THE GLOBAL RISE IN CROSS-ASSET CORRELATION

by

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Abstract

Global financial markets have become more connected over time, in terms of both information and capital flows. The impact this increased connectedness on asset prices is unclear. This thesis investigates co-movement characteristics among various asset classes including: equities, credit, foreign exchange, commodities, and interest rates. I find that many assets classes that may have been formerly unrelated are now seeing significant, measurable interrelatedness. For investment managers, understanding cross-asset correlations, especially in an environment where correlations are rising, becomes an important consideration when developing risk-mitigating portfolio strategies.

Keywords: correlation, financial markets, asset classes

Introduction and Research Question

Global financial markets have become more connected over time, in terms of both information and capital flows. The impact this increased connectedness on asset prices is unclear. This thesis investigates co-movement characteristics among various asset classes from commodities to equities. I find that many assets classes that may have been formerly unrelated are now seeing significant, measurable interrelatedness. Understanding the relatedness and the drivers of relatedness between various asset classes is crucial in constructing a diversified portfolio that yields superior risk-adjusted returns.

The importance of understanding relatedness and subsequently, the need to diversify out relatedness in a portfolio, is derived from the Modern Portfolio Theory. This highly influential theory quantifies the benefits of diversification using the notion of covariance or correlation (Fabozzi, Gupta, & Markowitz, 2002). The correlation coefficient serves as the measure that determines the degree to which two variables are related and is measured between -1 and 1, the former indicating an inverse relationship between the returns of two securities and latter indicating a perfect positive relationship between the returns of two securities. When thought about in the context of diversification, "two assets that are uncorrelated could be expected to show no systematic, linear relationship between their returns over time. By combining uncorrelated assets, the movements of one asset can be expected to at least partially mitigate the movements of the second asset, reducing the average volatility of a portfolio" (Phillips, Walker, & Kinniry Jr. , 2012, p. 2). The use of asset classes with negative to low correlations to diversify risk in a portfolio will be a central theme in this paper.

Today's globalized financial markets have paved the way for new cross-asset correlations that can serve as a significant hurdle to developing a truly diversified portfolio. Investors have recently seen a “significant increase of correlation between equities as well as an increase of correlations between other risky assets such as credit foreign exchange, interest rates, and commodities” (Kolanovic, 2011, p. 3). Highly correlated assets across multiple classes typically point to a common source of risk that is present in the market. A concentrated area of risk in today’s integrated markets can serve as a source of contagion, spilling into all asset classes and global economies.

While global cross-asset correlations may not directly explain why a global contagion event similar to the Financial Crisis of 2007-2008 occurred, it is very useful to better understand and appreciate the complexities of today’s highly technical, highly integrated financial markets. This study aims analyze the most recent correlative relationships between global equities, credit, foreign exchange, interest rates, and commodities in order to better understand how the integrated global economy is reacting to changes in technology and market structure.

The impact of changing cross-asset correlations impacts not only multi-asset portfolio, but equity-only portfolios as well. To give a brief example, a rising correlation between equities and the price of crude oil has been witnessed since the recovery from the global financial crisis in 2008-2009. It has been observed that “extreme oil price changes did have spillover effects on stock markets, mainly after the onset of the financial crisis, meaning that abrupt changes in oil prices exacerbate extreme movements in stock markets, whereas moderate positive or negative oil price changes have no significant impact on stock price movements” (Reboredo & Ugolini, 2015, p. 14). This equity-commodity relationship does have implications and should be considered by equity investors who seek to implement risk management strategies to protect against large, unexpected changes in the price of crude oil. This thinking discounts a formerly popular investment view that commodities provide hedge protection in an investment portfolio

(Lombardi & Ravazzolo, 2016, p. 4). A plethora of similar cross-asset correlations have been witnessed in recent capital markets.

By analyzing of the historical returns of two different asset classes from two different time periods, changes in correlation can be witnessed and measured in order to better understand the linear dependence of the two sets of data. This understanding will help investors formulate risk-mitigating strategies to protect against correlative risk.

Review of Literature

Harry Markowitz' journal article "*Portfolio Selection*" provides many key building blocks to understanding modern portfolio theory, asset allocation and more narrowly, the concept of cross-asset correlation. Markowitz (1952) introduces the fundamental idea of risk adjusted returns as the "rate at which the investor can gain expected return by taking on variance, or reduce variance by giving up expected return" (p. 79). Markowitz attributes diversification as the significant factor in limiting the variance of a portfolio and displays a keen understanding of the right type of diversification necessary to generate superior risk-adjusted returns. Rather than investing in a sheer number of securities as a means for diversification, Markowitz (1952) encourages investor to "avoid investing in securities with high covariances among themselves;" instead, he points out that investors should "diversify across industries because firms in different industries, especially industries with different economic characteristics, have lower covariances than firms within an industry" (p. 89). Considering that covariance is normalized into the correlation coefficient, Markowitz' recommendation to diversify across industries helps explain why today's investors seek diversification benefits from multiple different asset classes in their portfolios. However, the issue of rising cross-asset correlation must be constantly monitored.

In a journal article titled "*The Legacy of Modern Portfolio Theory*," Markowitz, Fabozzi, and Gupta (2002) give credence to investing across more asset classes rather than just across different industries as previously mentioned (p. 13). There is little argument that diversifying across a greater number of asset classes yields greater risk-adjusted returns, but investors must remain wary of relationship-related risk associated between asset classes. Because technology has made foreign investment more cost-effective, cross-asset and cross-regional portfolios have been widely adopted. In this article, the authors outline the idea of "Modern Portfolio Theory: A Top-Down Asset Class Application" used by investment managers to select the asset classes needed to create an optimal portfolio for their clients (Fabozzi, Gupta, & Markowitz, 2002, p. 9).

Fabozzi's, Gupta's, and Markowitz' (2002) study laid out the following method:

> They begin by selecting a set of asset classes (e.g., domestic large-cap and small-cap stocks, long-term bonds, international stocks). To obtain estimates of the returns and volatilities and correlations, they generally start with the historical performance of the indexes representing these asset classes (p. 9).

This widely accepted method of portfolio construction further highlights the importance of understanding relationships among asset classes in order to mitigate the risks of a global rise in cross-asset correlation. Using correlation analysis of historical returns of different asset classes is a reasonable method for determining whether there are relational risks in the market. Other key considerations brought up in this article shed light on the subjective nature of analyzing historical data.

Fabozzi, Gupta, and Markowitz (2002) note:

> The truth is that there is no right answer. In reality, as mentioned earlier, if portfolio managers believe that the inputs based on the historical performance of an asset class are

> not a good reflection of the future expected performance of that asset class, they may objectively or subjectively alter the inputs. There are some purely objective arguments as to why we can place more faith in the estimates obtained from historical data for some assets over others. (p. 11)

In today's complex world of financial markets, thousands of different indices exist across multiple asset classes and are traded on multiple exchanges. This has allowed asset classes from high yield bond indices to timber exchange-traded funds (ETFs) to realize a tangible value derived from their historical prices, which can then be used to analyze historical correlations. The opportunities are now endless for comparing the relationships of certain assets classes; however, selecting the asset class indices with the most reliable and statistically significant historical price information is a premium when analyzing these relationships.

A blend of stocks and treasury bonds has been considered efficient in reducing expected volatility while increasing expected returns in a portfolio. Phillips, Walker, and Kinniry Jr. (2012) argue that in recent years, "only U.S. Treasury bonds have been proven to be a true diversifier" in the market, maintaining their historically low correlation with equities while riskier asset classes have "seemingly moved in lockstep, with correlations to U.S. equities" (p. 1). Over the past couple decades, these riskier assets have been added to portfolios as a new source of diversification. The advent of the ETF has unlocked low-cost access to risk-premium assets classes and sub-asset classes such commodities, real estate, emerging-market bonds, and micro-cap stocks; while these assets are riskier than bonds, they do provide higher returns and demonstrate diversifying properties (Phillips, Walker, & Kinniry Jr. , 2012, p. 6). According to Phillips, Walker, and Kinniry Jr. (2012), investors have been flocking to these assets hoping to "lower total portfolio volatility, increase total portfolio returns, or generate some combination of higher returns and lower volatility" (p. 7). Investors have developed a sort of Recency Bias for the higher returns associated with new premium-risk assets, despite a lack of clarity regarding their correlations with equities. Regardless, as capital continues to move to these assets, investors must begin to recognize and interpret new cross-asset correlations.

At the crux of rising cross-asset correlation lies rising cross-regional correlation since all major international markets have become more interconnected, with the ability to share both information in capital instantaneously. In a study of major foreign markets as compared to the U.S. market, Solnik, Boucrelle, and Le Fur (1996) examine two major questions: first, "has the growth in international capital flows and market integration raised the general level of correlation in the past 30 years," and second, "is correlation increasing in periods of high market volatility?" (p. 17). After analyzing both return and volatility correlations between the U.S. market and the German, French, British, Swiss, and Japanese markets the researchers did find increased cross-regional correlations, but they noticed that this typically occurred during times of high market volatility. National factors such as business cycles typically determined each nation's market fluctuations, rather than their originally international factors, as they originally hypothesized. The authors did point to a concern very relevant in today's highly correlated global markets, explaining that "when the domestic market is subject to a strong negative shock is precisely when the benefits of international risk diversification are needed most, but the increased correlation reduces the benefit" (Solnik, Boucrelle, & Le Fur, 1996, p. 33). It must be accepted that correlations will fluctuate just as the prices they are derived from, and these fluctuations can be very significant over time. High volatility unequivocally leads to significant correlation risk across asset classes and international markets; Solnik, Boucrelle, and Le Flur (1996) heed warning to investors with global portfolios during these times of high volatility suggesting that the purely domestic portfolio with outperform in those times of uncertainty (p.33).

As previously mentioned, the issue of global market contagion is very relevant in exploring the idea of cross-asset correlation, and these two concepts have been used in conjunction to justify a global market meltdown similar to the Financial Crisis of 2007-2008. In the journal article "*No Contagion, Only Interdependence: Measuring Stock Market Comovements*", Forbes and Rigobon (2002) argue that market comovement following a financial shock in one country does not necessarily lead to contagion across other markets. Defined in this article as "a significant increase in cross-market linkages after a shock to one country (or group of countries)," Forbes and Rigobon (2002) assert that contagion can only result from a rapid increase in comovement that was not formerly present between two economies (Forbes & Rigobon, 2002, p. 2224). This article explores the financial shocks following the 1997 East Asian crisis, the 1994 Mexican peso devaluation, and the 1987 U.S. stock market crash, ultimately concluding that "there is virtually no evidence of a significant increase in cross-market correlation coefficients" resulting from these three incidents (Forbes et al., 2002, p. 2250).

Methods & Results

The first decision I made regarding data aggregation stemmed from "Modern Portfolio Theory: *A Top-Down Asset Class Application*" and involved researching then selecting various asset classes to test the hypothesis that a global rise in cross-asset correlation is present in today's financial markets. I began by researching financial asset classes by value, relevant indices, and available historical data. Ultimately, my asset classes of study included: equities (both developed and emerging markets), credit, foreign exchange, interest rates, and commodities. This broad data set tapped into many aspects of the global economy and provided me with enough historical data to perform correlation analysis.

Within each asset class, different indices and were selected based on their market values, component securities, number of historical data points and subjective opinions regarding each index's ability to adequately represent the broader asset class. See table 1. In order to ensure my ability to compare asset class correlations between different time periods, I selected only indices which had historical returns that would be statistically significant dating back twenty or more years.

Table 1

Selected Asset Classes and Corresponding Indices

Asset Class	Index
Equity	MSCI World Index (Ex. Emerging Markets)
Equity	MSCI Emerging Markets Index
Equity	S&P 500 Index
Equity	S&P 500 Economic Sector Indices
Credit	Bank of America/Merrill Lynch US High Yield Index
Foreign Exchange	MSCI Emerging Markets Currency Index
Interest Rates	US Generic Government 10yr Yield
Commodity	Bloomberg Commodity Index

Using Bloomberg Research, I was able to search between thousands of different indices in order to come up the test group seen above. The equity asset class was selected for the majority of the cross-asset correlations that I conducted, given that this class' indices had the most historical data available. When looking at real world application of cross-asset correlations, especially in the United States financial markets, most cross-asset correlative conclusions are drawn from a comparison between the stock market and some other asset class (e.g. bonds, currencies, commodities, etc.). This is the main reason why most of my cross-asset correlation results compare an equity benchmark with some other asset class.

Once I had selected the data to be tested, parameters were set to control the different time periods to be analyzed in order to compare correlation results results. Analyzing the most recent data was a key focus, but it was also critical to make sure that the time periods were large enough so that my results would be statistically significant. After studying the research methodology used by Solnik, Boucrelle and Le Fur (1996) in their article "*International Market Correlation and Volatility*", I decided set the parameters to capture monthly prices over two ten 10 year periods. The first period captured a date range between October 1990 and October 2000, while the more recent date range captured returns between October 2006 and October 2016. These parameters would be used consistently for each correlation analysis.

Correlation is measured numerically as the correlation coefficient and is a number between -1 and +1 that is calculated to represent the linear dependence of two sets of data. The formula for the correlation coefficient is:

$$r_{x,y} \equiv \frac{Cov(r_x, r_y)}{\sigma_x \sigma_y}$$

where Cov(r_x, r_y) = the covariance of the variables x and y, σ_x = the sample standard deviation of the variable x, and σ_y = the sample standard deviation of the variable y (Columbia University, 2003). This equation divides the covariance of two variables, indices in this example, by the product of each variable's standard deviation. Covariance is calculated as:

$$Cov(x, y) \equiv \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n - 1}$$

where x = the independent variable, y = the dependent variable, n = the number of data points in the sample, $\bar{x}$ = the mean of the independent variable x, and $\bar{y}$ = the mean of the dependent variable y (Columbia University, 2003). Using covariance to analyze the relationship between two securities allows you to determine whether units are increasing or decreasing, but it does not measure to what degree variables move together, given covariance does not use one standard unit of measure (Columbia University, 2003). Understanding the correlation coefficient formula, what the correlation coefficient means, and how it is derived was very important when I began to interpret my results. The strength of a correlation is measured between -1 and 1, with the strongest relationships existing on the lower and upper ends at that range. If the correlation coefficient is 1, a true, positive relationship exists between the two variables meaning that for any movement by one variable, the second move proportionally in the same direction. If the correlation coefficient is 0, the variables are considered uncorrelated and no predictions can be made about the movement of one variable relative to the other. Finally, if the correlation coefficient is -1, any movement from one variable will be complimented by a proportional movement in the other variable in the opposite direction.

Now, with my parameters set and an understanding of the output values' significance, I began to execute my correlation analysis using Bloomberg Regression Analysis. This highly technical group of functions provide and in-depth analysis of two securities' return volatilities and quantifies them with outputs such as Beta, Alpha, coefficient of determination (R^2), and correlation coefficient (R). Correlation analysis is considered the best practice for comparing the one-to-one relationship of two securities; whereas, Beta and R^2 measure the volatility of a single security relative to the broader market. Considering I was comparing market indices against one another, the correlation coefficient would yield the data most aligned with my research goals.

The table below (Table 2) summarizes the cross-asset correlations that I tested, their historical correlations from 1990-2000, their more recent correlations from 2006-2016, and the differences in correlations between the two time periods.

Table 2

Correlation Coefficients of Assets Classes Over Two Different 10 Year Periods

Asset Class	Correlation Between	1990-2000	2006-2016	Change
Equity	DM & EM Indices	64%	87%	23%
Equity	Economic Sectors	70%	83%	13%
Credit	HY & S&P 500 Indices	40%	74%	34%
Foreign Exchange	EM Currencies & Equities	41%	78%	37%
Interest Rates	10YR Rate & Equities	-19%	27%	46%
Commodities	Commodities & Equities	19%	58%	39%

Note. Average correlation from: 1990-2000 = 36%, 2006-2016 = 69%

Test Group 1

My first correlation test compared developed market and emerging market economies. The developed market index I chose to use was the MSCI World Index (MXWO), while the emerging market index I chose was the MSCI Emerging Markets Index (MXEF). The MSCI World Index consists of 23 Developed Markets (DM) countries with 1,648 constituent indices, representing approximately 85% of each country's equity market capitalization (MSCI Inc., 2017). The MSCI Emerging Markets Index also consists of 23 countries with 829 constituent indices representing approximately 85% of market capitalization in each country (MSCI Inc., 2017). The MSCI Emerging Markets Index now represents 10% of world market capitalization. My original expectation regarding these two asset classes was to see a rising correlation, resulting primarily from further "integration of global economies and capital markets" (Kolanovic, 2011, p. 3). Correlations between developed and emerging markets increased 23% and have more recently displayed a very strong, positive relationship with a correlation coefficient nearing 1 for the latter time period. The test compared 120 historical index prices form 1990-2000 and 120 historical index prices from 2006-2016.

Test Group 2

The second test compared S&P 500 economic sector indices with the broader S&P 500 Index. The S&P 500 sector indices tested included: Information Technology, Financials, Health Care, Industrials, Consumer Discretionary, Consumer Staples, Energy, Telecom, Utilities, and Materials. The S&P 500's newest sector, REITS, was not included, given there was no data from 1990-2000. For this test, I calculated correlation coefficients between each sector index and the S&P 500 Index for the two time periods and then averaged all of the correlation coefficients. Today's investment managers create portfolios that display very different characteristics from the broader market, overweighting and underweighting certain sectors in order to outperform other managers. If cross-sector correlations rise and display similar return characteristics, it will become much harder for managers to differentiate themselves from other managers and indexes (Callahan, 2012, para. 4). Between these two time periods, correlation between economic sectors indices and the S&P 500 Index rose an average of 13%. Each time period and each sector tested 120 historical price points. Of note, the S&P 500 Materials Index experienced an increased correlation of 22%, the largest increase of any sector with the broader market. The S&P 500 Industrials Index displayed the strongest correlation with the broader market from 2006-2016 with 95% correlation.

Test Group 3

The third example tested the correlation between the Bank of America/Merrill Lynch US High Yield Index and the S&P 500 Index. This was the first test I conducted between two entirely different asset classes, credit and equities. The BAML US HY Index tracks the performance of USD denominated, sub-investments grade corporate debt issued in the United States with in excess of $100 million outstanding (Federal Reserve Bank of St. Louis, 2017). I expected to see at least a positive correlation between these two asset classes, as high-yield bonds, while technically still bonds, are much riskier than investment grade bonds and demonstrate trading movements similar to stocks because of this risk. Correlations rose significantly, up 34%, when comparing the two time periods. 120 historical data points were tested for each time interval.

Test Group 4

For the fourth example, I examined the changing relationship of emerging market currencies with a global equity benchmark. To do this, I tested the correlatoin coefficients of the MSCI Emerging Markets Currency Index with the MSCI World Index between the two aformention time periods. Prior to testing, I anticipated, again, a rising correlationcaused by the risk on/off flow of capital to emerging markets.

Kolanovic (2011) further explains this market tendency:

> It is well known that an increased risk appetite of investors results in an inflow of capital into Emerging Market stocks. In order to purchase these stocks, funds need to be converted into local EM currencies. Given the liquidity of EM stocks and currencies, these inflows typically cause both assets (EM stocks and currencies) to appreciate at the same time, giving rise to positive correlation between equities and EM currencies (p. 7).

The correlation coefficient rose 37% when comparing the 1990-2000 time interval with the 2006-2016 time interval. The two time periods tested did have a different number of data points. However, the results still reflected a normal sample distribution which will be discussed later. The 1990-2000 time frame tested only 22 observations whereas the 2006-2016 time frame tested 120 observations.

Test Group 5

The 5th correlation analysis saught to examine the changing relationship between interest rates and equities. This test involved correlation analysis of US 10 YR Treasury Yields and the MSCI World Index. My pre-testing research focused on the traditonal, text-book relationship between stocks and treasuries. Schaeffer (2015) describes this relationship, noting that when the price of bonds falls, yields tend to rise increasing borrwoing costs; these higher yields encourage greater investment in the treasury market and also constrict corporate spending and drive down equities (para. 3). This thinking suggests that a negative correlation should exist between treasury yields and equities. After running the analysis, I came to find that the the 10 YR Treasury and global equities demonstrated a negative correlaton of -19% during the first testing period and a positive correlation of 27% during the second testing period. This 46% change was the largest in all of the test groups. Both testing periods examined 120 historical data points.

Test Group 6

The final testing pair was commodities and equities. The Bloomberg Commodity Index was used to test the commodities asset class, while the MSCI World Index was tested to represent the equities asset class. The Bloomberg Commodity Index is used to track futures contracts of multiple commodities in the global commodity market. Commodites have also demonstrated a strengthening correlations with the broader equities markets, with the correlation coefficient increasing 39% from the first period as compared to the second. The 1990-2000 time period had 117 data points, and the 2006-2016 time period had 120 data points.

After gathering all of my results, I utilized a program developed by Kristopher J. Preacher from Vanderbilt University to ensure that the data tested was normally distributed. A z-score output would be used to measure whether the data was normally distriubted.

Preacher (2002) describes his web utility as such:

> This interactive calculator yields the result of a test of the hypothesis that two correlation coefficients obtained from independent samples are equal. The result is a *z*-score which may be compared in a 1-tailed or 2-tailed fashion to the unit normal distribution. By convention, values greater than |1.96| are considered significant if a 2-tailed test is performed. First, each correlation coefficient is converted into a *z*-score using Fisher's *r*-to-*z* transformation. Then, making use of the sample size employed to obtain each coefficient, these *z*-scores are compared using formula 2.8.5 from Cohen and Cohen (1983, p. 54).

Table 3, below, summarizes the z-score outputs generated from testing the correlation coefficients of each test along with the data points for each test. Each z-score had absolute value greater than 1.96, meaning that correlation samples are normally distributed.

Table 3

Z-Score Test of Correlation Coefficients' Independent Sample Sizes

	Correlation		Sample Size		
	1990-2000	2006-2016	1990-2000	2006-2016	Z-Score
DM & EM Indices	64%	87%	131	120	-4.495
Economic Sectors	70%	83%	120	120	-2.454
HY & S&P 500 Indices	40%	74%	120	120	-4.029
EM Currencies & Equities	41%	78%	22	120	-2.465
10YR Rate & Equities	-19%	27%	120	120	-3.589
Commodities & Equities	19%	58%	117	120	-3.572

Note: Z-score outputs calculated using computer software developed by Preacher (2002).

Discussion of Results

The results of this study point to a rise of cross-asset correlation between select asset classes. An average correlation increase of 33% between the test periods 1990-2000 and 2006-2016 warrants consideration before making investment decisions. Across the financial community, it has been accepted that correlations have increased in the market. A highly involved study of equity correlations by Quinn and Voth (2008) revealed that “over the last century, capital account liberalizations have been accompanied by higher correlations of national stock markets with those abroad” (p. 539). Having accepted the notion that advanced, open financial markets do increase global equity correlations, it is still difficult to predict exactly what these relationship will mean going forward.

In regard to the study conducted in this paper, the methods used were sound within the context of analyzing a few select cross-asset relationships. Unfortunately, the data sets were too small to make any type of broad, definite conclusion regarding a global rise in correlation across all asset classes. Ample historical data does not yet exist for many of these new asset classes, some of which have only been in existence for 30 or so years.

When looking at the results but refraining from making any conjectures about the total rise in global cross-asset correlation, the results do strongly suggest that correlation relationships do change over time and should be researched in further detail. Before starting this analysis, I was expecting to see rising correlation on average; however, I did not anticipate the degree to which correlations increased between the two time periods. One of the more interesting correlation increases was between stocks and bonds. Ilmanen (2003) proposes that stock-bond correlations tended to be lowest when equity markets were suppressed and volatile (as cited in Phillips, Walker, & Kinnirny Jr., 2012, p.6). The results from my analysis are in conflict with this assumption. The correlation between the HY bond market and the global equities market actually turned positive for the 10 year time period that captured data from historically suppressed equity markets and extreme volatility resulting from the 2007-2008 Financial Crisis. I propose that the positive correlation between HY bonds and equities occurred for the second time period tested because the HY bond market selloff first trigged the global crisis; the staggering tailwind of this selloff then brought down equities and other asset classes.

A further in-depth study of rising cross-asset correlation will require more time, more data points. The financial community better understands the correlation between the U.S. stock market and the 10 YR US treasury as opposed to the correlation between emerging market indices and high yield bond indices. There is simply more data to be tested for longer-lived asset classes like developed market equities and treasuries.

Fabozzi, Gupta, and Markowitz (2002) confirm this need for more precise data:

> Since there are varying lengths of histories available for different assets (for instance, U.S. and European markets not only have longer histories, but their data are also more accurate), inputs of some assets can generally be estimated more precisely than the estimates of others (p. 9).

Regardless of this small slack in precise domestic data, tremendous strides in the global economy have been made, unlocking resources and capital in areas of the world that are still relatively misunderstood. In order to make any sort of decisive conclusion regarding newer correlations in the market, we will just need more time and more data.

A second limitation was analyzing a data set that included significant volatility following the global financial crisis of 2007-2008. Forbes and Rigobon (2002) note, “the unadjusted correlation coefficient is conditional on market movements over the time period under consideration, so that during a period of turmoil when stock market volatility increases, standard estimates of cross-market correlations will be biased upward" (p. 1). Heightened volatility following the crisis likely skewed the data to reflect stronger correlations during the time period form 2006-2016.

For future studies, a broader range of indices should be used to capture relationships between assets classes. This study examined the returns of one index against the returns of another single index, and then made conclusions for entire asset classes based on just one correlation calculation. While comparing the correlations of two indices can serve as a good proxy for tendencies that two broader asset class should display, single indices can demonstrate abnormal behavior that does not truly reflect the behavior of the broader asset class, potentially resulting in skewed correlation coefficients. Each correlation under study in this paper dealt with the correlation of a certain asset class with global equities. Future studies would benefit from examining correlative tendencies between two non-equity asset classes and should include more test indices and time periods. After reviewing the literature surrounding this topic, it became clear that volatility is a key driver of cross-regional and cross-asset correlations. Future studies should also look at incorporating correlation analysis of a particular asset class with the CBOE Volatility Index. This should yield great insight to the relationship between certain asset classes and broad market volatility. Understanding how certain asset classes respond to changes in volatility would add significant value to the research.

Implications

The implications of any type of heightened risk in the global financial markets affect billions of people around the globe, whether it be correlation risk or liquidity risk. A global rise in correlation across all asset classes will affect entities from the individual investor to pension funds to sovereign wealth funds. A sharp rise in cross-asset correlation could leave trillions of dollars susceptible to a downturn in the market and leave investment managers with fewer diversification opportunities. While correlation does impact investment decisions of trillions of dollars contributed by billions of people around the globe, it is by no means possesses the same sweeping market consequences like a significant credit crunch or liquidity crisis. For the non-academic, understanding correlation simply boils down ensuring that portfolios are properly diversified.

For the investment managers, correlation should be carefully considered and hold equal weight with expected return and expected volatility when constructing a diversified portfolio. It is important to keep in mind that correlations between asset classes often change over time; examining past correlations may not necessarily predict future correlations. Investment managers should treat correlation changes with the same long term view that Warren Buffett and other successful long-equity investors view the equity markets. There will be times of heightened volatility and rising correlations, leaving investment managers unsure of the right strategy to counteract correlation risk. Phillips, Walker, and Kinniry Jr. (2012) suggest that during times of markets distress when correlations appear to be going to 1, “investors can take solace that a modicum of diversification can be achieved when assets do not move by the same amount, even when they move in the same direction” (p. 13). Until cross-asset correlations reach true 1, diversification opportunities will exist in the market, although they may be harder to exploit.

Individual companies should not be as concerned with correlation risk in the same way that investment managers must be concerned. Businesses that have a significant portion of their short term assets tied up in marketable securities may be more conscientious of rising volatility and subsequently rising correlations relative to companies that just hold cash. This conjecture is made based on the tested examples in this paper which suggested that asset classes are experiencing rising correlations relative to equities. Similar tests of different asset classes relative to a particular currency could either confirm or oppose the aforementioned recommendation that companies with a greater percentage of short term assets tied up in marketable securities should be more conscientious of correlation risk.

Conclusion

Rising correlations on their own will not necessarily bring down the global economy like the 2007-2008 Financial Crisis; however, a significant market event or correction can be compounded by a period of highly correlated assets across integrated financial markets, ultimately leading to significant investment losses. In conducting my research, I first analyzed the relevant literature surrounding this topic. Beginning with Markowitz' "*Portfolio Selection*," I was able to grasp the framework of traditional asset class selection as a means for diversification. From there, the literature became more narrowly focused on specific nuances of specific correlative relationships found under the umbrella of cross-asset correlation. With this research and knowledge at my immediate disposal, I was able to begin formulating tests that would give credence to or deny the original hypothesis that cross-asset correlations are rising and present a risk to the highly integrated, global economy. Indices were then selected as a representation of their broader asset class. Research parameters were set and correlation analysis was run between the testable examples using Bloomberg Research. The relationships tested yielded an average rise in correlation of 33% from the 1990-2000 time period as compared to the 2006-2016 time period. I was able to confirm that all of the data tested was normally distributed.

In analyzing these results, it became clear that some of the relationships were more easily explained than others. The primary limitation of this study was a lack of historical data.

Understanding new, complex relationships between asset classes that are still relatively new in the market is much harder to synthesize than the correlations of historical asset class like the domestic stock market and U.S. Treasuries. Moving forward, investment managers must continue to take time to understand correlative relationships as a means of diversifying risk.

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