# 7

## **Trend-Cycle Forecasting with Turning Points**

The only function of economic forecasting is to make astrology look respectable.

EZRA SOLOMON (1920-2002), although often attributed to

JOHN KENNETH GALBRAITH (1908-2006)

This chapter describes how to

- use economic leading indicators as trend-cycle factors of demand
- characterize the variability in trending patterns
- identify serial correlation in trend-cycle data patterns
- detect and remove non-stationary trending behavior in time series
- create trend-cycle demand forecasts with a turning point forecasting (TPF) method.

So far, we have seen how economic time series show historical patterns primarily in terms of trend, business cycle, and to a lesser extent seasonality. In this chapter, we consider how a lack of time dependence in the average behavior and variability relates to the uncertainty factor in demand forecasting.

When statistical techniques are combined with economic theory, it makes up what is known as **econometrics**. Econometric techniques have been widely applied as a way to model a macro economy. Macroeconomic demand analysis and econometric methods are used extensively in forecasting, structural and policy analysis in a wide variety of business planning applications. In this chapter, we offer an overview, without much technical detail, of the uses and pitfalls of econometric analysis in demand forecasting.

We discuss the method of **leading indicators** as the most important aspect of any macroeconomic forecasting activity dealing with business forecasts of the levels of economic indicators in econometric models.

We also discuss the measurement of the impact of expansions and contractions on businesses, government, or public sector organizations; and policy studies to assess the impact of changing economic and demographic assumptions on business and public programs.

## Demand Forecasting with Economic Indicators

Before creating forecasting models for products and services, demand forecasters need to identify the important features, uses, and interpretations of the factors that model the macroeconomy so that maximum benefit can be derived from these techniques in practical situations. The goal is to acquire the information needed to select the indicators that will help structure a framework for demand forecast modeling and judgment from a macro or top-down perspective.

Econometric methods have been widely applied as a way to model the macroeconomy. Macroeconomic demand deals with the aggregates of income, employment, and price levels. The uses of econometric modeling and analysis techniques can be classified by the way outputs are required. The outputs produce three classes of applications for econometric modeling (structural models, policy analysis and forecasting), of which the most widely applicable use is that of **econometric forecasting**.

## Applications of econometrics include structural models, policy analysis, and forecasting.

In econometric forecasting, the general focus is the development of a set of equations based on economic rationale, whose parameters are estimated using a statistical methodology. The model is designed to provide the business variable(s) with some explanatory underpinnings, but is also able to generate extrapolative values for future periods. That is, the model offers predictive values for the output variable(s) outside the sample of data actually observed. In practice, the statistical estimation procedures are evaluated from the perspective of forecasting performance through the up- and downturns of business cycles and using leading indicators.

## **Origin of Leading Indicators**

The method of leading indicators dates back to the sharp business recession of 1937–1938.



At that time, an effort was initiated by the US National Bureau of Economic Research (NBER) to devise a system that would signal the end of a recession. Arthur F. Burns (1904–1987), *left*, and Wesley C. Mitchell (1874–1948), *right*, first developed a comprehensive description of business cycle activity in the economy that became the foundation of classical methods of business cycle analysis.



A considerable amount of data, assembled by the NBER since the 1920s, has been analyzed to gain a better understanding of business cycles. These data, which included monthly, quarterly, and annual series on prices, employment, and production, resulted in a collection of 21 promising economic indicators that were selected on the basis of past performance and to the first recession in a decade and the tenth since World War II.

This recession lasted eight months, ending in November 2001. Figure 7.1 illustrates business cycle turning points for historical U.S. data from future promise as reliable indicators of business revival. Over the years, this effort has been greatly expanded to other public and private agencies. To this day, the NBER publishes turning points of business cycle peaks and troughs. The longest economic expansion on record ended in March 2001 and gave way the mid-1800s to 2009.



#### BUSINESS CYCLE REFERENCE DATES

### DURATION IN MONTHS

Peak	Trough	Contraction	Expansion	Cycle	
Quarterly dates		Peak	Previous trough	Trough from	Peak from
are in parentheses		to	to	Previous	Previous
		Trough	this peak	Trough	Peak
	December 1854 (IV)				
June 1857(II)	December 1858 (IV)	18	30	48	
October 1860(III)	June 1861 (III)	8	22	30	40
April 1865(I)	December 1867 (I)	32	46	78	54
June 1869(II)	December 1870 (IV)	18	18	36	50
October 1873(III)	March 1879 (I)	65	34	99	52
March 1882(I)	May 1885 (II)	38	36	74	101
March 1887(II)	April 1888 (I)	13	22	35	60
July 1890(III)	May 1891 (II)	10	27	37	40
January 1893(I)	June 1894 (II)	17	20	37	30
December 1895(IV)	June 1897 (II)	18	18	36	35
June 1899(III)	December 1900 (IV)	18	24	42	42
September 1902(IV)	August 1904 (III)	23	21	44	39
May 1907(II)	June 1908 (II)	13	33	46	56
January 1910(I)	January 1912 (IV)	24	19	43	32
January 1913(I)	December 1914 (IV)	23	12	35	36
August 1918(III)	March 1919 (I)	7	44	51	67
January 1920(I)	July 1921 (III)	18	10	28	17
May 1923(II)	July 1924 (III)	14	22	36	40
October 1926(III)	November 1927 (IV)	13	27	40	41
August 1929(III)	March 1933 (I)	43	21	64	34
May 1937(II)	June 1938 (II)	13	50	63	93
February 1945(I)	October 1945 (IV)	8	80	88	93
November 1948(IV)	October 1949 (IV)	11	37	48	45
July 1953(II)	May 1954 (II)	10	45	55	56
August 1957(III)	April 1958 (II)	8	39	47	49
April 1960(II)	February 1961 (I)	10	24	34	32
December 1969(IV)	November 1970 (IV)	11	106	117	116
November 1973(IV)	March 1975 (I)	16	36	52	47
January 1980(I)	July 1980 (III)	6	58	64	74
July 1981(III)	November 1982 (IV)	16	12	28	18
July 1990(III)	March 1991(I)	8	92	100	108
March 2001(I)	November 2001 (IV)	8	120	128	128
December 2007 (IV)	June 2009 (II)	18	73	91	81
Average, all cycles:					
1854-2009 (33 cycles)	17	.5 3	38.7 56.	2 56.4*	
1854-1919 (16 cycles)	21	21.6 20		2 48.9**	
1919-1945 (6 cycles)	18	.2 .	35.0 53.	2 53.0	
1945-2009 (11 cycles)	11	.1 !	58.4 69.	5 68.5	
* 32 cycles ** 15 cycles					

Figure 7.1 Business cycle reference dates, 1857–2009. (Source: NBER)





Figure 7.2 Coincident indicator of the U.S. economy: (*top*) Bar chart of GDP annual percent change in billions of chained 2009 dollars for 1950 to 2015; (*bottom*) percentage change of GDP quarterly seasonally adjusted annual rates for 1950:I–2016:III. (*Source: https://www.bea.gov/*)

A number of time series, such as employment, indexes of consumer and producer prices, and manufacturers' orders, are published in newspapers, business journals and websites. As indicators of the nation's economic health, professional economists and the business community follow them very closely, especially during periods of rapid change in the pace of business activity.

For convenience of interpretation, economic indicators have been classified into three groups: leading, coincident, and lagging. Leading indicators are those that provide advance warning of probable changes in economic activity. Indicators that confirm changes previously indicated are known as lagging indicators. Coincident indicators are those that reflect the current performance of the economy. Coincident indicators provide a measure of current economic activity. They are the most familiar and include GDP, industrial production, personal income, retail sales, and employment.

## Economic indicators are classified as leading, lagging or coincident with changes in economic activity.

Figure 7.2 (*top*) shows the annual GDP percentage changes in billions of chained 2009 dollars from 1950 to 2015. The GDP is mostly trending, but the economic cycles are nevertheless in evidence. To highlight the quarter-to-quarter changes, Figure 7.2 (*bottom*) depicts the percentage changes in seasonally adjusted annual rates for the period 1950: I–2016: III. The GDP is a coincident indicator of the U.S. economy.

## Use of Leading Indicators

It would be very useful to demand forecasters and planners to have some advance warning of an impending change in the local, national, or world economy. Whereas **coincident indicators** are used to indicate whether the economy is currently experiencing expansion, recession, or inflation, leading indicators help forecasters to assess short-term trends in the coincident indicators. In addition, leading indicators help planners and policy makers anticipate adverse effects on the economy and examine the feasibility of taking corrective steps.

In individual sectors, such as agriculture, leading indicators have played a major part in short-term production forecasting. For example, the estimation of the number of acres planted to spring wheat is a good indication of harvested acreage. Economic indicator analysis has also been used to assist investors in optimizing the rate of return in their asset allocation between stocks and fixed income securities.

Knowledge of current economic conditions can be found in the duration, rate, and magnitude of recovery or contractions in business cycles.

Among the leading indicators in business forecasting, housing starts, new orders for durable goods, construction contracts, formation of new business enterprises, hiring rates, and average length of workweek are the most commonly mentioned. In recent times, weekly initial employment claims, expressed in terms of a 4-week moving average, are getting a great deal of attention in the media. Housing starts, a key leading indicator plotted in Figure 7.3, tend to lead fluctuations in overall economic activity.





A useful set of indicators for revealing and explaining the economy's broad cyclical movements includes manufacturers' shipments and orders (Figure 7.4). These are comprehensive indicators of industrial activity and are especially important to demand forecasters because the durable goods sector (plant equipment and durable machinery, automobiles, etc.) is the economy's most volatile component.

Figure 7.4a displays total manufacturers' shipments and the 3-month moving average in billions of dollars for the time period May 1999 to May 2001, Figure 7.4b shows total manufacturers' orders, Figure 7.4c shows total inventory, and Figure 7.4d displays the ratios of unfilled orders and total inventory to shipments.

Shipments are an indicator of current economic activity, measuring the dollar value of products sold by all manufacturing establishments. Orders, on the other hand, are a valuable leading indicator. They measure the dollar value of new orders and the net order cancellations received by all manufacturers. The two series are distorted by inflation because there is no relevant price index to convert it to real terms. It is the difference between shipments and orders, which shows what is happening to the backlog of unfilled orders that gives insight into the degree of sustainability of current national output.

The data are widely used by private economists, corporations, trade associations, investment consultants, and researchers for market analysis and economic forecasting; and by the news media in general business coverage and specialized commentary.

An example of a lagging indicator is the unemployment rate (Figure 7.5). Although it is frequently quoted in the press, demand forecasters should realize that the unemployment rate is not an indicator of future or even current labor market conditions.



Figure 7.4 Time plots of (a) Total Manufacturers' Shipments, (b) Total Manufacturers' Orders, (c) Total Inventory, and (d) ratios of Unfilled Orders and Total inventory to Shipments in billions of seasonally adjusted current dollars for May 1999 to May 2011.

### **Civilian Unemployment Rate: Percent: SA**



Figure 7.5 Time plot of U.S. civilian unemployment rates, January 2000–November 2016.

A composite indicator provides a single measure of complicated economic activities that experience common fluctuations.

### **Composite Indicators**

Economists have developed composite indicators to reduce the number of series that must be reviewed and at the same time not lose a great deal of information. These series provide single measures of complicated economic activities that experience common fluctuations. The procedure involved includes amplitude adjustment, in which the month-to-month percentage change of each series in the composite is standardized so that all series are expressed in comparable units. The average month-to-month change, without regard to sign, is 1.0. The score it receives from the scoring plan weights each individual series.

If an index shows an increase of 2.0 in a month, it is rising twice as fast as its average rate of change in the past. If an index increases by 0.5, it is rising only one-half as fast as its historical rate of increase. Composite indicators have been developed for the leading, coincident, and lagging series.

One problem with interpreting an index of leading indicators is that its month-to-month changes can be erratic (Figure 7.5); however, comparing movements of the index over a longer span helps to bring out the underlying cyclical movements. For example, Figure 7.7 shows the percentage change in the current level of the leading index from the average level of the preceding 12 months. On that basis, the leading indicators have declined (i.e., fallen below zero) before every one of the seven recessions since 1970.

## The complete chapter can be found in

## Change & Chance Embraced

# ACHIEVING AGILITY WITH DEMAND FORECASTING IN THE SUPPLY CHAIN

## HANS LEVENBACH, PhD

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