a(v, t)}^0 + \frac{p_2(v, t)}{b(v, t)} \int_0^{b(v, t)} \right) K^\gamma(u, q) dq,$$

$$g_2(v, t) \equiv \frac{1}{1 - \gamma} \left( \left( \frac{c_0^*(v, t)}{c_0^{(\text{reg})}(v, t)} \right)^\gamma - \gamma \left( \frac{c_0^*(v, t)}{c_0^{(\text{reg})}(v, t)} \right) \right) ,$$

$$g_3(v, t) = +\kappa_v(t)(\theta_v(t) - v) + \gamma \rho \sigma_v(t) v u_0^*(v, t),$$

$$g_4(v, t) = g_2(v, t) + g_3(v, t) y_v(v, t) + \frac{1}{2} \sigma_v^2(t) v (y_{vv} - \gamma((y_v)^2/y)) (v, t).$$

\* 10.2.8. CRRA Time-Variance Dependent Component in Formal “Bernoulli” PDE ( $\gamma = 0$ ; Kelly Criterion):

*Famous Users: Ed Thorp, Warren Buffet, George Soros.*

In this medium risk-averse case of the logarithmic CRRA utility, the formal, implicit canonical solution has two terms,

$$J^*(w, v, t) = \ln(w)J_0(v, t) + J_1(v, t), \quad (10.34)$$

with final boundary conditions  $J_0(v, t) = 1$  and  $J_1(v, t) = 0$ .

The regular controls satisfy,

$$c^{(\text{reg})}(w, v, t) = w c_0^{(\text{reg})}(v, t) \equiv w / J_0(v, t),$$

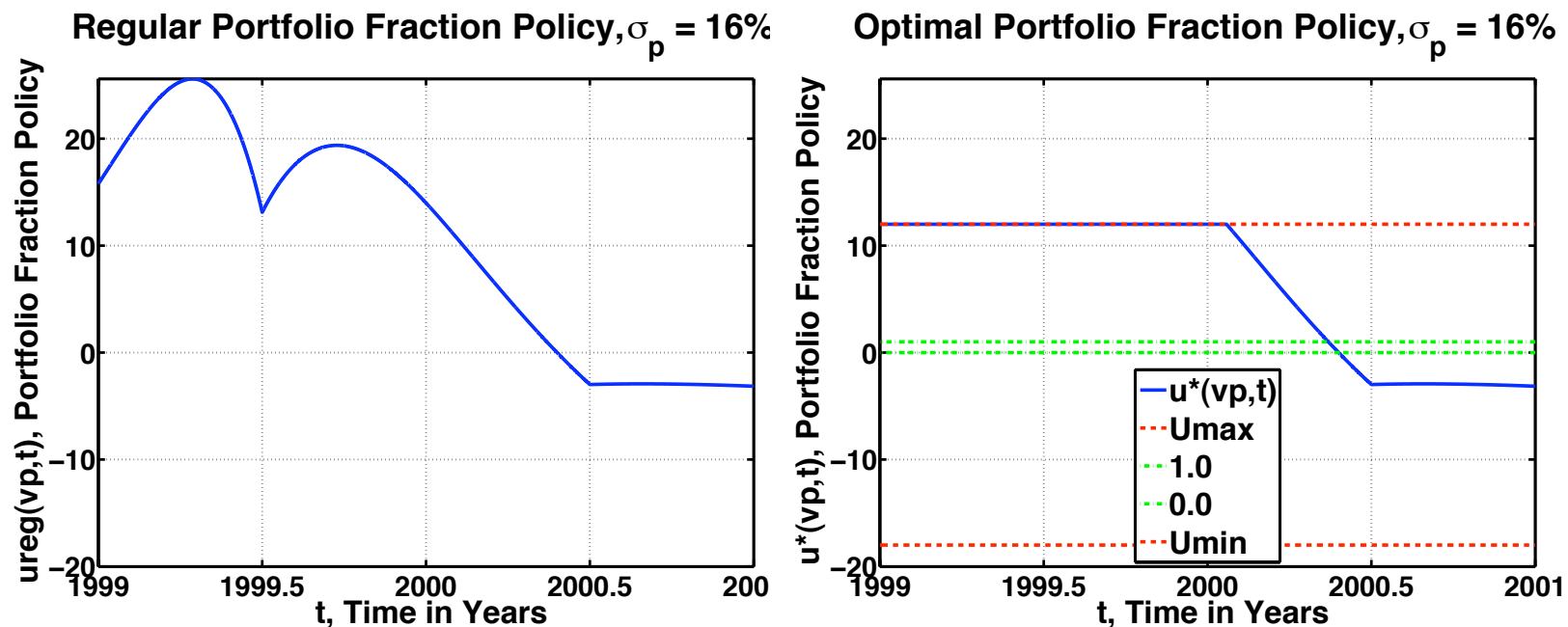
$$\begin{aligned} u^{(\text{reg})}(w, v, t) &= u_0^{(\text{reg})}(v, t) \\ &\equiv \frac{1}{v} \left( \mu_s(t) - r(t) + \rho \sigma_v(t) (J_{0,v} / J_0)(v, t) \right. \\ &\quad \left. + \lambda_s(t) I_1 \left( u_0^{(\text{reg})}(v, t), v, t \right) \right), \quad v > 0. \end{aligned}$$

## \* 10.2.9. Computational Considerations and Results:

### ○ *Computational Considerations:*

- The primary problem is having stable computations and much smaller time-steps  $\Delta t$  are needed compared to variance-steps  $\Delta V$ , since the computations are *drift-dominated* over the diffusion coefficient, in that the mesh coefficient associated with  $J_{0,v}$  can be hundreds times larger than that associated with  $J_{0,vv}$  for the variance-diffusion.
- *Drift-upwinding* is needed so the finite differences for the drift-partial derivatives follow the sign of the drift-coefficient, while central differences are sufficient for the diffusion partials.
- *Iteration calculations in time, controls and volatility* are sensitive to small and negative deviations, as well as the form of the iteration in terms of the formal implicitly-defined solutions.

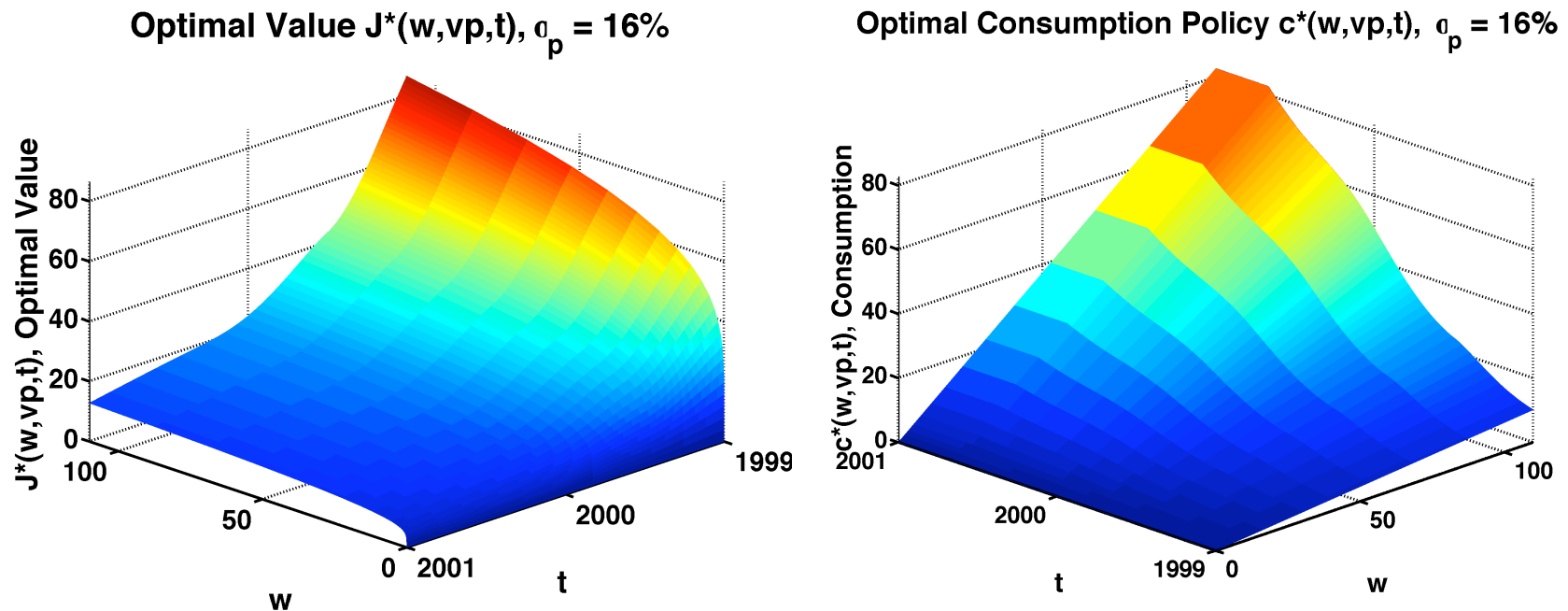
- *Results for Regular  $u^{(\text{reg})}(v_p, t)$  and Optimal  $u^*(v_p, t)$  Portfolio Fraction Policies,  $\sigma_p = \sqrt{v_p} = 16\%$ :*



(a) Regular fraction policy  $u^{(\text{reg})}(v_p, t)$ . (b) Optimal fraction policy,  $u^*(v_p, t)$ .

Figure 10.7: Regular and optimal portfolio stock fraction policies,  $u^{(\text{reg})}(v_p, t)$  and  $u^*(v_p, t)$  on  $t \in [1999.0, 2001.0]$ , while  $u^*(v_p, t) \in [-18, 12]$ .

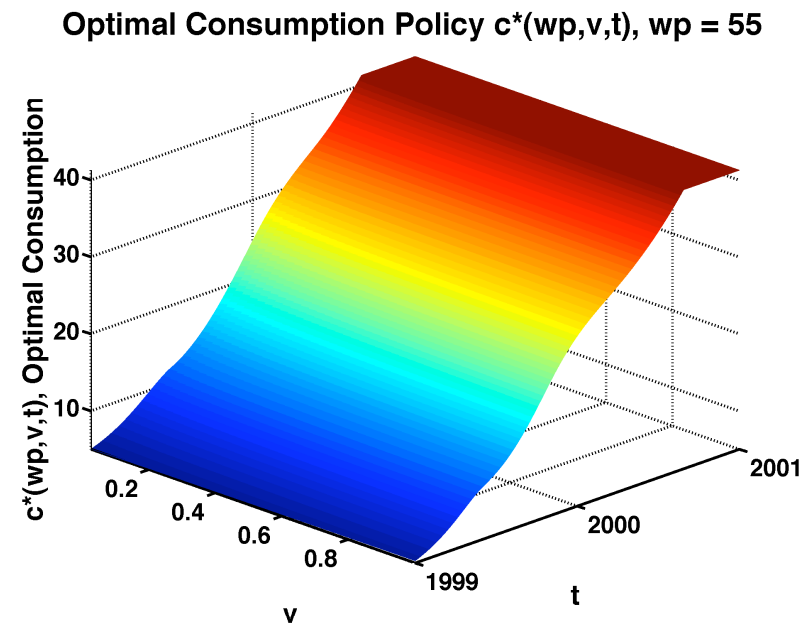
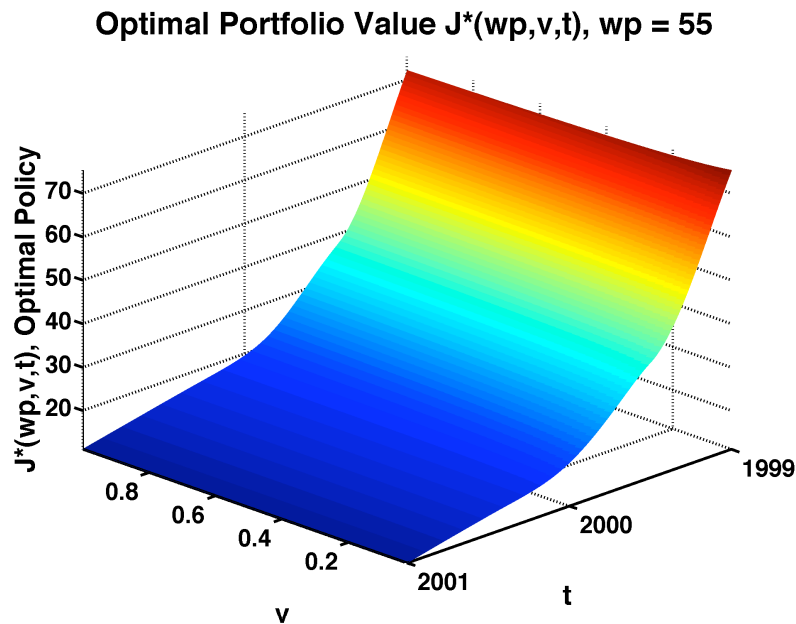
- *Results for Optimal Value  $J^*(w, v_p, t)$  and Optimal Consumption  $c^*(w, v_p, t)$ , Portfolio Fraction Policies,  $\sigma_p = \sqrt{v_p} = 16\%$  :*



(a) Optimal portfolio value  $J^*(w, v_p, t)$ . (b) Optimal consumption policy  $c^*(w, v_p, t)$ .

Figure 10.8: Optimal portfolio value  $J^*(w, v_p, t)$  and optimal consumption policy  $c^*(w, v_p, t)$  for  $(w, v_p, t) \in [0, 110] \times [1999.0, 2001.0]$ , while  $c^*(w, v_p, t) \in [0, 0.75 \cdot w]$  is enforced near  $t = 2001$ .

- *Results for Optimal Value  $J^*(w_p, v, t)$  and Optimal Consumption  $c^*(w_p, v, t)$ ,  $w_p = 55$ :*



(a) Optimal portfolio value  $J^*(w_p, v, t)$ .      (b) Optimal consumption  $c^*(w_p, v, t)$ .

Figure 10.9: Optimal portfolio value  $J^*(w_p, v, t)$  and optimal consumption  $c^*(w_p, v, t)$  at  $w_p = 55$  for  $(v, t) \in \times [v_{\min}, 1.0] \times [1999.0, 2001.0]$ , while  $c^*(w_p, v, t) \in [0, 0.75 \cdot w_p]$  is enforced near  $t = 2001$ .

- *Results for Optimal Portfolio Fraction  $u^*(v, t)$ :*

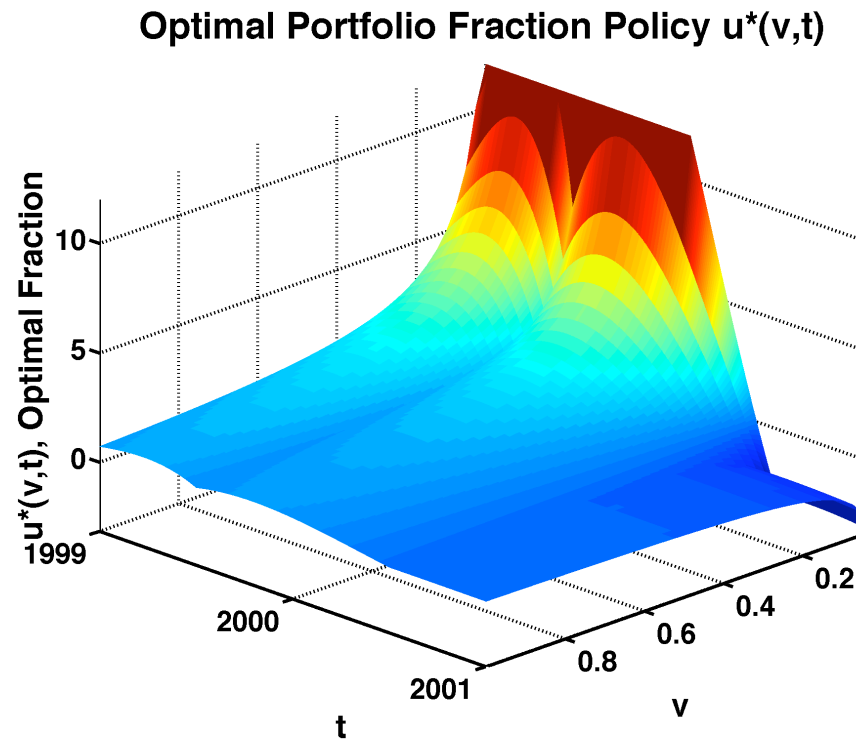


Figure 10.10: Optimal portfolio fraction policy  $u^*(v, t)$  for  $(v, t) \in \times [v_{\min}, 1.0] \times [1999.0, 2001.0]$ , while  $u^*(v, t) \in [-18, 12]$  is enforced near small variance  $v = v_{\min} > 0$ .

## \* 10.2.10. Conclusions for SVJD Optimal Portfolio and Consumption Problem :

- *Generalized the optimal portfolio and consumption problem for jump-diffusions to include stochastic volatility/variance* .
- Confirmed significant effects on *variation of instantaneous stock fraction policies* due to time-dependence of interest and discount rates for SVJD optimal portfolio and consumption models.
- *Showed jump-amplitude distributions with compact support are much less restricted on short-selling and borrowing* compared to the infinite support case in the SVJD optimal portfolio and consumption problem.
- Noted that the CRRA reduced canonical optimal portfolio problem is *strongly drift-dominated* for sample market parameter values over the diffusion terms, so at least first order drift-upwinding is essential for stable Bernoulli PDE computations.



## Summary of Lecture 10?

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