#### A jump telegraph model for option pricing

Nikita Ratanov

Universidad del Rosario, Bogotá, Colombia

Recife, Brasil

August, 13th, 2008

A jump telegraph model for option pricing -p. 1/4

Consider the following random processes (stock prices):  $S_k = S_k(t), \ k = 1, ..., N, \ t \ge 0$ and the deterministic function (bond price)  $S_0 = S_0(t), \ t \ge 0$ .

Consider the following random processes (stock prices):  $S_k = S_k(t), \ k = 1, ..., N, \ t \ge 0$ and the deterministic function (bond price)  $S_0 = S_0(t), \ t \ge 0$ .

To operate with assets  $S_0, S_1, \ldots, S_N$  we consider a self-financing strategy (dynamic portfolio) as (N+1)-dimensional predictable processes

$$\Pi(t) = (\varphi_0(t), \varphi_1(t), \ldots, \varphi_N(t)), t \ge 0.$$

Consider the following random processes (stock prices):  $S_k = S_k(t), \ k = 1, ..., N, \ t \ge 0$ and the deterministic function (bond price)  $S_0 = S_0(t), \ t \ge 0$ .

To operate with assets  $S_0, S_1, \ldots, S_N$  we consider a self-financing strategy (dynamic portfolio) as (N+1)-dimensional predictable processes

$$\Pi(t) = (\varphi_0(t), \varphi_1(t), \ldots, \varphi_N(t)), t \ge 0.$$

The strategy value is defined as  $F(t) = \sum_{k=0}^{N} \varphi_k(t) \cdot S_k(t)$ .

Consider the following random processes (stock prices):  $S_k = S_k(t), \ k = 1, ..., N, \ t \ge 0$ and the deterministic function (bond price)  $S_0 = S_0(t), \ t \ge 0$ .

To operate with assets  $S_0, S_1, \ldots, S_N$  we consider a self-financing strategy (dynamic portfolio) as (N+1)-dimensional predictable processes

$$\Pi(t) = (\varphi_0(t)), (\varphi_1(t)), \dots, (\varphi_N(t))), t \ge 0.$$

The strategy value is defined as  $F(t) = \sum_{k=0}^{N} (\varphi_k(t)) \cdot S_k(t)$ .

Here  $\varphi_k(t)$  is number of units of *k*th asset in the current portfolio.

This strategy is self-financing, if the increments in the strategy value F = F(t) are provoked only by the increments in assets' prices:

$$\mathrm{d}F(t) = \sum_{k=0}^{N} \varphi_k(t) \mathrm{d}S_k(t).$$

This strategy is self-financing, if the increments in the strategy value F = F(t) are provoked only by the increments in assets' prices:

$$\mathrm{d}F(t) = \sum_{k=0}^{N} \varphi_k(t) \mathrm{d}S_k(t).$$

The strategy is admissible, if  $F(t) \ge 0$ , for all  $t \ge 0$ .

This strategy is self-financing, if the increments in the strategy value F = F(t) are provoked only by the increments in assets' prices:

$$\mathrm{d}F(t) = \sum_{k=0}^{N} \varphi_k(t) \mathrm{d}S_k(t).$$

The strategy is admissible, if  $F(t) \ge 0$ , for all  $t \ge 0$ .

A trading strategy  $\Pi = \Pi(t)$  is called an arbitrage strategy (at time *T*) if its initial capital is zero: F(0) = 0, and  $\mathbb{P}(F(T) > 0) > 0$ .

This strategy is self-financing, if the increments in the strategy value F = F(t) are provoked only by the increments in assets' prices:

$$\mathrm{d}F(t) = \sum_{k=0}^{N} \varphi_k(t) \mathrm{d}S_k(t).$$

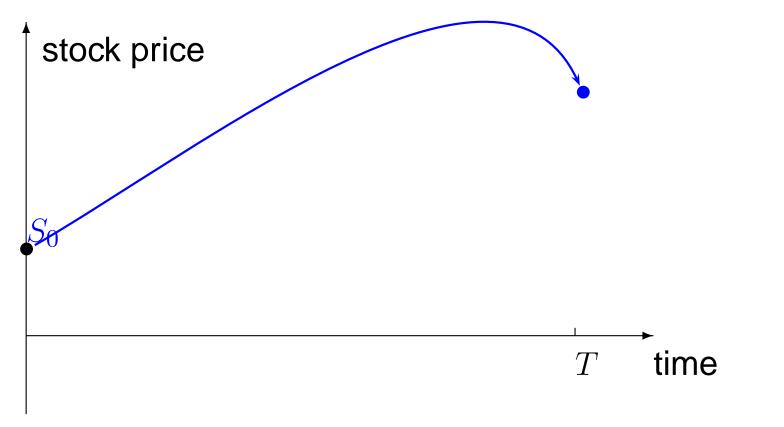
The strategy is admissible, if  $F(t) \ge 0$ , for all  $t \ge 0$ .

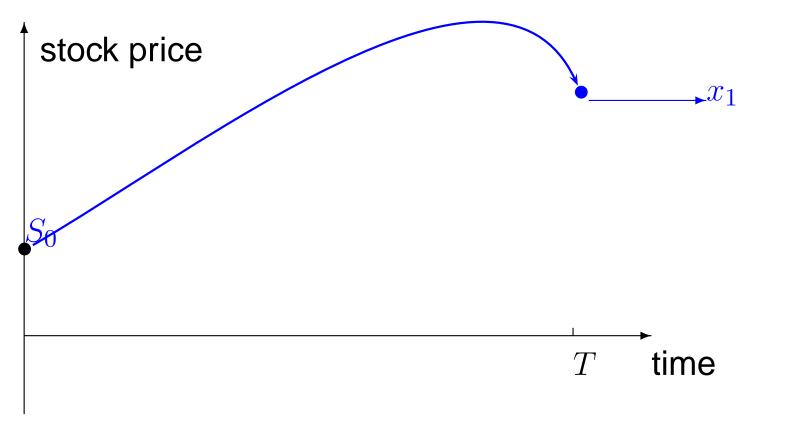
A trading strategy  $\Pi = \Pi(t)$  is called an arbitrage strategy (at time *T*) if its initial capital is zero: F(0) = 0, and  $\mathbb{P}(F(T) > 0) > 0$ . Our main objective is to construct arbitrage-free and complete market models.

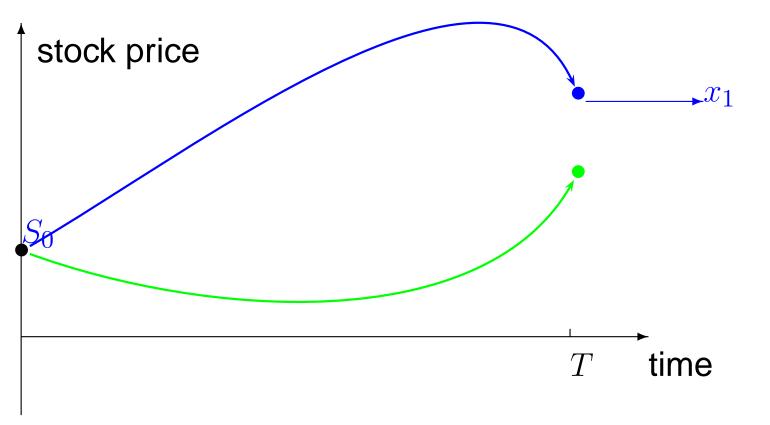
Consider a contract which gives to its holder the payment X (*claim*) at some specified expiry date, T (*maturity time*). The value X depends on the terminal state of the market,  $X = f(\mathbf{S}(T))$ . This contract is called the *European option*.

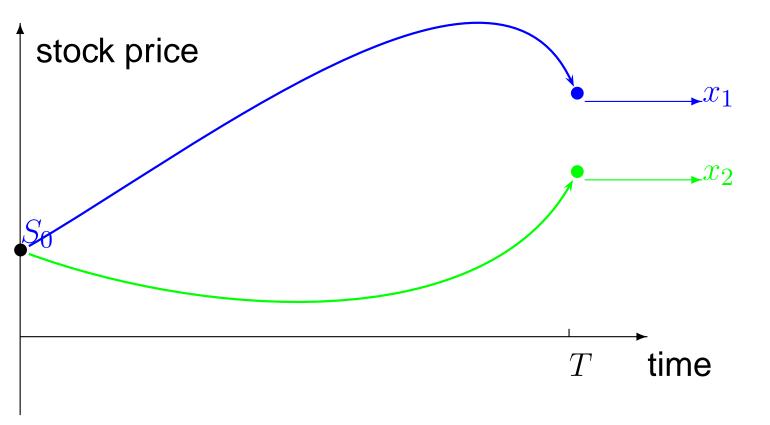
stock price



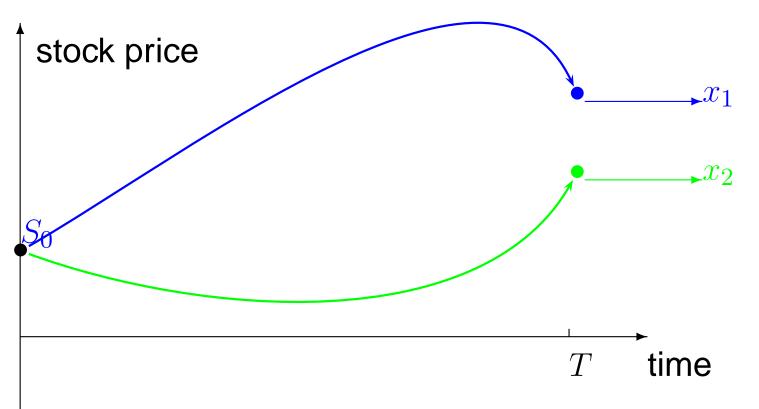








Consider a contract which gives to its holder the payment X (*claim*) at some specified expiry date, T (*maturity time*). The value X depends on the terminal state of the market,  $X = f(\mathbf{S}(T))$ . This contract is called the *European option*.



Denote its price at time t = 0 by c.

The strategy  $\Pi = \Pi(t)$  is called a hedging strategy, if it is self-financing, admissible and replicated. The latter means that the terminal strategy value coincides with the option claim, F(T) = X.

The strategy  $\Pi = \Pi(t)$  is called a hedging strategy, if it is self-financing, admissible and replicated. The latter means that the terminal strategy value coincides with the option claim, F(T) = X. Hence the option price c = F(0).

The strategy  $\Pi = \Pi(t)$  is called a hedging strategy, if it is self-financing, admissible and replicated. The latter means that the terminal strategy value coincides with the option claim, F(T) = X.

Hence the option price c = F(0).

If an arbitrary random claim X can be replicated by an admissible and self-financing strategy then the market is called complete.

The strategy  $\Pi = \Pi(t)$  is called a hedging strategy, if it is self-financing, admissible and replicated. The latter means that the terminal strategy value coincides with the option claim, F(T) = X.

Hence the option price c = F(0).

If an arbitrary random claim X can be replicated by an admissible and self-financing strategy then the market is called complete.

The main questions of the theory are

- 1) What is the fair option price?
- 2) What is the respective trading strategy?

### **Standard European options**

Two principal standard options have the following claims.

### **Standard European options**

Two principal standard options have the following claims.

The claim

$$X = (S(T) - K)^{+} = \begin{cases} S(T) - K, & \text{if } S(T) > K, \\ 0, & \text{if } S(T) < K \end{cases}$$

defines

the call option with the strike K.

### **Standard European options**

Two principal standard options have the following claims.

The claim

$$X = (S(T) - K)^{+} = \begin{cases} S(T) - K, & \text{if } S(T) > K, \\ 0, & \text{if } S(T) < K \end{cases}$$
 defines  
the call option with the strike *K*.

The claim

$$X = (K - S(T))^{+} = \begin{cases} 0, & \text{if } S(T) > K, \\ K - S(T), & \text{if } S(T) < K \end{cases}$$
 defines

the put option with the strike K.

### **Option pricing & risk-neutral measure**

The measure  $\mathbb{P}^*$  is named the risk-neutral measure, if  $B(t)^{-1}\mathbf{S}(t)$  is a martingale:

 $\mathbb{E}_{\mathbb{P}^*} \{ B(t)^{-1} \mathbf{S}(t) | \mathcal{F}_{\tau} \} = B(\tau)^{-1} \mathbf{S}(\tau), \ \tau < t.$ 

### **Option pricing & risk-neutral measure**

The measure  $\mathbb{P}^*$  is named the risk-neutral measure, if  $B(t)^{-1}\mathbf{S}(t)$  is a martingale:

$$\mathbb{E}_{\mathbb{P}^*} \{ B(t)^{-1} \mathbf{S}(t) | \mathcal{F}_{\tau} \} = B(\tau)^{-1} \mathbf{S}(\tau), \ \tau < t.$$

If the risk-neutral measure exists, and if it is unique, then the option price of the option with claim X is

### **Option pricing & risk-neutral measure**

The measure  $\mathbb{P}^*$  is named the risk-neutral measure, if  $B(t)^{-1}\mathbf{S}(t)$  is a martingale:

$$\mathbb{E}_{\mathbb{P}^*} \{ B(t)^{-1} \mathbf{S}(t) | \mathcal{F}_{\tau} \} = B(\tau)^{-1} \mathbf{S}(\tau), \ \tau < t.$$

If the risk-neutral measure exists, and if it is unique, then the option price of the option with claim X is

$$\mathbf{c} = \mathbb{E}_{\mathbb{P}^*} \{ B(T)^{-1} X \}$$
  
and  
$$F(t) = \mathbb{E}_{\mathbb{P}^*} \{ B(T)^{-1} X | \mathcal{F}_t \}.$$

#### **Black-Scholes model**

Assume that the stock price moves according to geometric Brownian motion:

$$S(t) = S(0)e^{vw(t)+at}, \ B(t) = B(0)e^{rt}, \ t \ge 0,$$

where  $v, r > 0, a \in (-\infty, \infty)$  are constants.

#### **Black-Scholes model**

Assume that the stock price moves according to geometric Brownian motion:

$$S(t) = S(0)e^{vw(t)+at}, \ B(t) = B(0)e^{rt}, \ t \ge 0,$$

where  $v, r > 0, a \in (-\infty, \infty)$  are constants. It is proved that the risk-neutral measure  $\mathbb{P}^*$  exists and it is unique.

#### **Black-Scholes model**

Assume that the stock price moves according to geometric Brownian motion:

$$S(t) = S(0)e^{vw(t)+at}, \ B(t) = B(0)e^{rt}, \ t \ge 0,$$

where  $v, r > 0, a \in (-\infty, \infty)$  are constants.

It is proved that the risk-neutral measure  $\mathbb{P}^*$  exists and it is unique.

The option prices c = c(X) for many particular claims *X* can be expressed exactly. For example, the standard call option with strike *K* has the following expression for its price:

$$\mathbf{c} = S_0 \cdot \Phi(z_+) - \mathrm{e}^{-rT} K \cdot \Phi(z_-),$$

where  $z_{\pm} = \frac{\ln(S_0/K) + (r \pm v^2/2)T}{v\sqrt{T}}$  and  $\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-x^2/2} dx$ .

It is widely accepted that the dynamics of asset returns cannot be adequately described by geometric Brownian motion with constant volatility *v*. These models (Black-Scholes and its derivatives) have infinite propagation velocities, independent log-returns increments on separated time intervals among others.

It is widely accepted that the dynamics of asset returns cannot be adequately described by geometric Brownian motion with constant volatility *v*. These models (Black-Scholes and its derivatives) have infinite propagation velocities, independent log-returns increments on separated time intervals among others.

Something bothers a financial market at one point (say, in Rio), then (at the same instant) the total world market is disturbed (say, in Bogotá).

It is widely accepted that the dynamics of asset returns cannot be adequately described by geometric Brownian motion with constant volatility v. These models (Black-Scholes and its derivatives) have infinite propagation velocities, independent log-returns increments on separated time intervals among others.

Something bothers a financial market at one point (say, in Rio), then (at the same instant) the total world market is disturbed (say, in Bogotá).

The PDEs which describe a behaviour of probability densities of log-returns are *parabolic*.

It is widely accepted that the dynamics of asset returns cannot be adequately described by geometric Brownian motion with constant volatility v. These models (Black-Scholes and its derivatives) have infinite propagation velocities, independent log-returns increments on separated time intervals among others.

Something bothers a financial market at one point (say, in Rio), then (at the same instant) the total world market is disturbed (say, in Bogotá).

The PDEs which describe a behaviour of probability densities of log-returns are *parabolic*.

The main goal of this work is to create the financial model which is free from the shortages of the parabolic world.

# Hyperbolic world

Hyperbolic equations, having a finite velocity of propagation and a finite dependence range, look more attractive. Random motions with finite velocities form a basis of this world.

# Hyperbolic world

Hyperbolic equations, having a finite velocity of propagation and a finite dependence range, look more attractive. Random motions with finite velocities form a basis of this world.

Let  $\sigma_i(t), t \ge 0$  be a Markov chain with values in the finite set I, |I| = d and with initial state  $i: \sigma_i(0) = i, i \in I$ . For given numbers  $c_i, i \in I$  we define the processes

$$X_i(t) = \int_0^t c_{\sigma_i(\tau)} \mathrm{d}\tau, \ t \ge 0 \tag{1}$$

# Hyperbolic world

Hyperbolic equations, having a finite velocity of propagation and a finite dependence range, look more attractive. Random motions with finite velocities form a basis of this world.

Let  $\sigma_i(t), t \ge 0$  be a Markov chain with values in the finite set I, |I| = d and with initial state  $i: \sigma_i(0) = i, i \in I$ . For given numbers  $c_i, i \in I$  we define the processes

$$X_i(t) = \int_0^t c_{\sigma_i(\tau)} \mathrm{d}\tau, \ t \ge 0 \tag{1}$$

Consider the asset with the price dynamic  $S = S(t), t \ge 0$ 

 $dS(t) = S(t)dX_i(t) \Leftrightarrow dS = S(t)c_{\sigma_i(t)}dt \Leftrightarrow S(t) = S(0)\exp(X_i(t)),$  $-i \in I.$ 

# Hyperbolic world

Hyperbolic equations, having a finite velocity of propagation and a finite dependence range, look more attractive. Random motions with finite velocities form a basis of this world.

Let  $\sigma_i(t), t \ge 0$  be a Markov chain with values in the finite set I, |I| = d and with initial state  $i: \sigma_i(0) = i, i \in I$ . For given numbers  $c_i, i \in I$  we define the processes

$$X_i(t) = \int_0^t c_{\sigma_i(\tau)} \mathrm{d}\tau, \ t \ge 0 \tag{1}$$

Consider the asset with the price dynamic  $S = S(t), t \ge 0$ 

 $dS(t) = S(t)dX_i(t) \Leftrightarrow dS = S(t)c_{\sigma_i(t)}dt \Leftrightarrow S(t) = S(0)\exp(X_i(t)),$ 

 $i \in I$ . This model admits arbitrage opportunities.

For given numbers  $h_i > -1$  we define jump process

$$J_{i}(t) = \sum_{j=1}^{N_{i}(t)} h_{\sigma_{i}(\tau_{j}-)}, \ t \ge 0$$
(3)

For given numbers  $h_i > -1$  we define jump process

$$J_{i}(t) = \sum_{j=1}^{N_{i}(t)} h_{\sigma_{i}(\tau_{j}-)}, \ t \ge 0$$
(3)

and consider the stock price dynamics of the form

$$dS(t) = S(t-)[dX_i(t) + dJ_i(t)], \qquad (4)$$

where  $X_i$  is defined in (1) and  $N_i(t), t \ge 0$  is the Poisson process which counts the number of switchings of  $\sigma_i$ .

For given numbers  $h_i > -1$  we define jump process

$$J_{i}(t) = \sum_{j=1}^{N_{i}(t)} h_{\sigma_{i}(\tau_{j}-)}, \ t \ge 0$$
(3)

and consider the stock price dynamics of the form

$$dS(t) = S(t-)[dX_i(t) + dJ_i(t)], \qquad (4)$$

where  $X_i$  is defined in (1) and  $N_i(t), t \ge 0$  is the Poisson process which counts the number of switchings of  $\sigma_i$ . Integrating we have

 $S(t) = S(0)\mathcal{E}_t(X_i + J_i) = S(0) \exp(X_i(t)) \cdot \prod_{j=1}^{N_i(t)} (1 + h_{\sigma_i(\tau_j)}).$ 

We assume the process S(t),  $t \ge 0$  to be right-continuous.

We assume the process S(t),  $t \ge 0$  to be right-continuous. The price of the non-risky asset has the form

$$B(t) = e^{Y_i(t)}, \qquad Y_i(t) = \int_0^t r_{\sigma_i(\tau)} d\tau, \qquad r_i > 0.$$
 (5)

We assume the process S(t),  $t \ge 0$  to be right-continuous. The price of the non-risky asset has the form

$$B(t) = e^{Y_i(t)}, \qquad Y_i(t) = \int_0^t r_{\sigma_i(\tau)} d\tau, \qquad r_i > 0.$$
 (5)

Assume that the parameters of model (4)-(5) satisfy the conditions

$$\lambda_i^* := \frac{r_i - c_i}{h_i} > 0, \qquad i \in I.$$
(6)

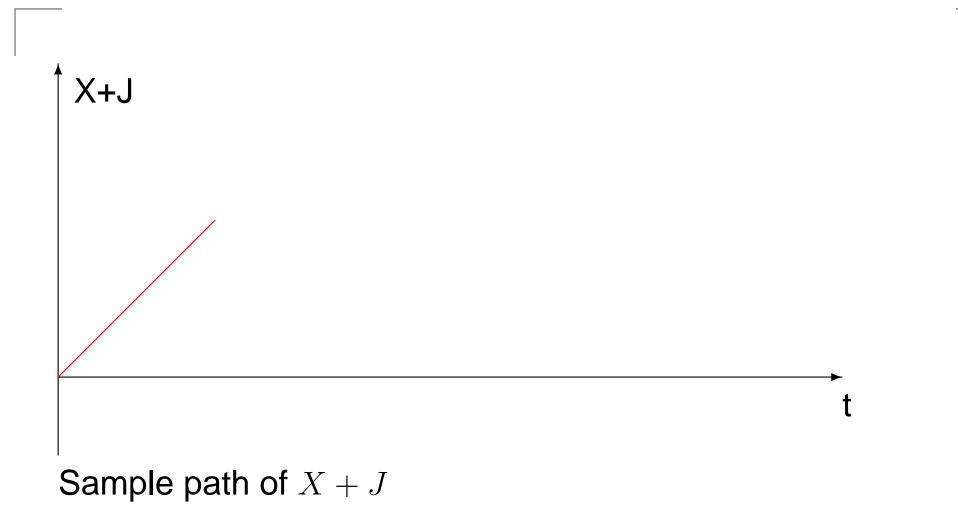
We assume the process S(t),  $t \ge 0$  to be right-continuous. The price of the non-risky asset has the form

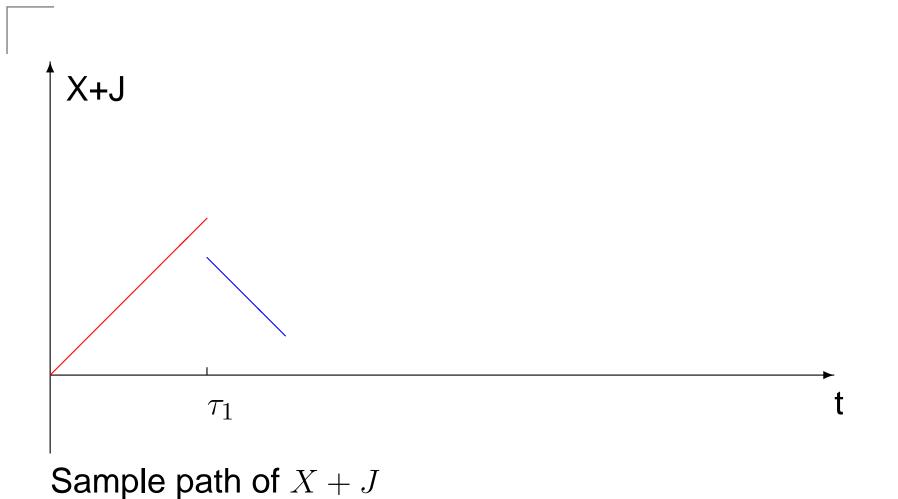
$$B(t) = e^{Y_i(t)}, \qquad Y_i(t) = \int_0^t r_{\sigma_i(\tau)} d\tau, \qquad r_i > 0.$$
 (5)

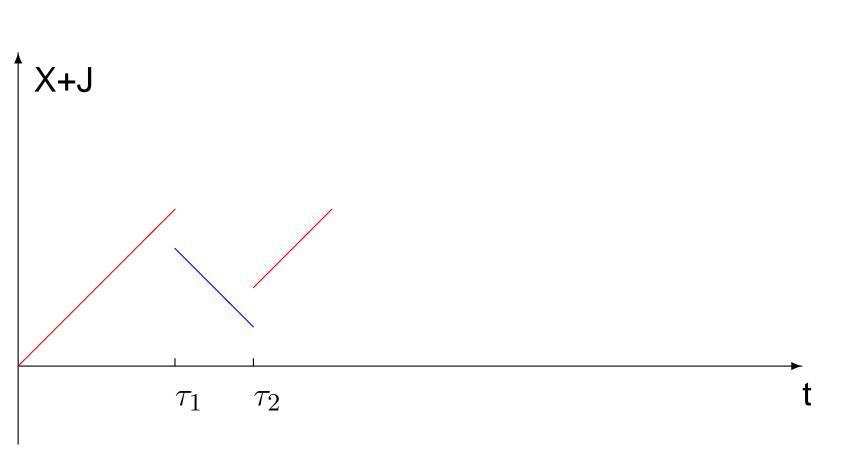
Assume that the parameters of model (4)-(5) satisfy the conditions

$$\lambda_i^* := \frac{r_i - c_i}{h_i} > 0, \qquad i \in I.$$
(6)

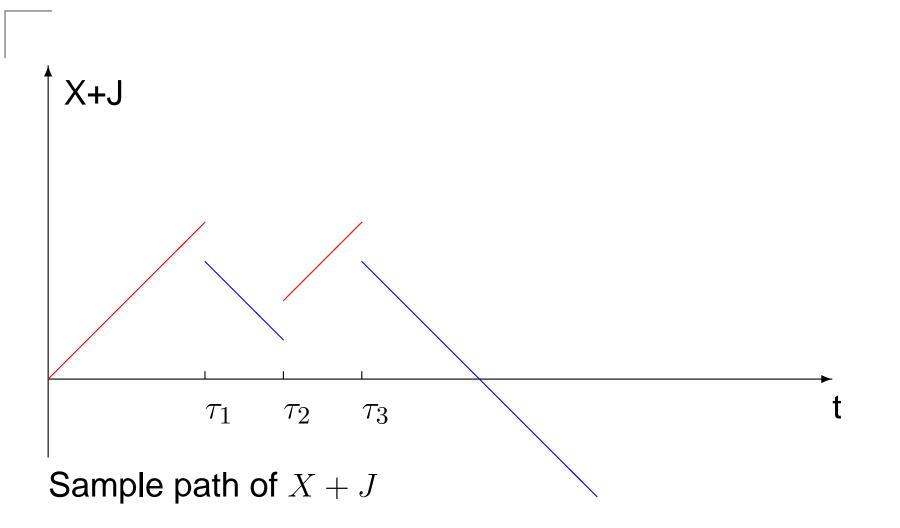
Seeking for simplicity, we consider two-state Markov chain, |I| = 2.

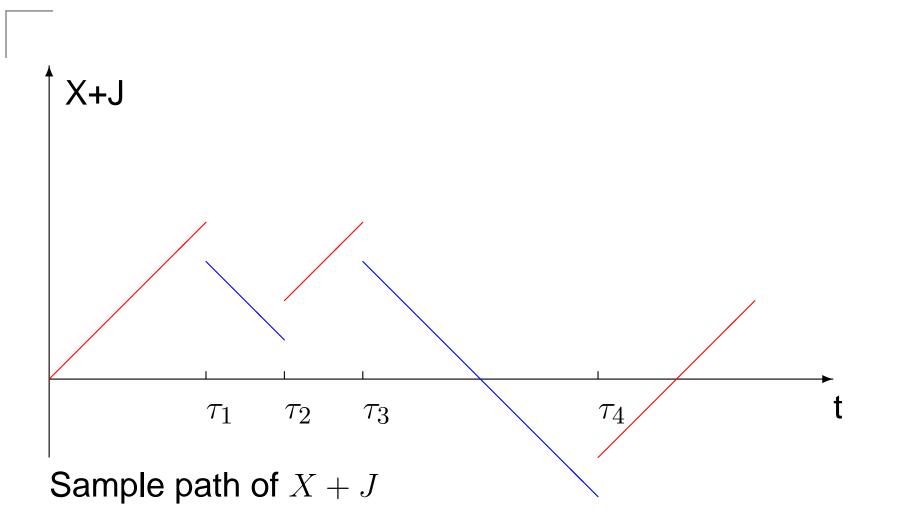


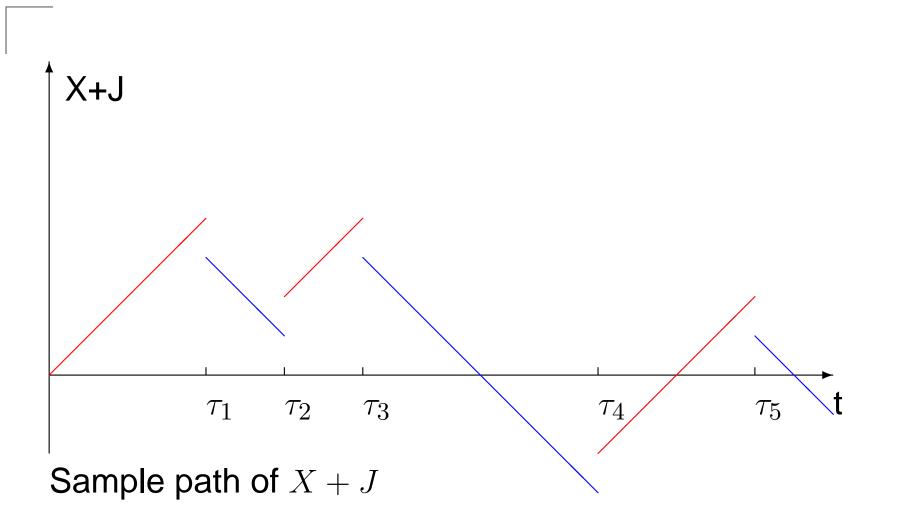




Sample path of X + J







From the point of view of technical analysis, market prices can be described using continuous price trends (upward or downward) between random instants. Changes in these trends are accompanied by jumps. The proposed model reflects this key viewpoint.

From the point of view of technical analysis, market prices can be described using continuous price trends (upward or downward) between random instants. Changes in these trends are accompanied by jumps. The proposed model reflects this key viewpoint.

Moreover this model reflects oversold/overbought market situations: changes are gradually building up before crashes and spikes.

We study the model that is both realistic and general enough to enable us to incorporate different trends and extreme events. This is the complete market model and hedging is perfect. Jump component here is supplied not only by reasons of adequacy. Jumps serve as the unique tool to avoid arbitrage opportunities.

We study the model that is both realistic and general enough to enable us to incorporate different trends and extreme events. This is the complete market model and hedging is perfect. Jump component here is supplied not only by reasons of adequacy. Jumps serve as the unique tool to avoid arbitrage opportunities.

At the same time, the model allows to get closed form solutions for hedging and investment problems.

We study the model that is both realistic and general enough to enable us to incorporate different trends and extreme events. This is the complete market model and hedging is perfect. Jump component here is supplied not only by reasons of adequacy. Jumps serve as the unique tool to avoid arbitrage opportunities.

At the same time, the model allows to get closed form solutions for hedging and investment problems.

Moreover this model has some features of models with memory, but it is rather more simple.

We study the model that is both realistic and general enough to enable us to incorporate different trends and extreme events. This is the complete market model and hedging is perfect. Jump component here is supplied not only by reasons of adequacy. Jumps serve as the unique tool to avoid arbitrage opportunities.

At the same time, the model allows to get closed form solutions for hedging and investment problems.

Moreover this model has some features of models with memory, but it is rather more simple.

Under suitable rescaling the jump telegraph model converges to classic Black-Scholes model, which permits to interpret volatility.

## **Telegraph martingales**

The next theorem could be considered as a version of the Doob-Meyer decomposition for telegraph processes with alternating intensities.

**Theorem 1.** Let  $X_i$ , i = 0, 1 be the telegraph process with velocities  $c_0$ and  $c_1$ , and  $J_i$  be the jump process with jump values  $h_0$ ,  $h_1 > -1$ , which is defined in (3). Then  $X_i + J_i$  is a martingale if and only if

$$\lambda_0 h_0 = -c_0, \qquad \lambda_1 h_1 = -c_1.$$

Here  $\lambda_i$  is the intensity of leaving of the state *i*.

## **Telegraph martingales**

The next theorem could be considered as a version of the Doob-Meyer decomposition for telegraph processes with alternating intensities.

**Theorem 1.** Let  $X_i$ , i = 0, 1 be the telegraph process with velocities  $c_0$ and  $c_1$ , and  $J_i$  be the jump process with jump values  $h_0$ ,  $h_1 > -1$ , which is defined in (3). Then  $X_i + J_i$  is a martingale if and only if

$$\lambda_0 h_0 = -c_0, \qquad \lambda_1 h_1 = -c_1.$$

Here  $\lambda_i$  is the intensity of leaving of the state *i*. **Remark.** In particular, it means that any (nontrivial) telegraph process without jumps (i.e. if  $h_i = 0$ ) never possess a martingale measure. So Markov-modulated persistent dynamics is the arbitrage model.

### **Change of measure**

Let  $X_i^*$  be the telegraph process with the velocities  $c_i^*$ , and  $J_i^* = -\sum_{j=1}^{N_i(t)} c_{\sigma_i(\tau_j-)}^* / \lambda_{\sigma_i(\tau_j-)}$  be the jump process with jump values  $h_i^* = -c_i^* / \lambda_i > -1$ .

#### **Change of measure**

Let  $X_i^*$  be the telegraph process with the velocities  $c_i^*$ , and  $J_i^* = -\sum_{j=1}^{N_i(t)} c_{\sigma_i(\tau_j-)}^* / \lambda_{\sigma_i(\tau_j-)}$  be the jump process with jump

values  $h_i^* = -c_i^*/\lambda_i > -1$ . Consider a probability measure  $\mathbb{P}_i^*$  with a local density  $Z_i$  with respect to  $\mathbb{P}_i$ , i = 0, 1:

$$Z_i(t) = \frac{\mathrm{d}\mathbb{P}_i^*}{\mathrm{d}\mathbb{P}_i}|_t = \mathcal{E}_t(X_i^* + J_i^*), \qquad 0 \le t \le T.$$

#### **Change of measure**

Let  $X_i^*$  be the telegraph process with the velocities  $c_i^*$ , and  $J_i^* = -\sum_{j=1}^{N_i(t)} c_{\sigma_i(\tau_j-)}^* / \lambda_{\sigma_i(\tau_j-)}$  be the jump process with jump

values  $h_i^* = -c_i^*/\lambda_i > -1$ . Consider a probability measure  $\mathbb{P}_i^*$  with a local density  $Z_i$  with respect to  $\mathbb{P}_i$ , i = 0, 1:

$$Z_i(t) = \frac{\mathrm{d}\mathbb{P}_i^*}{\mathrm{d}\mathbb{P}_i}|_t = \mathcal{E}_t(X_i^* + J_i^*), \qquad 0 \le t \le T.$$

Using properties of stochastic exponentials, we obtain

$$Z_{i}(t) = e^{X_{i}^{*}(t)} \cdot \prod_{j=1}^{N_{i}(t)} \left(1 + h_{\sigma_{i}(\tau_{j}-)}^{*}\right)$$

#### **Girsanov theorem**

**Theorem 2.** Under the probability measure  $\mathbb{P}_i^*$ ,

- Process  $N_i = N_i(t), 0 \le t \le T$  is the Poisson process with intensities  $\lambda_0^* = \lambda_0 c_0^* = \lambda_0(1 + h_0^*)$  and  $\lambda_1^* = \lambda_1 c_1^* = \lambda_1(1 + h_1^*).$
- Process  $X_i = X_i(t), 0 ≤ t ≤ T$  is the telegraph process with states  $(c_0, \lambda_0^*)$  and  $(c_1, \lambda_1^*)$ .

#### **Girsanov theorem**

**Theorem 2.** Under the probability measure  $\mathbb{P}_i^*$ ,

- Process N<sub>i</sub> = N<sub>i</sub>(t), 0 ≤ t ≤ T is the Poisson process with
   intensities  $\lambda_0^* = \lambda_0 c_0^* = \lambda_0(1 + h_0^*)$  and
    $\lambda_1^* = \lambda_1 c_1^* = \lambda_1(1 + h_1^*).$
- Process  $X_i = X_i(t), 0 ≤ t ≤ T$  is the telegraph process with states  $(c_0, \lambda_0^*)$  and  $(c_1, \lambda_1^*)$ .

Theorems 1 and 2 allows us to give a following characterization of the martingale measure.

#### Martingale measure

**Theorem 3.** Measure  $\mathbb{P}_i^*$  is the martingale measure for the process  $B_i(t)^{-1}S_i(t), t \ge 0$  if and only if

$$c_0^* = \lambda_0 - \frac{r_0 - c_0}{h_0}, \quad c_1^* = \lambda_1 - \frac{r_1 - c_1}{h_1}$$

Moreover, under the probability measure  $\mathbb{P}_i^*$ , process  $N_i$  is the Poisson process with alternating intensities  $\lambda_0^* = \frac{r_0 - c_0}{h_0}$  and  $\lambda_1^* = \frac{r_1 - c_1}{h_1}$ .

### **Fundamental equation (1)**

Consider a European option with maturity time T and payoff function f(S(T)). We assume f is a continuous and piecewise smooth function. To price these options, we need to study the function

$$F(t, x, i) = \mathbb{E}_{i}^{*} \left[ e^{-Y_{i}(T-t)} f(x e^{X_{i}(T-t)} \kappa_{i}(T-t)) \right], \quad (7)$$
$$i = 0, 1, \ 0 \le t \le T,$$

where  $\mathbb{E}_i^*$  denotes the expectation with respect to the martingale measure  $\mathbb{P}_i^*$ .

#### **Fundamental equation (1)**

Consider a European option with maturity time T and payoff function f(S(T)). We assume f is a continuous and piecewise smooth function. To price these options, we need to study the function

$$F(t, x, i) = \mathbb{E}_{i}^{*} \left[ e^{-Y_{i}(T-t)} f(x e^{X_{i}(T-t)} \kappa_{i}(T-t)) \right], \quad (7)$$
$$i = 0, 1, \ 0 < t < T,$$

where  $\mathbb{E}_{i}^{*}$  denotes the expectation with respect to the martingale measure  $\mathbb{P}_{i}^{*}$ .

 $F_t := F(t, S_i(t), \sigma_i(t))$  is the strategy value at time  $t, 0 \le t \le T$  of the option with claim  $f(S_i(T))$  at the maturity time T.

#### **Fundamental equation (2)**

**Theorem 4.** Function F is a solution of the following hyperbolic system: for 0 < t < T,

$$\frac{\partial F}{\partial t}(t,x,i) + c_i x \frac{\partial F}{\partial x}(t,x,i)$$

$$= (r_i + \lambda_i^*) F(t, x, i) - \lambda_i^* F(t, x(1+h_i), 1-i), \ i = 0, 1$$
 (8)

with the terminal condition F(T, x, i) = f(x). Here  $\lambda_i^* = (r_i - c_i)/h_i$ .

#### **Fundamental equation (2)**

**Theorem 4.** Function F is a solution of the following hyperbolic system: for 0 < t < T,

$$\frac{\partial F}{\partial t}(t,x,i) + c_i x \frac{\partial F}{\partial x}(t,x,i)$$

$$= (r_i + \lambda_i^*) F(t, x, i) - \lambda_i^* F(t, x(1+h_i), 1-i), \ i = 0, 1$$
 (8)

with the terminal condition F(T, x, i) = f(x). Here  $\lambda_i^* = (r_i - c_i)/h_i$ .

This system plays the same role for our model as the classical parabolic equation for Black-Scholes model:

$$\frac{1}{2}v^2x^2\frac{\partial^2 F}{\partial x^2} + rx\frac{\partial F}{\partial x} + \frac{\partial F}{\partial t} = rF \tag{9}$$

#### **Fundamental equation (3)**

In contrast with classical theory, system (8) is hyperbolic. In particular, it implies the finite velocity of propagation, which corresponds better to the intuitive understanding of financial markets and to the viewpoint of technical analysis.

Note that these equations do not depend on  $\lambda_i$ , just as the equation (9) in the Black-Scholes model does not depend on the drift parameter.

### **Convergence to Black-Scholes (1)**

It is known that (homogeneous) telegraph process  $X = X(t), t \ge 0$  converges to the standard Brownian motion  $w(t), t \ge 0$ , if  $c, \lambda \to \infty, c/\sqrt{\lambda} \to 1$ .

### **Convergence to Black-Scholes (1)**

It is known that (homogeneous) telegraph process  $X = X(t), t \ge 0$  converges to the standard Brownian motion  $w(t), t \ge 0$ , if  $c, \lambda \to \infty, c/\sqrt{\lambda} \to 1$ . The following theorem provides a similar connection (under respective scaling) between stock prices driven by geometric jump telegraph processes and geometric Brownian motion.

#### **Convergence to Black-Scholes (1)**

It is known that (homogeneous) telegraph process  $X = X(t), t \ge 0$  converges to the standard Brownian motion  $w(t), t \ge 0$ , if  $c, \lambda \to \infty, c/\sqrt{\lambda} \to 1$ . The following theorem provides a similar connection (under respective scaling) between stock prices driven by geometric jump telegraph processes and geometric Brownian motion.

Let  $c_1 - c_0 \to \infty$  ,  $\lambda_0, \lambda_1 \to \infty, h_0, h_1 \to 0$  and

$$\frac{c_1 - c_0}{\sqrt{\lambda_1} + \sqrt{\lambda_0}} \to \sigma, \qquad \sqrt{\frac{\lambda_1}{\lambda_0}} \to \gamma, \qquad \sqrt{\lambda_i} h_i \to \alpha_i, \qquad (10)$$

$$\frac{\sqrt{\lambda_1}}{\sqrt{\lambda_1}} \qquad (\alpha + \lambda_1 + \lambda_2 + \lambda_2 + \lambda_3 + \lambda_4) \rightarrow (\alpha + \lambda_1 + \lambda_3 + \lambda_3 + \lambda_4) \rightarrow (11)$$

$$\frac{1}{\sqrt{\lambda_1} + \sqrt{\lambda_0}} (c_0 + \lambda_0 h_0) + \frac{1}{\sqrt{\lambda_1} + \sqrt{\lambda_0}} (c_1 + \lambda_1 h_1) \to \delta.$$
(11)

## **Convergence to Black-Scholes (2)**

**Theorem 5.** Under the scaling conditions (10)-(11) model (4) converges to the Black-Scholes:

$$S(t) \xrightarrow{D} S_0 \exp\{vw(t) + (\delta - \beta^2/2)t\},\$$

where 
$$v = \sqrt{\left(\sigma + (\gamma \alpha_1 - \alpha_0)/(1 + \gamma)\right)^2 + \beta^2}$$
 and  $\beta^2 = \frac{\alpha_1^2 + \gamma \alpha_0^2}{1 + \gamma}$ 

#### **Convergence to Black-Scholes (2)**

**Theorem 5.** Under the scaling conditions (10)-(11) model (4) converges to the Black-Scholes:

$$S(t) \xrightarrow{D} S_0 \exp\{vw(t) + (\delta - \beta^2/2)t\},\$$

where  $v = \sqrt{(\sigma + (\gamma \alpha_1 - \alpha_0)/(1 + \gamma))^2 + \beta^2}$  and  $\beta^2 = \frac{\alpha_1^2 + \gamma \alpha_0^2}{1 + \gamma}$ . Remark. Under the martingale measure  $\mathbb{P}^*$  transition intensities take a form  $-c_i/h_i$  (if  $r_i = 0$ ). Thus the drift vanishes,  $\Delta = \frac{\sqrt{\lambda_1}}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} (c_0 + \lambda_0 h_0) + \frac{\sqrt{\lambda_0}}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} (c_1 + \lambda_1 h_1) = 0$ . Moreover, in this case  $\sigma = \lim \frac{c_1 - c_0}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} = -\lim \frac{\lambda_1 h_1 - \lambda_0 h_0}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} = -\frac{\gamma \alpha_1 - \alpha_0}{1 + \gamma}$ . The limiting volatility v in this case coincides with  $\beta: v = \beta = \sqrt{\frac{\alpha_1^2 + \gamma \alpha_0^2}{1 + \gamma}}$ .

# **Convergence to Black-Scholes (3)**

Remark. Condition (11) in this theorem means that the total drift  $\Delta \equiv A + \frac{\sqrt{\lambda_1 \lambda_0}}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} (\sqrt{\lambda_1} h_1 + \sqrt{\lambda_0} h_0) \text{ is asymptotically finite. Here} \\ A = \frac{\sqrt{\lambda_0 c_0 + \sqrt{\lambda_1 c_1}}}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} \text{ is generated by the velocities of the telegraph} \\ \text{process, and the summand } \frac{\sqrt{\lambda_1 \lambda_0}}{\sqrt{\lambda_1 + \sqrt{\lambda_0}}} (\sqrt{\lambda_1} h_1 + \sqrt{\lambda_0} h_0) \text{ represents the} \\ \text{drift component (possibly with infinite asymptotics) that is motivated only} \\ \text{by jumps. If here the limits of } \lambda_i h_i \text{ are finite, then } A \to const, \text{ and} \\ \alpha_1 = \alpha_0 = 0. \text{ In this case the volatility of limit is} \\ v = \sigma = \lim(c_1 - c_0)/(\sqrt{\lambda_1} + \sqrt{\lambda_0}). \end{cases}$ 

# **Convergence to Black-Scholes (3)**

**Remark.** Condition (11) in this theorem means that the total drift  $\Delta \equiv A + \frac{\sqrt{\lambda_1 \lambda_0}}{\sqrt{\lambda_1} + \sqrt{\lambda_0}} (\sqrt{\lambda_1} h_1 + \sqrt{\lambda_0} h_0)$  is asymptotically finite. Here  $A = \frac{\sqrt{\lambda_0}c_0 + \sqrt{\lambda_1}c_1}{\sqrt{\lambda_1} + \sqrt{\lambda_0}}$  is generated by the velocities of the telegraph process, and the summand  $\frac{\sqrt{\lambda_1\lambda_0}}{\sqrt{\lambda_1}+\sqrt{\lambda_0}}(\sqrt{\lambda_1}h_1+\sqrt{\lambda_0}h_0)$  represents the drift component (possibly with infinite asymptotics) that is motivated only by jumps. If here the limits of  $\lambda_i h_i$  are finite, then  $A \rightarrow const$ , and  $\alpha_1 = \alpha_0 = 0$ . In this case the volatility of limit is  $v = \sigma = \lim(c_1 - c_0)/(\sqrt{\lambda_1} + \sqrt{\lambda_0}).$ Hence in jump telegraph model value  $(c_1 - c_0)/(\sqrt{\lambda_1} + \sqrt{\lambda_0})$  can be interpreted as "telegraph" component of volatility, and  $\sqrt{\lambda_i}h_i$  are volatility components engendered by jumps.

# **Convergence to Black-Scholes (4)**

In general, the limiting volatility

 $v = \sqrt{(\sigma + (\gamma \alpha_1 - \alpha_0)/(1 + \gamma))^2 + \beta^2}$  depends both on "telegraph" and jump components.

# **Convergence to Black-Scholes (4)**

In general, the limiting volatility

$$v = \sqrt{(\sigma + (\gamma \alpha_1 - \alpha_0)/(1 + \gamma))^2 + \beta^2}$$
 depends both on

"telegraph" and jump components. So it is natural to define volatility of jump telegraph market as

$$\operatorname{vol}^{2} = \left(\frac{c_{1} - c_{0}}{\sqrt{\lambda_{1}} + \sqrt{\lambda_{0}}}\right)^{2} \left(1 + \frac{\lambda_{1}h_{1} - \lambda_{0}h_{0}}{c_{1} - c_{0}}\right)^{2} + \frac{\sqrt{\lambda_{0}}\lambda_{1}h_{1}^{2} + \sqrt{\lambda_{1}}\lambda_{0}h_{0}^{2}}{\sqrt{\lambda_{1}} + \sqrt{\lambda_{0}}}.$$

# **Pricing call options (1)**

According to the theory on option pricing, we have

$$c^{i} = \mathbb{E}_{i}^{*} \left[ B_{i}(T)^{-1} (S_{i}(T) - K)^{+} \right],$$

where *K* is the strike price and  $\mathbb{E}_{i}^{*}(\cdot)$  is the expectation with respect to the martingale measure  $\mathbb{P}_{i}^{*}$ . In case of the model (4)-(5), one can rewrite  $c^{i}$  as

$$c^{i} = S_{0}U^{(i)}(y,T) - Ku^{(i)}(y,T), \qquad i = 0,1$$
 (12)

# **Pricing call options (2)**

with

$$u^{(i)}(y,T) = \sum_{n=0}^{\infty} u_n^{(i)}(y - b_n^{(i)},T),$$

$$U^{(i)}(y,T) = \sum_{n=0}^{\infty} U_n^{(i)}(y - b_n^{(i)},T),$$

where  $y = \ln K/S_i(0)$ ,  $b_n^{(i)} = \sum_{j=1}^n \ln(1 + h_{\sigma_i(\tau_j)})$ , and functions

 $u_n^{(i)}, U_n^{(i)}, n \ge 0, i = 0, 1$  can be directly calculated.

# **Pricing call options (3)**

First, notice

$$u_n^{(i)}(y,t) = \mathbb{E}_i^* \left[ B_i(t)^{-1} \mathbf{1}_{\{X_i(t) > y, N_i(t) = n\}} \right],$$

$$U_n^{(i)}(y,t) = \mathbb{E}_i^* \left[ B_i(t)^{-1} \mathcal{E}_t(X_i + J_i) \mathbf{1}_{\{X_i(t) > y, N_i(t) = n\}} \right],$$

## **Pricing call options (3)**

First, notice

$$u_n^{(i)}(y,t) = \mathbb{E}_i^* \left[ B_i(t)^{-1} \mathbf{1}_{\{X_i(t) > y, N_i(t) = n\}} \right],$$
$$U_n^{(i)}(y,t) = \mathbb{E}_i^* \left[ B_i(t)^{-1} \mathcal{E}_t(X_i + J_i) \mathbf{1}_{\{X_i(t) > y, N_i(t) = n\}} \right],$$
and  $U_n^{(i)}(y, t; \lambda_i^*, c_i, r_i) = u_n^{(i)}(y, t; \lambda_i^*(1 + h_i), c_i, 0).$ 

## **Pricing call options (4)**

Finally, these functions can be calculated as

$$u_n^{(i)} = \begin{cases} 0, \quad y > c_1 t, \\ w_n^{(i)}(p, q), \quad c_0 t \le y \le c_1 t, \quad i = 0, 1, \\ \rho_n^{(i)}(t), \quad y < c_0 t, \end{cases}$$

$$p = \frac{c_1 t - y}{c_1 - c_0}$$
,  $q = \frac{y - c_0 t}{c_1 - c_0}$ , where

$$\begin{split} w_n^{(i)} &= e^{-(\lambda_1^* + r_1)q - (\lambda_0^* + r_0)p} \Lambda_n^{(i)} v_n^{(i)}(p, q), \\ \rho_n^{(i)}(t) &= e^{-(\lambda_0^* + r_0)t} \Lambda_n^{(i)} P_n^{(i)}(t) \text{ with} \\ \Lambda_n^{(i)} &= (\lambda_i^*)^{[(n+1)/2]} (\lambda_{1-i}^*)^{[n/2]}, i = 0, 1, n \ge 0 \end{split}$$

# **Pricing call options (5)**

Functions 
$$P_n^{(i)}$$
 and  $v_n^{(i)}$  are defined as follows:  
 $P_0^{(1)} = e^{-at}, P_0^{(0)} \equiv 1,$   
 $P_n^{(i)} = P_n^{(i)}(t) = \frac{t^n}{n!} \left[ 1 + \sum_{k=1}^{\infty} \frac{(m_n^{(i)}+1)_k}{(n+1)_k} \cdot \frac{(-at)^k}{k!} \right], i = 0, 1, \text{ where}$   
 $m_n^{(1)} = [n/2], m_n^{(0)} = [(n-1)/2],$   
 $(m)_k = m(m+1) \dots (m+k-1), a = \lambda_1^* - \lambda_0^* + r_1 - r_0;$ 

## **Pricing call options (5)**

Functions 
$$P_n^{(i)}$$
 and  $v_n^{(i)}$  are defined as follows:  
 $P_0^{(1)} = e^{-at}, P_0^{(0)} \equiv 1,$   
 $P_n^{(i)} = P_n^{(i)}(t) = \frac{t^n}{n!} \left[ 1 + \sum_{k=1}^{\infty} \frac{(m_n^{(i)}+1)_k}{(n+1)_k} \cdot \frac{(-at)^k}{k!} \right], i = 0, 1, \text{ where}$   
 $m_n^{(1)} = [n/2], m_n^{(0)} = [(n-1)/2],$   
 $(m)_k = m(m+1) \dots (m+k-1), a = \lambda_1^* - \lambda_0^* + r_1 - r_0;$   
 $v_0^{(0)} \equiv 0, v_0^{(1)} = e^{-ap}, v_1^{(i)} = P_1(p) \text{ and for } n \ge 1$ 

$$v_{2n+1}^{(i)} = v_{2n+1}^{(i)}(p, q) = P_{2n+1}(p) + \sum_{k=1}^{n} \frac{q^k}{k!} \varphi_{k,n}(p),$$
  

$$v_{2n}^{(0)} = v_{2n}^{(0)}(p, q) = P_{2n}^{(0)}(p) + \sum_{k=1}^{n-1} \frac{q^k}{k!} \varphi_{k+1,n}(p),$$
  

$$v_{2n}^{(1)} = v_{2n}^{(1)}(p, q) = P_{2n}^{(1)}(p) + \sum_{k=1}^{n} \frac{q^k}{k!} \varphi_{k-1,n-1}(p).$$

## **Pricing call options (6)**

Here 
$$\varphi_{0,n}=P_{2n+1}$$
,

$$\varphi_{k,n} = \sum_{j=0}^{k-1} a^{k-j-1} \beta_{k,j} P_{2n-j}^{(-)}, \ 1 \le k \le n,$$

where 
$$eta_{k,j}=rac{(k-j)_{[j/2]}}{[j/2]!}$$
 .

### **Pricing call options (6)**

Here 
$$\varphi_{0,n}=P_{2n+1}$$
,

$$\varphi_{k,n} = \sum_{j=0}^{k-1} a^{k-j-1} \beta_{k,j} P_{2n-j}^{(-)}, \ 1 \le k \le n,$$

where  $\beta_{k,j} = \frac{(k-j)_{[j/2]}}{[j/2]!}$ . In particular case  $\lambda_1^* = \lambda_0^* = \lambda$ ,  $r_1 = r_0 = r$  these functions have a more simple form  $\rho_n^{(i)}(t) = e^{-(\lambda+r)t} \frac{(\lambda t)^n}{n!}$ ,  $w_n^{(i)} = e^{-(\lambda+r)t} \frac{\lambda^n}{n!} \sum_{0}^{m_n^{(i)}} {n \choose k} q^k p^{n-k}$ . Here  $m_n^{(1)} = [n/2], m_n^{(0)} = [(n-1)/2]$ .

#### **Memory effects and historical volatility**

Historical volatility is defined as

$$HV(t) = \sqrt{\frac{\operatorname{Var}\{\log S(t+\tau)/S(\tau)\}}{t}}.$$
(13)

For classical Black-Scholes model  $\log S(t+\tau)/S(\tau) \stackrel{D}{=} at + vw(t)$  the historical volatility is constant:  $HV_{BS}(t) \equiv v$ .

#### Memory effects and historical volatility

Historical volatility is defined as

$$HV(t) = \sqrt{\frac{\operatorname{Var}\{\log S(t+\tau)/S(\tau)\}}{t}}.$$
(13)

For classical Black-Scholes model  $\log S(t + \tau)/S(\tau) \stackrel{D}{=} at + vw(t)$  the historical volatility is constant:  $HV_{BS}(t) \equiv v$ . In a moving-average type model

$$\log S(t) / S(0) = at + vw(t) - v \int_{0}^{t} d\tau \int_{-\infty}^{\tau} p e^{-(q+p)(\tau-u)} dw(u),$$

where v, q, q + p > 0 the historical volatility is

# Memory and historical volatility (2)

$$HV(t) = \frac{\sigma}{2\lambda} \sqrt{q^2 + p(2q+p)\Phi_{\lambda}(t)}$$

with  $2\lambda = q + p$  and  $\Phi_{\lambda}(t) = \frac{1 - e^{-2\lambda t}}{2\lambda t}$ . Recently this type of models have been applied to capture memory effects of the market.

# Memory and historical volatility (2)

$$HV(t) = \frac{\sigma}{2\lambda} \sqrt{q^2 + p(2q+p)\Phi_{\lambda}(t)}$$

with  $2\lambda = q + p$  and  $\Phi_{\lambda}(t) = \frac{1 - e^{-2\lambda t}}{2\lambda t}$ . Recently this type of models have been applied to capture memory effects of the market.

Historical volatility in the jump telegraph model (in particular case  $\lambda_0 = \lambda_1 = \lambda$ ) is

$$HV_i(t) = \sqrt{\sigma^2 + \kappa^2 \Phi_{2\lambda}(t)/\lambda + \gamma_i \Phi_{\lambda}(t) - 2B\kappa(-1)^i e^{-2\lambda t}}$$

with 
$$\sigma^2 = a^2/\lambda + \lambda B^2$$
,  $\kappa = a + \lambda b$ ,  $\gamma_i = -2a(\kappa - (-1)^i \lambda B)/\lambda$ .  
Here  $b = \frac{1}{2} \ln \frac{1+h_1}{1+h_0}$ ,  $B = \frac{1}{2} \ln(1+h_1)(1+h_0)$ ,  $c = (c_1 - c_0)/2$ ,  
 $a = (c_1 + c_0)/2$ .

In general, we have the following limits

$$\lim_{t \to 0} \mathrm{HV}_i(t) = \sqrt{\lambda_i} \ln(1 + h_i),$$

$$\lim_{t \to \infty} \mathrm{HV}_i(t) = \sqrt{\frac{\lambda_1 \lambda_0}{2\Lambda^3}} [(\lambda_0 B - c)^2 + (\lambda_1 B + c)^2]$$

In general, we have the following limits

$$\lim_{t \to 0} \mathrm{HV}_i(t) = \sqrt{\lambda_i} \ln(1 + h_i),$$

$$\lim_{t \to \infty} \mathrm{HV}_i(t) = \sqrt{\frac{\lambda_1 \lambda_0}{2\Lambda^3}} [(\lambda_0 B - c)^2 + (\lambda_1 B + c)^2]$$

These limits look reasonable: the limit at 0 is engendered by jumps only, the limit at  $\infty$  contains both "velocity" component and a long term influence of jumps.

# **Memory and historical volatility(3)**

The limits of historical volatility under a standard diffusion scaling are more complicated. Nevertheless, in the symmetric case  $\lambda_1 = \lambda_0 = \lambda$ , we have under the scaling conditions  $\lambda$ ,  $a \to \infty$ ,  $h_i \to 0$ ,  $a^2/\lambda \to \sigma^2$ ,  $\sqrt{\lambda}h_i \to \alpha_i$  that the historical volatility  $HV_i(t)$  converges to

$$\sqrt{\sigma^2 + (\alpha_1 + \alpha_0)^2/4}.$$

# **Memory and historical volatility(3)**

The limits of historical volatility under a standard diffusion scaling are more complicated. Nevertheless, in the symmetric case  $\lambda_1 = \lambda_0 = \lambda$ , we have under the scaling conditions  $\lambda$ ,  $a \to \infty$ ,  $h_i \to 0$ ,  $a^2/\lambda \to \sigma^2$ ,  $\sqrt{\lambda}h_i \to \alpha_i$  that the historical volatility  $HV_i(t)$  converges to

 $\sqrt{\sigma^2 + (\alpha_1 + \alpha_0)^2/4}$ . Notice, that under the martingale measure  $\mathbb{P}^*$ , we have  $\lambda = -c_i/h_i$ ,  $\sigma = (-\alpha_1 + \alpha_0)/2$ , and the diffusion limit of historical volatility equals to  $v = \sqrt{(\alpha_1^2 + \alpha_0^2)/2}$ , which coincides with the volatility expression for the diffusion scaling.

## **Implied volatility**

Define the Black-Scholes call price function  $f(\mu,v)$  ,  $\mu = \log K$  by

$$f(\mu, v) = \begin{cases} F\left(\frac{-\mu}{\sqrt{v}} + \frac{\sqrt{v}}{2}\right) - e^{\mu}F\left(\frac{-\mu}{\sqrt{v}} - \frac{\sqrt{v}}{2}\right), & \text{if } v > 0, \\ (1 - e^{\mu})^+, & \text{if } v = 0. \end{cases}$$

The processes  $V_i(\mu, t), t \ge 0, \mu \in \mathbb{R}$  defined by the equation

$$\mathbb{E}\left[\left(S(t+\tau)/S(\tau) - e^{\mu}\right)^{+} |\mathcal{F}_{\tau}^{(i)}\right] = f(\mu, \ V_{\sigma_{i}(\tau)}(\mu, t))$$

are referred to as implied variance processes.

#### **Implied volatility is Markov-modulated**

The implied volatilities  $W_i(\mu, t)$  are defined as

$$\mathbf{N}_{i}(\mu,\tau,t) = \sqrt{\frac{V_{\sigma_{i}(\tau)}(\mu,t)}{t}}.$$

#### **Implied volatility is Markov-modulated**

The implied volatilities  $W_i(\mu, t)$  are defined as

$$\mathbb{N}_{i}(\mu,\tau,t) = \sqrt{\frac{V_{\sigma_{i}(\tau)}(\mu,t)}{t}}.$$

Notice that

$$\mathbf{N}_i(\mu, \tau, t) = \mathbf{N}_{\sigma_i(\tau)}(\mu, 0, t).$$

So the implied volatility is Markov-modulated, but it does not move in parallel shifts.

#### **Numerical results**

We performed the numerical valuation of the jump telegraph volatility and the historical volatility, which are compared with the implied volatilities with respect to different moneyness and to the initial market states.

#### **Numerical results**

We performed the numerical valuation of the jump telegraph volatility and the historical volatility, which are compared with the implied volatilities with respect to different moneyness and to the initial market states.

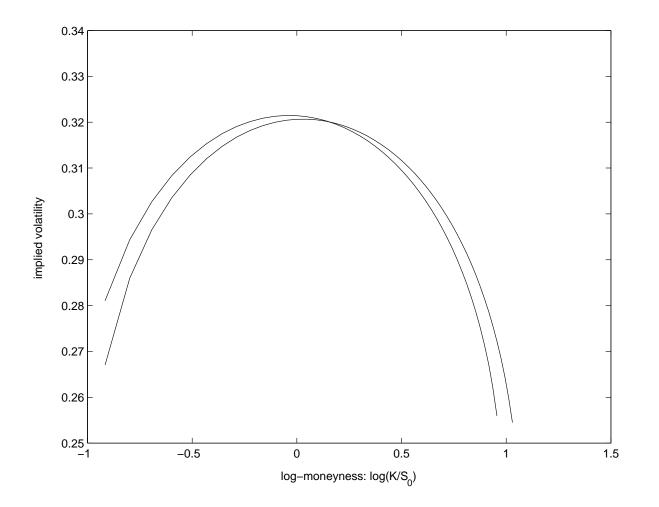
We assume  $S_0 = 100, T = 1$ .

First, consider the symmetric case:  $\lambda_i = 10, c_i = \pm 1$  and  $h_i = \pm 0.1$ .

The results are the following:  $HV_0 = HV_1 = 0.3162$ , jump telegraph volatility=0.3162.

Notice that these frowned smiles of implied volatilities  $W_0$ and  $W_1$  intersect at  $K/S_0 = 1.17$ .

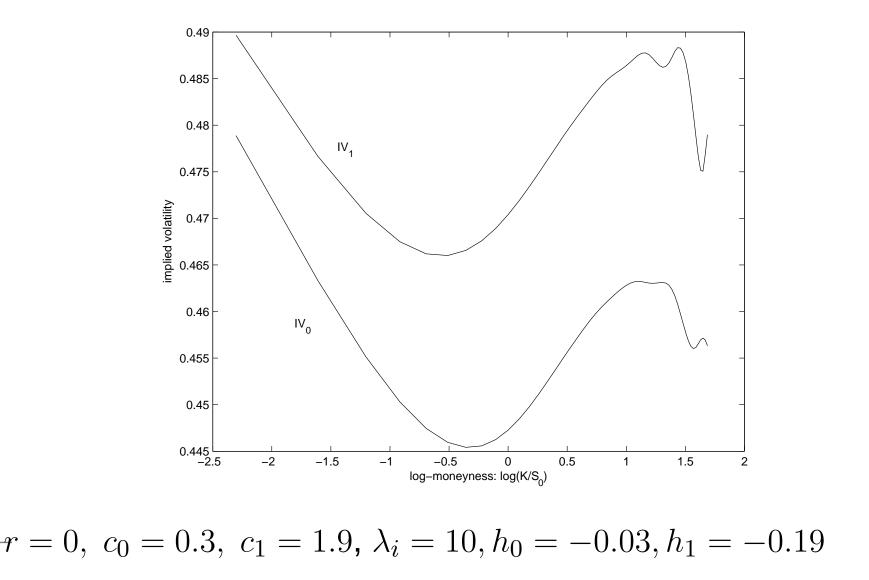
#### **Volatility smile (1)**



 $\lambda_i = 10, c_i = \pm 1, h_i = \mp 0.1$ 

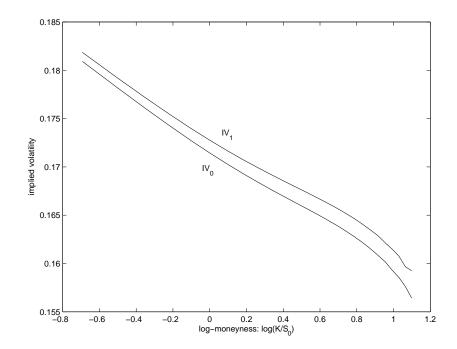
#### **Volatility smile (2)**

#### $HV_0 = 0.4198, HV_1 = 0.4402$ ; tel. volatility=0.4301



# **Volatility smile (3)**

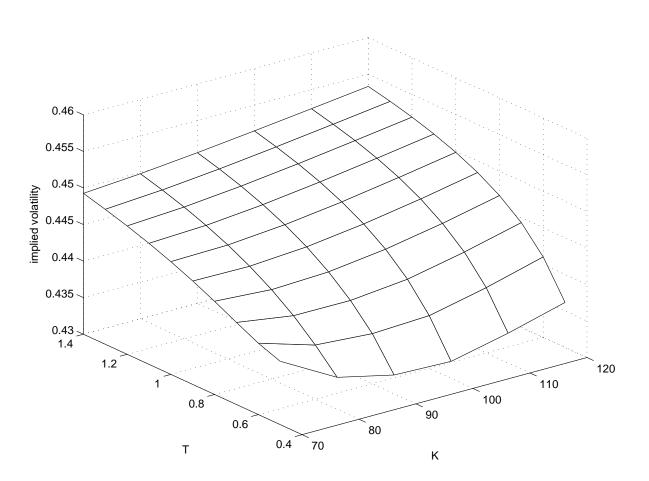
Dow-Jones industrial average July 1971-Aug 1974



 $\lambda_0 = 48.53, \lambda_1 = 34.61, h_0 = -0.0126, h_1 = -0.0358,$  $c_0 = 0.61, c_1 = 1.24; \text{HV}_0 = 0.1630, \text{HV}_1 = 0.1642;$ jump telegraph volatility=0.1661

## **Volatility smile (4)**

 $\mathrm{IV}_{\mathrm{0}}$ 



 $\lambda_i = 10, h_0 = -0.03, h_1 = -0.19, c_0 = 0.3, c_1 = 1.9$ 

(a) Velocities move through a binary tree (as in CRR-model);
 (b) Calibration of the parameters of jump telegraph model according to real market data;
 (c) inhomogeneous case:

$$c_i = c_i(x,t), \ \lambda_i = \lambda_i(x,t), \ h_i = h_i(x,t)$$

(a) Velocities move through a binary tree (as in CRR-model);
 (b) Calibration of the parameters of jump telegraph model according to real market data;
 (c) inhomogeneous case:

 $c_i = c_i(x, t), \ \lambda_i = \lambda_i(x, t), \ h_i = h_i(x, t)$ 

Jump and/or velocity values are *random*. In this case the model is incomplete

(a) Velocities move through a binary tree (as in CRR-model);
 (b) Calibration of the parameters of jump telegraph model according to real market data;
 (c) inhomogeneous case:

 $c_i = c_i(x,t), \ \lambda_i = \lambda_i(x,t), \ h_i = h_i(x,t)$ 

- Jump and/or velocity values are random. In this case the model is incomplete
- Arcsine law for jump telegraph processes and path dependent options

(a) Velocities move through a binary tree (as in CRR-model);
 (b) Calibration of the parameters of jump telegraph model according to real market data;
 (c) inhomogeneous case:
 c<sub>i</sub> = c<sub>i</sub>(x,t), λ<sub>i</sub> = λ<sub>i</sub>(x,t), h<sub>i</sub> = h<sub>i</sub>(x,t)

Jump and/or velocity values are random. In this case the model is incomplete

- Arcsine law for jump telegraph processes and path dependent options
- Application of branching telegraph processes to market models



- N. Ratanov, Telegraph evolutions in inhomogeneous media, Markov Processes Relat. Fields 5 (1999), 53-68
- N. Ratanov, Pricing options under telegraph processes, Rev. Econ. Ros., 8 (2005), no.2, 131-150
- A. Melnikov, N. Ratanov, Inhomogeneous telegraph processes and their application to financial market modeling. Doklady Mathematics, 75 (2007), No 1/2
- N. Ratanov, Telegraph models of financial markets, Rev. Col. Matem. 41 (2007)

- N. Ratanov, A jump telegraph model for option pricing. Quantitative Finance, 7, No 5, 2007, 575-583
- N. Ratanov, Jump telegraph models and financial markets with memory. J. Appl. Math. Stoch. Anal., vol. 2007, Article ID 72326, 19 pages, 2007. doi:10.1155/2007/72326
- N. Ratanov N., Melnikov A. On financial markets based on telegraph processes. Stochastics: An International Journal of Probability and Stochastic Processes 80, No. 2-3, 2008, 247-268
- Ratanov N. An option pricing model based on jump telegraph processes. To appear in *Proc. Appl. Math. Mech.* (PAMM), 2008