Exponential Smoothing Methods

Chapter Topics

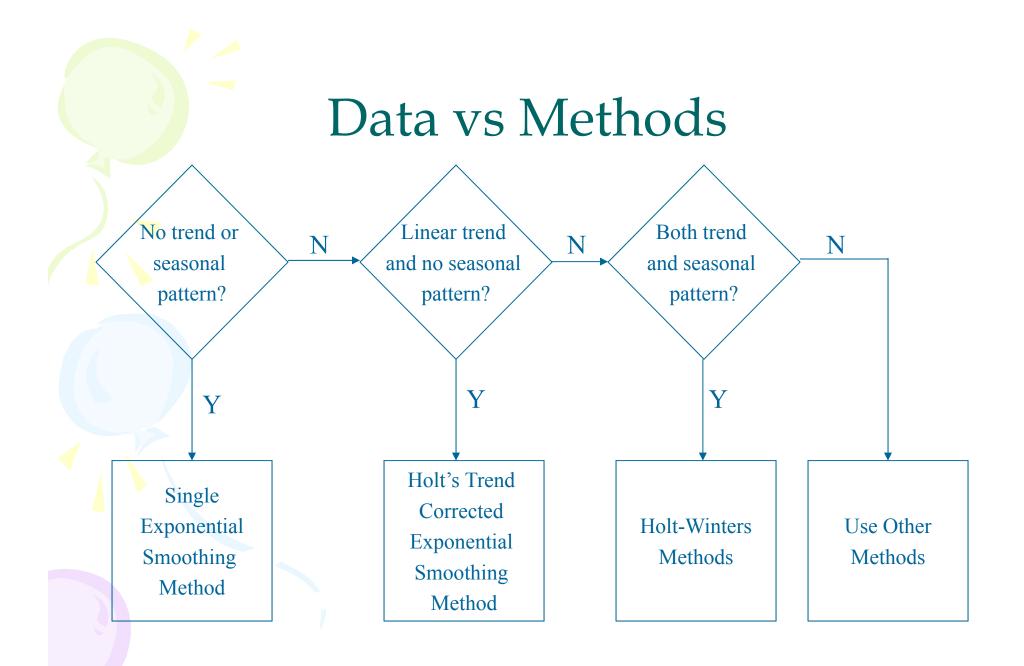
- Introduction to exponential smoothing
- Simple Exponential Smoothing
- Holt's Trend Corrected Exponential Smoothing
- Holt-Winters Methods
 - Multiplicative Holt-Winters method
 - Additive Holt-Winters method

Motivation of Exponential Smoothing

- Simple moving average method assigns equal weights (1/*k*) to all *k* data points.
- Arguably, recent observations provide more relevant information than do observations in the past.
- So we want a weighting scheme that assigns decreasing weights to the more distant observations.

Exponential Smoothing

- Exponential smoothing methods give larger weights to more recent observations, and the weights decrease exponentially as the observations become more distant.
- These methods are most effective when the parameters describing the time series are changing SLOWLY over time.



Simple Exponential Smoothing

- The <u>Simple Exponential Smoothing</u> method is used for forecasting a time series when there is no trend or seasonal pattern, but the mean (or level) of the time series y_t is slowly changing over time.
- NO TREND model

$$y_t = \beta_o + \varepsilon_t$$

Procedures of Simple Exponential Smoothing Method

 Step 1: Compute the initial estimate of the mean (or level) of the series at time period t = 0

$$\ell_0 = \overline{y} = \frac{\sum_{t=1}^{t} y_t}{n}$$

• **Step 2**: Compute the updated estimate by using the <u>smoothing equation</u>

$$\ell_T = \alpha y_T + (1 - \alpha) \ell_{T-1}$$

where α is a <u>smoothing constant</u> between 0 and 1.

Procedures of Simple Exponential Smoothing Method

Note that

$$\ell_{T} = \alpha y_{T} + (1-\alpha)\ell_{T-1}$$

$$= \alpha y_{T} + (1-\alpha)[\alpha y_{T-1} + (1-\alpha)\ell_{T-2}]$$

$$= \alpha y_{T} + (1-\alpha)\alpha y_{T-1} + (1-\alpha)^{2}\ell_{T-2}$$

$$= \alpha y_{T} + (1-\alpha)\alpha y_{T-1} + (1-\alpha)^{2}\alpha y_{T-2} + \dots + (1-\alpha)^{T-1}\alpha y_{1} + (1-\alpha)^{T}\ell_{0}$$
The coefficients measuring the contributions of the observations decrease exponentially over time.

Simple Exponential Smoothing

• Point forecast made at time *T* for y_{T+p}

$$\hat{y}_{T+p}(T) = \ell_T$$
 (p = 1, 2, 3,...)

• SSE, MSE, and the standard errors at time *T*

$$SSE = \sum_{t=1}^{T} [y_t - \hat{y}_t (t-1)]^2$$

$$MSE = \frac{SSE}{T-1}, \quad s = \sqrt{MSE}$$

Note: There is no theoretical justification for dividing SSE by (T – number of smoothing constants). However, we use this divisor because it agrees to the computation of *s* in Box-Jenkins models introduced later.

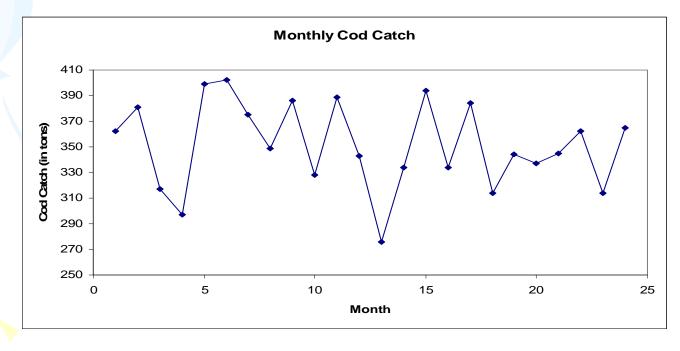
• The Bay City Seafood Company recorded the monthly cod catch for the previous two years, as given below.

Cod Catch (In Tons)

Month	Year 1	Year 2
January	362	276
February	381	334
March	317	394
April	297	334
May	399	384
June	402	314
July	375	344
August	349	337
September	386	345
October	328	362
November	389	314
December	343	365

• The plot of these data suggests that there is no trend or seasonal pattern. Therefore, a NO TREND model is suggested: $y_t = \beta_o + \varepsilon_t$

It is also possible that the mean (or level) is slowly changing over time.



Step 1: Compute l₀ by averaging the first twelve time series values.

$$\ell_0 = \frac{\sum_{t=1}^{12} y_t}{12} = \frac{362 + 381 + \dots + 343}{12} = 360.6667$$

Though there is no theoretical justification, it is a common practice to calculate initial estimates of exponential smoothing procedures by using HALF of the historical data.

• **Step 2**: Begin with the initial estimate $\ell_0 = 360.6667$ and update it by applying the smoothing equation to the 24 observed cod catches.

Set α = 0.1 arbitrarily and judge the appropriateness of this choice of α by the model's in-sample fit.

 $\ell_1 = \alpha y_1 + (1 - \alpha)\ell_0 = 0.1(362) + 0.9(360.6667) = 360.8000$ $\ell_2 = \alpha y_2 + (1 - \alpha)\ell_1 = 0.1(381) + 0.9(360.8000) = 362.8200$



One-period-ahead Forecasting

n	alpha	SSE	MSE	S	
24	0.1	28735.1092	1249.3526	35.3462	
Time		Smoothed Estimate	Forecast Made	Forecast	Squared Forecast
Period	У	for Level	Last Period	Error	Error
0		360.6667			
1	362	360.8000	360.6667	1.3333	1.7777
2	381	362.8200	360.8000	20.2000	408.0388
3	317	358.2380	362.8200	-45.8200	2099.4749
4	297	352.1142	358.2380	-61.2380	3750.0956
5	399	356.8028	352.1142	46.8858	2198.2762
6	402	361.3225	356.8028	45.1972	2042.7869
7	375	362.6903	361.3225	13.6775	187.0735
8	349	361.3212	362.6903	-13.6903	187.4234
9	386	363.7891	361.3212	24.6788	609.0411
10	328	360.2102	363.7891	-35.7891	1280.8609
11	389	363.0892	360.2102	28.7898	828.8523
12	343	361.0803	363.0892	-20.0892	403.5753
13	276	352.5722	361.0803	-85.0803	7238.6517
14	334	350.7150	352.5722	-18.5722	344.9281
15	394	355.0435	350.7150	43.2850	1873.5899
16	334	352.9392	355.0435	-21.0435	442.8295
17	384	356.0452	352.9392	31.0608	964.7756
18	314	351.8407	356.0452	-42.0452	1767.8027
19	344	351.0566	351.8407	-7.8407	61.4769
20	337	349.6510	351.0566	-14.0566	197.5894
21	345	349.1859	349.6510	-4.6510	21.6317
22	362	350.4673	349.1859	12.8141	164.2015
23	314	346.8206	350.4673	-36.4673	1329.8638
24	365	348.6385	346.8206	18.1794	330.4918

• Results associated with different values of α

Smoothing Constant	Sum of Squared Errors
0.1	28735.11
0.2	30771.73
0.3	33155.54
0.4	35687.69
0.5	38364.24
0.6	41224.69
0.7	44324.09
0.8	47734.09

• Step 3: Find a good value of α that provides the minimum value for MSE (or SSE).

SSE

– Use Solver in Excel as an illustration

Solver Parameters	×
Set Target Cell: \$C\$2	<u>S</u> olve
Equal To: O Max O Min O Value of: 0 By Changing Cells:	Close
\$8\$2 <u>G</u> uess	
Subject to the Constraints:	Options
\$8\$2 <= 1 \$8\$2 >= 0	
Change	Reset All
✓ <u>D</u> elete	Help

alpha

	Α	В	С	D	E	F
1	n	alpha	SSE	MSE	s	
2	24	0.03435	28089.1479	1221.2673	34.9466	
3						
- 4	Time		Smoothed Estimate	Forecast Made	Forecast	Squared Forecast
5	Period	у	for Level	Last Period	Error	Error
6	0		360.6667			
7		362	360.7125	360.6667	1.3333	1.7777
8		381	361.4095	360.7125	20.2875	411.5825
9		317	359.8838	361.4095	-44.4095	1972.1994
1		297	357.7235	359.8838	-62.8838	3954.3759
1		399	359.1415	357.7235	41.2765	1703.7457
1		402	360.6139	359.1415	42.8585	1836.8477
1		375	361.1081	360.6139	14.3861	206.9605
1		349	360.6921	361.1081	-12.1081	146.6059
1		386	361.5616	360.6921	25.3079	640.4879
1		328	360.4086	361.5616	-33.5616	1126.3778
1		389	361.3908	360.4086	28.5914	817.4685
1		343	360.7590	361.3908	-18.3908	338.2219
1	9 13	276	357.8472	360.7590	-84.7590	7184.0916
2		334	357.0280	357.8472	-23.8472	568.6912
2		394	358.2981	357.0280	36.9720	1366.9281
2		334	357.4634	358.2981	-24.2981	590.3991
2		384	358.3750	357.4634	26.5366	704.1911
2		314	356.8506	358.3750	-44.3750	1969.1431
2		344	356.4091	356.8506	-12.8506	165.1376
2		337	355.7424	356.4091	-19.4091	376.7141
2		345	355.3733	355.7424	-10.7424	115.3981
2		362	355.6010	355.3733	6.6267	43.9130
2		314	354.1718	355.6010	-41.6010	1730.6402
3	0 24	365	354.5438	354.1718	10.8282	117.2494

• If a time series is increasing or decreasing approximately at a fixed rate, then it may be described by the LINEAR TREND model

 $y_t = \beta_0 + \beta_1 t + \varepsilon_t$

If the values of the parameters β_0 and β_1 are slowly changing over time, Holt's trend corrected exponential smoothing method can be applied to the time series observations.

<u>Note</u>: When neither β_0 nor β_1 is changing over time, regression can be used to forecast future values of y_t .

• Level (or mean) at time $T: \beta_0 + \beta_1 T$ Growth rate (or trend): β_1

- A smoothing approach for forecasting such a time series that employs two smoothing constants, denoted by α and γ.
- There are two estimates ℓ_{T-1} and b_{T-1} .
 - ℓ_{T-1} is the estimate of the level of the time series constructed in time period *T*-1 (This is usually called the <u>permanent component</u>).
 - *b*_{T-1} is the estimate of the growth rate of the time series constructed in time period *T*–1 (This is usually called the trend component).

• Level estimate

$$\ell_T = \alpha y_T + (1 - \alpha)(\ell_{T-1} + b_{T-1})$$

• Trend estimate

$$b_{T} = \gamma (\ell_{T} - \ell_{T-1}) + (1 - \gamma) b_{T-1}$$

where α = smoothing constant for the level ($0 \le \alpha \le 1$) γ = smoothing constant for the trend ($0 \le \gamma \le 1$)

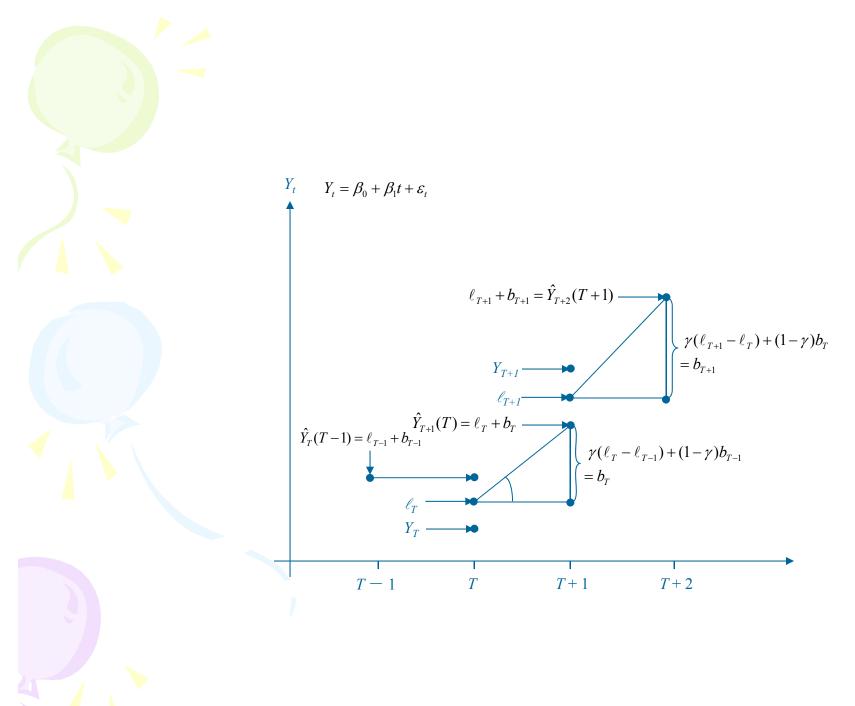


• Point forecast made at time *T* for y_{T+p}

$$\hat{y}_{T+p}(T) = \ell_T + pb_T$$
 (p = 1, 2, 3,...)

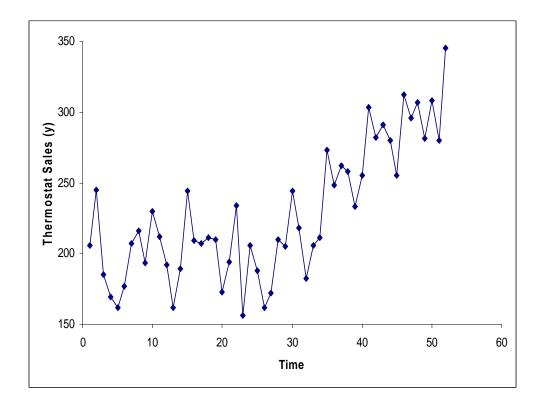
• MSE and the standard error *s* at time *T*

$$SSE = \sum_{t=1}^{T} [y_t - \hat{y}_t (t-1)]^2$$
$$MSE = \frac{SSE}{T-2}, \quad s = \sqrt{MSE}$$



• Use the example of Thermostat Sales as an illustration

Weekly Thermostat Sales							
206	189	172	255				
245	244	210	303				
185	209	205	282				
169	207	244	291				
162	211	218	280				
177	210	182	255				
207	173	206	312				
216	194	211	296				
193	234	273	307				
230	156	248	281				
212	206	262	308				
192	188	258	280				
162	162	233	345				



- Findings:
 - Overall an upward trend
 - The growth rate has been changing over the 52-week period
 - There is no seasonal pattern
 - ⇒ Holt's trend corrected exponential smoothing method can be applied

- **Step 1**: Obtain initial estimates ℓ_0 and b_0 by fitting a least squares trend line to HALF of the historical data.
 - *y*-intercept = ℓ_0 ; slope = b_0

- Example
 - Fit a least squares trend line to the first 26 observations
 - Trend line

 $\hat{y}_t = 202.6246 - 0.3682t$

 $- \ell_0 = 202.6246; b_0 = -0.3682$

SUMMARY OUTPUT	
Regression St	atistics
Multiple R	0.111769555
R Square	0.012492433
Adjusted R Square	-0.028653715
Standard Error	25.5551741
Observations	26
ANOVA	
	df
Regression	1
Residual	24
Total	25
	Coefficients
Intercept	202.6246154
X Variable 1	-0.368205128

• **Step 2**: Calculate a point forecast of *y*₁ from time 0

$$\hat{y}_{T+p}(T) = \ell_T + pb_T$$
 $T = 0, p = 1$

• Example

$$\hat{y}_1(0) = \ell_0 + b_0 = 202.6246 - 0.3682 = 202.2564$$

- **Step 3**: Update the estimates ℓ_T and b_T by using some predetermined values of smoothing constants.
- Example: let $\alpha = 0.2$ and $\gamma = 0.1$

 $\ell_1 = \alpha y_1 + (1 - \alpha)(\ell_0 + b_0)$ = 0.2(206) + 0.8(202.6246 - 0.3682) = 203.0051

 $b_1 = \gamma(\ell_1 - \ell_0) + (1 - \gamma)b_0$ = 0.1(203.0051 - 202.6246) + 0.9(-0.3682) = -0.2933

 $\hat{y}_2(1) = \ell_1 + b_1 = 203.0051 - 0.2933 = 202.7118$

1	n	alpha	gamma	SSE	MSE	S	
2	52	0.2	0.1	39182.4705	783.6494	27.993739	
3							
4					Forecast		Squared
5	Time			Growth	Made Last	Forecast	Forecast
6	Period	У	Level	Rate	Period	Error	Error
7	0		202.6246	-0.3682			
8	1	206	203.0051	-0.2933	202.2564	3.7436	14.0145
9	2	245	211.1694	0.5524	202.7118	42.2882	1788.2923
10	3	185	206.3775	0.0180	211.7219	-26.7219	714.0582
11	4	169	198.9164	-0.7299	206.3955	-37.3955	1398.4224
12	5	162	190.9492	-1.4536	198.1865	-36.1865	1309.4608
13	6	177	186.9964	-1.7036	189.4955	-12.4955	156,1383
14	7	207	189.6343	-1.2694	185.2929	21.7071	471.1995
15	8	216	193.8919	-0.7167	188.3649	27.6351	763.6997
16	9	193	193.1402	-0.7202	193.1752	-0.1752	0.0307
17	10	230	199.9360	0.0314	192.4199	37.5801	1412.2609
18	11	212	202.3739	0.2720	199.9673	12.0327	144.7850
19	12	192	200.5167	0.0591	202.6459	-10.6459	113.3354
20	13	162	192.8607	-0.7124	200.5758	-38.5758	1488.0961
21	14	189	191.5186	-0.7754	192.1483	-3.1483	9.9117
22	15	244	201.3946	0.2898	190.7433	53.2567	2836.2799
23	16	209	203.1475	0.4361	201.6844	7.3156	53.5182
24	17	207	204.2669	0.5044	203.5836	3.4164	11.6718
25	18	211	206.0170	0.6290	204.7713	6.2287	38.7969
26	19	210	207.3168	0.6961	206.6460	3.3540	11.2492
27	20	173	201.0103	-0.0042	208.0129	-35.0129	1225.9019

52	45	255	280.9500	4.4428	287.4375	-32.4375	1052.1900
53	46	312	290.7142	4.9749	285.3928	26.6072	707.9453
54	47	296	295.7513	4.9811	295.6891	0.3109	0.0966
55	48	307	301.9860	5.1065	300.7324	6.2676	39.2823
56	49	281	301.8740	4.5846	307.0924	-26.0924	680.8155
57	50	308	306.7669	4.6155	306.4586	1.5414	2.3759
58	51	280	305.1059	3.9878	311.3823	-31.3823	984.8515
59	52	345	316.2750	4.7059	309.0937	35.9063	1289.2627

• **Step 4**: Find the best combination of α and γ that minimizes SSE (or MSE)

🚽 SSE

• Example: Use Solver in Excel as an illustration

	Solver Parameters	×
	Set Target Cell: 50\$2 3 Equal To: O Max O Min O Value of: 0 By Changing Cells:	Solve Close
alpha	\$B\$2,\$C\$2 Guess	Options
	\$8\$2 <= 1	Reset All
gamma 🖌	<u>D</u> elete	Help

1	n	alpha	gamma	SSE	MSE	S			
2	52	0.247	0.0951	38884.2448	777.6849	27.887002			
3									
4					Forecast		Squared		
5	Time			Growth	Made Last	Forecast	Forecast		
6	Period	У	Level	Rate	Period	Error	Error		
7	0		202.6246	-0.3682					
8	1	206	203.1805	-0.2804	202.2564	3.7436	14.0145		
9	2	245	213.2921	0.7074	202.9001	42.0999	1772.4001		
10	3	185	206.8413	0.0270	213.9996	-28.9996	840.9751		
11	4	169	197.5208	-0.8615	206.8683	-37.8683	1434.0063		
12	5	162	188.1039	-1.6747	196.6593	-34.6593	1201.2665		
13	6	177	184.1017	-1.8960	186.4292	-9.4292	88.9096		
14	7	207	188.3260	-1.3142	182.2057	24.7943	614.7576		
15	8	216	194.1673	-0.6341	187.0117	28.9883	840.3188		
16	9	193	193.4016	-0.6466	193.5332	-0.5332	0.2843		
17	10	230	201.9486	0.2273	192.7550	37.2450	1387.1882		
•••••					• •	• • • • •			

52	45	255	281.4910	4.1454	290.1732	-35.1732	1237.1566
53	46	312	292.1440	4.7640	285.6364	26.3636	695.0399
54	47	296	296.6839	4.7427	296.9080	-0.9080	0.8245
55	48	307	302.8023	4.8734	301.4265	5.5735	31.0637
56	49	281	301.0910	4.2475	307.6757	-26.6757	711.5940
57	50	308	305.9955	4.3100	305.3386	2.6614	7.0832
58	51	280	302.8248	3.5989	310.3055	-30.3055	918.4227
59	52	345	315.9460	4.5040	306.4237	38.5763	1488.1288

- *p*-step-ahead forecast made at time *T*
 - $\hat{y}_{T+p}(T) = \ell_T + pb_T$ (p = 1, 2, 3, ...)
- Example
 - In period 52, the one-period-ahead sales forecast for period 53 is

$$\hat{y}_{53}(52) = \ell_{52} + b_{52} = 315.9460 + 4.5040 = 320.45$$

 In period 52, the three-period-ahead sales forecast for period 55 is

$$\hat{y}_{55}(52) = \ell_{52} + 3b_{52} = 315.9460 + 3(4.5040) = 329.458$$

• Example

- If we observe y_{53} = 330, we can either find a new set of (optimal) α and γ that minimize the SSE for 53 periods, or
- we can simply revise the estimate for the level and growth rate and recalculate the forecasts as follows:

$$\ell_{53} = \alpha y_{53} + (1 - \alpha)(\ell_{52} + b_{52})$$

= 0.247(330) + 0.753(315.946 + 4.5040) = 322.8089

 $b_{53} = \gamma(\ell_{53} - \ell_{52}) + (1 - \gamma)b_{52}$

= 0.095(322.8089 - 315.9460) + 0.905(4.5040) = 4.7281

 $\hat{y}_{54}(53) = \ell_{53} + b_{53} = 322.8089 + 4.7281 = 327.537$

 $\hat{y}_{55}(53) = \ell_{53} + 2b_{53} = 322.8089 + 2(4.7281) = 332.2651$



Holt-Winters Methods

- Two Holt-Winters methods are designed for time series that exhibit linear trend
 - <u>Additive Holt-Winters method</u>: used for time series with constant (additive) seasonal variations
 - <u>Multiplicative Holt-Winters method</u>: used for time series with increasing (multiplicative) seasonal variations
- Holt-Winters method is an exponential smoothing approach for handling SEASONAL data.
- The multiplicative Holt-Winters method is the better known of the two methods.

Multiplicative Holt-Winters Method

- It is generally considered to be best suited to forecasting time series that can be described by the equation:
 - $y_t = (\beta_0 + \beta_1 t) \times SN_t \times IR_t$
 - *SN*_t: seasonal pattern
 - *IR_t*: irregular component
- This method is appropriate when a time series has a linear trend with a multiplicative seasonal pattern for which the level ($\beta_0 + \beta_1 t$), growth rate (β_1), and the seasonal pattern (SN_t) may be slowly changing over time.

Multiplicative Holt-Winters Method

• Estimate of the level

$$\ell_T = \alpha(y_T / sn_{T-L}) + (1 - \alpha)(\ell_{T-1} + b_{T-1})$$

• Estimate of the growth rate (or trend)

$$b_{T} = \gamma (\ell_{T} - \ell_{T-1}) + (1 - \gamma) b_{T-1}$$

• Estimate of the seasonal factor

$$sn_T = \delta(y_T / \ell_T) + (1 - \delta)sn_{T-L}$$

where α , γ , and δ are smoothing constants between 0 and 1,

L = number of seasons in a year (L = 12 for monthly data, and L = 4 for quarterly data)



Multiplicative Holt-Winters Method

• Point forecast made at time T for y_{T+p}

 $\hat{y}_{T+p}(T) = (\ell_T + pb_T)sn_{T+p-L}$ (p = 1, 2, 3, ...)

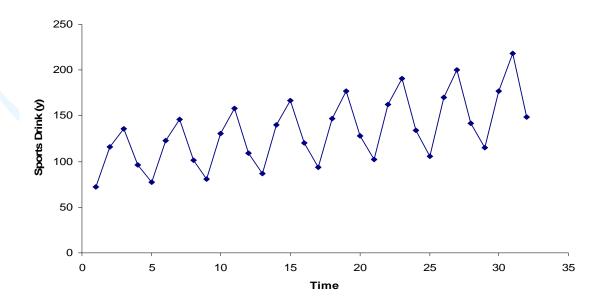
• MSE and the standard errors at time *T*

$$SSE = \sum_{t=1}^{T} [y_t - \hat{y}_t (t-1)]^2$$

$$MSE = \frac{SSE}{T-3}, \quad s = \sqrt{MSE}$$

• Use the Sports Drink example as an illustration

	Quarterly sales of Tiger Sports Drink									
Year										
Quarter	1	2	3	4	5	6	7	8		
1	72	77	81	87	94	102	106	115		
2	116	123	131	140	147	162	170	177		
3	136	146	158	167	177	191	200	218		
4	96	101	109	120	128	134	142	149		



• Observations:

- Linear upward trend over the 8-year period
- Magnitude of the seasonal span increases as the level of the time series increases
- ⇒ Multiplicative Holt-Winters method can be applied to forecast future sales

• **Step 1**: Obtain initial values for the level ℓ_0 , the growth rate b_0 , and the seasonal factors sn_{-3} , sn_{-2} , sn_{-1} , and sn_0 , by fitting a least squares trend line to <u>at</u> <u>least four or five years</u> of the historical data.

- *y*-intercept = ℓ_0 ; slope = b_0

- Example
 - Fit a least squares trend line to the first 16 observations
 - Trend line

 $\hat{y}_t = 95.2500 + 2.4706t$

 $- \ell_0 = 95.2500; b_0 = 2.4706$

SUMMARY OUTPUT	
Regression Sta	atistics
Multiple R	0.403809754
R Square	0.163062318
Adjusted R Square	0.103281055
Standard Error	27.58325823
Observations	16
ANOVA	
	df
Regression	1
Residual	14
Total	15
	Coefficients
Intercept	95.25
X Variable 1	2.470588235

- **Step 2**: Find the initial seasonal factors
 - 1. Compute \hat{y}_t for the in-sample observations used for fitting the regression. In this example, t = 1, 2, ..., 16.

 $\hat{y}_1 = 95.2500 + 2.4706(1) = 97.7206$

 $\hat{y}_2 = 95.2500 + 2.4706(2) = 100.1912$

•••••

 $\hat{y}_{16} = 95.2500 + 2.4706(16) = 134.7794$

- **Step 2**: Find the initial seasonal factors
 - 2. Detrend the data by computing $S_t = y_t / \hat{y}_t$ for each time period that is used in finding the least squares regression equation. In this example, t = 1, 2, ..., 16.

 $S_1 = y_1 / \hat{y}_1 = 72 / 97.7206 = 0.7368$ $S_2 = y_2 / \hat{y}_2 = 116 / 100.1912 = 1.1578$

•••••

 $S_{16} = y_{16} / \hat{y}_{16} = 120 / 134.7794 = 0.8903$

- **Step 2**: Find the initial seasonal factors
 - 3. Compute the average seasonal values for each of the *L* seasons. The *L* averages are found by computing the average of the detrended values for the corresponding season. For example, for quarter 1,

$$\overline{S}_{[1]} = \frac{S_1 + S_5 + S_9 + S_{13}}{4}$$
$$= \frac{0.7368 + 0.7156 + 0.6894 + 0.6831}{4} = 0.7062$$

Step 2: Find the initial seasonal factors

4. Multiply the average seasonal values by the normalizing constant

$$CF = \frac{L}{\sum_{i=1}^{L} \overline{S}_{[i]}}$$

such that the average of the seasonal factors is 1. The initial seasonal factors are

$$sn_{i-L} = \overline{S}_{[i]}(CF)$$
 (*i* = 1, 2, ..., *L*)

- **Step 2**: Find the initial seasonal factors
 - 4. Multiply the average seasonal values by the normalizing constant such that the average of the seasonal factors is 1.
 - Example CF = 4/3.9999 = 1.0000

 $sn_{-3} = sn_{1-4} = \overline{S}_{[1]}(CF) = 0.7062(1) = 0.7062$ $sn_{-2} = sn_{2-4} = \overline{S}_{[2]}(CF) = 1.1114(1) = 1.1114$ $sn_{-1} = sn_{3-4} = \overline{S}_{[3]}(CF) = 1.2937(1) = 1.2937$ $sn_{0} = sn_{4-4} = \overline{S}_{[1]}(CF) = 0.8886(1) = 0.8886$

Step 3: Calculate a point forecast of y₁ from time 0
 using the initial values

$$\hat{y}_{T+p}(T) = (\ell_T + pb_T)sn_{T+p-L} \quad (T = 0, \ p = 1)$$
$$\hat{y}_1(0) = (\ell_0 + b_0)sn_{1-4} = (\ell_0 + b_0)sn_{-3}$$
$$= (95.2500 + 2.4706)(0.7062)$$
$$= 69.0103$$

Step 4: Update the estimates l_T, b_T, and sn_T by using some predetermined values of smoothing constants.
Example: let α = 0.2, γ = 0.1, and δ = 0.1

$$\begin{split} \ell_1 &= \alpha (y_1 / sn_{1-4}) + (1 - \alpha)(\ell_0 + b_0) \\ &= 0.2(72 / 0.7062) + 0.8(95.2500 + 2.4706) = 98.5673 \\ b_1 &= \gamma (\ell_1 - \ell_0) + (1 - \gamma) b_0 \\ &= 0.1(98.5673 - 95.2500) + 0.9(2.4706) = 2.5553 \\ sn_1 &= \delta (y_1 / \ell_1) + (1 - \delta) sn_{1-4} \\ &= 0.1(72 / 98.5673) + 0.9(0.7062) = 0.7086 \\ \hat{y}_2(1) &= (\ell_1 + b_1) sn_{2-4} \\ &= (98.5673 + 2.5553)(1.1114) = 112.3876 \end{split}$$

$$\ell_{2} = \alpha (y_{2}/sn_{2-4}) + (1-\alpha)(\ell_{1}+b_{1})$$

= 0.2(116/1.1114) + 0.8(98.5673 + 2.5553)
= 101.7727
$$b_{2} = \gamma (\ell_{2} - \ell_{1}) + (1-\gamma)b_{1}$$

= 0.1(101.7727 - 98.5673) + 0.9(2.5553)
= 2.62031
$$sn_{2} = \delta (y_{2}/\ell_{2}) + (1-\delta)sn_{2-4}$$

= 0.1(116/101.7727) + 0.9(1.1114)
= 1.114239
$$\hat{y}_{3}(2) = (\ell_{2} + b_{2})sn_{3-4}$$

= (101.7727 + 2.62031)(1.2937)
= 135.053

$$\ell_{4} = \alpha (y_{4}/sn_{4-4}) + (1-\alpha)(\ell_{3} + b_{3})$$

= 0.2(96/0.8886) + 0.8(104.5393 + 2.6349)
= 107.3464
$$b_{4} = \gamma (\ell_{4} - \ell_{3}) + (1-\gamma)b_{3}$$

= 0.1(107.3464 - 104.5393) + 0.9(2.6349)
= 2.65212
$$sn_{4} = \delta (y_{4}/\ell_{4}) + (1-\delta)sn_{4-4}$$

= 0.1(96/107.3464) + 0.9(0.8886)
= 0.889170
$$\hat{y}_{5}(4) = (\ell_{4} + b_{4})sn_{5-4}$$

= (107.3464 + 2.65212)(0.7086)
= 77.945

1	n	alpha	gamma	delta	SSE	MSE	S	
2	32	0.2	0.1	0.1	177.3223	6.1146	2.4728	
3								
4								
5						Forecast		Squared
6				Growth	Seasonal	Made Last	Forecast	Forecas
7	Time	у	Level	Rate	Factor	Period	Error	Error
8	-3	-			0.7062			
9	-2				1.1114			
10	-1				1.2937			
11	0		95.25	2.4706	0.8886			
12	1	72	98.56729	2.5553	0.7086	69.0103	2.9897	8.9384
13	2	116	101.7726	2.6203	1.1142	112.3876	3.6124	13.049
14	3	136	104.5393	2.6349	1.2944	135.0531	0.9469	0.8967
15	4	96	107.3464	2.6521	0.8892	95.2350	0.7650	0.5853
16	5	77	109.731	2.6254	0.7079	77.9478	-0.9478	0.8984
17	6	123	111.9629	2.5860	1.1127	125.1919	-2.1919	4.8043
18	7	146	114.1974	2.5509	1.2928	148.2750	-2.2750	5.1755
19	8	101	116.1165	2.4877	0.8872	103.8091	-2.8091	7.8911
20	9	81	117.7668	2.4040	0.7059	83.9641	-2.9641	8.7858
21	10	131	119.6835	2.3552	1.1109	133.7108	-2.7108	7.3482
22	11	158	122.0734	2.3587	1.2930	157.7754	0.2246	0.0504
23	12	109	124.1164	2.3271	0.8863	110.4005	-1.4005	1.961
24	13	87	125.8035	2.2631	0.7045	89.2593	-2.2593	5.1044
25	14	140	127.6589	2.2224	1.1094	142.2642	-2.2642	5.1268
26	15	167	129.7369	2.2079	1.2924	167.9337	-0.9337	0.8718

38	27	200	156.1396	2.1752	1.2903	202.0396	-2.0396	4.1601
39	28	142	158.5505	2.1988	0.8908	140.9508	1.0492	1.1008
40	29	115	161.2803	2.2519	0.7047	113.1314	1.8686	3.4918
41	30	177	162.8178	2.1804	1.1046	180.9529	-3.9529	15.6252
42	31	218	165.7889	2.2595	1.2928	212.8988	5.1012	26.0220
43	32	149	167.8899	2.2437	0.8905	149.7057	-0.7057	0.4981

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- **Step 5**: Find the most suitable combination of α , γ , and δ that minimizes SSE (or MSE)
- Example: Use Solver in Excel as an illustration

_SSF

	1002	
	Solver Parameters	×
	Set Target Cell: \$5\$2	<u>S</u> olve
	Equal To: O Max O Min O Value of: 0 By Changing Cells:	Close
alpha	\$8\$2,\$C\$2,\$D\$2	
	Subject to the Constraints:	Options
	\$B\$2 <= 1 \$B\$2 >= 0	
gamma 🔶 🚽	\$C\$2 <= 1 \$C\$2 >= 0	Reset All
	\$D\$2 <= 1 \$D\$2 >= 0	Help
delta*		

1	n	alpha	gamma	delta	SSE	MSE	S	
2	32	0.3356	0.0455	0.1342	168.4747	5.8095	2.4103	
3								
4								
5						Forecast		Squared
6				Growth	Seasonal	Made Last	Forecast	Forecast
7	Time	у	Level	Rate	Factor	Period	Error	Error
8	-3	-			0.7062			
9	-2				1.1114			
10	-1				1.2937			
11	0		95.25	2.4706	0.8886			
12	1	72	99.14144	2.5353	0.7089	69.0103	2.9897	8.9384
13	2	116	102.5816	2.5765	1.1140	113.0035	2.9965	8.9789
14	3	136	105.1469	2.5760	1.2937	136.0431	-0.0431	0.0019
15	4	96	107.8277	2.5808	0.8888	95.7226	0.2774	0.0769
16	5	77	109.8084	2.5534	0.7079	78.2674	-1.2674	1.6064
17	6	123	111.7076	2.5236	1.1123	125.1717	-2.1717	4.7164
18	7	146	113.7703	2.5027	1.2923	147.7768	-1.7768	3.1569
19	8	101	115.3868	2.4623	0.8870	103.3468	-2.3468	5.5075
20	9	81	116.7014	2.4100	0.7060	83.4207	-2.4207	5.8597

3	8	27	200	155.9042	2.2691	1.2906	202.1107	-2.1107	4.4552
3	9	28	142	158.5811	2.2876	0.8915	140.9173	1.0827	1.1721
4	0	29	115	161.7496	2.3278	0.7044	113.1540	1.8460	3.4078
4	1	30	177	162.7095	2.2655	1.1038	181.5085	-4.5085	20.3262
4	2	31	218	166.2957	2.3256	1.2934	212.9210	5.0790	25.7957
4	3	32	149	168.1213	2.3028	0.8908	150.3283	-1.3283	1.7643

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Multiplicative Holt-Winters Method

• *p*-step-ahead forecast made at time *T*

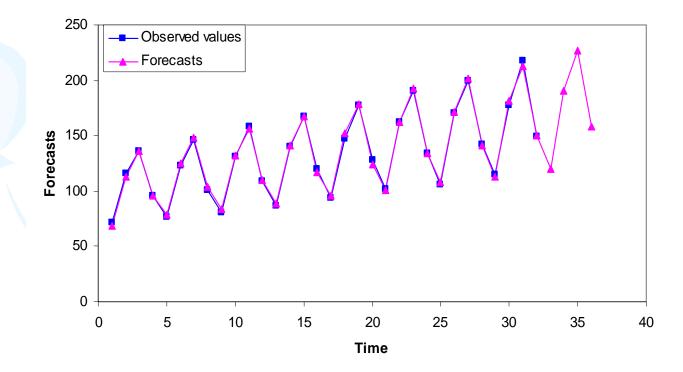
 $\hat{y}_{T+p}(T) = (\ell_T + pb_T)sn_{T+p-L} \quad (p = 1, 2, 3, ...)$

• Example

 $\begin{aligned} \hat{y}_{33}(32) &= (\ell_{32} + b_{32})sn_{33-4} = (168.1213 + 2.3028)(0.7044) = 120.0467 \\ \hat{y}_{34}(32) &= (\ell_{32} + 2b_{32})sn_{34-4} = [168.1213 + 2(2.3028)](1.1038) = 190.6560 \\ \hat{y}_{35}(32) &= (\ell_{32} + 3b_{32})sn_{35-4} = [(168.1213 + 3(2.3028)](1.2934) = 226.3834 \\ \hat{y}_{36}(32) &= (\ell_{32} + 4b_{32})sn_{36-4} = [(168.1213 + 4(2.3028)](0.8908) = 157.9678 \end{aligned}$

Multiplicative Holt-Winters Method

• Example



Forecast Plot for Sports Drink Sales

- It is generally considered to be best suited to forecasting a time series that can be described by the equation:
 - $y_t = (\beta_0 + \beta_1 t) + SN_t + IR_t$
 - *SN*_t: seasonal pattern
 - *IR_t*: irregular component
- This method is appropriate when a time series has a linear trend with a constant (additive) seasonal pattern such that the level $(\beta_0 + \beta_1 t)$, growth rate (β_1) , and the seasonal pattern (SN_t) may be slowly changing over time.

• Estimate of the level

$$\ell_T = \alpha(y_T - sn_{T-L}) + (1 - \alpha)(\ell_{T-1} + b_{T-1})$$

• Estimate of the growth rate (or trend)

$$b_{T} = \gamma(\ell_{T} - \ell_{T-1}) + (1 - \gamma)b_{T-1}$$

• Estimate of the seasonal factor

$$sn_T = \delta(y_T - \ell_T) + (1 - \delta)sn_{T-L}$$

where α , γ , and δ are smoothing constants between 0 and 1,

L = number of seasons in a year (L = 12 for monthly data, and L = 4 for quarterly data)



• Point forecast made at time *T* for y_{T+p}

$$\hat{y}_{T+p}(T) = \ell_T + pb_T + sn_{T+p-L}$$
 (p = 1, 2, 3,...)

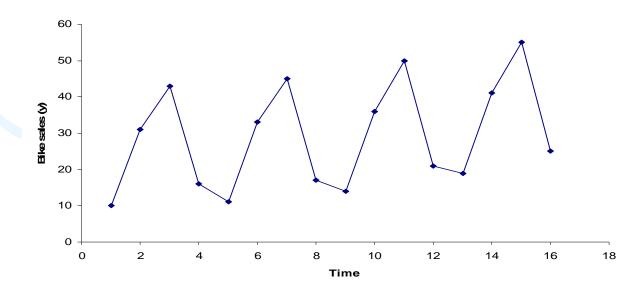
• MSE and the standard error *s* at time *T*

$$SSE = \sum_{t=1}^{T} [y_t - \hat{y}_t (t-1)]^2$$

$$MSE = \frac{SSE}{T-3}, \quad s = \sqrt{MSE}$$

• Consider the Mountain Bike example,

	Quarterly sales of the TRK-50 Mountain Bike								
		ar							
Quarter	1	2	3	4					
1	10	11	14	19					
2	31	33	36	41					
3	43	45	50	55					
4	16	17	21	25					



- Observations:
 - Linear upward trend over the 4-year period
 - Magnitude of seasonal span is almost constant as the level of the time series increases
 - ⇒ Additive Holt-Winters method can be applied to forecast future sales

• **Step 1**: Obtain initial values for the level ℓ_0 , the growth rate b_0 , and the seasonal factors $sn_{.3}$, $sn_{.2}$, $sn_{.1}$, and sn_0 , by fitting a least squares trend line to <u>at</u> <u>least four or five years</u> of the historical data.

- *y*-intercept = ℓ_0 ; slope = b_0

- Example
 - Fit a least squares trend line to all 16 observations
 - Trend line

 $\hat{y}_t = 20.85 + 0.980882 t$

 $-\ell_0 = 20.85; b_0 = 0.9809$

SUMMARY OUTPUT	
Regression St	atistics
Multiple R	0.320508842
R Square	0.102725918
Adjusted R Square	0.038634912
Standard Error	14.28614022
Observations	16
ANOVA	
	df
Regression	1
Residual	14
Total	15
	Coefficients
Intercept	20.85
Time	0.980882353

- **Step 2**: Find the initial seasonal factors
 - 1. Compute \hat{y}_t for each time period that is used in finding the least squares regression equation. In this example, t = 1, 2, ..., 16.

 $\hat{y}_1 = 20.85 + 0.980882(1) = 21.8309$

 $\hat{y}_2 = 20.85 + 0.980882(2) = 22.8118$

 $\hat{y}_{16} = 20.85 + 0.980882(16) = 36.5441$

- **Step 2**: Find the initial seasonal factors
 - 2. Detrend the data by computing $S_t = y_t \hat{y}_t$ for each observation used in the least squares fit. In this example, t = 1, 2, ..., 16.

$$S_1 = y_1 - \hat{y}_1 = 10 - 21.8309 = -11.8309$$
$$S_2 = y_2 - \hat{y}_2 = 31 - 22.8112 = 8.1882$$

$$S_{16} = y_{16} - \hat{y}_{16} = 25 - 36.5441 = -11.5441$$

- **Step 2**: Find the initial seasonal factors
 - 3. Compute the average seasonal values for each of the *L* seasons. The *L* averages are found by computing the average of the detrended values for the corresponding season. For example, for quarter 1,

$$\overline{S}_{[1]} = \frac{S_1 + S_5 + S_9 + S_{13}}{4}$$
$$= \frac{(-11.8309) + (-14.7544) + (-15.6779) + (-14.6015)}{4} = -14.2162$$

Step 2: Find the initial seasonal factors

4. Compute the average of the *L* seasonal factors. The average should be 0.



Step 3: Calculate a point forecast of y₁ from time 0
 using the initial values

$$\hat{y}_{T+p}(T) = \ell_T + pb_T + sn_{T+p-L} \quad (T = 0, p = 1)$$
$$\hat{y}_1(0) = \ell_0 + b_0 + sn_{1-4} = \ell_0 + b_0 + sn_{-3}$$
$$= 20.85 + 0.9809 + (-14.2162) = 7.6147$$

Step 4: Update the estimates l_T, b_T, and sn_T by using some predetermined values of smoothing constants.
Example: let α = 0.2, γ = 0.1, and δ = 0.1

$$\ell_1 = \alpha(y_1 - sn_{1-4}) + (1 - \alpha)(\ell_0 + b_0)$$

= 0.2(10 - (-14.2162)) + 0.8(20.85 + 0.9808) = 22.3079
$$b_1 = \gamma(\ell_1 - \ell_0) + (1 - \gamma)b_0$$

= 0.1(22.3079 - 20.85) + 0.9(0.9809) = 1.0286

 $sn_1 = \delta(y_1 - \ell_1) + (1 - \delta)sn_{1-4}$ = 0.1(10 - 22.3079) + 0.9(-14.2162) = -14.0254

$$\hat{y}_{2}(1) = \ell_{1} + b_{1} + sn_{2-4} = \ell_{1} + b_{1} + sn_{-2}$$

= 22.3079 + 1.0286 + 6.5529 = 29.8895

4				1.1.	0.05	1405		
1	n	alpha	gamma	delta	SSE	MSE	S	
2	16	0.2000	0.1000	0.1000	25.2166	1.9397	1.3927	
3								
4								
5						Forecast		Squared
6				Growth	Seasonal	Made Last	Forecast	Forecast
7	Time	у	Level	Rate	Factor	Period	Error	Error
8	-3				-14.2162			
9	-2				6.5529			
10	-1				18.5721			
11	0		20.85	0.9809	-10.9088			
12	1	10	22.30794	1.0286	-14.0254	7.6147	2.3853	5.6896
13	2	31	23.55864	1.0508	6.6418	29.8895	1.1105	1.2333
14	3	43	24.57314	1.0472	18.5575	43.1815	-0.1815	0.0329
15	4	16	25.87801	1.0729	-10.8057	14.7115	1.2885	1.6603
16	5	11	26.56583	1.0344	-14.1794	12.9256	-1.9256	3.7079
17	6	33	27.35185	1.0096	6.5424	34.2420	-1.2420	1.5427
18	7	45	27.97764	0.9712	18.4040	46.9190	-1.9190	3.6825
19	8	17	28.72023	0.9483	-10.8972	18.1431	-1.1431	1.3067
20	9	14	29.37074	0.9186	-14.2985	15.4892	-1.4892	2.2176
21	10	36	30.12295	0.9019	6.4759	36.8317	-0.8317	0.6918
22	11	50	31.1391	0.9133	18.4497	49.4289	0.5711	0.3262
23	12	21	32.0214	0.9102	-10.9096	21.1553	-0.1553	0.0241
24	13	19	33.00502	0.9176	-14.2692	18.6331	0.3669	0.1346
25	14	41	34.04291	0.9296	6.5240	40.3985	0.6015	0.3618
26	15	55	35.28807	0.9612	18.5759	53.4222	1.5778	2.4894
27	16	25	36.18131	0.9544	-10.9368	25.3396	-0.3396	0.1153

• **Step 5**: Find the most suitable combination of α , γ , and δ that minimizes SSE (or MSE)

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• Example: Use Solver in Excel as an illustration

	Solver Parameters	×
	Set Target Cell: §E\$2	Solve
	Equal To: O Max O Min O Value of: 0	Close
alpha	\$8\$2,\$C\$2,\$D\$2	
	-Subject to the Constraints:	Options
	\$8\$2 <= 1 \$8\$2 >= 0	
gamma 🔶 🚽	\$C\$2 <= 1 \$C\$2 >= 0	
Ŭ	\$D\$2 <= 1 \$D\$2 >= 0	<u>R</u> eset All
		<u>H</u> elp
delta		

1	n	alpha	gamma	delta	SSE	MSE	S	
2	16	0.5606	0.0000	0.0000	18.7975	1.4460	1.2025	
3								
4								
5						Forecast		Squared
6				Growth	Seasonal	Made Last	Forecast	Forecast
7	Time	У	Level	Rate	Factor	Period	Error	Error
8	-3				-14.2162			
9	-2				6.5529			
10	-1				18.5721			
11	0		20.85	0.9809	-10.9088			
12	1	10	23.16818	0.9809	-14.2162	7.6147	2.3853	5.6896
13	2	31	24.31613	0.9809	6.5529	30.7020	0.2980	0.0888
14	3	43	24.80977	0.9809	18.5721	43.8691	-0.8691	0.7553
15	4	16	26.41755	0.9809	-10.9088	14.8818	1.1182	1.2503
16	5	11	26.17496	0.9809	-14.2162	13.1823	-2.1823	4.7622
17	6	33	26.75847	0.9809	6.5529	33.7088	-0.7088	0.5024
18	7	45	27.00412	0.9809	18.5721	46.3114	-1.3114	1.7198
19	8	17	27.94229	0.9809	-10.9088	17.0762	-0.0762	0.0058
20	9	14	28.5268	0.9809	-14.2162	14.7070	-0.7070	0.4998
21	10	36	29.47369	0.9809	6.5529	36.0606	-0.0606	0.0037
22	11	50	31.00029	0.9809	18.5721	49.0266	0.9734	0.9474
23	12	21	31.94061	0.9809	-10.9088	21.0723	-0.0723	0.0052
24	13	19	33.0867	0.9809	-14.2162	18.7053	0.2947	0.0868
25	14	41	34.28034	0.9809	6.5529	40.6205	0.3795	0.1440
26	15	55	35.91533	0.9809	18.5721	53.8333	1.1667	1.3612
27	16	25	36.34264	0.9809	-10.9088	25.9874	-0.9874	0.9749

• *p*-step-ahead forecast made at time *T*

 $\hat{y}_{T+p}(T) = \ell_T + pb_T + sn_{T+p-L}$ (p = 1, 2, 3,...)

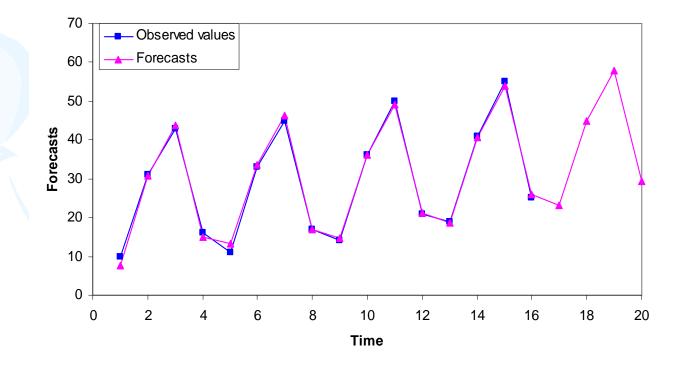
• Example

 $\hat{y}_{17}(16) = \ell_{16} + b_{16} + sn_{17-4} = 36.3426 + 0.9809 - 14.2162 = 23.1073$

 $\hat{y}_{18}(16) = \ell_{16} + 2b_{16} + sn_{18-4} = 36.3426 + 2(0.9809) + 6.5529 = 44.8573$ $\hat{y}_{19}(16) = \ell_{16} + 3b_{16} + sn_{19-4} = 36.3426 + 3(0.9809) + 18.5721 = 57.8573$ $\hat{y}_{20}(16) = \ell_{16} + 4b_{16} + sn_{20-4} = 36.3426 + 4(0.9809) - 10.9088 = 29.3573$

• Example

Forecast Plot for Mountain Bike Sales



Chapter Summary

- Simple Exponential Smoothing
 - No trend, no seasonal pattern
- Holt's Trend Corrected Exponential Smoothing
 - Trend, no seasonal pattern
- Holt-Winters Methods
 - Both trend and seasonal pattern
 - Multiplicative Holt-Winters method
 - Additive Holt-Winters Method