



# Chapter 7: Forecasting

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Statistics, Data Analysis, and  
Decision Modeling, Fifth Edition  
James R. Evans



# Forecasting Techniques

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- Qualitative and judgmental
- Statistical time series models
- Explanatory/causal models



# Qualitative and Judgmental Methods

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- **Historical analogy** – comparative analysis with a previous situation
- **Delphi Method** – response to a sequence of questionnaires by a panel of experts



# Indicators and Indexes

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- **Indicators** – measures believed to influence the behavior of a variable we wish to forecast
  - Leading indicators
  - Lagging indicators
- **Index** – a weighted combination of indicators
- Indicators and indexes are often used in economic forecasting



# Example Dept. of Commerce Index of Leading Indicators

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- Average weekly hours, manufacturing
- Average weekly initial claims, unemployment insurance
- New orders, consumer goods and materials
- Vendor performance—slower deliveries
- New orders, nondefense capital goods
- Building permits, private housing
- Stock prices, 500 common stocks (Standard & Poor)
- Money supply
- Interest rate spread
- Index of consumer expectations (University of Michigan)

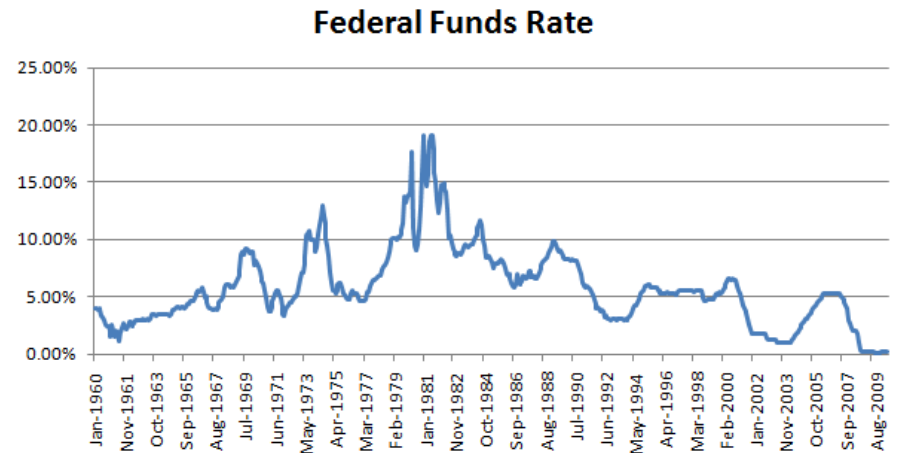
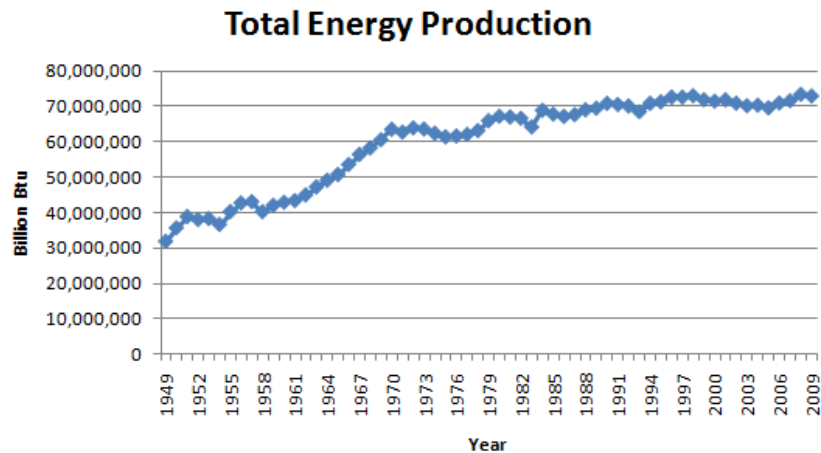


# Time Series

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- A **time series** is a stream of historical data
- Components of time series
  - Trend
  - Short-term seasonal effects
  - Longer-term cyclical effects

# Examples of Time Series





# Statistical Forecasting Methods

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- Moving average
- Exponential smoothing
- Regression analysis





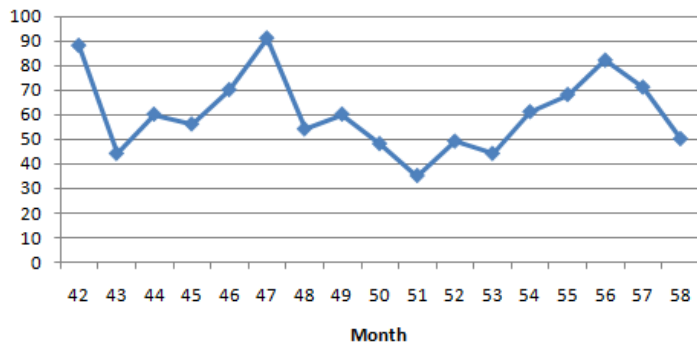
# Simple Moving Average

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- Average random fluctuations in a time series to infer short-term changes in direction
- **Assumption**: future observations will be similar to recent past
- Moving average for next period = average of most recent  $k$  observations

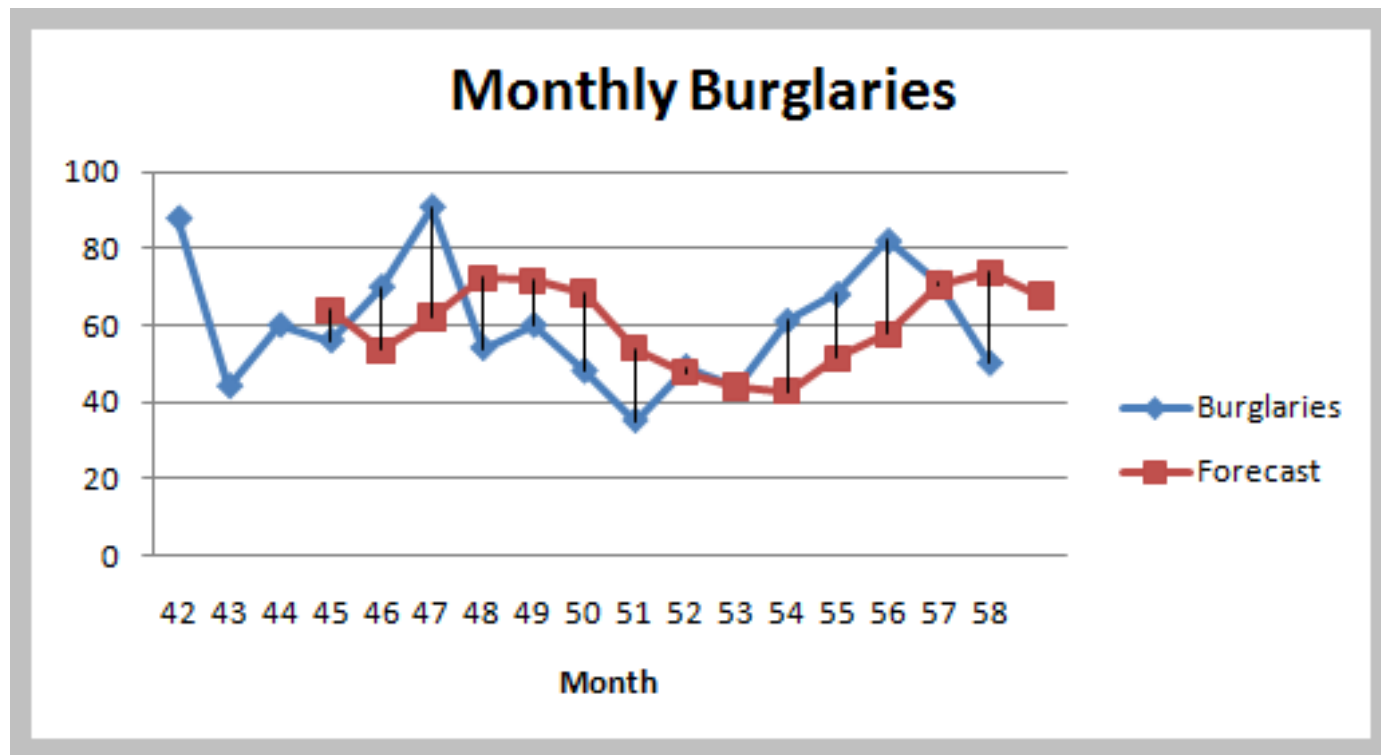
# Example: Moving Average Forecast With $k = 3$

Monthly Burglaries



	C	D	E	F
1	After Citizen-Police Program		Moving Average	
2	Month	Monthly burglaries	Forecast	
3	42	88		
4	43	44		
5	44	60		
6	45	56	64.00	Forecast for month 45 =AVERAGE(D3:D5)
7	46	70	53.33	
8	47	91	62.00	
9	48	54	72.33	
10	49	60	71.67	
11	50	48	68.33	
12	51	35	54.00	
13	52	49	47.67	
14	53	44	44.00	
15	54	61	42.67	
16	55	68	51.33	
17	56	82	57.67	
18	57	71	70.33	
19	58	50	73.67	Forecast for month 59 =AVERAGE(D17:D19)
20	59		67.67	
21				

# Time Series Data and Moving Averages



# Alternative Moving Average Models

	A	B	C	D	E	F	G	H
1	<b>After Citizen-Police Program</b>						<b>3 Period</b>	
2	<b>Month</b>	<b>Monthly burglaries</b>	<b>k = 2</b>	<b>Error</b>	<b>k = 3</b>	<b>Error</b>	<b>Weighted</b>	<b>Error</b>
3	42	88						
4	43	44						
5	44	60	66.00	-6.00				
6	45	56	52.00	4.00	64.00	-8.00	58.00	-2.00
7	46	70	58.00	12.00	53.33	16.67	56.00	14.00
8	47	91	63.00	28.00	62.00	29.00	64.80	26.20
9	48	54	80.50	-26.50	72.33	-18.33	81.20	-27.20
10	49	60	72.50	-12.50	71.67	-11.67	66.70	-6.70
11	50	48	57.00	-9.00	68.33	-20.33	61.30	-13.30
12	51	35	54.00	-19.00	54.00	-19.00	52.20	-17.20
13	52	49	41.50	7.50	47.67	1.33	41.40	7.60
14	53	44	42.00	2.00	44.00	0.00	44.70	-0.70
15	54	61	46.50	14.50	42.67	18.33	44.60	16.40
16	55	68	52.50	15.50	51.33	16.67	54.70	13.30
17	56	82	64.50	17.50	57.67	24.33	63.50	18.50
18	57	71	75.00	-4.00	70.33	0.67	75.70	-4.70
19	58	50	76.50	-26.50	73.67	-23.67	74.00	-24.00
20	59		60.50		67.67		59.50	



# Error Metrics and Forecast Accuracy

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- Mean absolute deviation (MAD)

$$\text{MAD} = \frac{\sum_{i=1}^n |A_t - F_t|}{n}$$

- Mean square error (MSE)

$$\text{MSE} = \frac{\sum_{i=1}^n (A_t - F_t)^2}{n}$$

- Mean absolute percentage error (MAPE)

$$\text{MAPE} = \frac{\sum_{i=1}^n \left| \frac{A_t - F_t}{A_t} \right|}{n}$$



# Summary of Error Metrics for Burglary Data

**TABLE 7.2** Error Metrics for Moving Average Models of Burglary Data

	$k = 2$	$k = 3$	Three-Period Weighted
MAD	13.63	14.86	13.70
MSE	254.38	299.84	256.31
RMSE	15.95	17.32	16.01
MAPE	23.63%	26.53%	24.46%



# Exponential Smoothing

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- Exponential smoothing model:

$$\begin{aligned} F_{t+1} &= (1 - \alpha)F_t + \alpha A_t \\ &= F_t + \alpha (A_t - F_t) \end{aligned}$$

- $F_{t+1}$  is the forecast for time period  $t+1$ ,
- $F_t$  is the forecast for period  $t$ ,
- $A_t$  is the observed value in period  $t$ , and
- $\alpha$  is a constant between 0 and 1, called the smoothing constant.

# Exponential Smoothing Example

	C	D	E	F	G	H	I	J	K	L	M
1	<b>After Citizen-Police Program</b>		<b>Smoothing Constant</b>								
2	<b>Month</b>	<b>Monthly burglaries</b>	<b>0.1</b>	<b>0.2</b>	<b>0.3</b>	<b>0.4</b>	<b>0.5</b>	<b>0.6</b>	<b>0.7</b>	<b>0.8</b>	<b>0.9</b>
3	42	88	88.00	88.00	88.00	88.00	88.00	88.00	88.00	88.00	88.00
4	43	44	88.00	88.00	88.00	88.00	88.00	88.00	88.00	88.00	88.00
5	44	60	83.60	79.20	74.80	70.40	66.00	61.60	57.20	52.80	48.40
6	45	56	81.24	75.36	70.36	66.24	63.00	60.64	59.16	58.56	58.84
7	46	70	78.72	71.49	66.05	62.14	59.50	57.86	56.95	56.51	56.28
8	47	91	77.84	71.19	67.24	65.29	64.75	65.14	66.08	67.30	68.63
9	48	54	79.16	75.15	74.37	75.57	77.88	80.66	83.53	86.26	88.76
10	49	60	76.64	70.92	68.26	66.94	65.94	64.66	62.86	60.45	57.48
11	50	48	74.98	68.74	65.78	64.17	62.97	61.87	60.86	60.09	59.75
12	51	35	72.28	64.59	60.45	57.70	55.48	53.55	51.86	50.42	49.17
13	52	49	68.55	58.67	52.81	48.62	45.24	42.42	40.06	38.08	36.42
14	53	44	66.60	56.74	51.67	48.77	47.12	46.37	46.32	46.82	47.74
15	54	61	64.34	54.19	49.37	46.86	45.56	44.95	44.70	44.56	44.37
16	55	68	64.00	55.55	52.86	52.52	53.28	54.58	56.11	57.71	59.34
17	56	82	64.40	58.04	57.40	58.71	60.64	62.63	64.43	65.94	67.13
18	57	71	66.16	62.83	64.78	68.03	71.32	74.25	76.73	78.79	80.51
19	58	50	66.65	64.47	66.65	69.22	71.16	72.30	72.72	72.56	71.95
20	59		64.98	61.57	61.65	61.53	60.58	58.92	56.82	54.51	52.20
21		<b>MAD</b>	19.33	17.16	16.15	15.36	14.93	14.71	14.72	14.88	15.36
22		<b>MSE</b>	496.07	390.84	359.18	346.56	340.77	338.41	339.03	343.32	352.38
23		<b>RMSE</b>	22.273	19.77	18.952	18.616	18.46	18.396	18.413	18.529	18.772
24		<b>MAPE</b>	38.28%	32.71%	30.12%	28.36%	27.54%	27.09%	27.09%	27.38%	28.23%





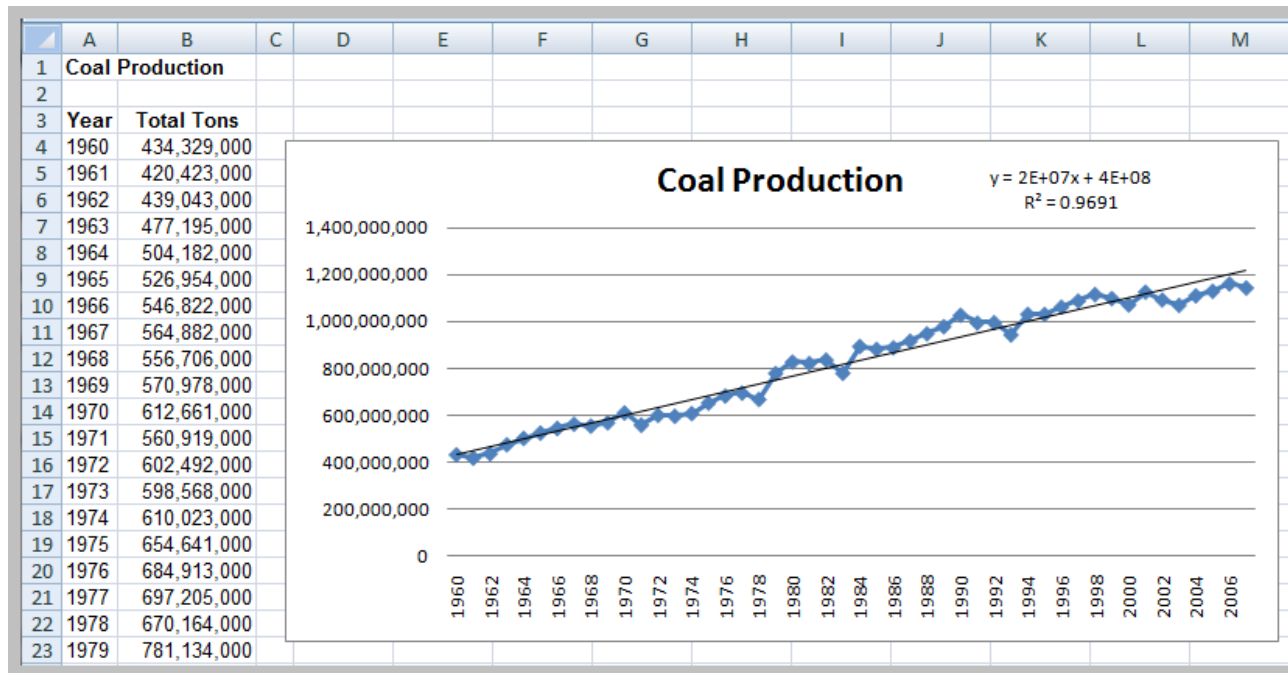
# Forecasting Models With Linear Trends

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- Double Moving Average
- Double Exponential Smoothing
- Based on the linear trend equation

$$F_{t+k} = a_t + b_t k$$

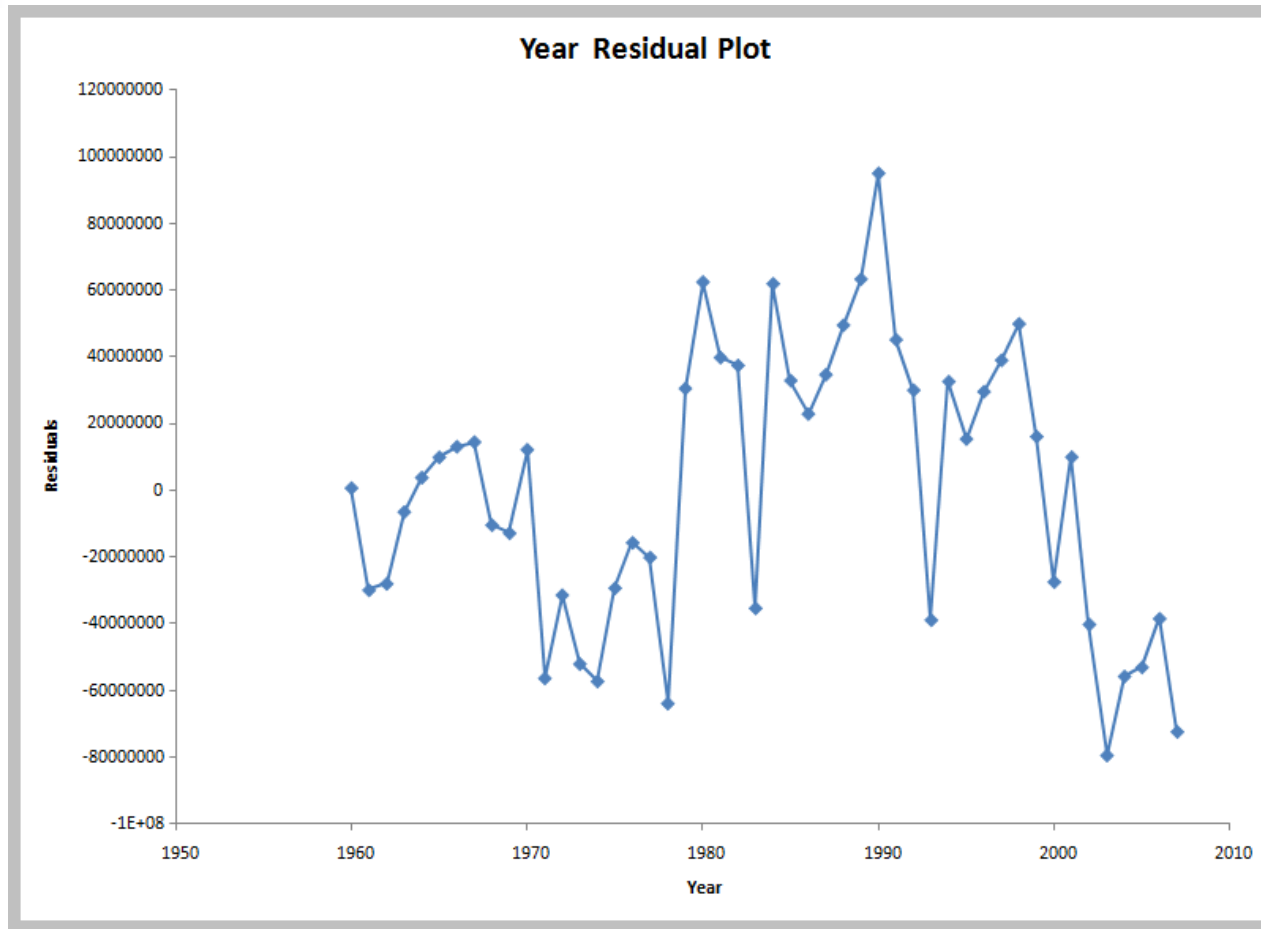
# Regression-Based Forecasting



A forecast for 2008 would be:

$$\text{Tons} = 416,896,322.7 + 16,685,398.57 * (49) = 1,234,480,853$$

# Autocorrelated Data





# Autoregressive Models

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- First-order autoregressive model
  - $Y_i = a_0 + a_1 Y_{i-1} + \delta_i$
- Second-order autoregressive model
  - $Y_i = a_0 + a_1 Y_{i-1} + a_2 Y_{i-2} + \delta_i$



# Portion of Coal Production File for Autoregressive Modeling

	A	B	C	D	E
1	<b>Coal Production</b>				
2					
3	<b>Year</b>	<b>Total Tons</b>	<b>Year - 1</b>	<b>Year - 2</b>	<b>Year - 3</b>
4	1960	434,329,000			
5	1961	420,423,000	434,329,000		
6	1962	439,043,000	420,423,000	434,329,000	
7	1963	477,195,000	439,043,000	420,423,000	434,329,000
8	1964	504,182,000	477,195,000	439,043,000	420,423,000
9	1965	526,954,000	504,182,000	477,195,000	439,043,000
10	1966	546,822,000	526,954,000	504,182,000	477,195,000

# Third-Order Autoregressive Model

	A	B	C	D	E	F	G
1	SUMMARY OUTPUT						
2							
3	<i>Regression Statistics</i>						
4	Multiple R	0.988073439					
5	R Square	0.97628912					
6	Adjusted R Square	0.974554178					
7	Standard Error	35247696.59					
8	Observations	45					
9							
10	ANOVA						
11		<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>	
12	Regression	3	2.09738E+18	6.99125E+17	562.721337	2.49811E-33	
13	Residual	41	5.09384E+16	1.2424E+15			
14	Total	44	2.14831E+18				
15							
16		<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>
17	Intercept	50332718.33	20917609.66	2.406236618	0.020709694	8088749.075	92576687.59
18	Year - 1	0.565292456	0.154196228	3.666058917	0.000700825	0.25388686	0.876698052
19	Year - 2	0.247260179	0.174243467	1.41904993	0.163442473	-0.104631637	0.599151996
20	Year - 3	0.156914847	0.151580327	1.035192694	0.306646344	-0.14920783	0.463037525

# Second-Order Autogressive Model

	A	B	C	D	E	F	G
1	SUMMARY OUTPUT						
2							
3	<i>Regression Statistics</i>						
4	Multiple R	0.988567258					
5	R Square	0.977265224					
6	Adjusted R Square	0.976207792					
7	Standard Error	34986337.08					
8	Observations	46					
9							
10	ANOVA						
11		<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>	
12	Regression	2	2.26249E+18	1.13125E+18	924.1877675	4.66498E-36	
13	Residual	43	5.26339E+16	1.22404E+15			
14	Total	45	2.31513E+18				
15							
16		<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>
17	Intercept	43087157.38	19471726.51	2.212806213	0.032269724	3818678.935	82355635.83
18	Year - 1	0.63224491	0.142019472	4.451818489	5.95528E-05	0.345835353	0.918654467
19	Year - 2	0.341258327	0.141128508	2.418067984	0.019912562	0.056645569	0.625871085



# Forecasting Models With Seasonality

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- Additive model

$$F_{t+k} = a_t + S_{t-s+k}$$

- Multiplicative model

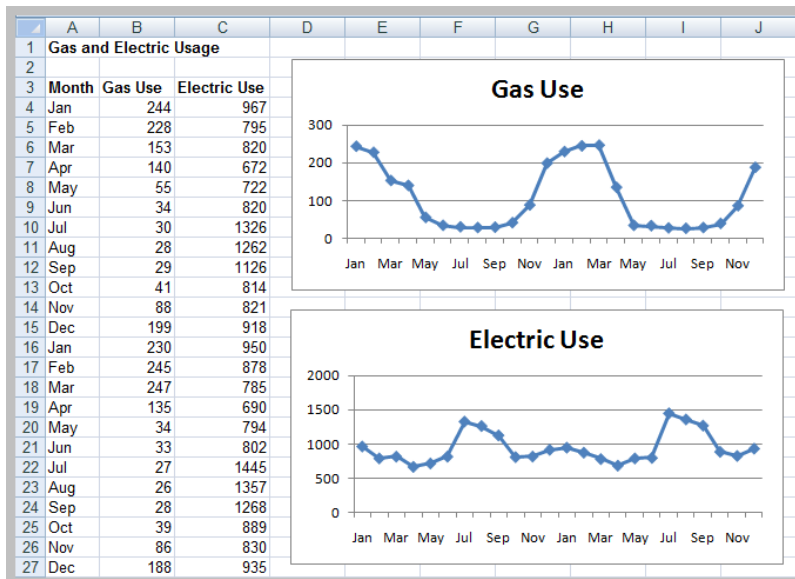
$$F_{t+k} = a_t S_{t-s+k}$$



# Incorporating Seasonality into Regression Models

- Use dummy variables. Example:

$$\begin{aligned}\text{Gas usage} = & \beta_0 + \beta_1 \text{Time} + \beta_2 \text{February} + \beta_3 \text{March} + \beta_4 \text{April} + \beta_5 \text{May} \\ & + \beta_6 \text{June} + \beta_7 \text{July} + \beta_8 \text{August} + \beta_9 \text{September} + \beta_{10} \text{October} \\ & + \beta_{11} \text{November} + \beta_{12} \text{December}\end{aligned}$$





# Data Matrix

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
3	Month	Gas Use	Time	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
4	Jan	244	1	0	0	0	0	0	0	0	0	0	0	0
5	Feb	228	2	1	0	0	0	0	0	0	0	0	0	0
6	Mar	153	3	0	1	0	0	0	0	0	0	0	0	0
7	Apr	140	4	0	0	1	0	0	0	0	0	0	0	0
8	May	55	5	0	0	0	1	0	0	0	0	0	0	0
9	Jun	34	6	0	0	0	0	1	0	0	0	0	0	0
10	Jul	30	7	0	0	0	0	0	1	0	0	0	0	0
11	Aug	28	8	0	0	0	0	0	0	1	0	0	0	0
12	Sep	29	9	0	0	0	0	0	0	0	1	0	0	0
13	Oct	41	10	0	0	0	0	0	0	0	0	1	0	0
14	Nov	88	11	0	0	0	0	0	0	0	0	0	1	0
15	Dec	199	12	0	0	0	0	0	0	0	0	0	0	1
16	Jan	230	13	0	0	0	0	0	0	0	0	0	0	0
17	Feb	245	14	1	0	0	0	0	0	0	0	0	0	0
18	Mar	247	15	0	1	0	0	0	0	0	0	0	0	0
19	Apr	135	16	0	0	1	0	0	0	0	0	0	0	0
20	May	34	17	0	0	0	1	0	0	0	0	0	0	0
21	Jun	33	18	0	0	0	0	1	0	0	0	0	0	0
22	Jul	27	19	0	0	0	0	0	1	0	0	0	0	0
23	Aug	26	20	0	0	0	0	0	0	1	0	0	0	0
24	Sep	28	21	0	0	0	0	0	0	0	1	0	0	0
25	Oct	39	22	0	0	0	0	0	0	0	0	1	0	0
26	Nov	86	23	0	0	0	0	0	0	0	0	0	1	0
27	Dec	188	24	0	0	0	0	0	0	0	0	0	0	1

# Regression Model Results

	A	B	C	D	E	F	G
1	SUMMARY OUTPUT						
2							
3	<i>Regression Statistics</i>						
4	Multiple R	0.985480895					
5	R Square	0.971172595					
6	Adjusted R Square	0.948997667					
7	Standard Error	19.54432831					
8	Observations	24					
9							
10	<i>ANOVA</i>						
11		<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>	
12	Regression	10	167292.2083	16729.22083	43.79597661	2.33344E-08	
13	Residual	13	4965.75	381.9807692			
14	Total	23	172257.9583				
15							
16		<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>
17	Intercept	236.75	9.772164157	24.22697738	3.33921E-12	215.6385229	257.8614771
18	Mar	-36.75	16.92588482	-2.171230656	0.04901621	-73.31615098	-0.183849024
19	Apr	-99.25	16.92588482	-5.863799799	5.55744E-05	-135.816151	-62.68384902
20	May	-192.25	16.92588482	-11.35834268	4.02824E-08	-228.816151	-155.683849
21	Jun	-203.25	16.92588482	-12.00823485	2.07264E-08	-239.816151	-166.683849
22	Jul	-208.25	16.92588482	-12.30364038	1.54767E-08	-244.816151	-171.683849
23	Aug	-209.75	16.92588482	-12.39226204	1.41949E-08	-246.316151	-173.183849
24	Sep	-208.25	16.92588482	-12.30364038	1.54767E-08	-244.816151	-171.683849
25	Oct	-196.75	16.92588482	-11.62420766	3.05791E-08	-233.316151	-160.183849
26	Nov	-149.75	16.92588482	-8.847395666	7.30451E-07	-186.316151	-113.183849
27	Dec	-43.25	16.92588482	-2.555257847	0.023953114	-79.81615098	-6.683849024



# Model

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Gas Usage = 236.75 – 36.75 March – 99.25 April – 192.25 May – 203.25 June  
– 208.25 July – 209.75 August – 208.25 September – 196.75 October  
– 149.75 November – 43.25 December



# Models for Trend and Seasonality

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- Holt-Winters Additive Model

$$F_{t+1} = a_t + b_t + S_{t-s+1}$$

- Holt-Winters Multiplicative Model

$$F_{t+1} = (a_t + b_t) S_{t-s+1}$$

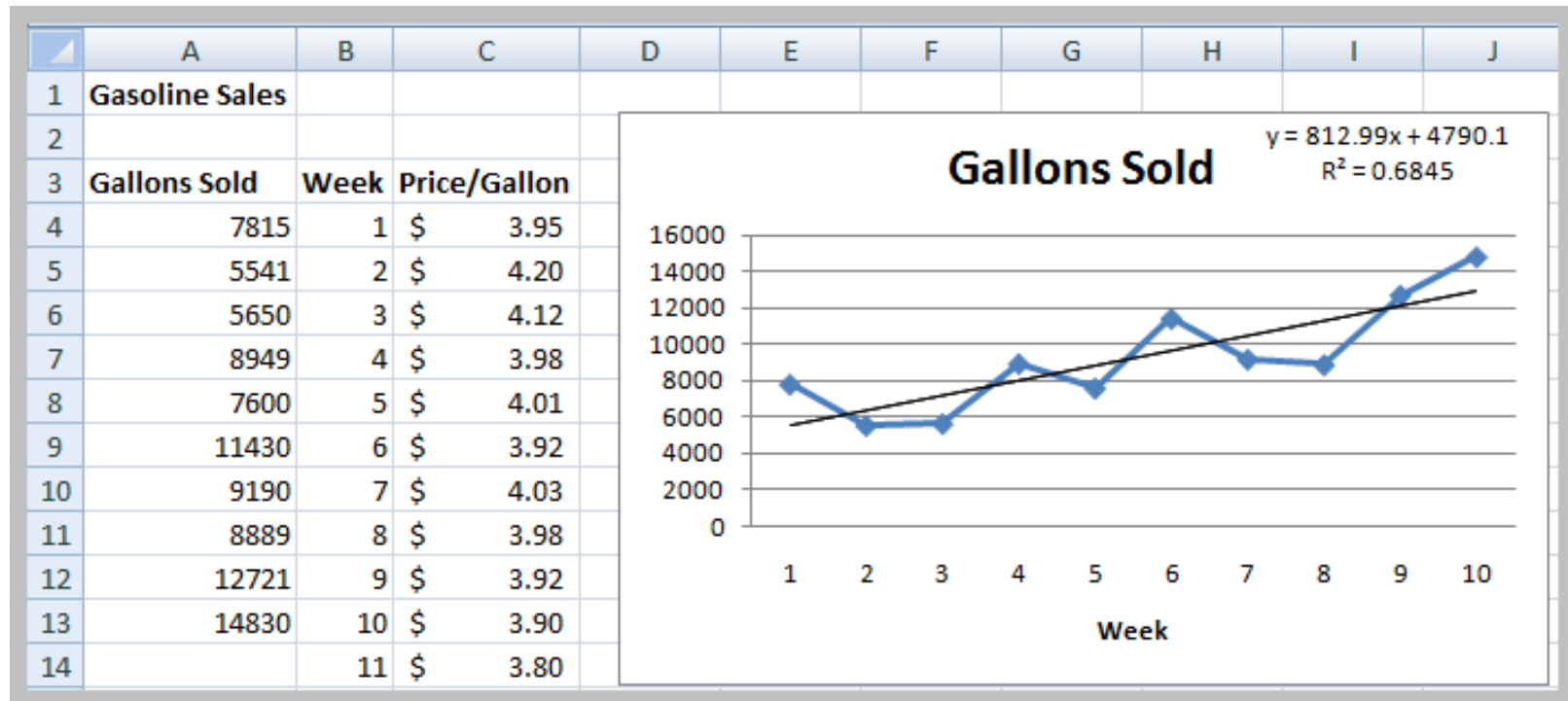


# Model Choice

**TABLE 7.3** Forecasting Model Choice

	No Seasonality	Seasonality
No Trend	Single moving average or single exponential smoothing	Seasonal additive or seasonal multiplicative model
Trend	Double moving average or double exponential smoothing	Holt–Winters additive or Holt–Winters multiplicative model

# Regression Forecasting With Causal Variables



Sales (week 11) =  $4790.1 + 812.00(11) = 13,733$  gallons

# Causal Model

- $\text{Sales} = \beta_0 + \beta_1 \text{Week} + \beta_2 \text{Price/Gallon}$
- $\text{Sales} = 72333.08 + 508.67 \text{ Week} - 16463.20 \text{ Price/Gallon}$

	A	B	C	D	E	F	G
1	SUMMARY OUTPUT						
2							
3	Regression Statistics						
4	Multiple R	0.930528528					
5	R Square	0.865883342					
6	Adjusted R Square	0.827564297					
7	Standard Error	1235.400329					
8	Observations	10					
9							
10	ANOVA						
11		df	SS	MS	F	Significance F	
12	Regression	2	68974748.7	34487374.35	22.59668368	0.000883465	
13	Residual	7	10683497.8	1526213.972			
14	Total	9	79658246.5				
15							
16		Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
17	Intercept	72333.08447	21969.92267	3.292368642	0.013259225	20382.47253	124283.6964
18	Week	508.6681395	168.1770861	3.024598364	0.019260863	110.9925233	906.3437558
19	Price/Gallon	-16463.19901	5351.082403	-3.076611005	0.017900405	-29116.49823	-3809.899789

$\text{Sales (week 11)} = 72333.08 + 508.67(11) - 16463.2(3.80) = 13,733 \text{ gallons}$

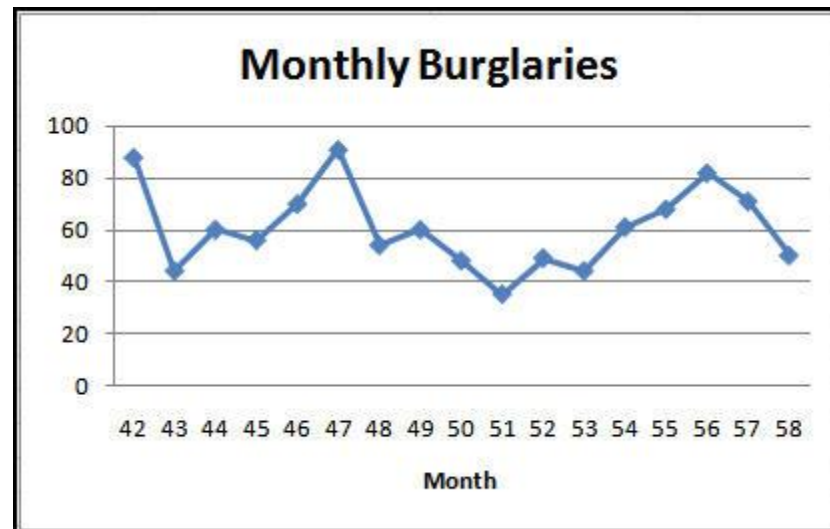




# *CB Predictor*

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- Excel add-in for forecasting
- Integrated with *Crystal Ball* software
- Example: Burglary Data



# Input Data Dialog

Predictor

Welcome

**Input Data**

Data Attributes

Methods

Options

Select location of data series

Location of data series:

Orientation

☐ Data in rows

☒ Data in columns

Headers

☒ Top row has headers

☐ Left column has dates

1 data series

41 rows of data

	B
4	Monthly burglaries
5	60
6	44
7	37
8	54
9	59
10	69
11	108
12	89
13	82
14	61
15	47
16	72
17	87
18	60

< Back

Next >

Run

Close

Help

# Data Attributes Dialog

The screenshot shows the 'Data Attributes' dialog box in the Predictor software. The left sidebar contains a navigation menu with 'Data Attributes' selected. The main area is titled 'Describe the characteristics of your data' and includes a line graph icon. The 'Data is in:' dropdown is set to 'periods'. The 'Seasonality' section has 'AutoDetect' selected, with a note that the data contains all non-seasonal series and a 'View Seasonality...' button. The 'Events' section has 'Include events' unchecked, with a note to add information about events to increase forecast accuracy and a 'View Events...' button. The 'Data screening' section has 'Fill-in missing values' checked and 'Adjust outliers' unchecked, with a 'View Screened Data...' button. At the bottom are buttons for '< Back', 'Next >', 'Run', 'Close', and 'Help'.

Predictor

Welcome  
Input Data  
**Data Attributes**  
Methods  
Options

Describe the characteristics of your data

Data is in: periods

Seasonality

AutoDetect Data contains all non-seasonal series.

Confirm the seasonality of your data visually: View Seasonality...

Events

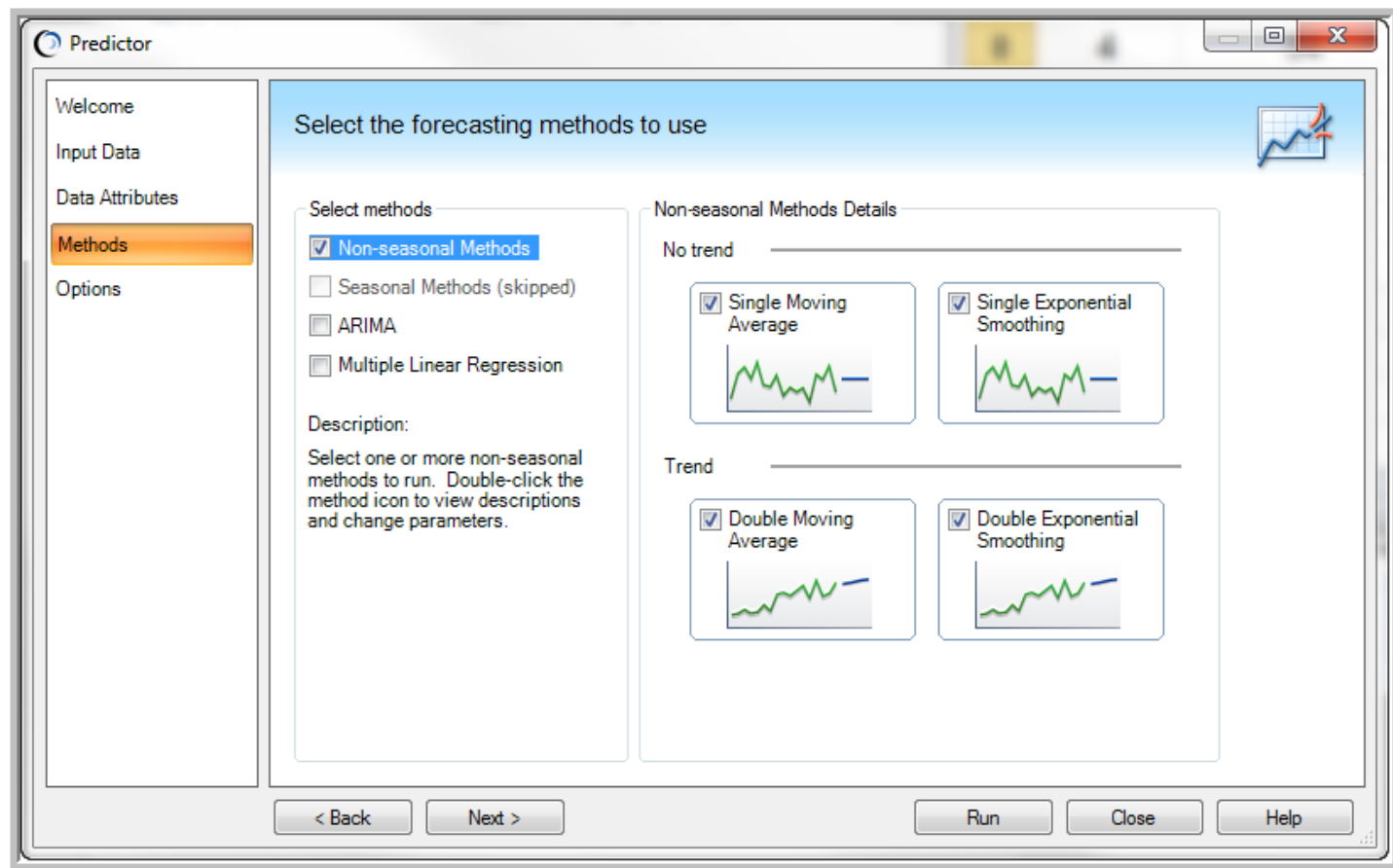
☐ Include events  
Add information about events to increase forecast accuracy: View Events...

Data screening

☒ Fill-in missing values  
☐ Adjust outliers View Screened Data...

< Back Next > Run Close Help

# Methods Dialog



# Options Dialog

**Predictor**

Welcome  
Input Data  
Data Attributes  
Methods  
**Options**

### Choose your options and run Predictor

**Error measure**

- ☒ RMSE - Root Mean Squared Error
- ☐ MAD - Mean Absolute Deviation
- ☐ MAPE - Mean Absolute Percent Error

Select the error measure that will be used to determine which time-series forecasting method is the best.

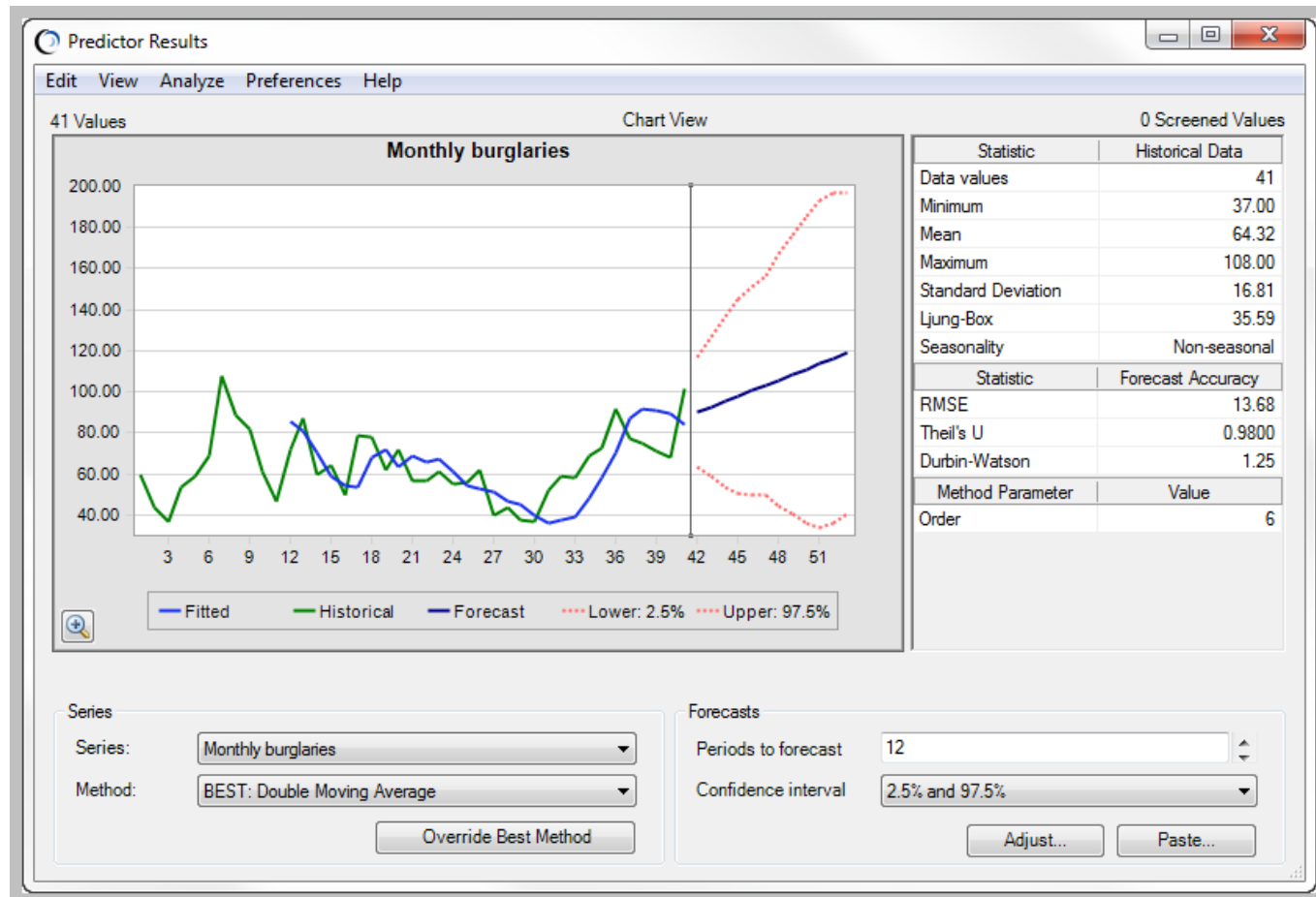
**Forecasting technique**

- ☒ Standard forecasting
- ☐ Simple lead:
- ☐ Weighted lead:
- ☐ Holdout:

Use Simple and Weighted leads to emphasize the importance of specific forecast periods. Use Holdout to measure errors based on excluded data points.

< Back   Next >   Run   Close   Help

# CB Predictor Results for Forecasting Burglaries



# CB Predictor Table View

**Predictor Results**

Edit View Analyze Preferences Help

41 Values Table View 0 Screened Values

Period	Historical Data	Lower: 2.5%	Fit & Forecast	Upper: 97.5%	Residuals
40	68.00		89.74		-21.74
41	102.00		83.78		18.22
42		63.23	90.05	116.87	
43		58.67	92.68	126.70	
44		53.71	95.32	136.92	
45		50.60	97.95	145.30	
46		50.11	100.58	151.06	
47		50.05	103.22	156.38	
48		44.85	105.85	166.85	
49		40.59	108.48	176.38	
50		36.47	111.12	185.76	
51		34.10	113.75	193.40	
52		35.93	116.38	196.84	
53		40.74	119.02	197.29	

Statistic	Historical Data
Data values	41
Minimum	37.00
Mean	64.32
Maximum	108.00
Standard Deviation	16.81
Ljung-Box	35.59
Seasonality	Non-seasonal

Statistic	Forecast Accuracy
RMSE	13.68
Theil's U	0.9800
Durbin-Watson	1.25

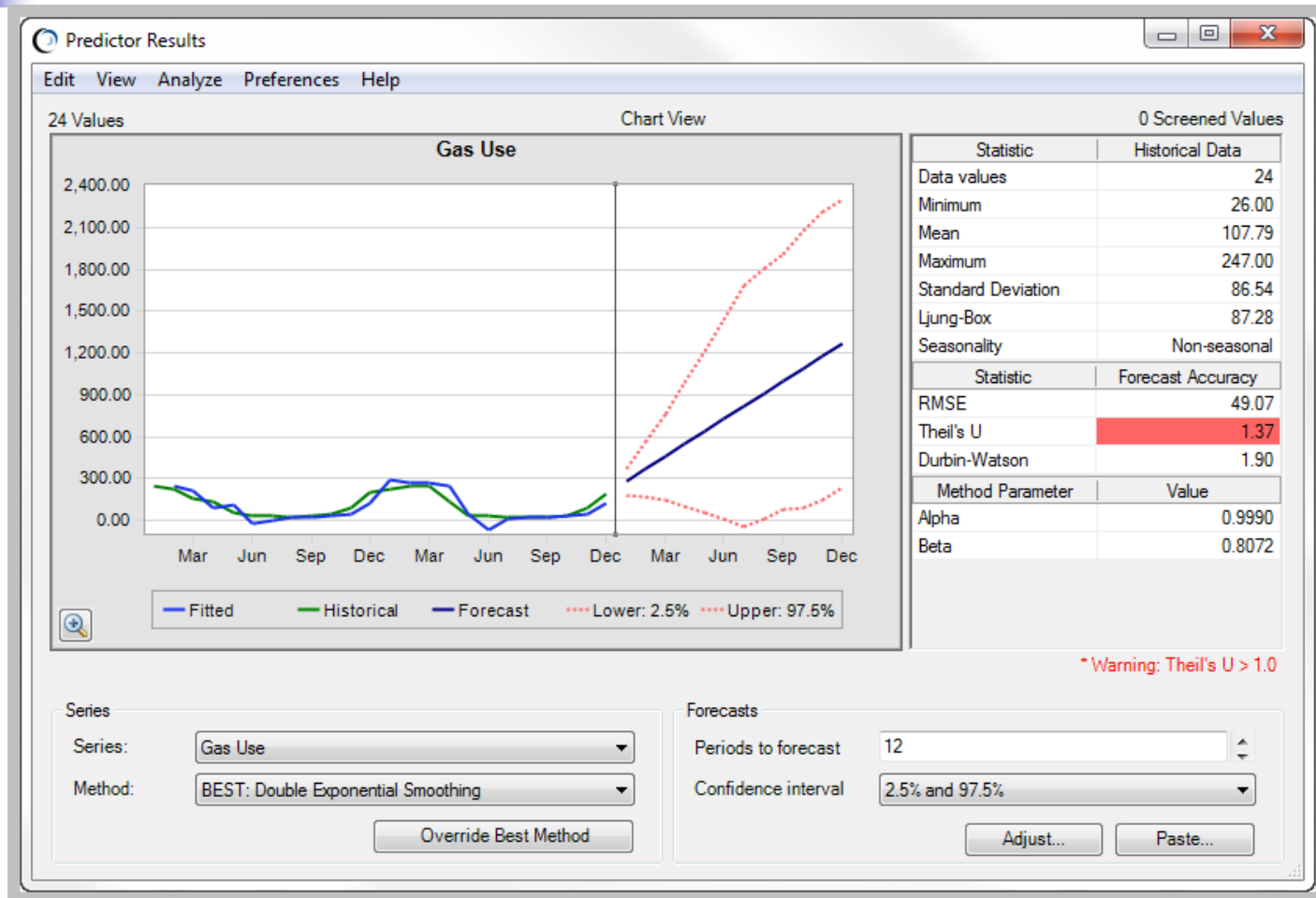
Method Parameter	Value
Order	6

Series: Monthly burglaries  
Method: BEST: Double Moving Average  
Override Best Method

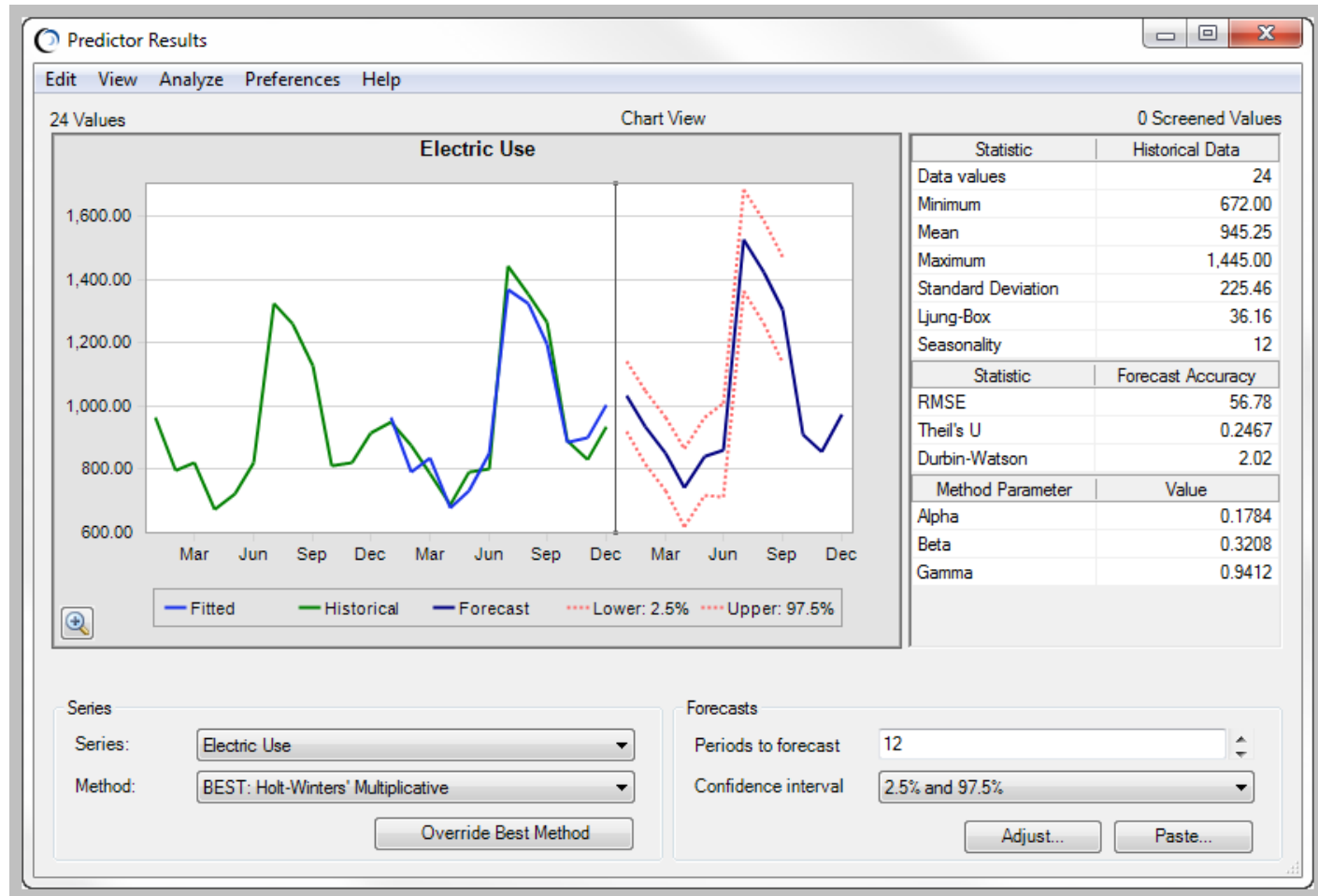
Forecasts: Periods to forecast: 12  
Confidence interval: 2.5% and 97.5%  
Adjust... Paste...

# CB Predictor Results for Gas Use Example

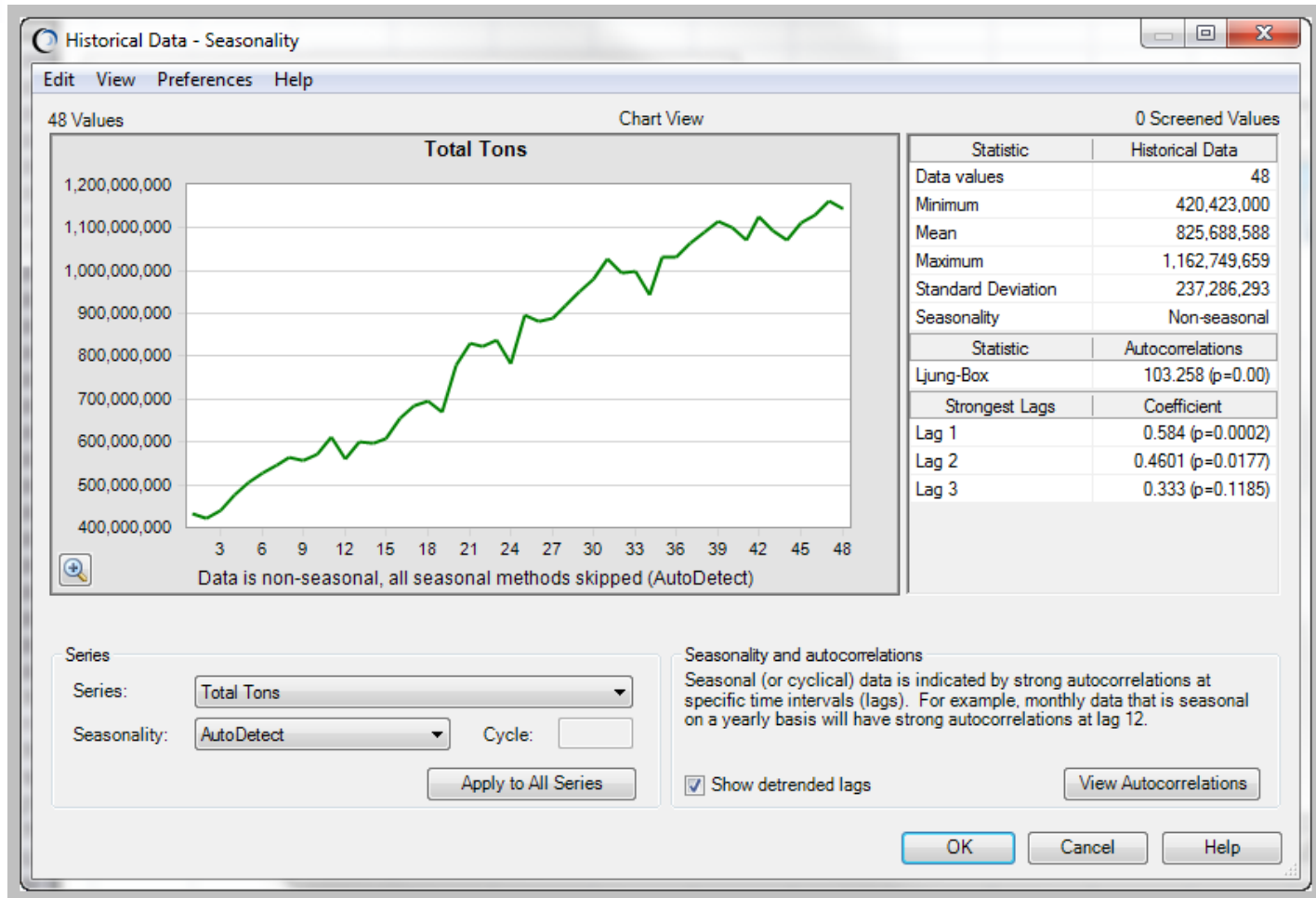




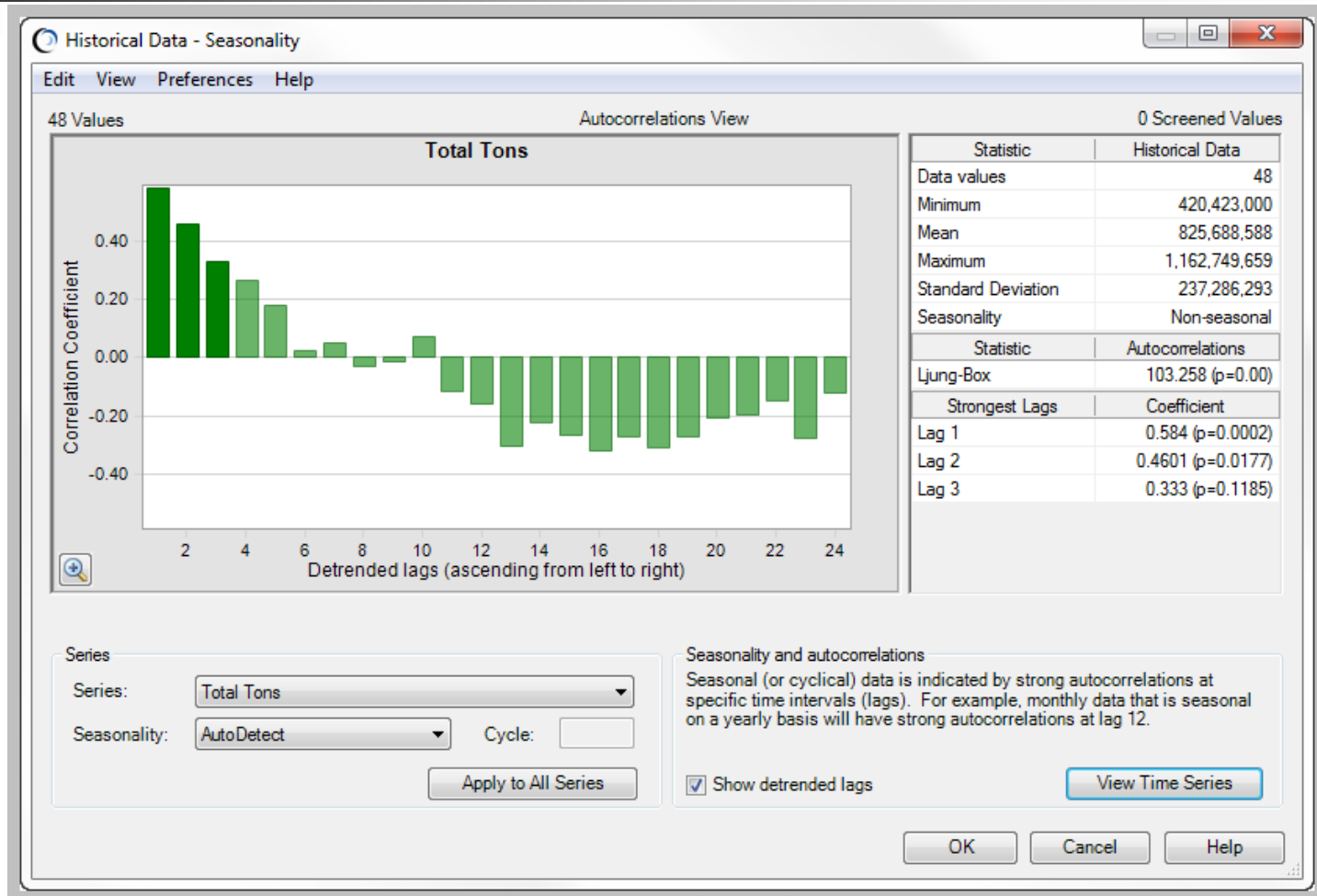
# CB Predictor Results for Electric Use Example



# CB Predictor Seasonality Dialog



# Autocorrelations in *CB Predictor*



# *CB Predictor* ARIMA Model for Coal Production

