RISK APPETITE AND THE JAPANESE YEN

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CS 170A Final Project

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INTRODUCTION TO THE TOPIC

Financial markets are prone to risk. There are times when investors are willing to take risk and invest in assets that could return high yields. There are also times when investors look to assets that are not known to provide high returns, but are known to preserve their value during times of significant market turmoil. These assets, in market lingo, are called *safe-havens*.

In this project, we shall explore one such safe-haven, the Japanese Yen. After the global financial crisis in 2008, investors turned to several safe haven assets (Gold was another popular one) to preserve their wealth. We start off by discussing the background of the Japanese Economy over the last two and a half decades, which sets the tone for the Yen to emerge as a safe-haven. We follow this up by discussing how currency trading works, with a special emphasis on carry trades as it plays a big role in the value of the Yen. After that, we analyze the relationship of the USD-JPY with some major global indices (which are directly correlated to the market's propensity for risk), which provides evidence to the project's theme.

ABOUT THE DATASET

I could have picked my dataset for this project in several different ways. One, I could have picked about 20 different global equity indices and compared them to the USDJPY, following it up with a Principal Component Analysis. This however, would have been too large of an analysis, not conducive to the required length of the assignment. Another way I could have done the analysis was by including a bunch of currency pairs, including the USDJPY and seeing how they related to global major indices. This, again, would have made the project inconveniently large. I decided to select some of the major benchmarks in the equity markets along with historical figures for the USDJPY spanning **10 years**, and analyze the numbers using mathematical tools learned in this course. Below is a brief intro to these indexes.

TIP FOR READER: Feel free to skip the next few pages where I discuss the indices and currency trading if you are familiar with how these markets work. They have been included for those who are not so acquainted with the data set to give the project a holistic feel. If short on time, the reader should look at last segment that covers the analysis of all the indices combined, as it proves our hypothesis to be true.

- S&P 500

  The S&P 500 is the most popular global benchmark for the financial markets. It tracks the performance of the top 500 companies in the United States, some of which also happen to be the largest and most influential in the world. After the financial crisis of 2008, the United States economy was affected the most with millions of people losing their jobs. The economy since then has slowly but surely improved as a consequence of monetary easing (popularly known as 'quantitative easing') by the Federal Reserve. The last two years have seen drastic improvement in the country's economy with reports indicating a robust recovery.

- NIKKEI

  The Nikkei focuses its attention on the 225 most important companies in Japan. The Bank of Japan, under the direction of Abenomics (economic policies introduced by the Prime Minister, Shinzo Abe), announced in 2012 that it planned on doubling the nation's monetary base to bring back growth in its economy. The bank started purchasing bonds from the markets, creating more liquidity. This enabled two things. First, businesses would get easy money that they could invest in their activities boosting earnings expectations. Second, people would invest money in the equity markets as they anticipated better earnings. There was money for everything – to invest locally and to invest abroad. While the extent of the policy's real impact on Japan's economy is still in question today, it has bought cheer to the Japanese equities, as the index is up by 70 percent after the introduction of Abenomics.

- DAX

  The Deutscher Aktienindex, popularly referred to as the 'DAX', is the benchmark index that tracks the performance of Germany's 30 major companies. Germany is the largest economy in the 17-country Eurozone and its performance can often be a strong reflection of the Eurozone in general (I stress on the 'can often' as until recently the German economy had been performing much better than the Eurozone in general). The nation has been recently pulled down by waning growth in the Eurozone. The European Central Bank has been making efforts to flood these markets with more liquidity through easing measures, but has so far been largely unsuccessful.

- FTSE

  Like the other two indices, the FTSE tracks the most important companies in the United Kingdom and is comprised of a 100 of them. The UK also happens to be the center of global FX transactions, as 41 percent of trades globally take place there. The economy of the UK has seen a trajectory in its recovery comparable to the United States post the 2008 crisis as the Bank of England (central bank of the UK) has implemented policies similar to that of the US Fed.

- MSCI World Index

  The MSCI World Index captures the performance of 1685 large and mid cap stocks across 23 developed economies across the globe. I considered using the MSCI Emerging markets index as well, but realized that I would need a base currency to pick the index in. As emerging market currencies have sharply dropped against the dollar in value over recent years, my data results might have been skewed so I ignored it for the time being.

- ASX200

  The ASX 200 is the index that tracks the performance of 200 major companies in Australia. Some have questioned my inclusion of Aussie data in my study – but I do have a strong reason behind my selection. While it isn't as significant globally as the United States or Germany, the country is a large exporter of raw materials used in manufacturing and is hence strongly linked to global risk sentiment. Since we are studying risk relations in our project, I felt it would be a great addition.

- USDJPY

  The most important element of our project is, of course, the currency pair. We use this to measure the relative value of the Japanese Yen that devalues as the value of the pair goes up and appreciates as the pair goes down. The US Dollar is a great pick for first currency because the Yen is essentially the driver of this pair's value, not the Dollar.

ACQUISITION AND MODIFICATION OF THE DATA

One of the beauties of the financial markets is that a lot of people follow it. This creates a demand for the data that these markets are likely to create which then becomes easily available through databases like Bloomberg, Capital IQ, Reuters, etc. Extracting the historical closing figures for the USDJPY and the six major indices used in this project wasn't the most difficult thing.

The one little change that I did incorporate was adjusting the closing prices of the indices and the USDJPY on the day that the corresponding market was closed. The code for that is attached below. Beyond that, any form of 'data cleaning' seemed unnecessary for our purposes and might have skewed results.

```
%extracting the dataset
data = csvread('projectdataset.csv',0,0);
k=0;
[n,p] = size(data);



% making modifications to the data set
for j = 1:p
    for i = 2:n
        if (data(i,j) == 0)
            data(i,j) = data(i-1,j);
            k = k+1;
        end
    end
end
```

STRUCTURE OF THE PROJECT AND MATHEMATICAL TOOLS USED

An initial look at the data set, along with a general idea suggested that the tools required to conduct the analysis would be not be extremely sophisticated to implement but would be powerful in what it would reveal.

We begin our study by computing basic **correlations** between the four major indices that we picked and the USDJPY. These correlations are calculated on a monthly, quarterly and yearly basis along with one on the complete data set. This helps us answer questions on current trends – when is the correlation the highest during the year? Has it been increasing, decreasing or remained the same over the last five years? We also have a matrix that reveals that the global indices picked do indeed correlate a lot.

In the next segment, we use **linear least squares** to fit the different indices to the USDJPY (since our dataset is linear). Following this, we use some **regression analysis** that unfortunately didn't do enough to back my initial hypothesis (discussed later). However, I did make some extremely interesting observations when instead of comparing the USDJPY to each individual index, I compared it to all of them combined at the same time. This in fact did enough to confirm our hypothesis. To satisfy myself, I did a quick check by computing errors using the **Euclidean norm**, which strongly backed my charts.

I did consider using more math heavy tools in my analysis like **Principal Components** (I actually computed the SVD matrix which revealed an elbow at the second principal component). However, as we were already dealing with major indices in out set, I didn't feel the need for greater isolation of the data. Also, by the time I reached that far with my analysis, it seemed almost impossible to refute my theory.

BACKGROUND OF THE JAPANESE ECONOMY

The onset of the 1990s saw a great slump in the Japanese economy after the housing price bubble between 1986 and 1991. The Bank of Japan (BOJ) had started easing monetary policy in 1986 to counter the appreciation of the Yen against the US Dollar (the US$ fell from 237 to 153 against the yen during this period, despite efforts from the BOJ). Soon, it had to reverse the trajectory of its interest rate because of a bubble that became eminent in the markets. However, it was all too late and the economy had already developed deep cracks. These 'cracks' went on to last a long time, as Japan today still struggles from poor growth and lack of inflation in its economy.

A consequence of this has been extremely low interest rates that the Bank of Japan (Japan's central bank) has been charging since the late 1980s. To encourage investment by making the cost of borrowing extremely low, central banks often cut back on their interest rates during times of recession or even slowing growth. This effort, however, was unable to propel Japan in any possible way and as a result, this cost of borrowing has remained low since then, making the Japanese currency unit the center of carry trades. We shall explain carry trades later in this article.

EMERGENCE OF THE YEN AS A SAFE HAVEN ASSET

In lieu of better returns on their assets, Japanese Investors have invested their money in assets abroad as growth in the country has been poor. However, during periods of market uncertainty, they repatriate their wealth and convert the foreign currency into the Yen. This creates an interesting scenario. During such a time, the value of the assets abroad fall as people are trying to sell it and exit the markets, resulting in more supply of it than there is demand. On the other hand, the demand for the Yen rises, creating more demand than there is supply and the currency's value appreciates.

However, when these investors change their sentiment and start looking for higher yields again, they turn to the foreign assets, selling their own currency to purchase foreign currency that is needed to acquire the targeted assets. The Yen, during these times, depreciates and the values of those foreign assets go up.

As this has been going on for sometime now, the idea that the Yen is a safe-haven has become *self-fulfilling*. Investors now, not only in Japan, but across the globe have started turning to the Yen during times of risk in the markets, as it is likely to increase in market value.

CURRENCY AND CARRY TRADES

A fact worth noting at this stage about currencies (especially for people who don't necessarily trade foreign exchange on a daily basis) is that they trade in pairs i.e. a currency is always purchased against the sale of another currency. When traders purchase a currency, they not only receive benefits (or bear losses) from its relative appreciation (or depreciation), but also receive or pay interest on that currency (as determined by the respective central banks that control the currencies).

For example, let us consider the currency pair of the Australian Dollar and the Japanese Yen (known as the AUDJPY). The Reserve Bank of Australia (Australia's central bank) currently charges an interest rate of 2.5 percent, while the Bank of Japan has a near-zero interest rate. This means that when a trader buys the AUDJPY (which means he buys the Australian Dollar and sells the Yen), his gains/losses not only include the change in relative value of the Aussie, but also the interest he receives due to the higher interest rate commanded by it. On the other hand, if he sells the AUDJPY (sells the Aussie and buys the Yen), he not only makes profits or losses from a shift in valuation, but also pays out interest to the higher yielding Aussie unit.

Trades that are placed with the idea that these relative values will not change and profits can be made by buying the higher interest bearing currency and selling the lower interest charging one are known as carry trades.

SO WHAT IS RISK APPETITE?

As we discussed earlier, fear dominates the market more than greed. When investors think the global economy is not expecting any near-term shocks and the headlines of newspapers will be devoid of geopolitical tensions, they start hunting for assets that may be slightly risky in nature but are more likely to yield higher returns. *These periods are generally described as 'risk-on' for the markets.*

On the other hand, when there is danger to the global economy (such as fears of deflation and recession in Europe) or geopolitical risk (such as a potential war between Russia and Ukraine), fear sets in regarding these high-risk assets. *These situations are often known as 'risk-averse' situations.* For example, a waning Chinese Economy often causes the Australian Dollar to depreciate in value. This is because China is Australia's biggest export partner and poor economic growth is likely to reduce demand for Australian exports, and consequently demand for its currency. The Australian Dollar here is the high-risk asset because its value is sensitive to external situations.

So how do we go about measuring this risk appetite? While there are several ways to do it, the major global indices such as the S&P 500, the DAX, the FTSE, the Nikkei and the ASX serve as benchmarks to observe current risk trends in the market. When these indices go up, investors are seen in the 'risk-on' mood of things, while when these indices go down, the markets are 'risk-averse'.

We now move onto the most important segment of this report, where we analyze the data set. An important point to note at this stage is that a rise in the USDJPY is synonymous with a depreciation of Japanese Yen, because it is the second currency in the pair. A rise implies that the US Dollar has gained value over the Yen, while a fall implies that the Yen has appreciated relative to the Dollar.

ANALYSIS LOG

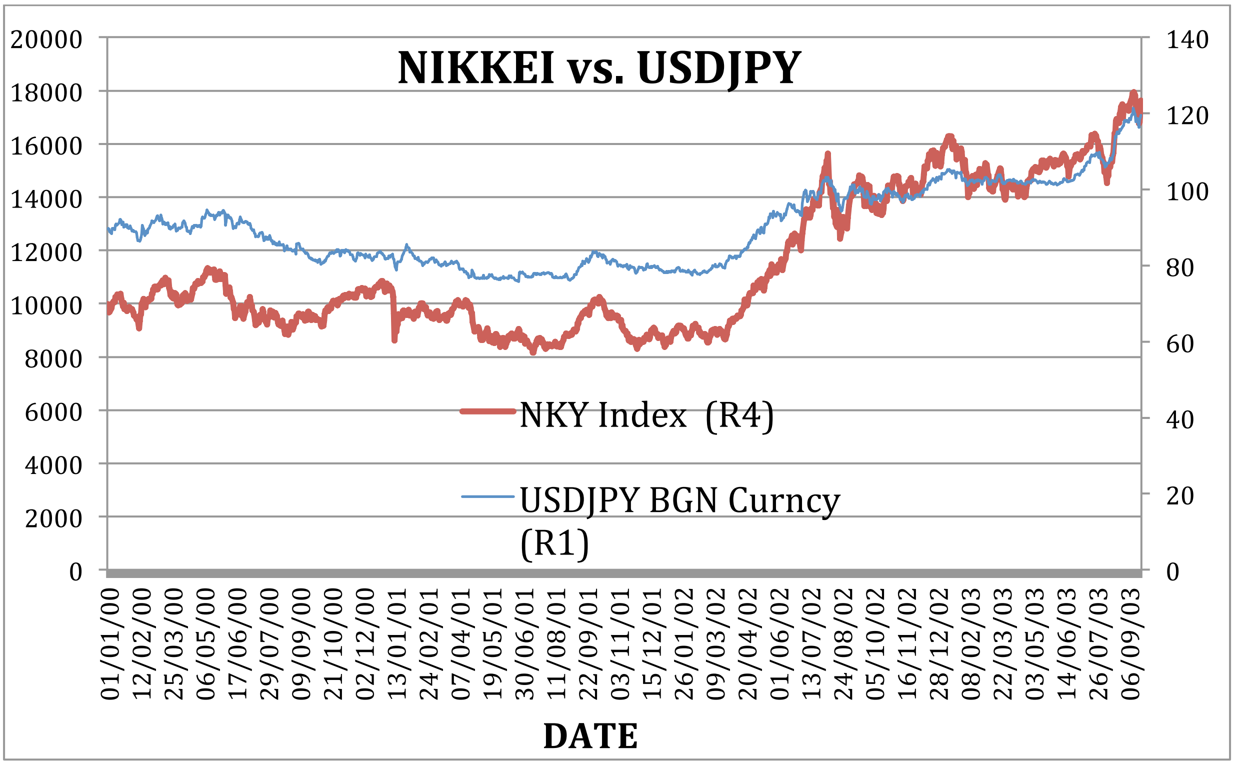
I. CORRELATIONS

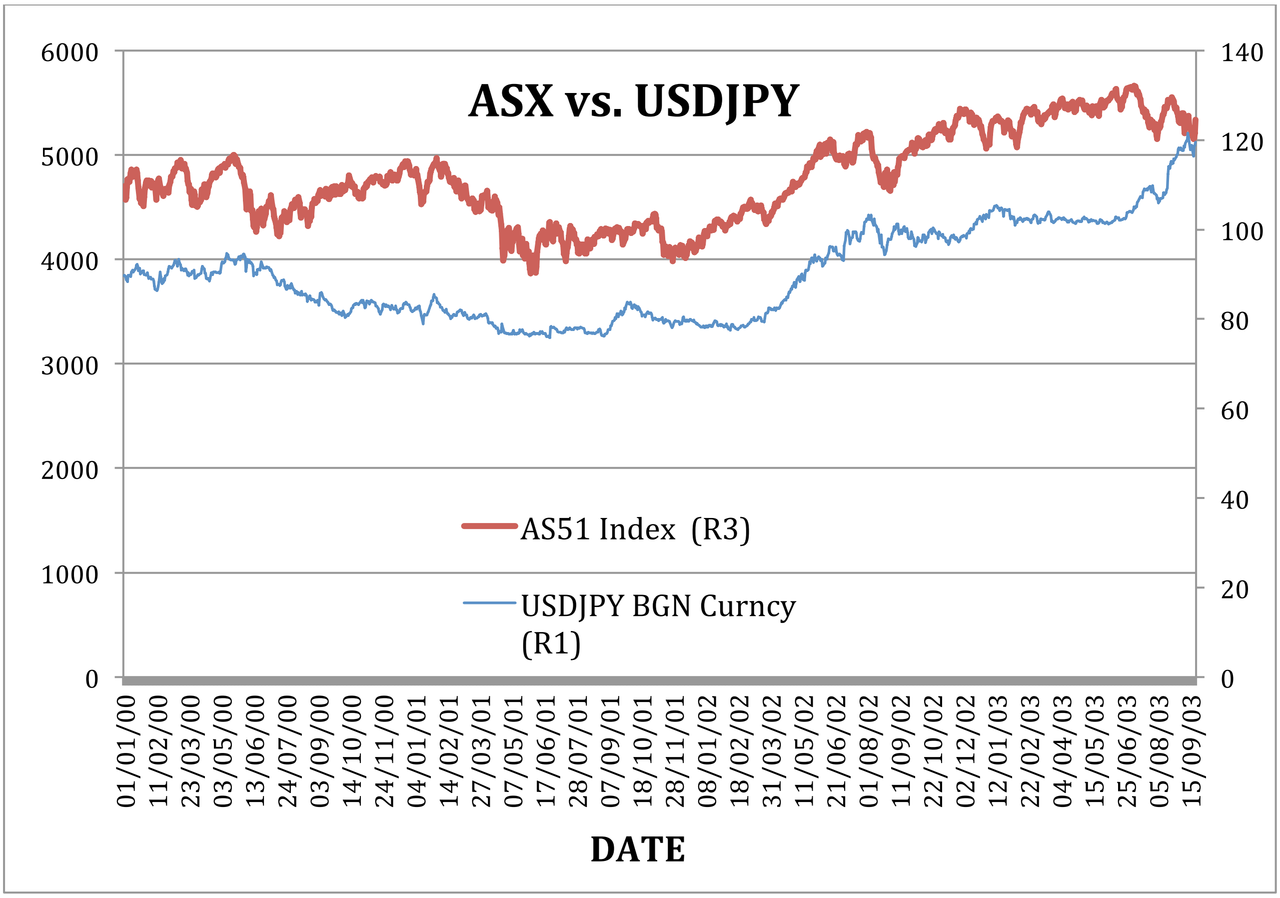
I thought the best way to begin this project would be to study the correlations between the individual indexes and the USDJPY (A good point to note is that the correlation between the least squares fit for each index and the USDJPY also return the same value). We used some Matlab code to compute our figures, which revealed the following:

TABLE: CORRELATIONS OVER A PERIOD OF 5 YEARS

	S&P 500	**NIKKEI**	**DAX**	**FTSE**	**MSCI**	**ASX**
USDJPY	0.7852	0.9534	0.7809	0.7313	0.7949	0.8781

Correlations over the last 5 years were indeed extremely strong, with the lowest reported at 0.7313, which isn't really low. In the graph of the charts comparing S&P 500 and the FTSE to the USDJPY attached below (I didn't attached all of them for the sake of the report's length, they can be seen in the file containing the data), we can see why these correlations are true.





I decided to use data over 10 years as well in my assignment to look at how much these correlations have changed over time. The numbers are truly fascinating (see table below) as they tell us that correlations have skyrocketed in recent times. The DAX, for example has a correlation of 0.7809 with the USDJPY in the last 5 years, but over the last 10 years that numbers fall to 0.0373, which is close to almost no correlation. This shows the Yen might have potentially become a more popular safe-haven in recent times.

CORRELATIONS OVER A PERIOD OF 10 YEARS

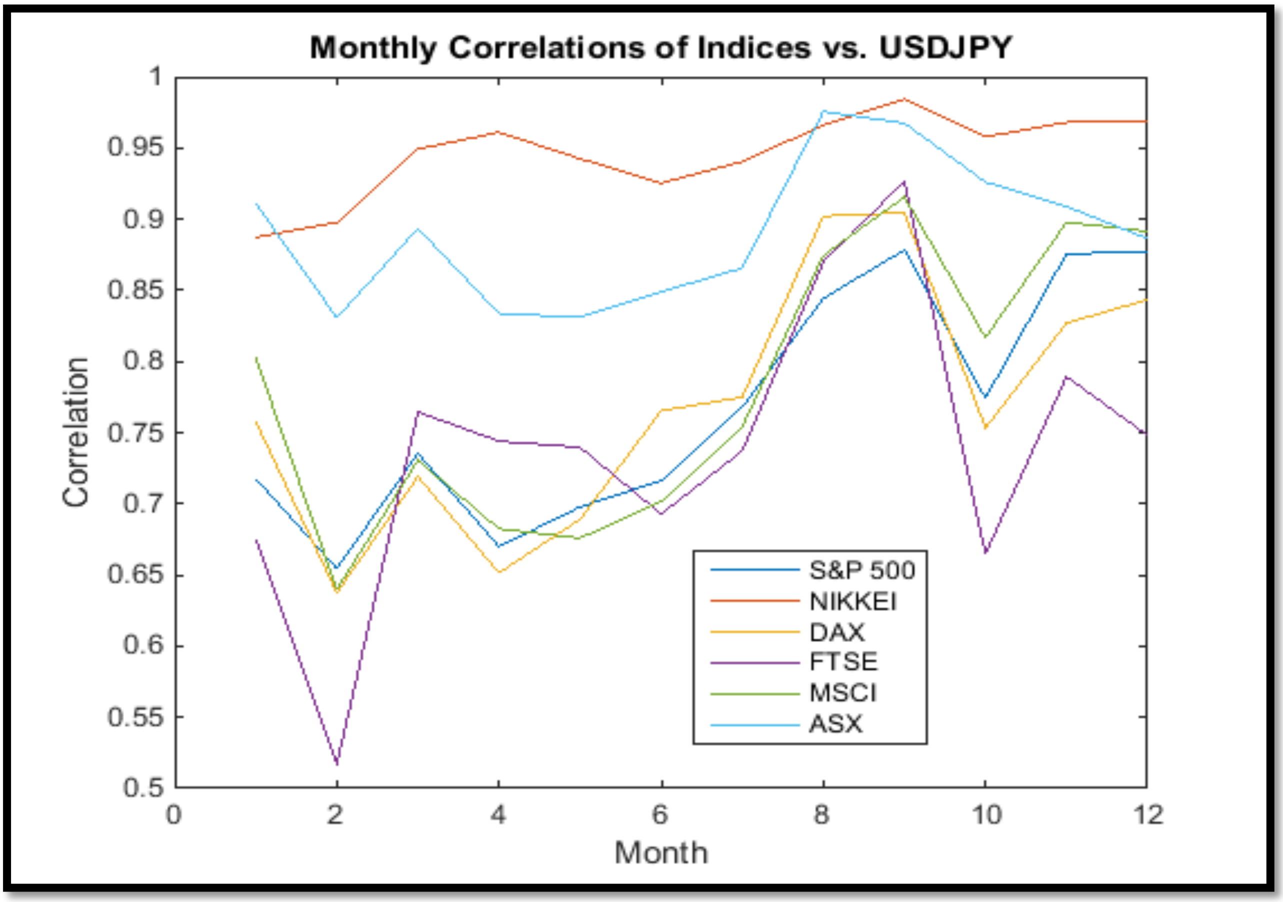
	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
USDJPY	0.2479	0.8559	0.0373	0.2486	0.3945	0.5507

So far, it seemed like an excellent start to my project. Strong correlations numbers seconded the initial idea that the Yen did, in fact, move with some relation to the major equity markets across the globe. Before I jumped onto the next tool to analyze my data set, I wanted to venture a little deeper into the trends of these correlations by studying them on a monthly, quarterly and yearly basis.

MONTHLY CORRELATIONS

USDJPY	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
January	0.7176	0.8871	0.7578	0.6749	0.8028	0.9109
February	0.6546	0.8976	0.6376	0.5172	0.6399	0.8307
March	0.7353	0.9492	0.7191	0.7645	0.7306	0.8934
April	0.6699	0.9610	0.6515	0.7440	0.6824	0.8337
May	0.6978	0.9425	0.6891	0.7397	0.6760	0.8311
June	0.7163	0.9254	0.7654	0.6928	0.7015	0.8490
July	0.7679	0.9403	0.7749	0.7372	0.7543	0.8656
August	0.8444	0.9661	0.9021	0.8700	0.8744	0.9756
September	0.8783	0.9844	0.9045	0.9268	0.9156	0.9674
October	0.7743	0.9579	0.7533	0.6651	0.8168	0.9260
November	0.8759	0.9680	0.8271	0.7894	0.8978	0.9088
December	0.8765	0.9694	0.8434	0.7481	0.8914	0.8864

We plotted these correlations to observe that indeed, they all seemed to rise and fall together during the year. This was an interesting observation and I wanted to mention it, but didn't seem to have as much relevance as the other segments explored later in the project.



Similarly, I did the computations for quarterly and yearly data.

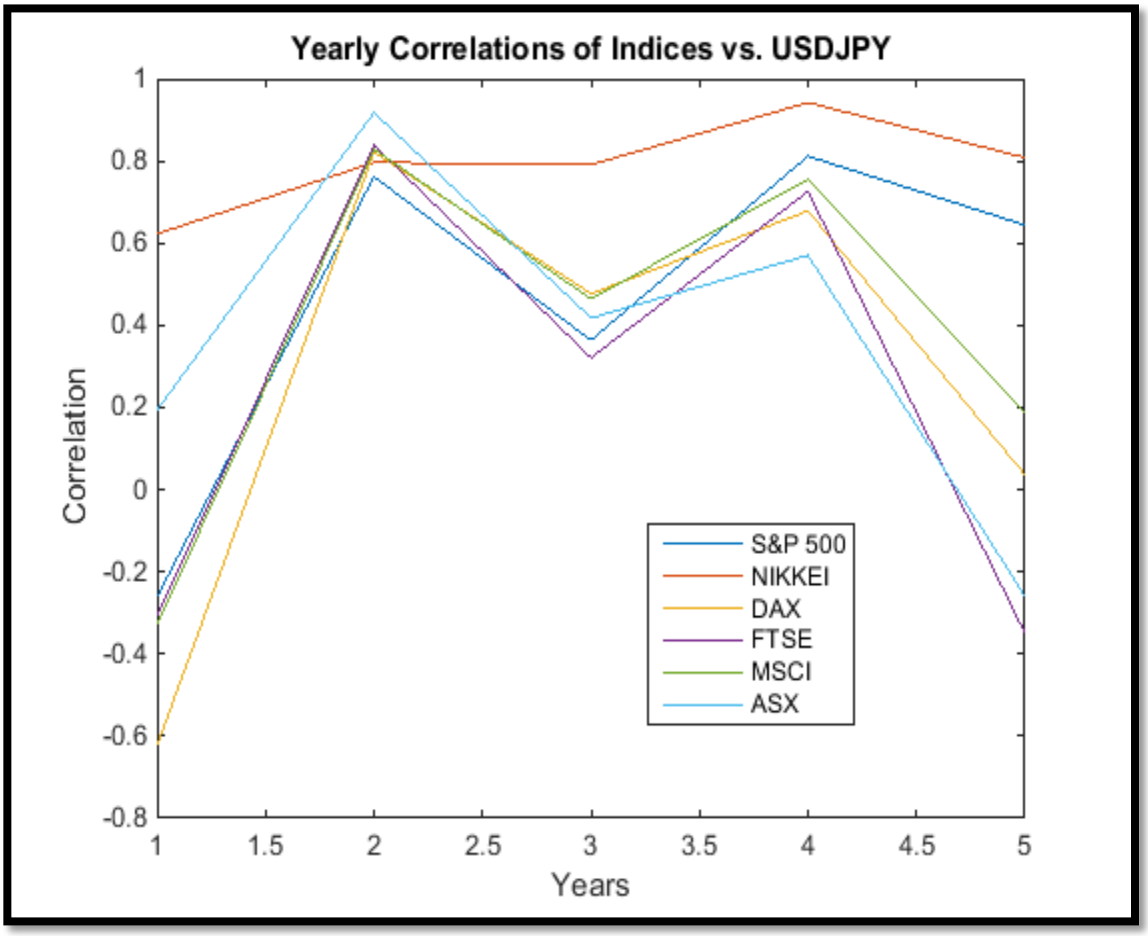
QUARTERLY DATA

USDJPY	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
Quarter 1	0.7026	0.9077	0.7070	0.6450	0.7287	0.8762
Quarter 2	0.6950	0.9400	0.7026	0.7163	0.6857	0.8298
Quarter 3	0.8322	0.9651	0.8657	0.8477	0.8501	0.9365
Quarter 4	0.8431	0.9657	0.8126	0.7354	0.8683	0.8953

YEARLY CORRELATIONS

USDJPY	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
2010	-0.2613	0.6224	-0.6232	-0.3077	-0.3288	0.1935
2011	0.7623	0.7962	0.8211	0.8383	0.8286	0.9177
2012	0.3637	0.7910	0.4769	0.3208	0.4643	0.4178
2013	0.8116	0.9420	0.6784	0.7259	0.7552	0.5703
2014	0.6442	0.8081	0.0358	-0.3498	0.1880	-0.2593

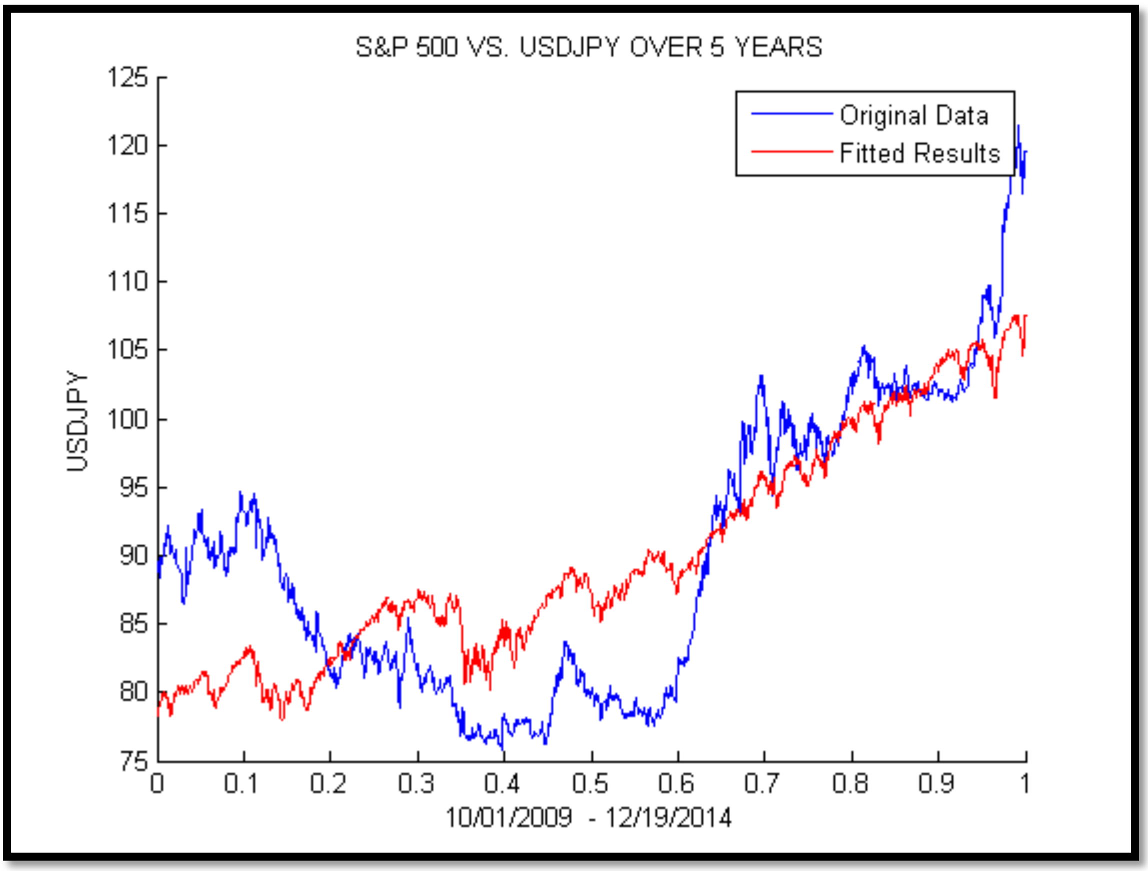
These figures also give the same hint that the Yen is a popular choice when people are looking to preserve their wealth, especially when uncertainty is less frequent (2013 was the best year for stocks in the last 5 years). A plot for these yearly numbers is below. Later on, we shall come back to study correlations when we combine all the indices and study them as one whole.



II. LEAST SQUARES FIT

S&P 500

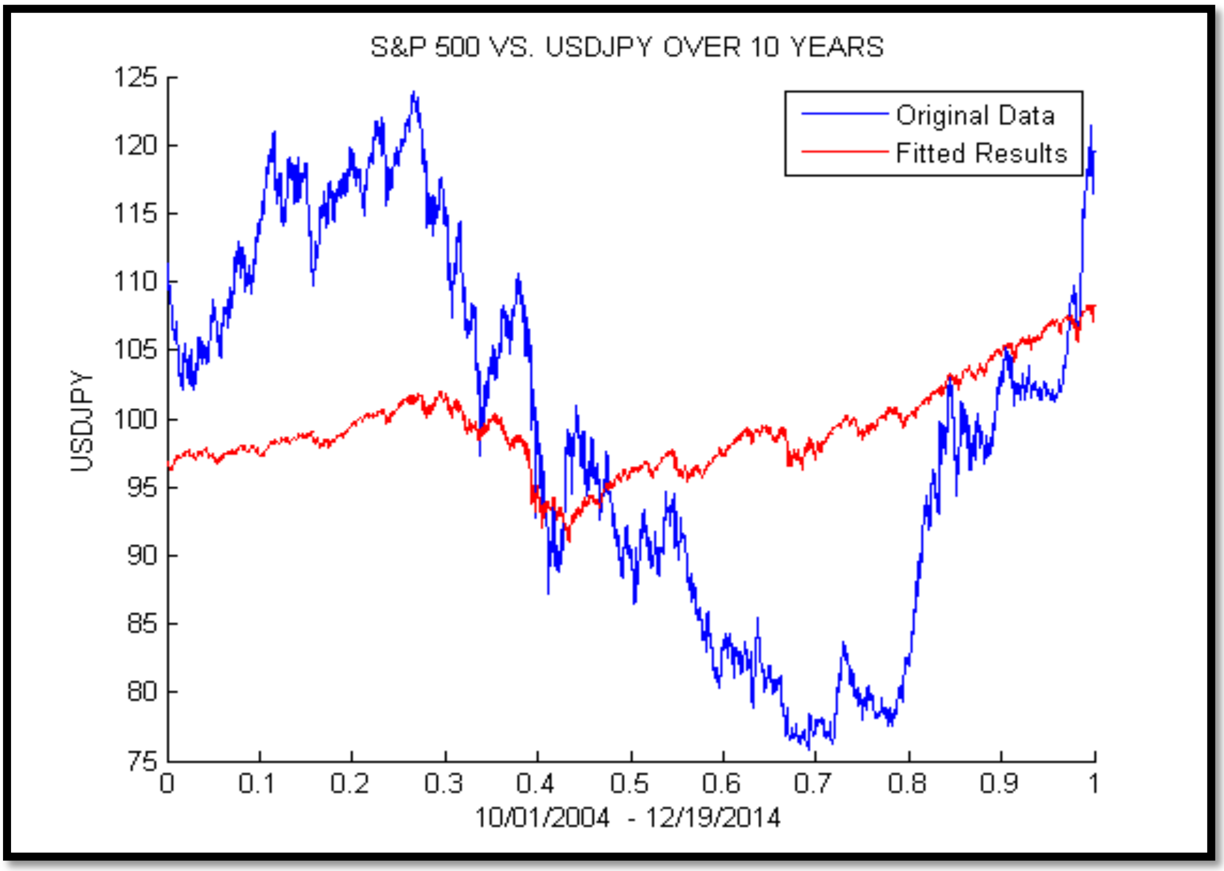
We now move onto to using the least squares fit model. We take each index individually and see how their linear model would fit the USDJPY. This would help us observe how the index drives the valuation of the currency pair. The code can be referred from the Matlab file. On our first test, we use the S&P 500 that gives us the following plot:



There were certain periods during the last five years that figures diverged, and that is not surprising at all considering the fact that the United States has been taking various measures to recover from the crisis of 2008. Correlation figures still remained strong at 0.785 though.

Before moving to Japan's very own Nikkei, I wanted to analyze how different results would have been had I taken 10 years of data – and indeed it was different. As the next graph shows, there was a lot less sync between what the USDJPY would have been had we computed a least squares fit over a decade.

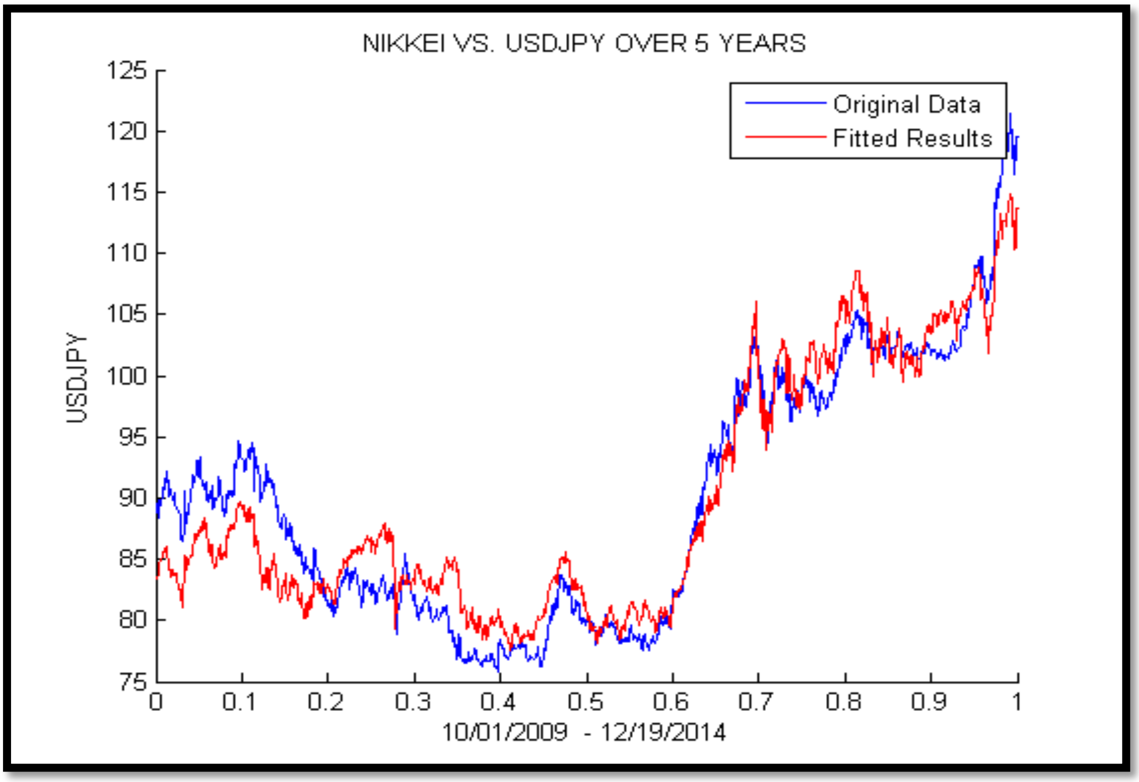
A quick look at the fit the S&P 500 produces on the USDJPY over the last 10 years reveals the following chart:



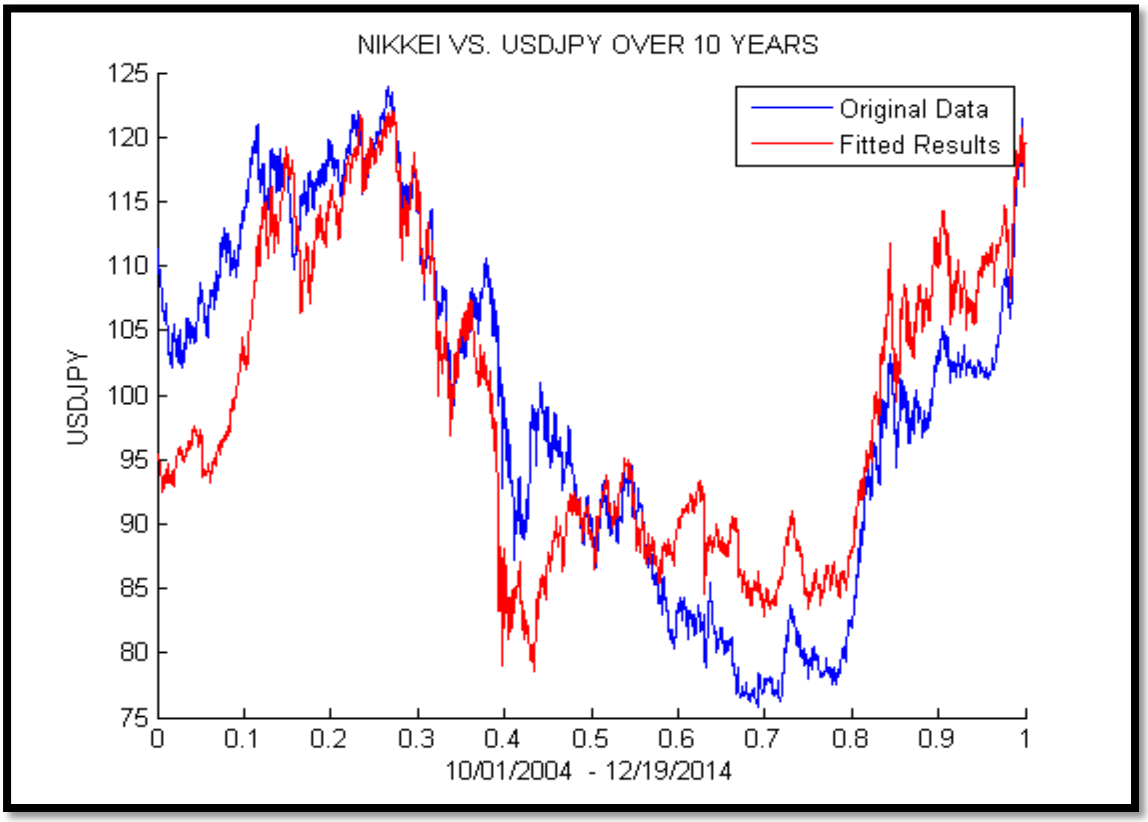
Correlation figures dropped to a 0.24 in this 10-year period, showing that the index and the currency pair have had a stronger relation in the near past.

NIKKEI

As Japan is home to the Yen, I wasn't surprised all at when reports suggested that country's main index showed the strongest correlation to the USDJPY. As we see in the chart below, the fit of the Nikkei moves alongside the appreciation and depreciation of the Yen, and does so better than any other index's fit.

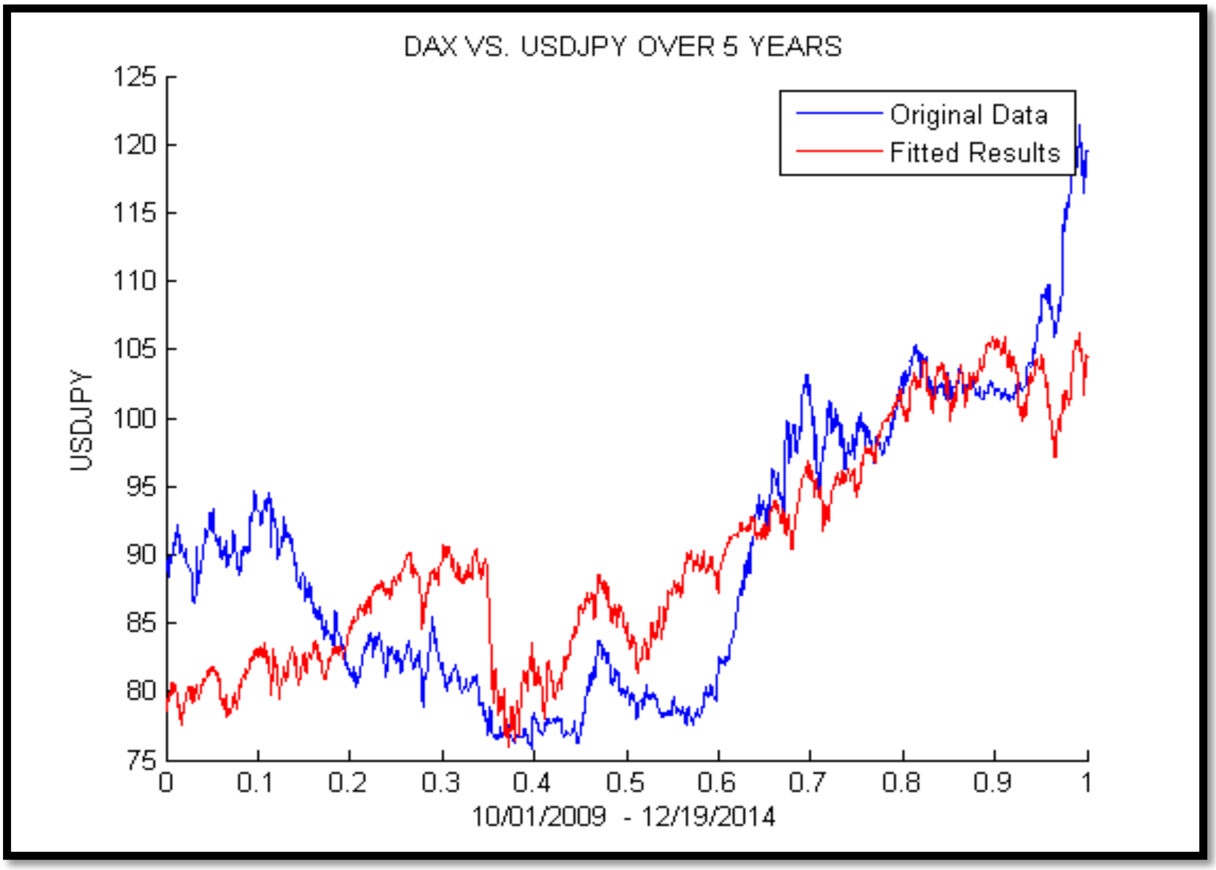


The 10-year chart also yields similar results. As the time frame gets longer, the error also gets higher, but the good thing for our purpose is that it never blows out of proportion to refute theories.



DAX

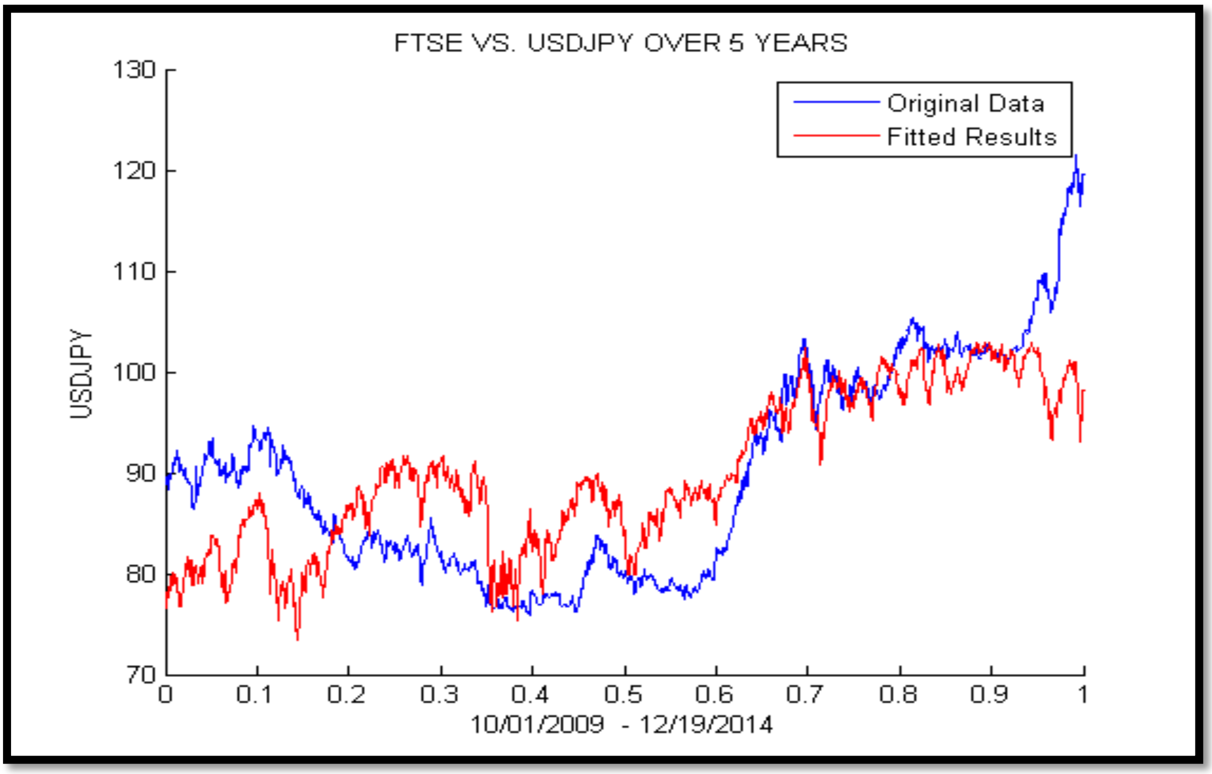
The DAX's fit on the pair, like the S&P 500, also shows deviations during certain phases of the 5-year period. It is also likely because of certain differences in economic cycles (like the ongoing Eurozone crisis) that the DAX doesn't align with the global sentiment all the time. Even then, correlations have remained high at 0.781 in recent times.



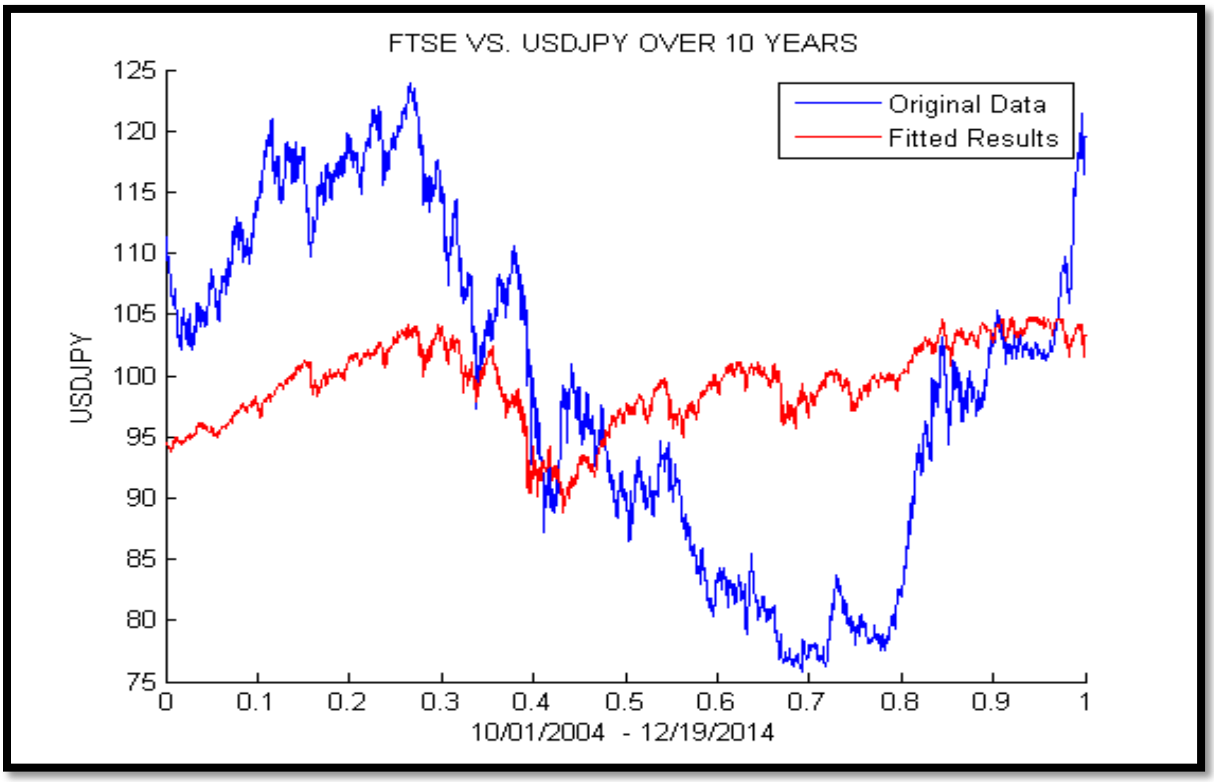
FTSE

The fit of the FTSE looks a lot like the fit of the S&P 500, which is not surprising to me at all. The United States and the United Kingdom have been staging similar recoveries in recent times post the 2008 crisis, with their central banks implementing similar policies to encourage borrowing and investing.

The linear fit for the FTSE looks something like this:

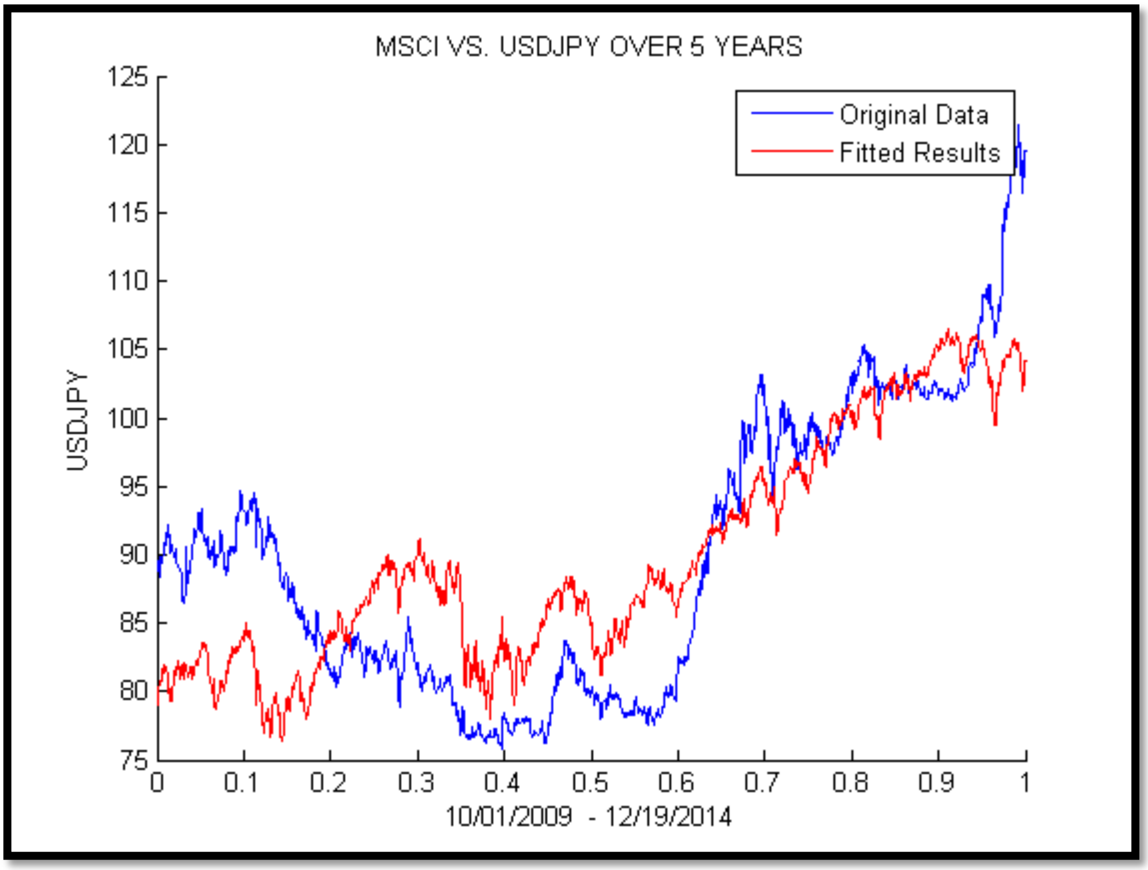


The 10-year chart shows the following fit, which is again similar to the S&P 500 for the same reasons.



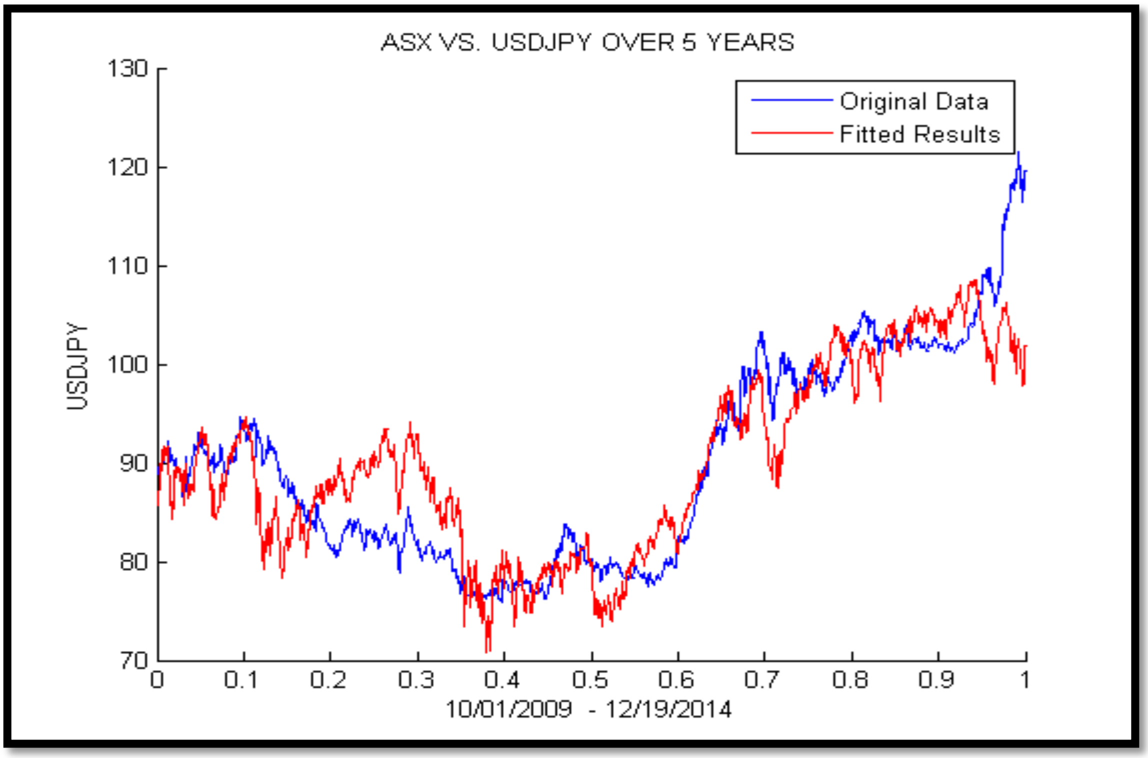
THE MSCI WORLD INDEX

As described in the introductory section, the MSCI tracks a relatively high number of companies compared to the other indexes, but yields results quite similar to them. This provides a good setup for the last stage of our analysis, which we shall see later.

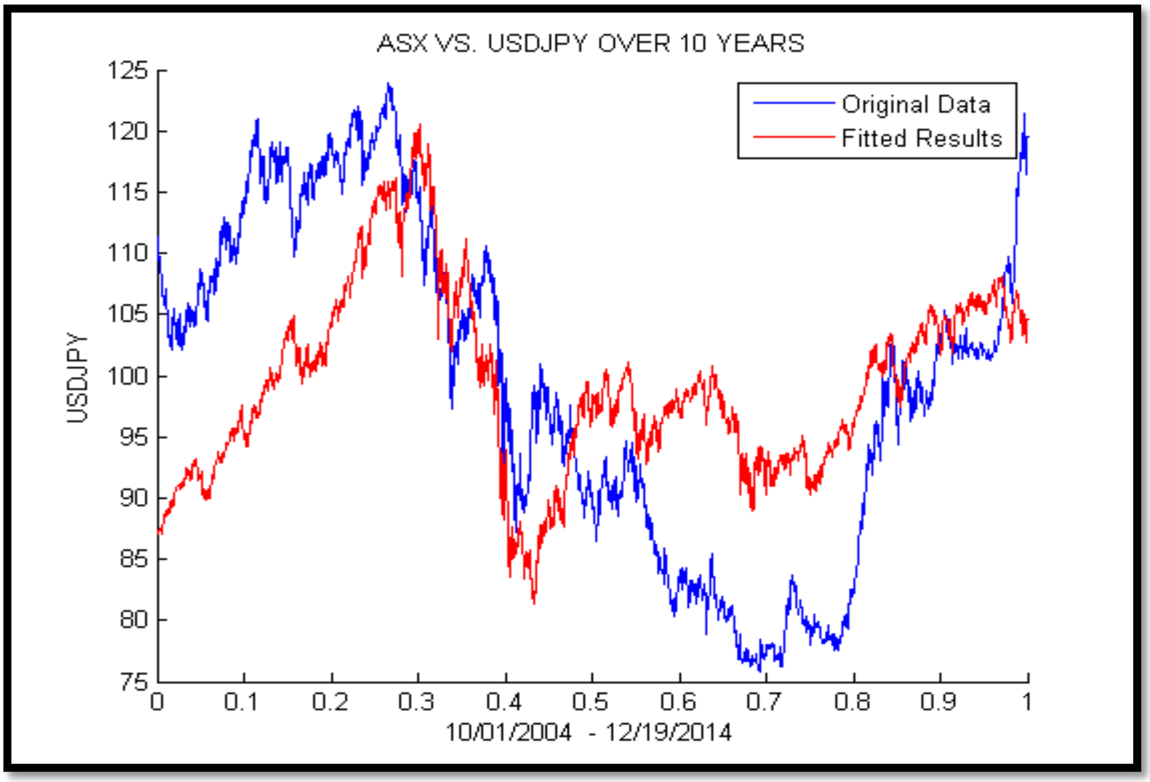


THE ASX

As we discussed earlier, the inclusion of a risk-sensitive economy was pivotal to our study, which is why I picked the Australia. And its sensitivity can be seen below in the chart, where like before we plotted the least squares fit for the ASX on the USDJPY. Correlations were the highest after the Nikkei, and as we shall see later regression numbers also cast a vote in showing that it was a good choice.



Over 10 years, the fit looked something like the following graph. The fit wasn't as close as the 5-year frame, just as it wasn't in the all the five previous observations. **This strongly suggests that the Yen may have, in recent times, gained more stature as a safe-haven.**



III. LINEAR REGRESSION DATA

The least squares fit and linear regression go hand-in-hand, as regression values measure the degree to which the data fit our model. The table below contains the results of our regression analysis on our data. Not surprising, the Nikkei and the ASX, which to the naked eye posted the best fits on the graph have the highest regression values. While I wouldn't say these numbers seemed to be a major setback to our analysis at this stage, they did say that things might go wrong.

TABLE: REGRESSION FIGURES FOR THE LAST 5 YEARS OF DATA

	S&P 500	**NIKKEI**	**DAX**	**FTSE**	**MSCI**	**ASX**
USDJPY	0.6165	0.9090	0.6098	0.5348	0.6318	0.7711

Regression figures were a lot lower during the last 10 years than the last 5. This is likely because several economies entered similar cycles post the global financial-crisis of 2008. I wouldn't be surprised that on analyzing the data again after 5 years would give us vastly different numbers. The figures for the 10-year period are in the table below, which show a drastic drop..

TABLE: REGRESSION FIGURES FOR THE LAST 10 YEARS OF DATA

	S&P 500	**NIKKEI**	**DAX**	**FTSE**	**MSCI**	**ASX**
USDJPY	0.0615	0.7326	0.0014	0.0618	0.1556	0.3033

The code I implemented to produce these results look something like this:

```
%linear regression
yresid = USDJPY - sol;
SSresid = sum(yresid.^2);
SStotal = (length(USDJPY)-1) * var(USDJPY);
rsq = 1 - SSresid/SStotal;
r = cat(1,r,rsq);
```

IV. ERROR ANALYSIS IN THE DATA

We live in a non-ideal world so error in our data sets is no big surprise. But, the extent of it could give us more direction. We calculated error in our fits using the Euclidian norm that gave us the following results. Again, the Nikkei lead the way with the least error in its fit (no surprises there) followed by the ASX. The other four indices happened to be relatively close to each other.

TABLE: FIGURES FOR THE LAST 5 YEARS OF DATA

	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
USDJPY	240.51	117.18	242.62	264.89	235.66	185.80

The period of 10 years showed a greater degree of error. This again should not have been surprisingly considering our plots were not perfect, especially when we expand our time frame to include one more economic cycle. The table below shows us the error for this time frame, with the indices observing a more-or-less similar order.

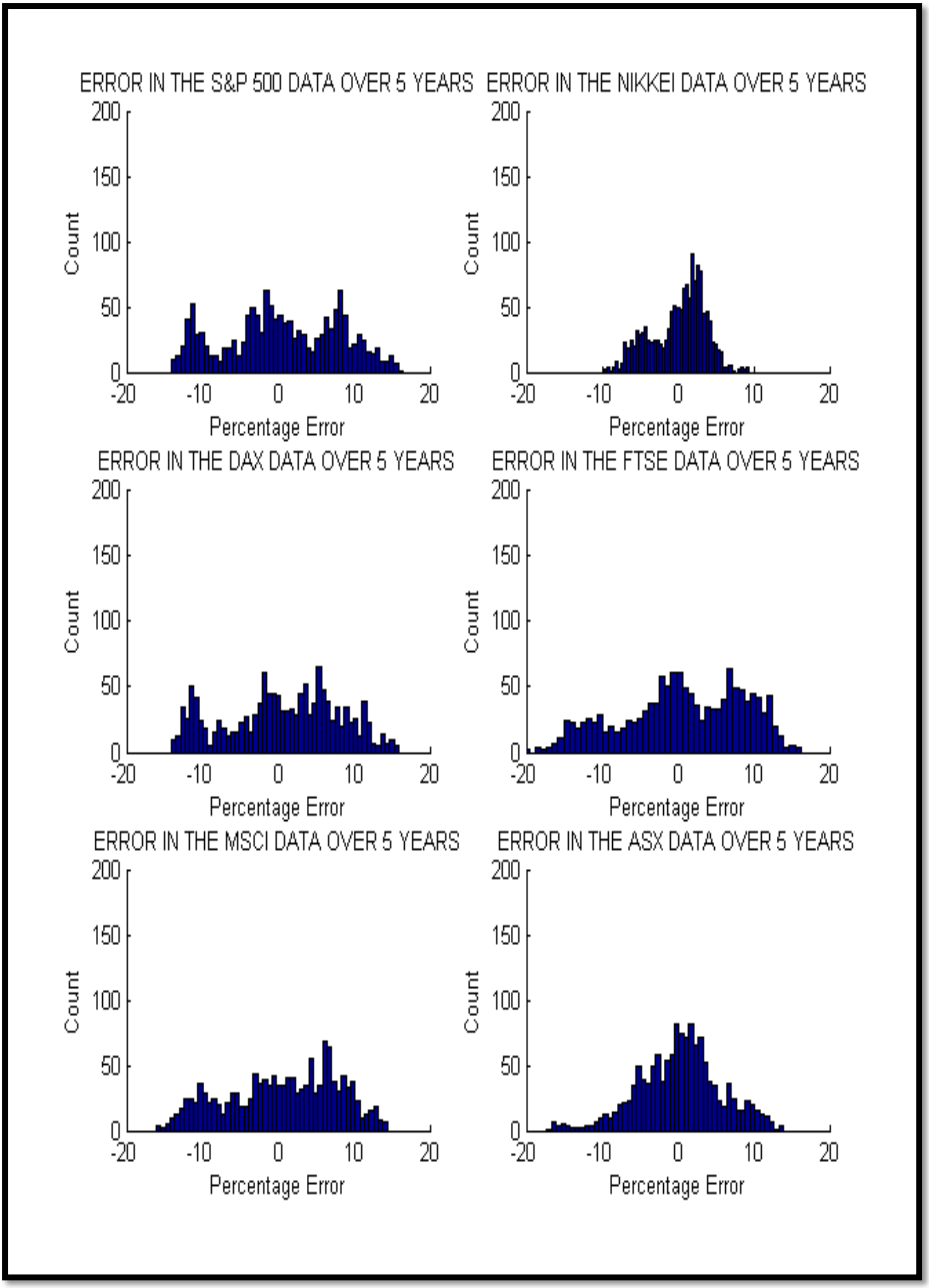
TABLE: FIGURES FOR THE LAST 10 YEARS OF DATA

	S&P 500	NIKKEI	DAX	FTSE	MSCI	ASX
USDJPY	682.41	364.22	703.91	682.28	647.27	587.96

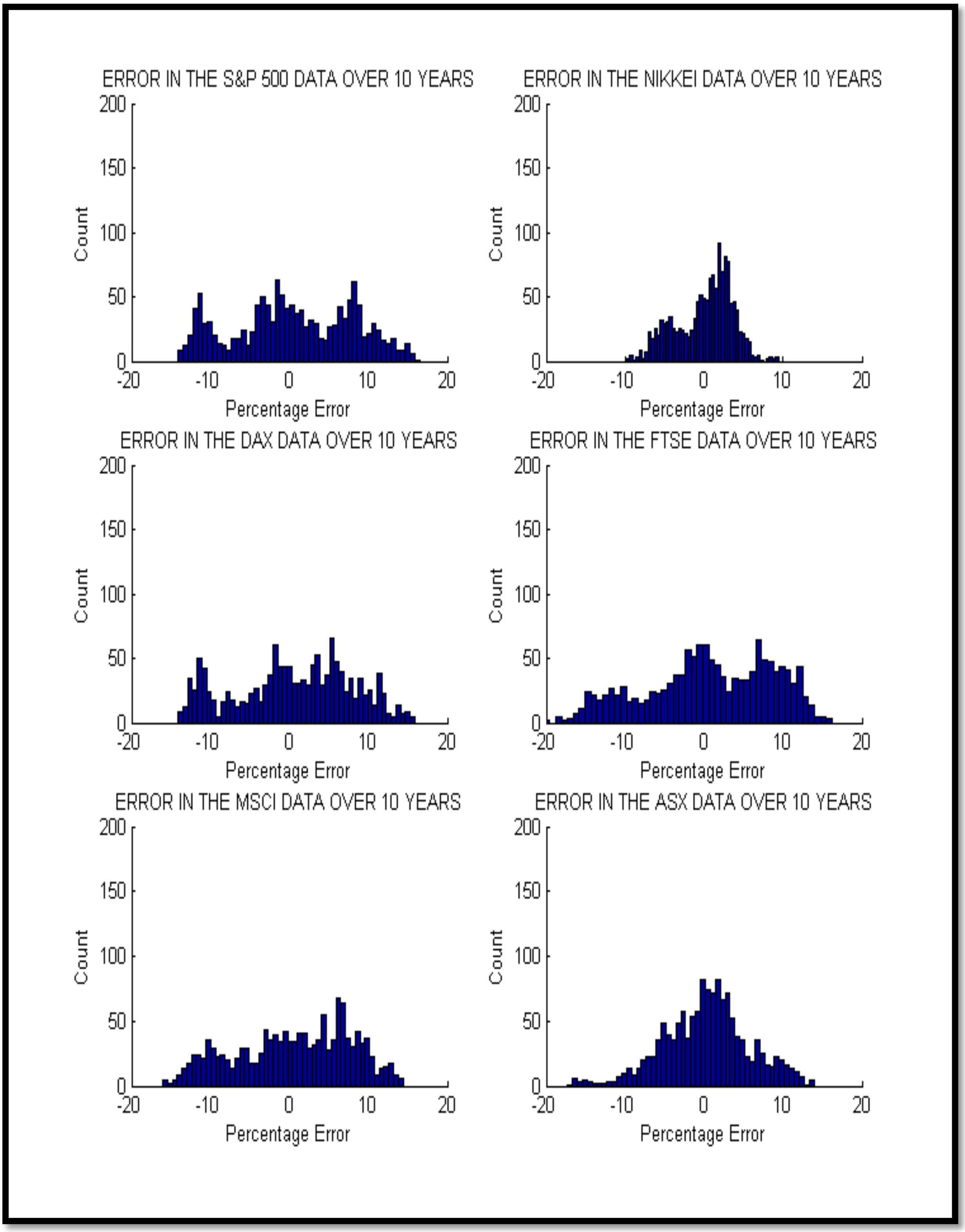
The code used to compute the error looked as follows:

```
%error computation of each indices
error = sol_mat(:,i-1)-USDJPY;
error_percent = (error./USDJPY)*100;
error_mat = cat(2,error_mat,error_percent);
```

The following histogram plots show us how the error is distributed over the 5 years. The charts looks a lot more normalized for the Nikkei and the ASX, while they start to spread a little more when we look at the other four. Code can be referenced in the Matlab file.


ERROR IN THE S&P 500 DATA OVER 5 YEARS
ERROR IN THE NIKKEI DATA OVER 5 YEARS
ERROR IN THE DAX DATA OVER 5 YEARS
ERROR IN THE FTSE DATA OVER 5 YEARS
ERROR IN THE MSCI DATA OVER 5 YEARS
ERROR IN THE ASX DATA OVER 5 YEARS
Count
Percentage Error
0
50
100
150
200
-20
-10
10
20

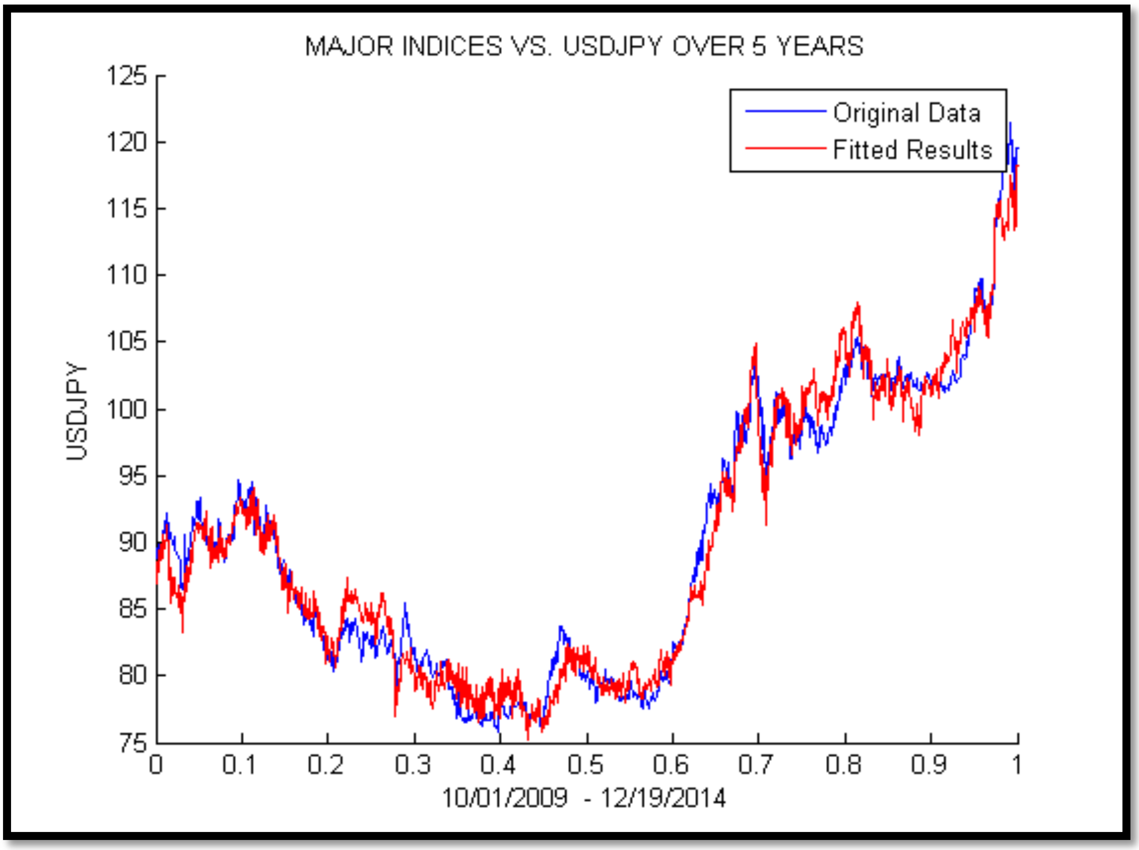
We also look at the error distribution over 10 years. Again, the normal fits are relatively maintained while the other indices expand further outward, flowing with the results that we obtained earlier.



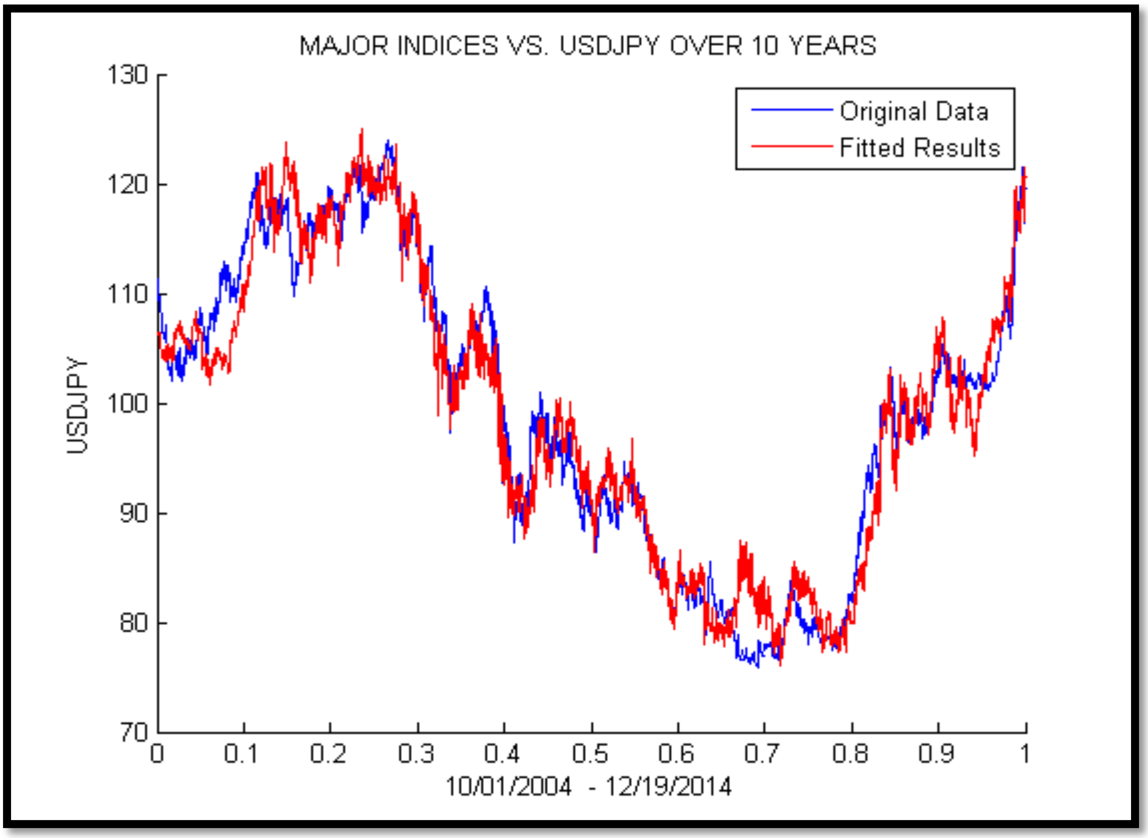
BUT SOMETHING REALLY INTERESTING HAPPENED WHEN I COMBINED ALL THESE INDEXES…

So far, we got good correlation figures and decent fits to say that Yen is strongly related to the risk sentiments of the markets. However, I wanted to see if I could convince myself of this trend with even better results. Since I was dealing with these high-flying global major indexes one-at-a-time, I thought to myself, "why not combine all of them as one?" When I did that, I got eye-catching results.

The least squares fit of the 6 indices combined was plotted against the actual figures of the USDJPY. We got the following graph:

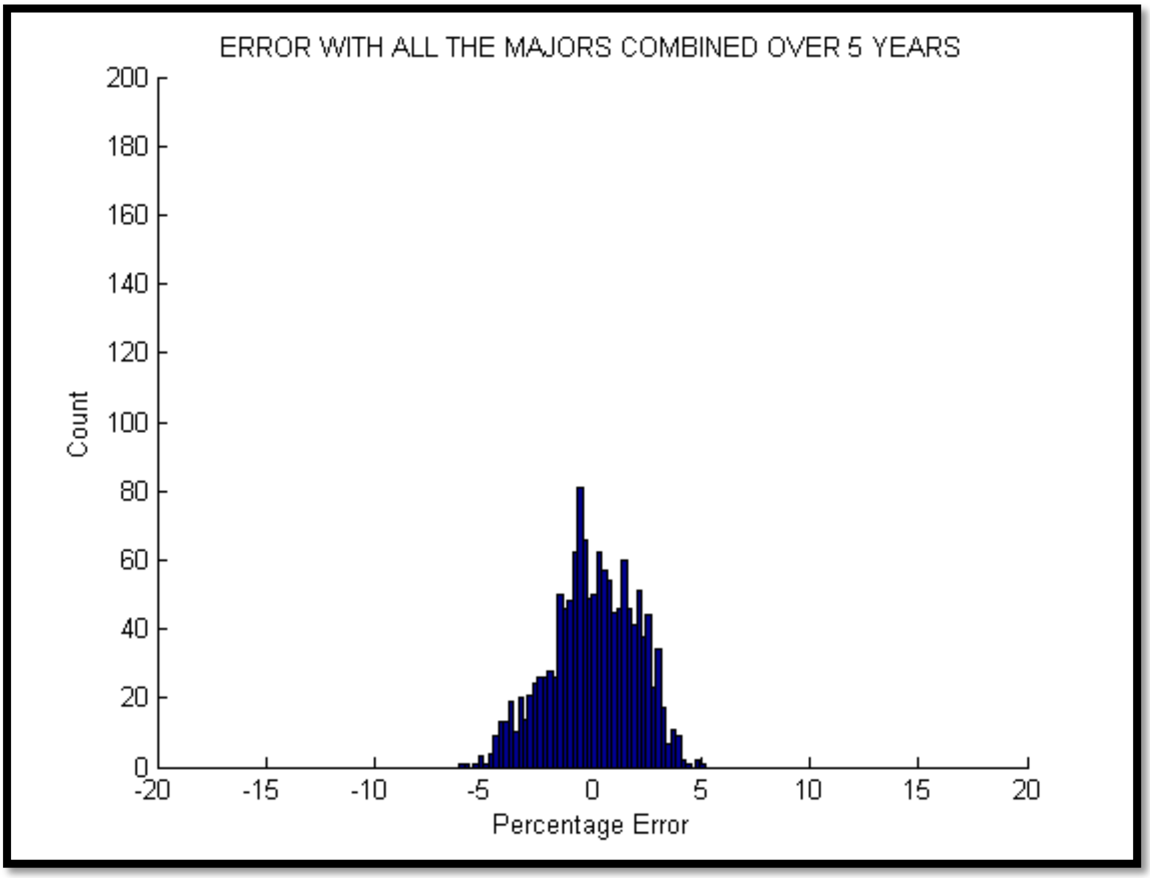


The fit almost seemed too good to be true! Excited to see this plot, I checked for the correlation, regression, and error figures that this combination of indices created. Correlation figures came in at a walloping 0.985! Regression numbers were going to be high as well (evident from our chart above), and were reported at 0.9712.



Excited to see these results, I did the same study, but this time expanded my data to 10 years. I was skeptic initially about getting strong results (refer to correlation matrix of all the indices in Section I of analysis), but I got the chart above. Correlation was reported at 0.9739 and regression was at 0.9414. Error was also the lowest when I fused these indices rather than compare them individually.

As we did for the individual benchmarks, we plotted our error data for 5 and 10 years on a histogram, which revealed a normal distribution. The charts are attached below. Error figures (see snapshot of data in table below) reveal that on combining these indices, the total error over 10 years is lower than the error for most of the individual benchmarks in 5 years!


ERROR WITH ALL THE MAJORS COMBINED OVER 5 YEARS
Count
Percentage Error
200
180
160
140
120
100
80
60
40
20
0
-20
-15
-10
-5
0
5
10
15
20

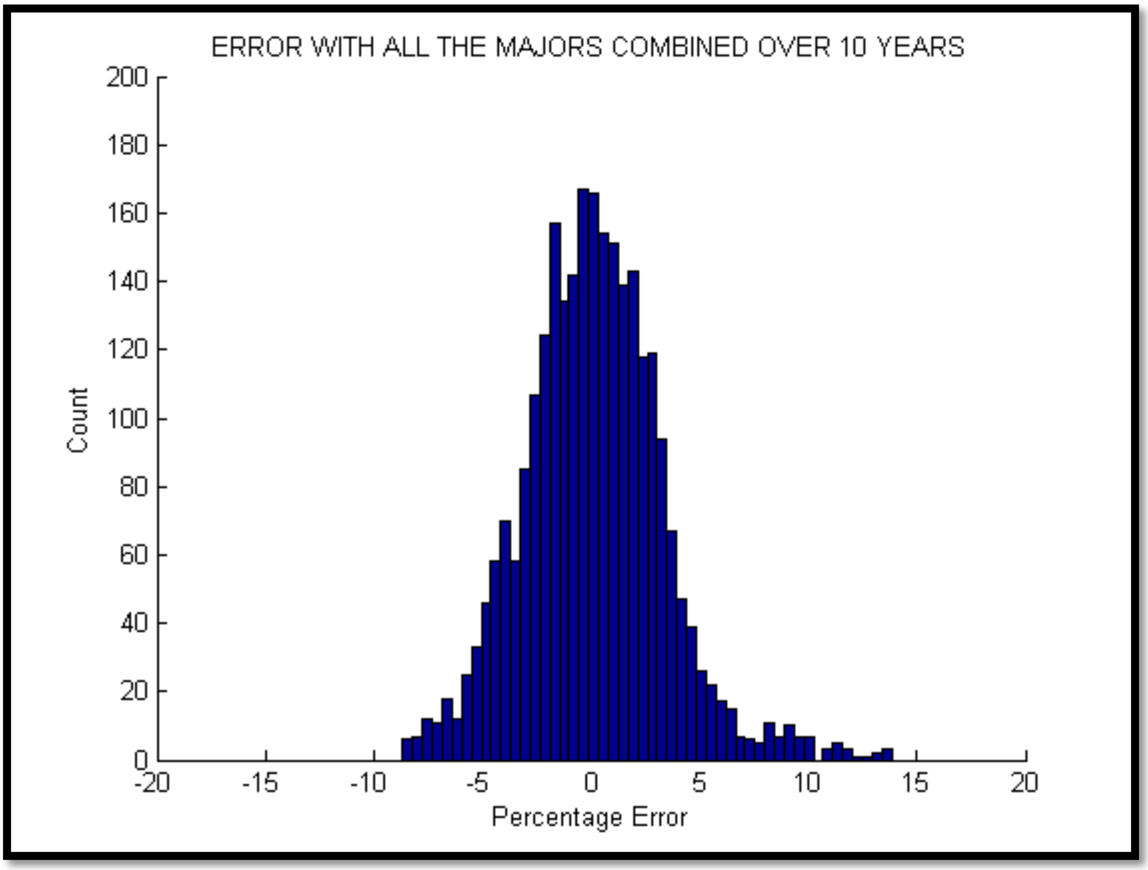

ERROR WITH ALL THE MAJORS COMBINED OVER 10 YEARS
Count
Percentage Error
200
180
160
140
120
100
80
60
40
20
0
-20
-15
-10
-5
0
5
10
15
20

TABLE: SNAPSHOT OF DATA AFTER COMBINING INDICES

	Correlation	**Regression**	**Error**
5 years	0.9855	0.9712	65.89
10 years	0.9739	0.9434	159.96

CONCLUDING REMARKS: SO WHAT DOES THIS ALL MEAN?

After using several tools of data mining to studying the data set, I'm extremely satisfied to say that I can assume our hypothesis as true. The Japanese Yen is truly connected to the risk-bearing sentiment of traders and investors around the global. **While the major benchmarks gave suggestive yet lukewarm results individually, combining them yielded exceptionally strong numbers to back the hypothesis.**

The benefits of doing this project were vast. Not only do I now have a model setup to study relations between indices and currency pairs, I have a base to build on and implement more tools. This gives me room to expand my data set to more indices and compare how each relate to a currency pair. I could do a PCA to discover which indices affect these currency pairs the most and track both their performance simultaneously, thereby getting good input while executing trades. Time invested in doing this project was completely worth it.

APPENDIX: SATIFYING THE GRADING CRITERIA

As the project description suggested, this last section describes how I satisfied the grading criteria that was required of this project.

1. DATA FAMILIARITY/INTEREST

I have spent my last three summers researching and trading in the equity and currency markets, so the project was something close to my interests. My familiarity with the markets helped me build the data set and analyze the results a lot better. For example, as I mentioned earlier, including the Australian equity benchmark in my study came because I knew that the index's performance is heavily linked to global risk sentiment.

2. DATA ACQUISITION EFFORT

Acquiring this dataset wasn't the most difficult task. Historical data for the financial markets is easily accessible from databases like Bloomberg, FactSet, Capital IQ, etc. Some modifications has to be made to account for the days during which trading was closed in some countries and open in others, but beyond that 'data cleaning' would only have potential to skew results. The three main data files are *'project data.xlsx'*, which contains the data from the last 5 and 10 years, *'project data 5 years.csv'* and *'project data 10 years.csv'* (.csv files are simpler to read in Matlab).

3. DATA NOVELTY

While the data wasn't very hard to find, I do pride myself on the fact that I combined historical data from the equity and the currency markets. **I wanted to further explore this getting data for different currency pairs and see how they correlate to global markets. However, that would have blown up the size of this project so I decided to leave it for anther time. I plan on doing that at a later stage since my initial steps have given strong results.**

4. ANALYSIS EFFORT

When I started writing code for this assignment, I did it pieceby-piece, writing individual code for each index, which I later cleaned and the size of the code significantly reduced. I did use a different class (in terms of a programming language) to study the correlations on a monthly, quarterly and yearly basis. Three sets of code have been attached – *projectclean.m* and *projectcorrcode.m* are the ones to be referenced first.

5. ANALYSIS METHODS

The methods that I had picked (correlations, linear least squares, regression and error analysis) seemed to be the most appropriate to me. These tools, although simplistic relative to ideas like normalizations and chi-squared tests discussed in this course, seemed most relevant at the time. I could have expanded my use to principal component analysis and data clustering by expanding my data set and taking benchmarks from a hundred different countries, but that would have prohibited me from studying the important ones closely (or, again, would have blown up the size of my project).

6. PROJECT DIFFICULTY

The code wasn't extremely hard to implement as the data didn't require a lot cleaning and implementations of the mathematical tools were done in assignments before. Data familiarity made analysis efforts more interesting as a lot of the results that came out were actually better than expectations, if not at par.

7. PROJECT RELATED TO THE COURSE

I was limited by the size of the project, or I could have expanded my data set that would have allowed me to include more tools like PCA and clustering. Even so, I feel this was a successful attempt at applying data mining to observe interesting relations in global financial markets.

8. PROJECT NOVELTY

I really liked the theme I picked. Online resources on risk appetite in the financial markets still remain limited to articles published by newspapers discussing its current state, and I was unable to find a broader discussion that picked the Yen as the center of study.

9. PROJECT REPORT

This is where I strongly feel my project stands out. Since extracting the data didn't take the long, I could spend more time elaborating this report. I ensured that the report contained short summaries of how the economies of the countries picked were doing, along with details of how currency trades work. This helps the reader who is not extremely familiar with the markets to figure out what I did in this project with minimum topics to look up on Google.

10. OVERALL EFFORT

I'm happy with the effort I put into the analysis and report for this project. I do plan to expand my dataset and study the principal components which affect the USDJPY the most, but that would have been too much to include in this project that is already past the size limit!