Univariate
Time Series Analysis

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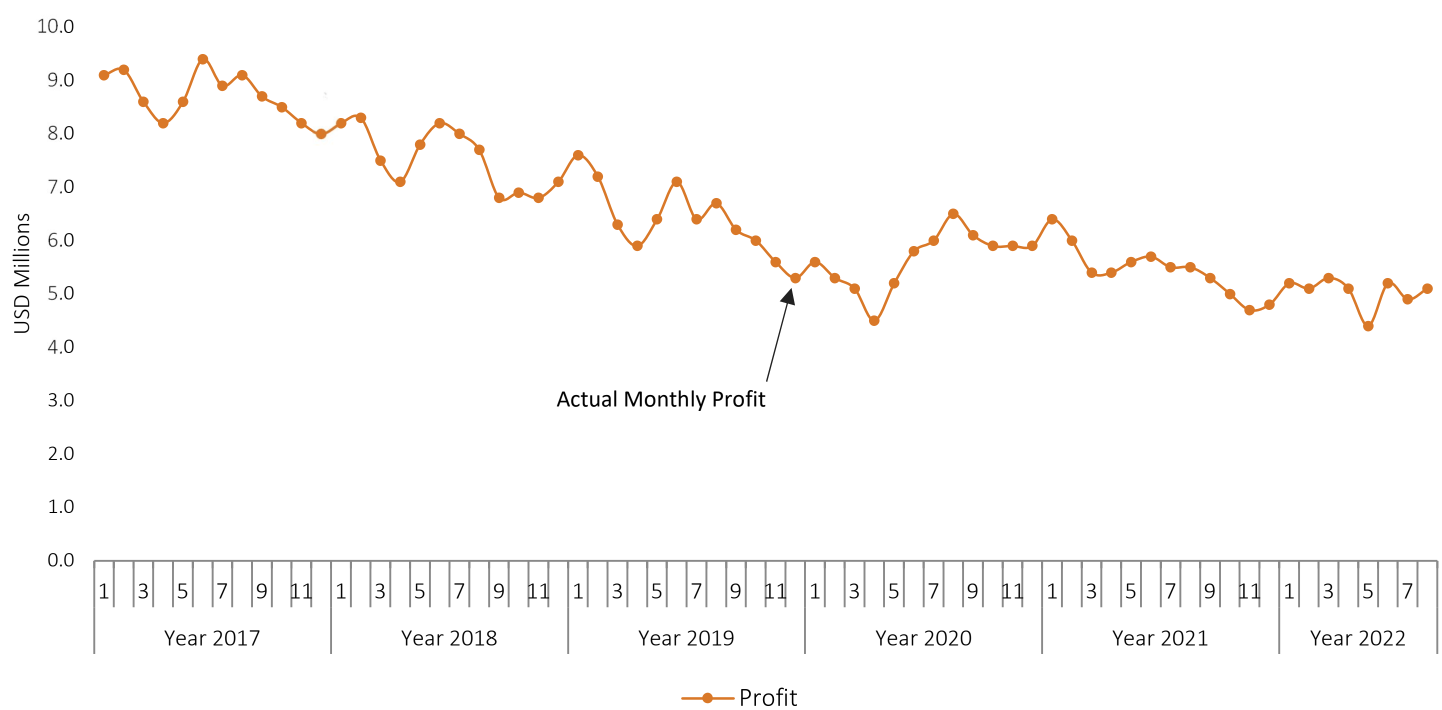
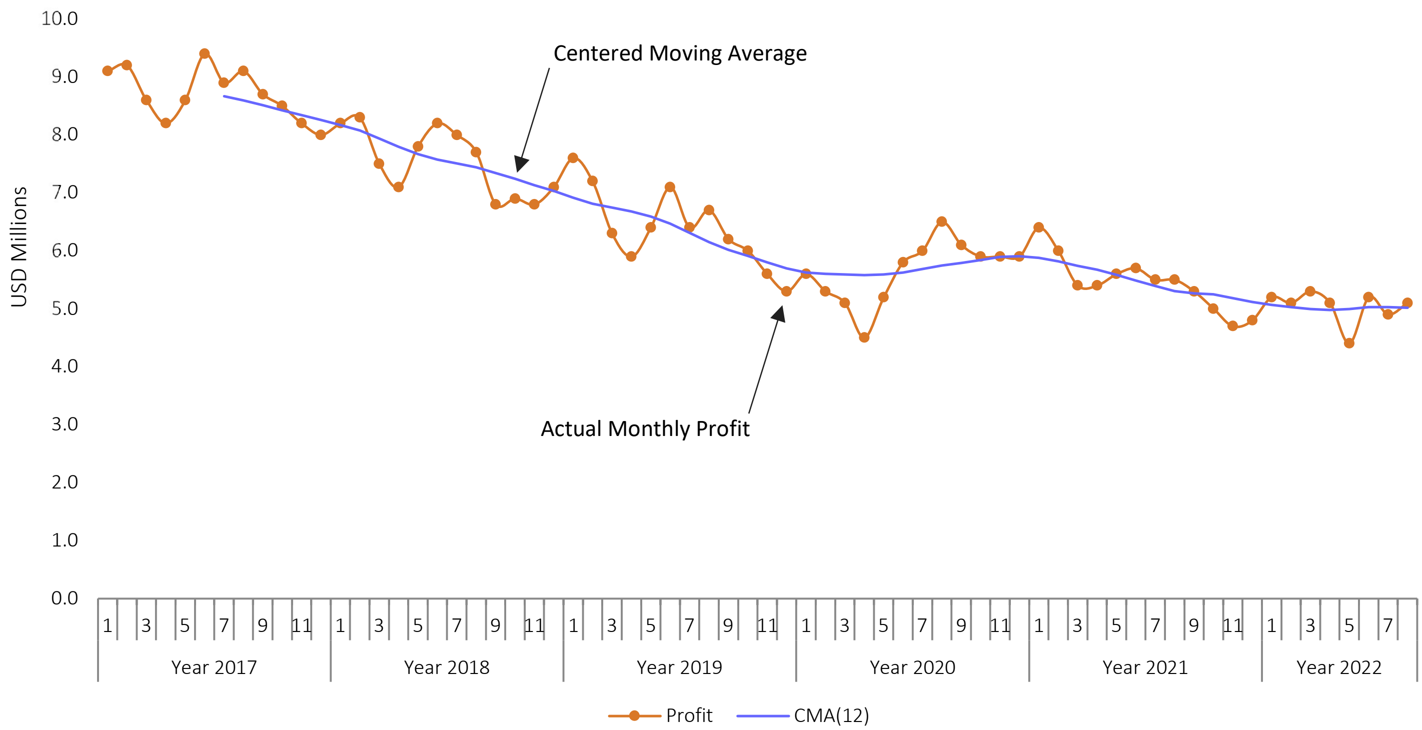
Time series analysis is an econometric technique economists, researchers, and other analysts use to model and subsequently forecast data, or moreover, other times series, where times are discrete (t=1,2,3…n) or continuous (t>0). It is most useful on large data sets, and consists of three primary components, including seasonality, trend, and random irregularity—or *noise*. Hence, both univariate and multivariate time series analysis can be used in a host of disciplines, not just economics. A simple example of a time series, without any analyses, is depicted in the figure below. Refer to output below and attempt to find the potential trend and seasonality in the monthly profit noted. The trend is obvious, but seasonality is more difficult to visualize in this case. In terms of random irregularity, we are going to accept that there exists noise in these data. Simply know that noise is the remaining random component after being separated from seasonality and trend; noise cannot be easily modeled, but it effects our data.



But in and of itself, this series tells us little; the data merely depict monthly profit from January 2017, through September 2022. However, given what appears to be a definitive trend, potential seasonality, and obvious noise we can use these data to project, or forecast, profit on future periods using univariate time series analysis. To do so, we must model these data, or in lay terms, we must develop a simple set of mathematical equations to forecast profit past September 2022. Such modeling would be beneficial for obvious reasons, such as estimating profit next month, quarter, or year so goals can then be set against strong projections. Remember, projections are not synonymous with goals; goals go beyond projections as definitively quantifiable, yet attainable, objectives which companies, teams, or individuals should strive. Projections and goals are simply not one in the same.

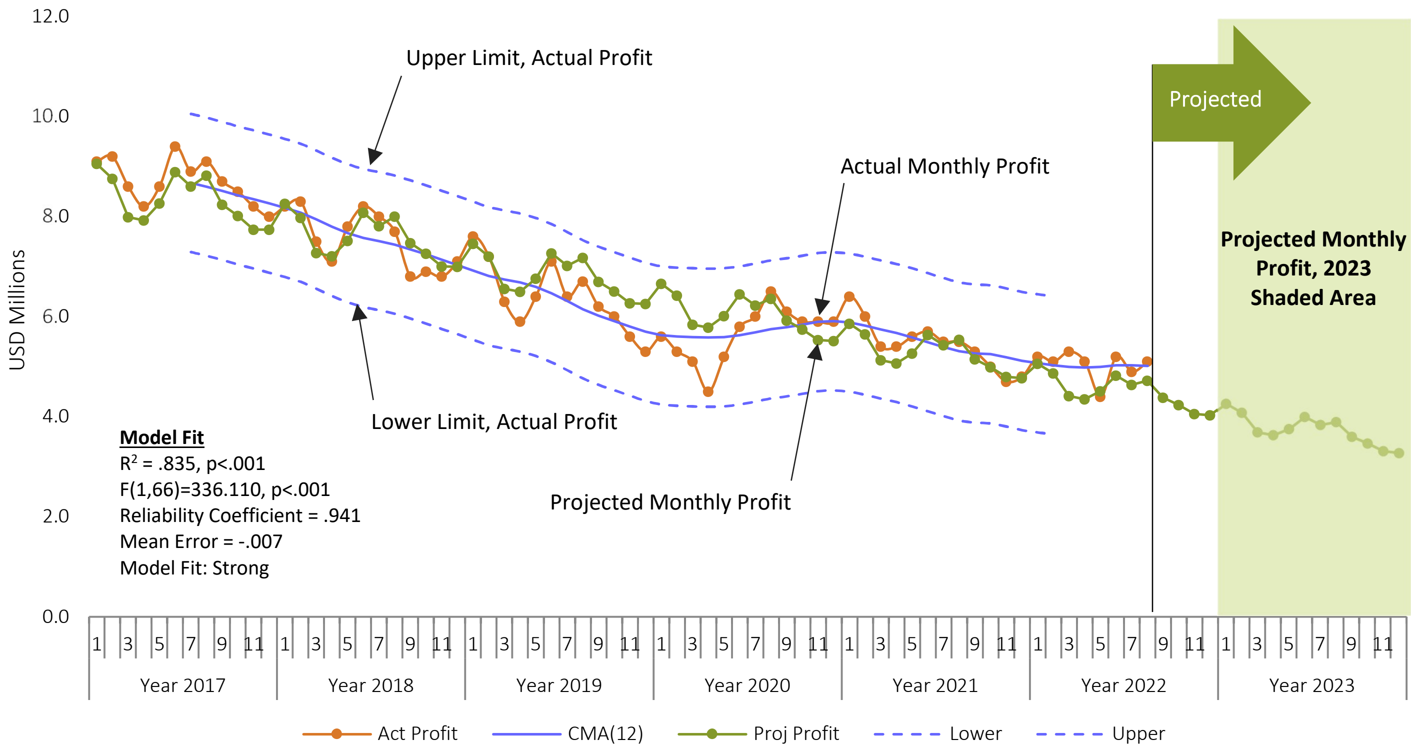
Before becoming too involved in our actual model, however, we need to calculate a moving average for these data to allow us to gain a snapshot in time using subseries of our total series. To do so, we first calculate a simple moving average, weighted moving average, or exponential moving average. There are arguments for and against these type averages, but for our case we will use a simple moving average, and more specifically, a *centered* moving average because we have an even number of observations (n=68). In calculating a centered moving average, we effectively smooth our data by removing the seasonal component and noise in our data. Refer to the figure below to review our series after we have added a centered moving average using 12 cycles.



After calculating a moving average, or centered moving average in our case, and plotting it, we next run a few simple calculations to develop our model; but allow me to first digress to discuss seasonality. The term *seasonality* should not be confused to imply the four meteorological seasons as earth rotates the sun. While such may in fact be the case, when we use the term seasonality, think in terms of our data being periodical, or cyclical, in that our variable profit moves similarly in some form of a cyclical basis.

Now that we have our moving average, we can consider how much of our profit was due to seasonality (S_t) and how much was due to irregularity, or noise (I_t). In brief, our profit variable (Y_t) divided by our centered moving average (CMA) calculates these components (S_t, I_t) combined. Now, we can consider the seasonality component (S_t) itself by isolating it from the irregularity component (I_t), which can be determined by "average" S_t,I_t for each of our 12 cycles, or in our case, months, year over year. Next, knowing the seasonal component, we deseasonalize profit by dividing profit, Y_t by the seasonal component, S_t.

We next decide how to calculate our trend component, T_t. There are different methods of doing so, depending upon the data, but in this case, we will use simple linear regression, with year as our independent variable (t=1, 2, 3….68) and our deseasonalized component as our dependent variable. Based upon our calculated intercept and slope coefficients, and assuming they are statistically significant, we then calculate our trend variable, T_t. Finally, knowing our seasonal component we next multiply our trend component, T_t, by the seasonal component, S_t, to project profit through December 2023. Then, of course, we can develop other models that leverage projected profit to predict other variables. Refer to the figure below to review actual profit against projected profit.



For these data, time series analysis proved to be the correct econometric method to model these data. Certainly, there are other methods, but trend, seasonality, and noise were inherent in the data, making the data a likely fit for time series analysis. In the end, overall model fit was considered strong, (R^2=.835, p<.001). In fact, the reliability coefficient between groups for actual profit and projected profit was close to perfect, at .941, and the alpha level was less than .001. The mean error was a negligible -.007, meaning the model slightly overpredicted, which is sometimes the case when using single independent variables in regression models. Much of the forecasting error occurred between November 2019 and May 2020, but overall, the model performed well, even extremely well. Then again, models are only as strong as the robustness of the data being modeled.

Herbert M Barber, Jr, PhD, PhD serves as the Managing Partner and Chief Investment Officer of Xicon Economics. Intersecting the fields of engineering, finance, econometrics, and statistics, Dr. Barber is an expert in computational financial economics as it relates to the subjugation of random walk theory and navigation of constructs surrounding efficient market hypotheses, especially within assets operating under extreme uncertainty. For over 30 years, he has provided advisory, consulting, and management of large capital investments in the private and public sectors. Additionally, Dr. Barber has published numerous scientific papers in refereed journals. Complementing his experience, Dr. Barber holds 5 academic degrees, including two research doctorates.

Xicon Economics provides investment research, financial and investment advisory, and asset management for corporations and investors. More specifically, we conduct scientific and applied research coupled with advanced statistical and econometric analyses and modeling to render complex financial and economic decisions to ensure investments are realized. While we have solved countless complex financial and economic problems, we concentrate our practice on leveraging our expertise to increase output on hedge funds and alternative investments. Additional information regarding Xicon Economics can be found at www.xiconeconomics.com.

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