

Share Option Models

Valuation Guidance and Techniques

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Objectives

- 1. To understand option constructs using replicating portfolios
- 2. To learn about mathematical concepts underlying options
- 3. To appreciate the derivation, advantages and limitations of the Binomial/ Lattice Model
- 4. To appreciate the derivation, advantages and limitations of the Black-Scholes Model
- 5. To understand simulation techniques and their application
- 6. To reinforce understanding of share option contracts



Definition of an 'Option'

A Call (Put) Option is a right, but not an obligation, to buy (sell) an underlying security at a particular time and at a predetermined Strike Price.

The time could be at the end of the life of the option i.e. European or at any time during the life of the option i.e. American



Another Definition of an 'Option'

An option is a contract manufactured from a replicating portfolio comprising Φ shares and Ψ cash.

No matter how the portfolio moves during a period, other things being constant, an option writer will never suffer a loss.

Options defer to the principle of `no arbitrage.'



Binomial Model Assumptions

In the binomial model it is assumed that:

- there are no trading costs or taxes
- there are no minimum or maximum units of trading
- stock and bonds can only be bought and sold at discrete times 1, 2, ...
- the principle of no arbitrage applies



The One-Period Binomial Model

At time 1, we have two possibilities:

 $\mathbf{S_1} = \left\{ \begin{array}{ll} \mathbf{S_0u} & \text{if stock price goes up} \\ \mathbf{S_0d} & \text{if stock price goes down} \end{array} \right.$

Here S_t represents the price of a non-dividend paying stock at discrete time intervals t {t= 0,1,2,...}. 'u' is the size of the up-jump, and 'd' of the down-jump

In order to avoid arbitrage we must have $d < e^r < u$

I.e. the Principle of No-Arbitrage.

Pause to understand e^r!



Say at time 0 we hold Φ units of stock and Ψ units of cash.

Then value of this portfolio at time 0 is

$$\mathbf{V_o} = \Phi \, \mathbf{S_o} + \Psi$$

At time 1 the same portfolio has the value:

$$\mathbf{V_1} \quad \left\{ \begin{array}{l} \mathbf{C_u} = \Phi \ \mathbf{S_ou} + \Psi \ \mathbf{e^r} \text{ if the stock price went up} \\ \mathbf{C_d} = \Phi \ \mathbf{S_od} + \Psi \ \mathbf{e^r} \text{ if the stock price went down} \end{array} \right.$$



Determination of Derivative price ... Contd.

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We put the results of
$$\Phi$$
 and Ψ in $\mathbf{V_o} = \Phi \mathbf{S_o} + \Psi$

To get the results of a two-state Binomial Model

$$V_0 = e^{-r} [c_u \frac{(e^r - d)}{(u - d)} + c_d \frac{(u - e^r)}{(u - d)}]$$

Indeed the value of the portfolio at time 0 i.e.V₀ is product of

- a) Present value i.e. e^{-r};
- b) Random variable of value if it went up and down i.e. C_u and C_d ; and
- c) Respective probability of going up and down i.e. (e^r-d)/ (u-d) and (u-e^r)/ (u-d)



Key Interim Learning

Note that Φ units of shares and Ψ cash is a replicating portfolio, i.e. whichever way the share moves, V₀ is the present value of V₁







$$C_{u} = \Phi S_{o}u + \Psi e^{r}$$

$$V_{0} = e^{-r} [c_{u} \frac{(e^{r} - d)}{(u - d)} + c_{d} \frac{(u - e^{r})}{(u - d)}]$$

$$C_{d} = \Phi S_{o}d + \Psi e^{r}$$

- If a portfolio of Φ shares and Ψ cash is set up, as long as d < $e^r < u$ an option can be valued using a one-step binomial model
- Provided it is possible to borrow at risk-free rate r and hold shares and cash even in fractions
- The probability of up-jump is (e^r-d)/ (u-d)
- And down-jump is (u-e^r)/ (u-d)
- The key is to know 'u' and 'd' the size of jumps





Q: If u is much higher than 1 and d much lower than 1, would an option be more valuable than otherwise?

A:

Hint: Volatility





Q: If u is much higher than 1 and d much lower than 1, would an option be more valuable than otherwise?

A: Yes, greater the size of upward or downward movement would make an option more valuable. Remember that the option gives the holder a right but not an obligation to buy or sell the underlying share.



Finding the size of jumps

The important step in the Binomial model is hence to find `u' and `d' i.e. the size of up and down jumps

Much theory postulates that share prices move as per a stochastic process called Geometric Brownian Motion

In that case:

$$\frac{S_{t+\delta t}}{S_t} \approx Lognormal[(r - \sigma^2 / 2)(\delta t), \sigma^2 \delta t)]$$



The Algebra of Lognormal Distribution

$$E \left[\ln\left(-\frac{S_{t+\delta t}}{S_{t}} \right) \right] = r \cdot \delta t$$

$$V \left[\ln\left(-\frac{S_{t+\delta t}}{S_{t}} \right) \right] = E \left[\ln\left(-\frac{S_{t+\delta t}}{S_{t}} \right)^{2} \right] - \left\{ E \left[\ln\left(-\frac{S_{t+\delta t}}{S_{t}} \right) \right] \right\}^{2}$$

The second term in the variance equation is of the order δt^2 and hence becomes 0

The first term of the variance equation becomes (In u)²

But, we already know that Variance is $\sigma^2 \cdot \delta t$

Setting $(\ln u)^2 = \sigma^2 \cdot \delta t$, we get $u = \exp(\sigma \cdot \sqrt{\delta t})$

Recombining Binomial Tree

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Finding Option value with Binomial model

Summary of the Binomial Option Pricing Model

Mathematically simple, but surprisingly powerful method to price options

- If the volatility σ is known, the size of up and down jumps can be estimated.
- The short time δt can be set up to have multiple nodes in the binomial tree
- Due to the uniform size of up and down jumps at different times, the binomial tree is a recombining one

Discounting the payouts at the final nodes helps us to value the European Call or Put option.



Calculating Volatility

Annualized Volatility is measured by Standard Deviation (σ)

e.
$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \overline{x})^2}{n}}$$

With regard to a share, x_i stands for

A) Daily Closing price of the share on the ith day

B) Daily Returns of the share on the ith day

C) Daily Closing price of the option on the ith day

D) Daily Returns of the option on the ith day



Calculating Volatility

Volatility is measured by Standard Deviation (σ)

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With regard to a share, x_i stands for

A) Daily Closing price of the share on the ith day

- B) Daily Returns of the share on the ith day
- C) Daily Closing price of the option on the ith day
- D) Daily Returns of the option on the ith day

Note: Annualized Volatility = 16σ





shares with market value S_t as:

$$V_t = -f_t + \frac{df}{dS_t} S_t$$



A portfolio of

The Option Writer and delta (Δ)

-1 Option; + Δ Shares;

or

+1 Option; - Δ Shares

Will be perfectly hedged (no profit or loss) for a writer if the change in value of Option is Δ times change in value of shares

That is, if Δ can be perfectly calculated, there is no risk to the writer

But Δ is not stationary; hence Δ is protected by setting up a portfolio with zero Γ (Γ or gamma = change in Δ)



Greeks





Greeks ... contd.





The lattice binomial model- An example

Consider the following share option :

Share price on the grant date= 10 units Exercise Price = 10 units Volatility=30% Risk free rate=5% Term of option=5 years Period between nodes =6 months No dividends

At t = 0 (the grant date), the lattice is started at the grant date share price (10 units in our example). At each node (a six month interval), two possible price changes are computed based on the share's volatility.



Lattice Example ... Contd.

The two new stock prices are computed as follows: • Upward movements are calculated as $u = \exp(\sigma \sqrt{\delta t})$ • Downward movements are calculated as d = 1/u*Where,* σ = annualised volatility t = time between nodes (based on a fraction of a year) (S1,1) 10 units (S0,0) Therefore, we calculate the upward movement as: $u = e^{(0.3 * \sqrt{0.5})} = 1.236$ (S1,0) So the price at S1,1 = 10 units * 1.236 = 12.36 units We calculate the downward movement as:

d = 1/1.236 = 0.809

So the price at S1,0 = 10 units * 0.809 = 8.09 units

This process of expanding the tree continues in the same fashion at each node, until the end of the contractual term is reached.

Modern day software packages perform operations at several nodes in little time





Limitations of the Binomial/ Lattice Model

Important Limitations

- Presupposes that Lognormal distribution applies to share price returns; not borne out in practice
- Assumes a perfect market with no trading and transaction costs
- Permits unlimited borrowing and lending at risk-free rate; in practice, credit rating determines the borrowing and lending rate/ practice



Black-Scholes Partial Differential Equation

Uses Ito's lemma

$$df = \frac{\delta f}{\delta t} dt + \frac{\delta f}{\delta S_t} dS_t + \frac{1}{2} \frac{\delta^2 f}{\delta S_t^2} (dS_t)^2$$

And Stochastic Differential Equation of Share Price Movement

$$dS_t = S_t (\mu dt + \sigma dZ_t)$$

Starting with the initial value of $V_t = portfolio$

$$-f_t + \frac{df}{dS_t} \cdot S_t$$

Finally leads to the B-S Partial Differential Equation

$$r.f = \frac{\delta f}{\delta t} + rS_t \frac{\delta f}{\delta S_t} + \frac{1}{2}\sigma^2 S_t^2 \frac{\delta^2 f}{\delta S_t^2}$$



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Pause to understand the B-S Partial Differential Equation

$$r \cdot f = \frac{\delta f}{\delta t} + rS_{t} \frac{\delta f}{\delta S_{t}} + \frac{1}{2}\sigma^{2}S_{t}^{2} \frac{\delta^{2} f}{\delta S_{t}^{2}}$$

LHS is Risk free rate x Value of Option

RHS accounts for 3 expressions which are added

- a) First: Theta Θ i.e. rate of change of option to small change in time
- b) Second: Risk free rate x Share Price x Delta (rate of change of option to small change in share price)
- c) Third: ¹/₂ x standard deviation of returns)² x (Share price)² x Gamma (rate of change of delta to small change in share price)



From Partial Differential Equation B-S Option Pricing Formula

Plenty of calculus involved

Indeed characterizes returns on shares Random Walk \rightarrow Geometric Brownian Motion \rightarrow Lognormal distribution

To finally derive the formula

$$c_{t} = S_{t} \Phi (d_{1}) - Ke^{-r(T-t)} \Phi (d_{2})$$

Where
$$d_{1} = \frac{Ln (\frac{S_{t}}{K}) + (r + \frac{\sigma^{2}}{2})(T - t)}{\sigma \sqrt{T - t}}$$

and
$$d_{2} = d_{1} - \sigma \sqrt{T - t}$$



Black – Scholes Formula Variables

The Black-Scholes-Merton formula is an example of a 'closed-form model' i.e. it uses an equation to produce an estimated fair value.

- c_t = price of a call at time t
- S_t = price of the underlying share at time t

 Φ = the cumulative probability distribution function; standard normal

q = dividend yield

- K = call option exercise price
- r = the continuously compounded risk-free rate
- σ = Annualized volatility of the returns on underlying share
- T t = time to expiration (in years)



Expected term of the option

Vesting period — the option's expected term must be at least as long as its vesting period. The length of time employees hold options after they vest may vary inversely with the length of the vesting period

- *History of employee exercise and termination patterns* for similar grants (adjusted for current expectations)
- *Price of the underlying shares* experience may indicate that employees tend to exercise options when the share price reaches a specified level above the exercise price
- *Employee's level within the organization* experience may indicate that higher level employees exercise options later than lower level employees

Expected volatility of the underlying share — on average, employees tend to exercise options on higher volatility stocks earlier



Assumptions Setting ... Contd.

Expected volatility

Implied volatility from traded share options on the entity's shares, or other traded instruments of the entity that include option features (such as convertible debt), if any

Historical volatility of the share price over the most recent period that is generally commensurate with the expected term of the option

Length of time an entity's shares have been publicly traded — a newly listed entity might have a high historical volatility, compared with similar entities that have been listed longer

Tendency of volatility to revert to its mean (i.e., its long-term average level), and other factors indicating that expected future volatility might differ from volatility in the immediate past appropriate and regular intervals for price observations



Assumptions Setting ... Contd.

Expected Dividends:

Based on current expectations about an entity's anticipated dividend policy. If an entity has never paid a dividend, but has announced that it will begin paying a dividend yielding 2% of the current share price, then it is likely that an expected dividend yield of 2% would be assumed in estimating the fair value of its options.

Risk free rate

The risk-free interest rate is the implied yield currently available on zerocoupon government issues denominated in the currency of the market in which the underlying shares primarily trade.



Limitations of the Black-Scholes Model

Primarily, the Model identifies stock price returns to the normal distribution family! Recall $dS_t = S_t (\mu dt + \sigma dZ_t)$

Consider the extract below from Chapter 15 of Nassim Taleb's 'The Black Swan': The Bell Curve, That Great Intellectual Fraud

Measures of uncertainty that are based on the bell curve simply disregard the probability, and the impact, of sharp jumps or discontinuities and are, therefore inapplicable in Extremistan.

Using them is like focusing on the grass and missing out on the (gigantic) trees.

Indeed, share prices face extreme movements, both on the upside and the downside more frequently than the Normal/ Bell Curve models (Source: own view)



NIFTY Returns Distribution Fit (Sep 08 – Mar 12)

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Nifty Returns (Sep 08 – Mar 12) Goodness of Fit

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Project Tree	Graphs	Summary Goodness of F	it										
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Infosys Table L&T table NIFTY TABLE	#	Distribution	Kolmog Smirn	orov	Ander Darli	son ng	Chi-Squ	ared					
Results 3 HUL Graph			Statistic	Rank	Statistic	Rank	Statistic	Rank					
Infosys Graph	6	Error	0.01918	1	0.68281	1	10.903	3					
L&T Graph	22	Laplace	0.01918	2	0.68281	2	10.903	4					
	4	Dagum (4P)	0.02718	3	1.0471	3	9.5807	2					
	20	Johnson SU	0.03443	7	1.0613	4	8.6747	1					
	24	Log-Logistic (3P)	0.02952	4	1.1221	5	12.622	6					
	2	Burr (4P)	0.03242	5	1.2689	6	12.0	5					
	14	Gen. Logistic	0.03336	6	1.545	7	12.691	7					
	18	Hypersecant	0.03462	8	1.9476	8	14.332	8					
	25	Logistic	0.04963	10	4.2969	9	32.071	9					
	3	Cauchy	0.05636	12	6.6317	10	65.64	11					
	28	Pearson 5 (3P)	0.07431	20	10.035	11	65.871	14					
	9	Fatigue Life (3P)	0.06894	14	11.483	12	65.779	13					
	19	Inv. Gaussian (3P)	0.07191	18	11.523	13	63.452	10					
	26	Lognormal (3P)	0.06884	13	11.556	14	66.654	17					
	13	Gen. Gamma (4P)	0.0716	17	11.763	15	65.871	15					
	27	Normal	0.07126	16	11.799	16	66.677	18					
	5	Erlang (3P)	0.07102	15	11.905	17	67.553	19					
	7	Error Function	0.07512	22	11.954	18	66.562	16					
	11	Gamma (3P)	0.07459	21	12.099	19	65.733	12					
	1	Beta	0.07306	19	12.438	20	69.512	20					
	38	Weibull (3P)	0.09129	23	19.502	21	N/A						



L&T returns (Sep 08 – Mar 12) Distribution Fit

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WIRC of ICAI, Seminar on Actuaries



L&T Returns (Sep 08 – Mar 12) Goodness of Fit

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Project Tree	Graphs	Summary Goodness of Fi							
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Results BAUL Graph			Statistic	Rank	Statistic	Rank	Statistic	Rank	
🐴 Infosys Graph	6	Error	0.02648	2	0.4548	1	4.564	1	
L&T Graph	22	Laplace	0.02648	З	0.4548	2	4.564	2	
	4	Dagum (4P)	0.03805	4	1.5624	3	13.201	3	
	2	Burr (4P)	0.03863	5	1.6994	4	17.191	6	
	18	Hypersecant	0.04375	8	1.7367	5	13.391	4	
	24	Log-Logistic (3P)	0.03939	6	1.7414	6	17,135	5	
	20	Johnson SU	0.04376	9	1.757	7	20.296	8	
	14	Gen. Logistic	0.04228	7	2.0607	8	19.863	7	
	25	Logistic	0.05912	11	3.8392	9	31.956	10	
	3	Cauchy	0.05322	10	5.5517	10	27.939	9	
	29	Pearson 6 (4P)	0.06805	14	7.8045	11	68.82	16	
	28	Pearson 5 (3P)	0.06756	13	7.83	12	72.438	20	
	11	Gamma (3P)	0.07042	19	7.9563	13	65.871	11	
	5	Erlang (3P)	0.07037	18	8.096	14	68.752	15	
	13	Gen. Gamma (4P)	0.07053	20	8.1323	15	67.369	13	
	1	Beta	0.07024	17	8.2878	16	76.585	21	
	26	Lognormal (3P)	0.06875	15	9.8097	17	68.198	14	
	9	Fatigue Life (3P)	0.06953	16	9.8561	18	66.793	12	
	19	Inv. Gaussian (3P)	0.08131	23	10.227	19	68.936	17	
	7	Error Function	0.0754	21	10.634	20	71.459	19	
	27	Normal	0.08028	22	10.721	21	70.651	18	



Infosys Returns (Sep 08 – Mar 12) Distribution Fit

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Infosys Returns (Sep 08 – Mar 12) Goodness of fit

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25 Logistic 0.03389 6 3.0263 9 23.017 7 26 Lognormal (3P) 0.04871 16 9.6974 10 61.677 13 9 Fatigue Life (3P) 0.0486 12 9.9511 11 63.764 15 13 Gen. Gamma (4P) 0.04966 17 9.974 12 64.431 16 11 Gamma (3P) 0.05176 19 10.006 13 61.053 10 29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04843 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05148 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17		22	Laplace	0.0446	11	2.4756	8	38.909	9		
26 Lognormal (3P) 0.04871 16 9.6974 10 61.677 13 9 Fatigue Life (3P) 0.04836 12 9.9511 11 63.764 15 13 Gen. Gamma (4P) 0.04966 17 9.974 12 64.431 16 11 Gamma (3P) 0.05176 19 10.006 13 61.053 10 29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04833 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.05176 21 13.536 20 70.69 20 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 21		25	Logistic	0.03389	6	3.0263	9	23.017	7		
9 Fatigue Life (3P) 0.04836 12 9.9511 11 63.764 15 13 Gen. Gamma (4P) 0.04966 17 9.974 12 64.431 16 11 Gamma (3P) 0.05176 19 10.006 13 61.053 10 29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04833 13 10.068 15 61.493 11 27 Normal 0.04833 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		26	Lognormal (3P)	0.04871	16	9.6974	10	61.677	13		
13 Gen. Gamma (4P) 0.04966 17 9.974 12 64.431 16 11 Gamma (3P) 0.05176 19 10.006 13 61.053 10 29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04853 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.0588 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.0593 22 14.868 21 165.23 21		9	Fatigue Life (3P)	0.04836	12	9.9511	11	63.764	15		
11 Gamma (3P) 0.05176 19 10.006 13 61.053 10 29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04843 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.0588 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		13	Gen. Gamma (4P)	0.04966	17	9.974	12	64.431	16		
29 Pearson 6 (4P) 0.04858 15 10.039 14 63.381 14 1 Beta 0.04843 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.051488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		11	Gamma (3P)	0.05176	19	10.006	13	61.053	10		
1 Beta 0.04843 13 10.068 15 61.493 11 27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05953 22 14.868 21 165.23 21 3 Cauchy 0.05953 22 14.868 21 165.23 21		29	Pearson 6 (4P)	0.04858	15	10.039	14	63.381	14		
27 Normal 0.04853 14 10.077 16 61.507 12 19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05953 22 14.868 21 165.23 21 3 Cauchy 0.05953 22 14.868 21 165.23 21		1	Beta	0.04843	13	10.068	15	61.493	11		
19 Inv. Gaussian (3P) 0.05088 18 10.356 17 68.036 19 5 Erlang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		27	Normal	0.04853	14	10.077	16	61.507	12		
S Enang (3P) 0.05488 20 10.704 18 65.155 18 7 Error Function 0.0619 23 11.15 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		19	Inv. Gaussian (3P)	0.05088	18	10.355	1/	68.036	19		
7 Error Function 0.0619 23 1115 19 64.672 17 28 Pearson 5 (3P) 0.05796 21 13.536 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		5	Erlang (3P)	0.05488	20	10.704	18	64,670	18		
20 Pearson 3 (3P) 0.03796 21 13.336 20 70.69 20 3 Cauchy 0.05953 22 14.868 21 165.23 21		/	Bearson 5 (2D)	0.0019	23	12,526	19	70.60	1/		
3 Caucity 0.03933 22 14.000 21 103.23 21		28	Couchy	0.05/90	21	14.060	20	165.00	20		
		3	Cauchy	0.05953	22	14.808	21	105.23	21		



HUL Returns (Sep 08 – Mar 12) Distribution Fit

Actuaries and Consultants





HUL Returns (Sep 08 – Mar 12) Goodness of Fit

Actuaries and Consultants

Project Tree	Graphs	Summary Goodness of Fit												
Data Tables III HUL Table	Goo	Goodness of Fit - Summary												
Infosys Table	#	Distribution	Kolmog Smirn	orov ov	Ander Darli	son ng	Chi-Squ	iared						
Results			Statistic	Rank	Statistic	Rank	Statistic	Rank						
Infosys Graph	20	Johnson SU	0.05812	4	1.086	1	29.709	3						
L&T Graph	24	Log-Logistic (3P)	0.05744	З	1.1242	2	32.47	5						
	14	Gen. Logistic	0.05588	1	1.1813	З	35.261	7						
	18	Hypersecant	0.06864	15	1.1908	4	25.466	1						
	4	Dagum (4P)	0.05677	2	1.3422	5	38.831	9						
	6	Error	0.07272	22	1.5246	6	25.595	2						
	25	Logistic	0.06676	14	1.7526	7	32.577	6						
	2	Burr (4P)	0.0697	18	2.4401	8	32.087	4						
	22	Laplace	0.07624	23	2.6613	9	52.816	10						
	26	Lognormal (3P)	0.06512	11	4.5785	10	70.142	17						
	29	Pearson 6 (4P)	0.06555	12	4.5946	11	69.512	16						
	9	Fatigue Life (3P)	0.06565	13	4.5983	12	69.512	15						
	28	Pearson 5 (3P)	0.06431	9	4.6767	13	136.38	23						
	11	Gamma (3P)	0.06047	6	4.6989	14	95.38	20						
	13	Gen. Gamma (4P)	0.06466	10	4.705	15	72.373	18						
	19	Inv. Gaussian (3P)	0.0705	20	4.7143	16	55.112	12						
	1	Beta	0.06895	16	4.768	17	59.896	14						
	27	Normal	0.07039	19	4.8305	18	57.544	13						
	5	Erlang (3P)	0.0724	21	5.1297	19	53.918	11						
	7	Error Function	0.06336	8	5.1477	20	139.85	24						
	3	Cauchy	0.06336	7	8.4392	21	160.87	25						
									<u></u>					



Limitations of the Black-Scholes Model ... Contd.

There are other limitations, though not as significant as the assumption of normal distribution.

- 1. Volatility is assumed to be constant. Especially when time to expiry is long, this assumption is questionable. B-S may not be appropriate for long tenor options.
- 2. Risk-free rate is assumed to be constant across maturities and unlimited borrowing/ lending is possible. In practice, availability of credit is greatly dependent on several factors including rating, liquidity and regulation.
- 3. Taxes and transaction costs are ignored.



Limitations of the Black-Scholes Model with regard to ESOP

Attributes of employee share options that render the Black-Scholes-Merton formula less effective as a valuation technique for employee share options are:

- *A) long term to expiration* An assumption of constant volatility, interest rates and dividends over the life of Employee share options that often have a long contractual term would be inappropriate.
- *B) non-transferable* —IFRS 2 provides for the use of an 'expected term' in place of the contractual life to reflect the possibility of early exercise resulting from the non-transferability of employee share options.



Limitations of Black Scholes formula with regard to ESOP ... Contd.

C) **subject to vesting provisions** — Employee share options often cannot be exercised prior to a specified vesting date. Vesting provisions therefore impact the valuation of share options because they affect the expected term of the options by, among other things, establishing a minimum expected term.

- *D)* **subject to term truncation** The term of an employee share option often is truncated upon termination of employment . Provisions regarding term truncation therefore will influence estimates of the expected term of the option.
- *E)* **subject to blackout periods** Black out periods during which certain employees are not allowed to trade are not readily incorporated in the Black Scholes valuation



Binomial/ Lattice and Black Scholes Formulae – A comparison

Black Scholes Model	Binomial/ Lattice Model
Black-Scholes-Merton formula uses static assumptions and is not the best method to estimate the fair value of ESOPs	A lattice model can explicitly use dynamic assumptions regarding the term structure of volatility, dividend yields, and interest rates.
Black-Scholes-Merton formula cannot handle the additional complexity of a market based performance condition .	The lattice model, that takes into account employee exercise patterns based on the dynamics of an entity's share price may result in a better estimate of fair value.

The longer the term of the option and the higher the dividend yield, the larger the amount by which the binomial lattice model value may differ from the Black-Scholes-Merton value.



Directional Impact of the change in assumptions

An increase in the	Results in a fair value estimate of a Call Option
Current price of the underlying share	Higher
Exercise price of the option	Lower
Expected volatility of the stock	Higher
Expected dividends on the stock	Lower
Risk-free interest rate	Higher
Expected term of the option	Higher

It is important to understand all the terms and conditions of a share-based payment arrangement because this enables the issuer to choose the most appropriate option pricing model.



There are certain complexities that a Lattice model cannot handle

For example, certain options may contain a condition based on total shareholder return (TSR) and the option may vest only if the entity's TSR falls within a specified range of rankings amongst a large peer group

For options with more complex market conditions such as these, Monte Carlo simulation is required.

The probability of meeting the hurdle is modeled using Monte Carlo simulation, and then the option is valued using either the lattice model or Black-Scholes-Merton model.

In that sense, the Monte Carlo simulation can sit on either the Black-Scholes or the Lattice Model



Actuaries and Consultants

Monte Carlo Simulation - Stylistically





Even though many entities estimate the value of share options using the Black-Scholes-Merton formula, most valuation specialists agree that lattice models (e.g. binomial models) generally provide a better estimate of the fair value

Options may have certain features that might preclude the use of the Black-Scholes-Merton formula in estimating option fair value

But even though a lattice model is regarded as often producing a better estimate of an option's fair value, it can be considerably more complicated than using the Black-Scholes-Merton formula, and not many are familiar with how a lattice model works



Whilst IFRS 2 on Share-based Payments to Employees does not obligate any particular method, the option-pricing model used must take into account a minimum of six inputs.

These are:

- **1.** Current price of the underlying share
- 2. Exercise price
- 3. Expected volatility of the price of the underlying share
- 4. Expected dividends on the underlying share
- 5. Risk-free interest rate for the expected term
- 6. Expected term of the option, taking into account both the contractual term of the option and the expected effects of employees' exercise and post-vesting behavior



Thank You Mayur Ankolekar FIAI, FIA, FCA **Consulting Actuary** mayur.ankolekar@ankolekar.in