Currency Markets, Correlation

# Worldwide Currency Relationships

Using Python to Construct a Correlation Matrix for Currencies Around the World

In recent months, the euro has headed towards parity with the U.S. dollar.

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In this quick snapshot report, we analyze correlations in the FX market. In a previous report, correlations of historical ten-year government bond yields were analyzed, and we discovered that, for our dataset, ten-year government bond yields from Denmark and Germany had a correlation coefficient of 0.994, almost a perfect linear relationship. Thus, in this report, we expand this analysis of historical bond yield correlations to see whether similar relationships exist between different currencies.

For each country in the dataset of this analysis, daily exchange rates going back to January 4th, 1999 were included for the following currencies: the Euro, the Japanese Yen, the Chinese Yuan, the Mexican Peso, the Brazilian Real, the South Korean Won, the Indian Rupee, the Australian Dollar, the Swiss Franc, the Malaysian Ringgit, the Thai Bhat, the Singapore Dollar, the Danish Kroner, the New Zealand Dollar, the Sir Lankan Rupee, the British Pound, the South African Rand, the Hong Kong Dollar, the Norwegian Kroner, and the Swedish Krona.

All data used in this analysis was retrieved from the Federal Reserve Economic Data Catalog. Note: all exchange rates were in terms of the U.S.

dollar (e.g. 102.42 yen per U.S. dollar). The correlation coefficient matrix for these exchange rates was determined using Python (with import pandas), and this matrix can be downloaded here. As always, the initial data of exchange rates used in this snapshot analysis can be found at the bottom of the report.

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

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 seen in our currency correlation matrix, correlation coefficients have large swings from currency pair to currency pair. For example, the Danish Kroner and the Indian Rupee have a correlation coefficient of only 0.05; thus, the historical exchange rates of these two currencies have practically no association. On the other hand, the Swiss Franc and the Australian Dollar have correlation coefficient of 0.92, a strong positive association, and the Chinese Yuan and the Sri Lankan Rupee have a correlation coefficient of -0.84, a fairly strong negative association. Clearly, correlation coefficients vary from currency pair to currency pair.

I wholeheartedly recommend looking through each column of this dataset, as each currency has interesting, unique correlations with other currencies. For example, the Singapore dollar has a strong positive correlation with the Chinese Yuan and the Thai Bhat, but the Singapore Dollar also has a slightly negative relationship with the South African Rand and the Indian Rupee. When constructing an investment portfolio, investors often want to hedge risk by purchasing securities with negative correlations. Thus, this currency correlation matrix can also help investors who are looking to hedge risk.


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