Correlation, Economic Indicators

Analyzing Historical Relationships Between Economic Attributes

Construction of a Correlation Matrix Using Python

Historically, prices of U.S. equities have had a slight positive relationship with oil prices.

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In past reports, we analyzed correlations in the FX market, correlations in historical global bond yields, and correlations in the worldwide stock market. We uncovered a variety of relationships between different assets in these analyses. For example, one previous correlation matrix we constructed revealed that historical ten-year government bond yields between Denmark and Germany have a correlation coefficient of 0.994, almost a perfect linear relationship. On the other hand, another correlation matrix we constructed showed that the historical prices of the Israeli Tel Aviv Stock Exchange Index have a relatively strong negative association with historical prices of the STOXX Europe 50 Index ($\rho_{STOXX,TelAviv}$ = -0.32). Since these correlation matrices are quick, useful tools for investors, policymakers, and economists, in this report, we will create a miniature *master correlation matrix* with a variety of financial attributes.

The following major financial attributes were used in this snapshot report: the spot WTI oil price, spot Henry Hub natural gas price, spot silver price, spot gold price, spot copper price, spot soybean price, spot corn price, LIBOR (1-month), Moody's AAA Corporate Bond Yield, Moody's BAA Corporate Bond Yield, Bank of America Merrill Lynch (BofA Merrill Lynch) U.S. CCC Bond Yield, BofA Merrill Lynch Asia Emerging Markets Corporate Plus Sub-Index Effective Yield, BofA Merrill Lynch US Corporate BBB Effective Yield, Emerging Markets Corporate Plus Sub-Index Effective Yield, BofA Merrill Lynch US High Yield BB Effective Yield, ten-year U.S. Treasury yield, two-year U.S. Treasury yield, the bank prime loan rate, the Wilshire U.S. Micro-Cap Price Index, the Wilshire U.S. Small-Cap Price Index, the Wilshire U.S. Mid-Cap Price Index, the Wilshire U.S. Large-Cap Price Index, Wilshire U.S. Real Estate Investment Trust Price Index (Wilshire U.S. REIT), the CBOE Volatility Index (VIX), the Bovespa opening price (Brazil), the Dow Jones Industrial Average opening price (or DJIA, United States), the Nikkei 225 opening price (Japan), the Shanghai Composite Index opening price (China), the STOXX Europe 50 opening price (Eurozone), the CAC 40 opening price (France), the Tel Aviv Stock Exchange Index opening price (Israel), the IPC opening price (Mexico), the MERVAL opening price (Argentina), the DAX opening price (Germany), the ASX 200 opening price (Australia), the TSX Composite opening price (Canada), the RTSI opening price (Russia), the KOSPI opening price (South Korea), the OMX Copenhagen 20 opening price (Demark), the TWSE opening price (Taiwan), the IBEX 35 opening price (Spain), the ATX opening price (Austria), the SMI opening price (Switzerland), the Euro exchange rate, the Japanese Yen exchange rate, the Chinese Yuan exchange rate, the Mexican Peso exchange rate, the Brazilian Real exchange rate, the South Korean Won exchange rate, the Indian Rupee exchange rate, the Australian Dollar exchange rate, the Swiss Franc exchange rate, the Malaysian Ringgit exchange rate, the Thai Bhat exchange rate, the Singapore Dollar exchange rate, the Danish Kroner exchange rate, the New Zealand Dollar exchange rate, the Sir Lankan Rupee exchange rate, the British Pound exchange rate, the South African Rand exchange rate, the Hong Kong Dollar exchange rate, the Norwegian Kroner exchange rate, the Swedish Krona exchange rate, the Economic Policy Uncertainty Index for United States, the TED Spread, the 5-Year Breakeven Inflation Rate, the 10-Year Breakeven Inflation Rate, and the 5-Year, 5-Year Forward Inflation Expectation Rate. Note: all exchange rates used in this analysis were in terms of the U.S. dollar (e.g. USD/JPY, or number of yen per one U.S. dollar).

For each attribute used in this analysis, daily recordings of the given attribute going back to January of 2003 were included in the dataset. All data used in this analysis was retrieved from either the Federal Reserve Economic Data Catalog (FRED) or Yahoo Finance. As usual, the correlation matrix for the prices of these stock market indices was determined using Python (with import pandas), and this matrix can be downloaded here. The initial daily data of stock market index prices used in this snapshot analysis can be found at the bottom of the report.

As outlined in previous analyses, the correlation coefficient of two financial attributes is simply the covariance of these attributes divided by the product of the individual standard deviations of each attribute. In mathematical terms, $\rho_{X, Y} = Cov_{X, Y} \div (\sigma_X * \sigma_Y)$, where X and Y represent two different financial attributes, $\rho_{X, Y}$ is the correlation coefficient between these attributes, $Cov_{X, Y}$ represents the covariance of these attributes, and $\sigma_X * \sigma_Y$ represents the product of the standard deviations of each attribute.

Again, correlation coefficients range from -1 to 1. A correlation coefficient of 0 represents no association between two variables, whereas a value greater than 0 represents a positive association between two variables. A larger correlation represents a stronger association, too, with a value of 1 representing a perfect linear relationship between two variables.

As stated in previous reports, I recommend looking through all columns of this correlation matrix, as correlation coefficients vary widely from attribute to attribute, and the only way to uncover these unexpected relationships between attributes is by looking through the entire matrix. As an example, let's look at correlations in this matrix for historical prices of the Bovespa, the main stock market index for Brazilian equities. Historical prices of the Bovespa have a fairly strong negative association ($\rho_{\text{Gold, Bovespa}} = -0.857$) with historical gold prices. On the other hand, historical prices of the Bovespa have a fairly strong positive association ($\rho_{\text{Copper, Bovespa}} = 0.853$, $\rho_{\text{Soybeans, Bovespa}} = 0.693$) with historical copper prices and also historical soybean prices. These simple correlation discoveries can lead to further questions for investors to dig into. For instance, because copper prices and Bovespa Index prices have historically had a strong positive relationship, an investor may hypothesize that Brazil is a large net exporter of copper, and exports of this metal are vital to the health of numerous companies that are part of the Bovespa. Consequently, if copper prices begin to rise, an investor may purchase Brazilian equities under the assumption that Brazilian companies will begin to thrive with higher copper prices in upcoming months. Of course, past trends are not necessarily accurate indicators of future market relationships, so investors should be wary of using historical trends to guide investment decisions. However, these past correlations can still help guide investors in the proper direction.

Continuing with the example of the Brazilian Bovespa Index from the previous paragraph, the correlation matrix reveals that past prices of the Bovespa Index have negative correlations with both past yields of the Moody's AAA Corporate Bond Index and also with past Henry Hub natural gas spot prices ($\rho_{\text{Moody's AAA, Bovespa}} = -0.302$, $\rho_{\text{Natural Gas, Bovespa}} = -0.107$). Thus, in past years, yield decreases (or price increases) for investment grade U.S. corporate debt has been associated with price increases for Brazilian equities. Historically, the Bovespa Index has also had a negative relationship with the Norwegian Krone, the Thai Bhat, and the Brazilian Real ($\rho_{\text{Norwegian Krone, Bovespa}}$ = -

0.601, $\rho_{\text{Thai Bhat, Bovespa}}$ = -0.879, $\rho_{\text{Brazilian Real, Bovespa}}$ = -0.842). Again, these exchange rates are in terms of the U.S. dollar (e.g. USD/JPY, number of yen per one U.S. dollar), so a negative correlation indicates that, historically, price increases of the Bovespa Index were associated with strengthening of the Brazilian Real, the Thai Bhat, and the Norwegian Krone. Clearly, this correlation matrix can open up hundreds of interesting relationships to further research.

Let's look into some other relationships in this matrix. Price increases of the DJIA are historically associated with strengthening of the Euro ($\rho_{\text{DJIA, Euro}}$ = -0.3327), and historical VIX Index readings are also negatively correlated with prices of the DJIA ($\rho_{\text{VIX, DJIA}}$ = -0.498). Thus, in past years, increased market volatility has been associated with price declines for U.S. equities. Interestingly, historical gold spot prices and the Chinese Yuan exchange rate (USD/CNY) have a correlation of 0.907 for this dataset. Thus, in past years, depreciation of the yuan has had a positive association with higher gold prices. On the other hand, historical gold prices have a correlation of -0.548 with prices of the Shanghai Composite Index, the main Chinese stock market index.

Continuing to dig into this correlation matrix, we see, historically, oil prices have a negative correlation with almost all currencies in this analysis (e.g. $\rho_{\text{Oil, Brazilian Real}}$ = -0.842, $\rho_{\text{Oil, Malaysian Ringgit}}$ = -0.832). Since all exchange rates used in this analysis are in terms of the U.S. dollar (e.g. USD/JPY, number of yen per one U.S. dollar), negative correlations between currencies and historical oil prices imply that, in past years, weakening of the U.S. dollar was associated with higher oil prices. Thus, these relationships make logical sense, as the price of oil is denominated in U.S. dollars - as the dollar weakens, oil becomes cheaper for foreign buyers, pushing up the price of this commodity. Clearly, although digging through this correlation matrix can reveal unexpected relationships, numerous associations uncovered in this matrix make logical, intuitive sense, too.

As stated in previous reports, although historical trends are not necessarily accurate predictors of future trends, this correlation matrix is yet another tool for investors to add to their decision-making toolbox. The relationships uncovered in this analysis can help guide investors who are attempting to construct diversified portfolios with the lowest possible variances, as investors often want to hedge risk by purchasing assets with negative correlations. For example, since Brazilian equities (e.g. the Bovespa Index) and gold spot prices have a historical correlation of -0.857, a relatively strong negative association, Brazilian investors may consider purchasing gold to reduce risk without drastically lowering their expected return.

Click here to download the data used in this snapshot financial report.