March 20, 2013

Economics Group

Special Commentary

John E. Silvia, Chief Economist
john.silvia@wellsfargo.com • (704) 410-3275
Azhar Iqbal, Econometrician
azhar.iqbal@wellsfargo.com • (704) 410-3270
Kaylyn Swankoski, Economic Analyst
kaylyn.swankoski@wellsfargo.com • (704) 410-3276

How Stationary Is My Economic North Star? The Study of Drift in Economic Benchmarks

Many decision makers suffer from an anchoring bias.

Effective economic decision making, in both the public and private sector, starts with a sense of benchmarks or guidelines to frame a view of the future. Yet, how reliable are these benchmarks? In fact, are they really benchmarks at all? Unfortunately, many decision makers suffer from an anchoring bias in making strategic decisions, and will set their expectations for the future based on what they perceive was true about the past.[1] For instance, a common practice by today's decision makers is to assume that a data series will continue to grow at its average rate over the past couple of decades, and that any deviation from trend growth will only be temporary. In other words, many decisions are based on the idea that today's economic data are mean-reverting.

What if the data are not mean-reverting? There are two essential elements of a decision making process: modeling and forecasting. Both of these processes assume the underlying dataset is mean-reverting, and if the data series is not mean-reverting, then the results, and therefore the decisions deduced from modeling and forecasting, would be spurious. So, if a decision maker is trying to forecast a series that is not mean-reverting, any results gained from the models will not be reliable or useful.[2]

In this report, we examine the patterns of five benchmark economic series, demonstrating both mean-reversion and non-mean-reversion. Furthermore, we describe how forming decisions based on past trends may have led to inaccurate predictions and improper decisions. We use an econometric technique known as the Augmented Dickey-Fuller test[3] to identify both the character of the change and the source of any diversion.

Benchmarks: Economic Growth and the Labor Market

In this report we focus on two broad areas of the U.S. economy: economic growth (output) and the labor market. The Great Recession produced the largest losses in terms of output (as measured by GDP) and jobs (nonfarm payrolls) in the post-World War II era. After experiencing such deep and severe losses, we are left questioning whether we will ever get back to the "normal" level. Will we see mean-reversion? Specifically, we test the behavior of U.S. GDP and industrial production to proxy output in the economy, and three indicators of the labor market: the U-3 unemployment rate, the U-6 unemployment rate and nonfarm payrolls.

---

[1] Silvia, J.E. (2011). Dynamic Economic Decision Making. Wiley Press. Pp. 71-73.
[2] Greene, William H. (2011). Econometric Analysis. 7th Edition, Prentice Hall, New Jersey.
[3] Dickey, D., and Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of American Statistical Association*, Vol. 74, pp. 427-431. Dickey, D., and Fuller, W. (1981). "Likelihood Ratio Tests for Autoregressive Time Series with a Unit Root". *Econometrica*, Vol. 49. Pp. 1057-1072.

Testing, Not Assuming, Economic Values

If a series is non-stationary, then the future values are unpredictable.

Fortunately for decision makers, econometric techniques are available to determine whether a series is mean-reverting. The process to quantify whether a series is mean-reverting is known as unit root testing. One standard test, and the one which we employ, is known as the Augmented Dickey-Fuller (ADF) test. The null hypothesis of the ADF test is that the underlying series is not mean-reverting (non-stationary) and the alternative hypothesis is therefore that the data series is mean-reverting (stationary).[4] If a series is non-stationary, then the behavior or change from one period to another is random. That is, the future values are unpredictable. For a forecaster, using a non-stationary dataset, and assuming that the series is stationary, would result not only in a misleading forecast, but also an inaccurate forecast interval.

So, how do we analyze the results? The goal of the forecaster is to predict the movement of data over time. To evaluate the movement of a time series, the decision maker can employ OLS regression analysis, which will provide the estimated mean value of the time series. However, because stationarity of the data, or constant variance, is a critical assumption of OLS regression, we use the ADF unit root test to evaluate whether we can take the mean as given or if the results are spurious. If the ADF test proves the data to be non-stationary, then we have violated an underlying assumption of OLS regression analysis and cannot draw any conclusions from the results. However, if the ADF test proves the data to be stationary, the next step is to define the stationary behavior of the data. There are three possibilities when it comes to stationarity. A data series can be zero-mean, which identifies the mean of the data series as zero; single-mean, which defines the data series as having a constant mean that is not zero; and trend growth, meaning that the data series does not have a constant mean over the time period, but follows a consistent time trend with finite error terms. Examining the time series in chart form is often very helpful in determining the form of stationarity of that data series.

Our Benchmark for Real GDP Growth

GDP data exhibits mean-reversion back to its 2.75 percent value.

Over the sample period, Q1-1982 to Q4-2012, the average annualized growth rate of real GDP in the United States was 2.75 percent, as illustrated in Figure 1 and confirmed with the OLS analysis in Table 1. Is this a reasonable benchmark to guide our expectations? The results in Table 1 show no evidence of a shift, or long-term deviation from the long-run average rate of GDP growth. Therefore, the GDP data series appears stationary and exhibits mean-reversion back to its 2.75 percent value.

Figure 1

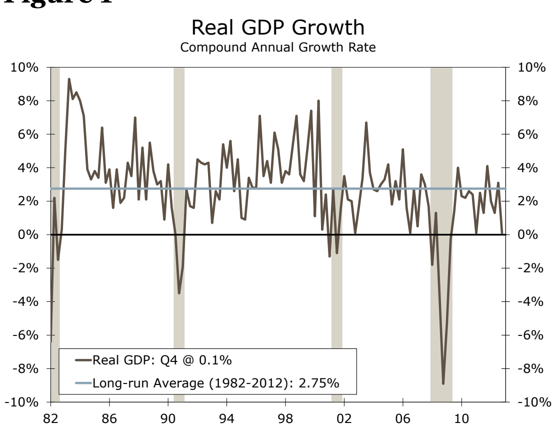

Table 1

The ADF Results		
Type	Tau-statistic	Pr < Tau
Zero-Mean	-2.3375	0.02*
Single-Mean	-4.3891	0.00*
Trend	-5.3303	0.00*
Estmated Mean-Value		
Estimated-Mean	2.75*	
t-value	10.98	

* Significant at 5 percent level

Source: U.S. Department of Commerce, SAS and Wells Fargo Securities, LLC

In the Augmented Dickey-Fuller unit root test illustrated in the top portion of Table 1, we can reject the null hypothesis of mean-diversion or non-stationary growth of GDP at the 5 percent

[4] For more details about the stationary and non-stationary concept see the appendix of this report.

significance level.[5] While Table 1 demonstrates the possibility of zero-mean, single-mean and trend growth, we identify the series as single-mean using the value of the mean from the OLS analysis. The OLS analysis finds that a mean of 2.75 percent is significant, and the chart also confirms our suspicions of a mean-reverting data series around 2.75 percent.

We can conclude that GDP growth is mean-reverting. For decision makers, the benchmark for strategic thinking is that growth will more likely be 2.75 percent over time and therefore divergent views from this growth rate are less than an even bet. This is especially true for outlooks beyond the next two years where such outlooks really reflect the longer-term trend of growth and in this case, the trend is more likely to fall around 2.75 percent rather than values such as 4 percent plus or a drop to zero growth. Finally, the evidence, so far, does not suggest a fundamental downshift in economic growth in recent years even though the average growth rate has been below 2.75 percent for several years. There is just not enough evidence to suggest a fundamental, statistically significant, shift in the growth rate of GDP.

Industrial Production: Another Case of Stationary Behavior

In a similar way, the OLS regression analysis estimates an average quarterly annualized growth rate of 2.29 percent for industrial production over the sample period. The unit root test demonstrates that industrial production data is stationary; therefore, we can validate the long-run average growth of industrial production to remain around 2.29 percent. As can be seen in Figure 2, industrial production growth demonstrates a cyclical pattern—falling during recession and bouncing back during the early phases of recovery. However, these expected deviations from the long-run mean are temporary in nature. Therefore, a decision maker can expect industrial production to continue to grow around its long-term trend.

A decision maker can expect industrial production to continue to grow around its long-term trend.

Figure 2

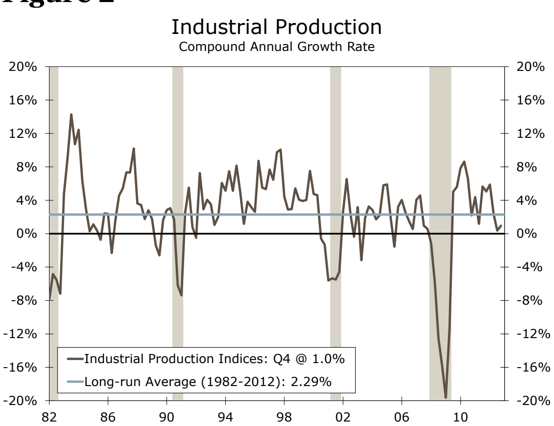

Table 2

The ADF Results		
Type	Tau-statistic	Pr < Tau
Zero-Mean	-4.3778	0.00*
Single-Mean	-5.4489	0.00*
Trend	-5.7754	0.00*
OLS Estmated Mean-Value		
Estimated-Mean	2.29*	
t-value	4.91	

* Significant at 5 percent level

Source: Federal Reserve Board, SAS and Wells Fargo Securities, LLC

Unemployment Rate U-3: A Surprising Result of Stationarity

Surprisingly, the unemployment rate, measured by the U-3 definition[6] that is commonly reported in the media as well as serving as a benchmark for stress testing suggested by the Federal Reserve, displays stationarity. These results may be surprising to some, especially given the persistently high, and seemingly outsized, unemployment rates since the latest recession. The results in Table 3 suggest that the official unemployment rate is mean-reverting around a long-term average rate of 6.37 percent. The long-run average is surprisingly close to the Federal Reserve's guidepost of 6.5 percent for raising the federal funds rate and, unfortunately, is higher than what is perceived

[5] The value of Pr < Tau of the ADF test will identify whether we accept or fail to accept the null hypothesis of non-stationarity. In this report we use the 5 percent significance level, therefore any probability value less than 0.05 identifies a significant relationship, implying that the series is stationary and therefore we can progress with the OLS regression model.
[6] The U-3 measurement of the unemployment rate counts the total number of unemployed persons as a percent of the civilian labor force. This is the official unemployment rate.

There is no evidence of a long-term fundamental shift in U-3 unemployment.

as full employment by some commentators who are subject to an anchoring bias looking at the past. Understanding that this unemployment series is stationary, and thereby does not exhibit any drift in the values over time, suggests that while perceptions that the long-term level of unemployment has shifted upward since the Great Recession, so far there is no statistical evidence of a fundamental shift in this series.

Figure 3

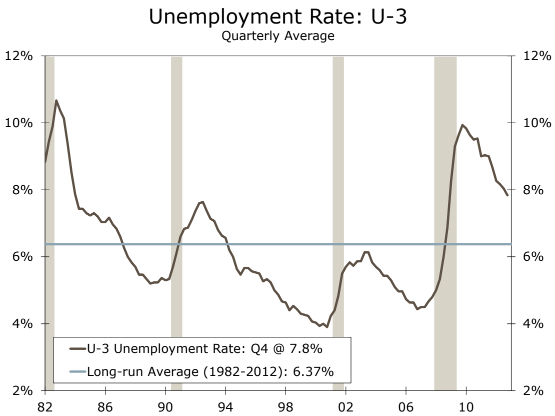

Table 3

The ADF Results		
Type	Tau-statistic	Pr < Tau
Zero-Mean	-1.4847	0.13
Single-Mean	-3.8003	0.00*
Trend	-3.6525	0.03*
OLS Estmated Mean-Value		
Estimated-Mean	6.37*	
t-value	41.67	

* Significant at 5 percent level

Source: U.S. Department of Labor, SAS and Wells Fargo Securities, LLC

Unemployment Rate U-6: A Rising "Gray" Labor Market?

Our view for many years has been that the labor market of the 21st century is behaving in a way that is different from prior years. This differential behavior reflects the ways in which the actual behavior of the labor market may deviate from the perfectly competitive marketplace that forms the basis for models that may frame decision making in both the public and private marketplace.[7]

The U-6 measure of unemployment, a much broader view of the labor market, shows a different picture, however.

While the U-3 measure of unemployment proved to be stationary and mean-reverting around a long-run average, the U-6 measure of unemployment, a much broader view of the labor market, shows a different picture. The U-6 measure of unemployment includes those unemployed that are captured in the U-3 measure plus those marginally attached to the labor force and those that are employed part time for economic reasons. In short, the U-6 measure of unemployment captures the fuller view of the labor market. The evidence suggests that the U-6 measure of unemployment series is not stationary, unlike the U-3 measure. As shown in Table 4, we cannot reject the null hypothesis of a unit root, and therefore, the mean value of the U-6 unemployment rate provided by the OLS estimation is not valid. Furthermore, looking at Figure 4, it appears that the mean value of this measure of unemployment is rising. This is consistent with the sentiment about what has been happening in the economy in recent years. There appears to be a developing gray area in unemployment that does not fit our historical view of the operation of the labor market. There is a growing part-time character to the labor market that suggests less attachment to the model of the full-time job. Decision makers should not rely heavily on the idea that the labor market will return to previous behavior.

[7] **See Romer, David. *Advanced Macroeconomics*, McGraw-Hill Irwin, Boston, Chapter 9 in particular.**

Figure 4

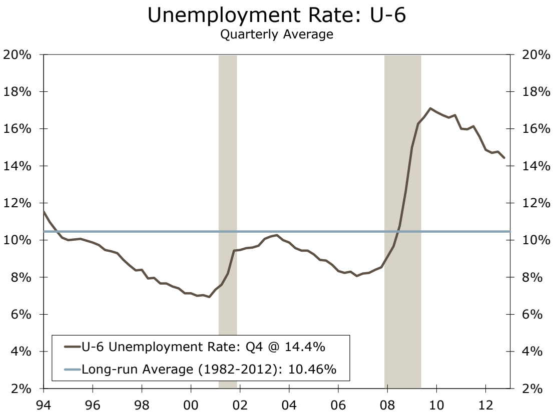

Table 4

The ADF Results		
Type	Tau-statistic	Pr < Tau
Zero-Mean	-0.0593	0.66
Single-Mean	-1.7258	0.41
Trend	-2.5204	0.32
OLS Estmated Mean-Value		
Estimated-Mean	10.46*	
t-value	29.92	

* Significant at 5 percent level

Source: U.S. Department of Labor, SAS and Wells Fargo Securities, LLC

Employment Growth: Surprisingly Stationary Despite Impressions

The growth in payrolls is surprisingly stationary.

The previous examples using different definitions of the unemployment rate demonstrates the changing face of the labor market, and suggests unemployment may not be mean-reverting, especially using the broader measure. However, we find that the growth in payrolls is surprisingly stationary. Public impressions today fall prey to the recency bias that assumes that the most recent experience is a signal of the future that is distinct from the past.[8] Yet, the evidence suggests that the annualized quarterly growth rate of nonfarm employment is actually a stationary series that is mean-reverting. The average growth rate is estimated at 1.28 percent over the Q1-1982 to Q4-2012 period. In Q4-2012, payrolls were growing at a 1.64 annualized rate, above the long-term trend.

Figure 5

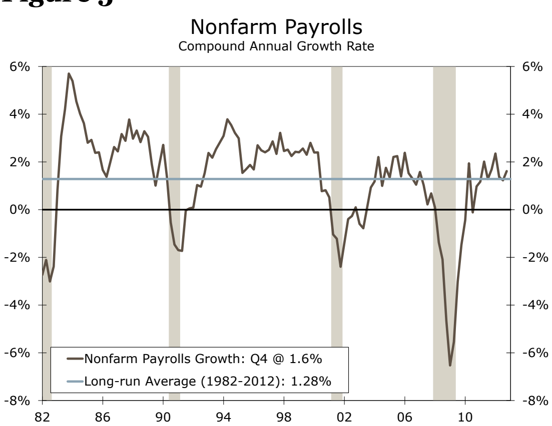

Table 5

The ADF Results		
Type	Tau-statistic	Pr < Tau
Zero-Mean	-3.1225	0.00*
Single-Mean	-4.2621	0.00*
Trend	-5.2546	0.00*
OLS Estmated Mean-value		
Estimated-Mean	1.28*	
t-value	6.98	

* Significant at 5 percent level

Source: U.S. Department of Labor, SAS and Wells Fargo Securities, LLC

[8] **See Silvia, J.E. (2011). Dynamic Economic Decision Making. Wiley Press. Pp. 208-210.**

Conclusion: For Some, Not Likely to Go Back to the Good Ol' Days

Often, in the decision making process, we utilize time series data to model and forecast a picture of the future. One of the key assumptions behind forecasting is that the dataset is stationary (mean-reverting). Decisions are based on the idea that a series will move around its long-run mean and that fluctuations from the mean are temporary. This assumption has serious consequences, especially if the series are not mean-reverting (non-stationary). In the case of non-stationary data, the modeled results would not be reliable, and thus, any decisions based on those expectations may prove inaccurate. Therefore, it is important to be familiar with the long-term behavior of the data and insure stationarity before making decisions.

Appendix

Unit Root Test: The Dickey-Fuller Tests

A stationary time series implies the mean and variance of the series are constant over time. If the mean and/or the variance are not constant over time, then the series is characterized as non-stationary—containing a unit root. A stationary series fluctuates around a constant, long-run mean with a finite (constant) variance that does not depend on time; it is therefore mean-reverting. A non-stationary series, on the other hand, has no tendency to return to its long-run mean and the variance of the series is time dependent.[9] If one or more time series are non-stationary, the OLS method cannot be employed because it assumes the underlying data series are stationary. If the data series are non-stationary (as is often the case for many time series) then the OLS results will be spurious since the stationary assumption is violated. Any perceived relationship between economic time series will not reflect the true relationship.

There are two major types of non-stationary behavior: difference-stationary (DS) and trend-stationary (TS).[10] It is important to identify the character of a time series as either DS or TS because both sources of non-stationarity have different implications for the path of the variable going forward. If a series follows the DS pattern, then the effect of any shock will be permanent. To convert the series into a stationary process an analyst would have to generate the difference of the series.[11] A common source of non-stationarity is TS behavior, which implies that the series has a deterministic trend (upward or downward) over time.

Furthermore, difference-stationary is divided into two categories: random walk and random walk with a drift. A random walk model implies that the current value of any series is equal to the lagged value of that series plus an error term. A random walk model is also known as a zero-mean model because it implies that the series has a mean of zero. But in practice, an economic series rarely has a zero-mean. When we allow for a non-zero mean, it is known as a random walk with a drift and we tested this under the single-mean heading.

Here, we focus on tests proposed by Dickey and Fuller (1979, 1981) as they introduced the eminent and first standard process for unit root testing: the ADF unit root test. [12]

Let y_t be a time series and consider a simple autoregressive of order one (AR (1)) process;

$$y_t = \rho y_{t-1} + \varepsilon_t \qquad (1)$$

$$\varepsilon_t \sim wn(0, \sigma^2)$$

The standard Dickey-Fuller (DF) test has the following form, after subtracting y_{t-1} from both side of the Equation 1:

$$\Delta y_t = \alpha y_{t-1} + \varepsilon_t \qquad (2)$$

Where $\alpha = \rho$ -1. The null and alternative hypothesis may be written as:

---

[9] For a detailed discussion about the unit root concept see Maddala, G.S., and Kim, In-Moo. (1998). Unit Roots, Cointegration, and Structural Change. Cambridge University Press. Cambridge, U.K.
[10] It is important to note that if a series is DS then it may contain a stochastic trend. A stochastic trend implies the trend is driven by random shocks and there is no particular trend to which it returns. For more details, see Maddala and Kim (1998).
[11] If the first difference of the series is stationary then the series is called first order stationary, or the order of integration is one. Using the general form I(d) where "I" stands for integration and "d" for the order of integration, first order stationary can be written as I(1).
[12] Dickey, D., and Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of American Statistical Association*, Vol. 74, pp. 427-431. Dickey, D., and Fuller, W. (1981). "Likelihood Ratio Tests for Autoregressive Time Series with a Unit Root". *Econometrica*, Vol. 49. Pp. 1057-1072.

H*o*: $\alpha = 0 \quad \Rightarrow y_t$ is non-stationary (unit root)

H*1*: $\alpha < 0 \quad \Rightarrow y_t$ is stationary (mean-reverting)

The key difference is that we use the Dickey-Fuller statistic, τ (tau) statistic, instead of the conventional t-distribution.

One important issue related with the DF test of unit root is that it is only valid if the series, y_t, follows an AR(1) process. If the series is correlated at a higher order lag and follows an AR (p) process, where AR (p) > AR (1), then the assumption of a white noise error term is violated. The Augmented Dickey-Fuller (ADF) offers a parametric correction for higher-order correlation by assuming that y_t follows an AR(p) process and adding up to *p* lags differenced terms of the dependent variable, Δy_t in this case, to the right-hand side of the test regression.

$$\Delta y_t = \gamma + \alpha y_{t-1} + \beta time + \sum_{j=1}^{p} \phi_j \Delta y_{t-j} + \varepsilon_t \qquad (3)$$

Where *p* is lag order. The standard ADF unit root test contains three different equations: the random walk case (zero-mean), the random walk with drift case (single-mean) and the linear deterministic trend (trend).

There are some other unit root tests. The Phillips and Perron (1988)[13] proposed an alternative to the ADF test, called the PP test, while Kwiatkowski, Phillips, Schmidt, and Shin (1992) introduced the KPSS test.[14] There are two more unit root tests which are known as efficient tests of unit root developed by Elliot, Rothenberg, and Stock (1996)[15] and Ng and Perron (2001).[16]

[13] Phillips, P. and Perron, P (1988). Testing for Unit Roots in Time Series Regression. *Biometrika*, Vol. 75.
[14] Kwiatkowski, D. Phillips, P. Schmidt, P and Shin, Y. (1992). Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root. *Journal of Econometrics*, Vol. 54.
[15] Elliott, G., Rothenberg, T. & Stock, J (1996). Efficient Tests for an Autoregressive Unit Root. Econometrica 64, 813—836.
[16]Ng, S. and Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*. Vol. 69, 1519–1554.

Wells Fargo Securities, LLC Economics Group

Diane Schumaker-Krieg	Global Head of Research, Economics & Strategy	(704) 410-1801 (212) 214-5070	diane.schumaker@wellsfargo.com
John E. Silvia, Ph.D.	Chief Economist	(704) 410-3275	john.silvia@wellsfargo.com
Mark Vitner	Senior Economist	(704) 410-3277	mark.vitner@wellsfargo.com
Jay Bryson, Ph.D.	Global Economist	(704) 410-3274	jay.bryson@wellsfargo.com
Sam Bullard	Senior Economist	(704) 410-3280	sam.bullard@wellsfargo.com
Eugenio Aleman, Ph.D.	Senior Economist	(704) 410-3273	eugenio.j.aleman@wellsfargo.com
Anika Khan	Senior Economist	(704) 410-3271	anika.khan@wellsfargo.com
Azhar Iqbal	Econometrician	(704) 410-3270	azhar.iqbal@wellsfargo.com
Tim Quinlan	Economist	(704) 410-3283	tim.quinlan@wellsfargo.com
Michael A. Brown	Economist	(704) 410-3278	michael.a.brown@wellsfargo.com
Sarah Watt	Economist	(704) 410-3282	sarah.watt@wellsfargo.com
Kaylyn Swankoski	Economic Analyst	(704) 410-3276	kaylyn.swankoski@wellsfargo.com
Sara Silverman	Economic Analyst	(704) 410-3281	sara.silverman@wellsfargo.com
Zachary Griffiths	Economic Analyst	(704) 410-3284	zachary.griffiths@wellsfargo.com
Peg Gavin	Executive Assistant	(704) 410-3279	peg.gavin@wellsfargo.com
Cyndi Flowe	Administrative Assistant	(704) 410-3272	cyndi.h.flowe@wellsfargo.com