# Are Safe Havens really safe?

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****Please note that following exploration of Four Square API it had limited usage in my location (Australia) as there is limited data and most places have not had reviews since 2013 or before. I therefore decided to look at another data science problem for which I could gather rich data and still use the different learnings from across the specialization as well as the geographical mapping. Below is the link to my Notebook to GitHub with the completed work****

[https://github.com/ThoughtLiberator/Data-Science-Project/blob/master/Investing%20with%20Assets%20.ipynb](https://github.com/ThoughtLiberator/Data-Science-Project/blob/master/Investing%20with%20Assets%20.ipynb)

## 1. Introduction

### 1.1 Background

There is a common saying in the financial markets that when there are market shocks there is a flight to safe havens. There are a number of safe havens that are commonly referred to when the money leaves the riskier assets. The difference between the risk assets and the safe havens should be considered. Risk assets are traditionally equities both in developed world and emerging markets. In addition most of the commodities are also considered riskier assets. The attraction of investing in the risker assets is that they can offer greater returns. However, during the times of market turmoil such as the GFC and the Current COVID-19 pandemic the losses can be significant.

On the other hand safe havens are assets that are not expected to appreciate significantly in the time of growth however they do offer a degree of protection during the market downturns. Examples of safe havens are bonds (particularly government issued i.e. US, Australia, UK), money markets, Gold, Japanese Yen and Swiss Franc.

There are many variations and possibilities of both the risk assets and safe havens. For the purposes of the project a range of Stock market Indices were picked covering Australia, Asia, Europe and US to serve as proxies for the risk assets. For the safe havens Gold, Japanese Yen and Swiss Franc were picked (the reasons and the deep dive will be covered in the Data section of this report).

### 1.2 Problem

Whenever one switches on a financial channel such as CNBC or Bloomberg or perhaps reads about the market performance during the time of a crisis they are bound to hear pundits, analysts, reporters, talk show hosts, bankers and others involved the finance say the phrase “flight to safe havens". The idea is that safe havens will hold their value or even appreciate during the times of crisis (the logic would then also hold that they would underperform during the growth times). The common wisdom has it that Japanese Yen, Gold and Swiss France are the pre-eminent "safe havens" and one should invest their money there in the time of the crisis. The purpose of this project was to check if this approach is indeed correct and by extension if one believes that a risk asset i.e. US equities will underperform should they be investing the safe havens

### 1.3 Interest

Traditionally this analysis would have been useful to a narrow group of financial services and investments professional and semi professionals who have access to significant capital and access to global markets to be able to reallocate assets in a rapid and effective manner. However, in the last 10 years the explosive growth of online platforms for trading meant that average investor now has access to sophisticated instruments with a high leverage and can also take advantage of this study.

## 2. Data

### 2.1 Data Selection

There is a significant choice when looking at the financial instruments that represent the risk assets and safe havens. The first step therefore was to narrow down and select the representative assets from both. For the initial exploration Dow Jones Industrial Average was selected to represent the risk assets. Rationale for this selection was that it is the best known global index and contains such bellwethers as Apple, Goldman Sachs, Microsoft and Walmart. For the safe havens *Gold, Japanese Yen and Swiss Franc* were selected as they are often quoted as being the location where the investors move their money during the times of economic shocks. During the later stage of the project a range of stock market indices from around the world was added to enhance the robustness of the analysis specifically these were:

- FTSE 100 – UK
- DAX – Germany
- CAC – France
- IBEX – Spain
- OMX – Sweden
- ASX – Australia
- ISEQ – Ireland
- Hang Seng – Hong Kong
- Nikkei 225 – Japan
- ATX – Austria
- AEX - Netherlands

## 2.2 Data Sources

Once the representative Risk assets and Safe Havens were defined the search on the internet revealed that the best source (unless signing up for a trial or paid subscription) was Yahoo historical quotes. In addition, for the geographic mapping / Folium maps the source presented in the labs was used to ascertain the polygons required for the correct mapping to occur.

## 2.3 Data Cleaning / Preparation

Once the data was downloaded  it was found to have extraneous columns volume and adjusted close which were removed. As the data analysis was occurring for the last 15 years the weekly granularity of the data was used.

The data was missing the % change from previous week which is the variable showing the assets return over the week. This had to be created using the following formula

*(Current Week Close – Previous Week Close)/Previous Week Close * 100*

The multiplication by 100 was used to convert the numbers into percentages so that it could be correctly processed in the data frames. An additional issue was found when downloading the data as for a number of assets there were null values in September 2019 and August 2008 that resulted in % change not being calculated. This data was filled manually by querying [www.tradingview.com](http://www.tradingview.com) for the closing data during the respective weeks.

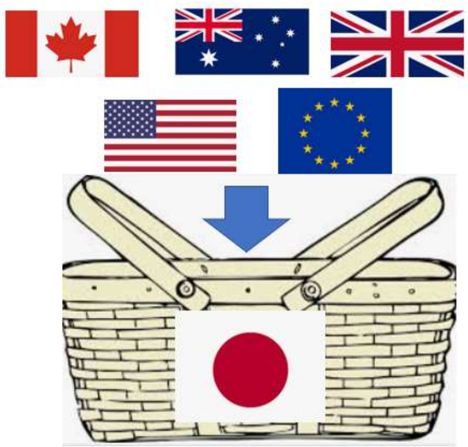
After loading the data into the data frames it was decided that columns Open, Close, High and Low can be dropped as they would not be used in the analysis as it was the percentage change that would carry the key information. Additional variables would then be introduced through adding more assets to the analysis to understand their impact on the data.

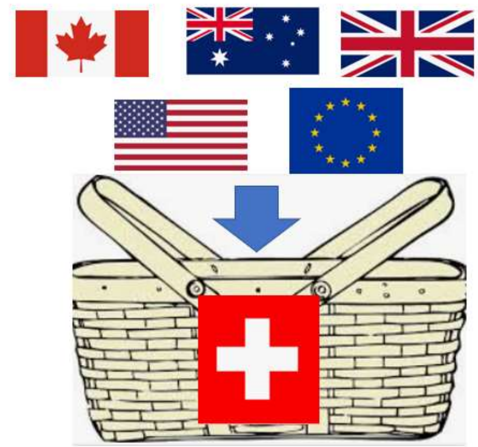
## 2.4 Data Overview

Following the data load across the individual assets each contained % change from previous weeks for 786 consecutive weeks starting from W/C 21/03/2005 – W/C 06/04/2020 providing a robust data set for sampling.

## 2.5 Currencies Baskets Preparation

One of the difficulties of analysing the price movement of Japanese yen (JPY) and Swiss Franc (CHF) is that it was not possible obtain the data representing the currency. Instead it was only possible to obtain individual currency crosses i.e. USDJPY which indicate the strength of US dollar against Japanese Yen. As the result for JPY and CHF the decision was taken to create a basket which would allow to gauge the strength of the currency. 5 currency crosses were selected for both JPY and CHF those are Australian Dollar, Canadian Dollar, EURO, Great Britain Pound, US Dollar





Each of the currency crosses was weighed the same 20%. So the formula for a specific week was:

(CHF  vs US Dollar + CHF vs Australian Dollar + CHF vs Canadian Dollar + CHF vs EURO + CHF vs Great Britain Pound)/5 = CHF Basket performance

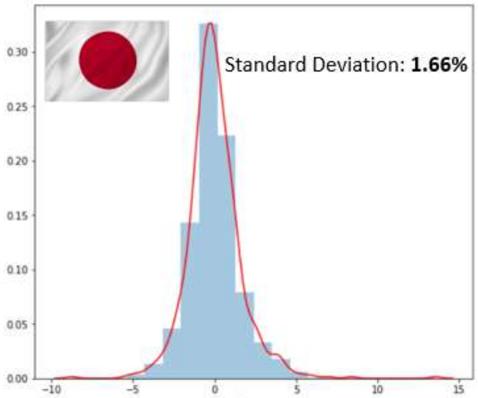
Please note that for JPY currency crosses the change was multiplied by -1 this was done because of how the JPY is quoted i.e. USDJPY moving from 110.10 to 115.10 represents JPY going down as opposed if CHFUSD moved from 1.01 to 1.05 which would show the appreciation of the Swiss Franc.

# 3. Methodology

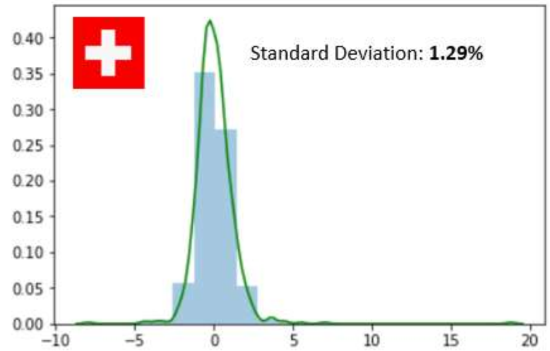
## 3.1 Exploratory Data Analysis

### 3.1.1 Safe Havens Weekly Returns Distribution

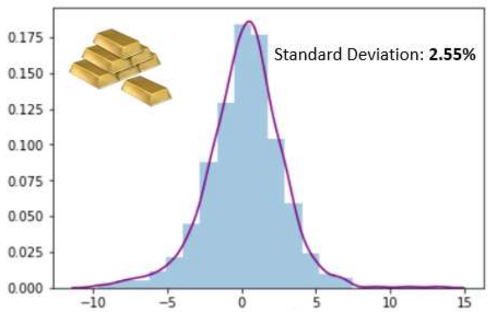
The initial concept was to map the three safe assets (JPY Basket, CHF Basket and Gold) together into a super asset called safe havens. Each of the three components would be weighed equally. To confirm the validity of this distribution of the returns across the three assets were plotted.




Distribution of % Weekly Change for JPY Basket




Distribution of % Weekly Change for CHF Basket




Distribution of % Weekly Change for Gold

The Weekly returns distributions while individually symmetrically distributed seemed had some significant differences between them. In particular gold had a wider returns distribution that either of the currency baskets. This suggested that Gold is far more volatile asset than either JPY or CHF. To confirm this standard deviation was calculated clearly showing Gold attaining a value of 2.55% (almost double that of CHF Basket).

This finding indicated that the thesis of combining safe havens into one asset class might be an erroneous one as they might have limited correlation and weekly returns produced be quite dissimilar from each other.

### 3.1.2 Safe Havens Correlation

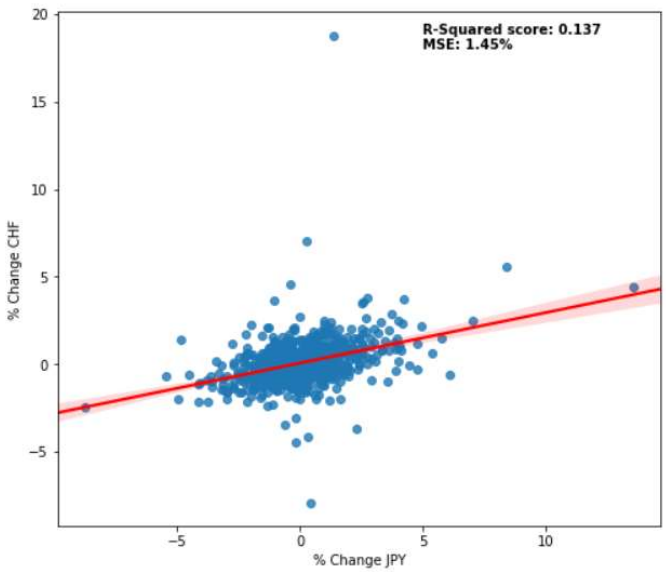
The next step was to find the correlation between the Safe Havens to assess if they can be combined into a single entity or perhaps be evaluated separately against the risk assets.

| | % Change JPY | % Change CHF | % Change Gold |
|---|---|---|---|
| **% Change JPY** | 1.000000 | 0.370377 | -0.022765 |
| **% Change CHF** | 0.370377 | 1.000000 | 0.154073 |
| **% Change Gold** | -0.022765 | 0.154073 | 1.000000 |

The table above provided a surprising insight the 3 safe haven assets appear to have very limited correlation with each other. The particularly noteworthy finding was the slightly negative correlation between Gold and JPY Basket which indicated that in the majority of the cases the flow of money between the two was in opposite directions (i.e. investors moving money from Gold into JPY). This finding indicated that investors perhaps do not flee to safe havens at the same rate. This required further investigation

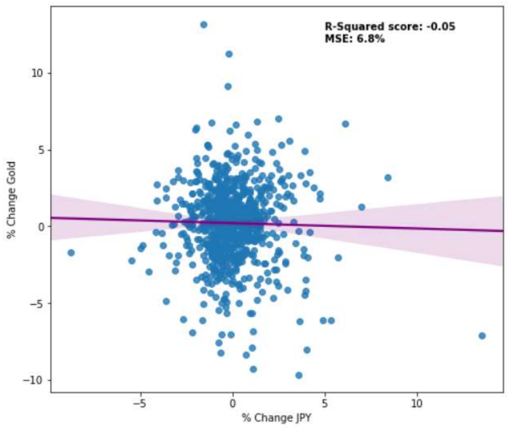
### 3.1.3 Safe Havens Linear Regression

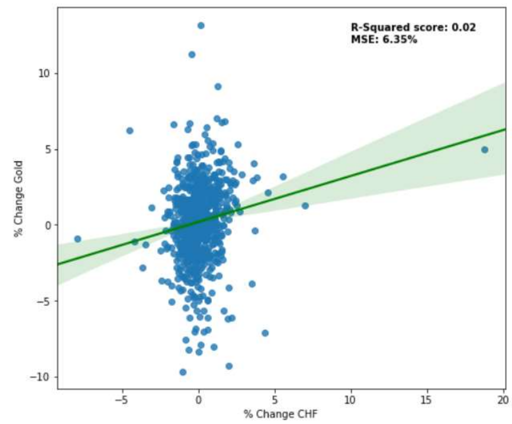
While the correlation between the safe haven assets did not indicate a statistically significant relationship one possibility was to test how if the returns in one asset class could predict returns in another class through regression analysis.




The first pair examined was JPY Basket versus the CHF basket utilizing the linear regression model. At the first glance it would appear that the regression works perfectly as the two data points on extreme left and right of the chart sit on the regression line which is only exacerbated by the observational bias (based on the commonly held belief that money moves uniformly into the Safe Havens. However, the R-Squared of 0.13 means that the regression model actually is only 13% accurate. Furthermore, the Mean Squared Error of 1.45% weekly return is extremely large if we consider that 1 standard deviation of JPY Basket is 1.66% and CHF 1.29%.

These results conclude that combing the three assets into 1 for testing against a risk asset would not be an appropriate approach. However, prior to making this decision the remaining two pairs (JPY Basket vs Gold and CHF Basket vs Gold were explored. The results are below.




***Weekly % Change JPY vs. Gold*** ***Weekly % Change CHF vs. Gold***

As can be seen from the charts above the regression of both JPY and CHF versus Gold produced even poorer results. In the case of JPY the proposed regression was in fact slightly negative and in both cases the MSE was very significant. In addition the large area of the shaded line indicated that the confidence interval was very significant hence the linear regression model lacked accuracy.

### 3.1.4 Safe Havens Polynomial Regression

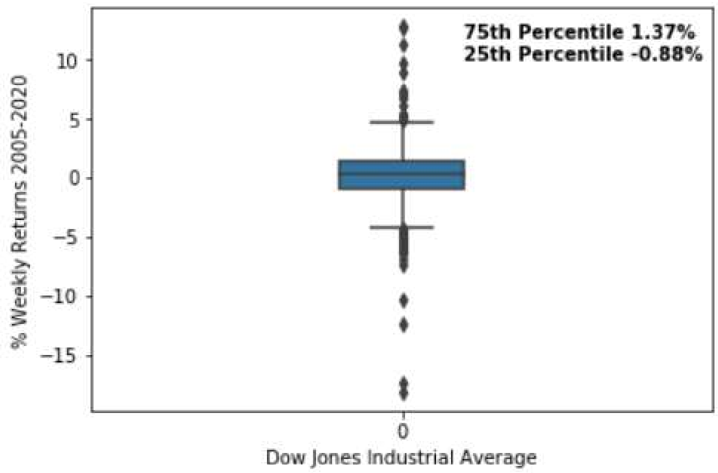
The final check that was needed to run prior to making the decision if the safe havens assets should be classed together was Polynomial regression. The table below provides the summary of R-Squared and MSE versus the different order polynomials

| | **JPY vs CHF** | | **JPY vs Gold** | | **CHF vs. Gold** | |
|---|---|---|---|---|---|---|
| *Polynomial Order* | *R Squared* | *MSE* | *R Squared* | *MSE* | *R Squared* | *MSE* |
| **2** | 0.13 | 1.20% | 0.01 | 2.53 | -0.11 | 2.68% |
| **3** | 0.13 | 1.20% | -0.05 | 2.61% | -0.11 | 2.68% |
| **5** | 0.14 | 1.20% | -0.05 | 2.61% | -0.11 | 2.68% |
| **10** | 0.15 | 1.19% | 0.03 | 2.51% | -0.11 | 2.68% |
| **50** | 0 | 1.29% | -0.04 | 2.59% | -0.08 | 2.65% |

The results indicated that polynomial regression did not show a significant improvement for the R-Squared evaluation across any of the test cases and while the MSE score did it was still very significant.

## 3.2 Risk Assets Exploration

The next step was to assess the Risk Assets which for the first part was represented by Dow Jones Industrial Average. Below is the chart showing the Weekly returns by Dow Jones Industrial Average.




While the data is spread between -18.15% and 12.85% the majority of the data (25th – 75th percentile) sits between -0.88% and 1.37%.

The next step is to asses the correlation between the 3 safe havens and DJIA which would indicate which of safe havens are most likely to have negative relationship with DJIA. The table below shows those relationships.

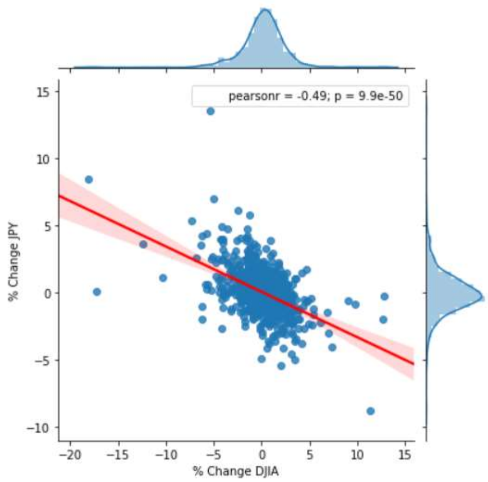
| | % Change DJIA | % Change JPY | % Change CHF | % Change Gold |
|---|---|---|---|---|
| % Change DJIA | 1.000000 | -0.494618 | -0.295404 | 0.052916 |
| % Change JPY | -0.494618 | 1.000000 | 0.370377 | -0.022765 |
| % Change CHF | -0.295404 | 0.370377 | 1.000000 | 0.154073 |
| % Change Gold | 0.052916 | -0.022765 | 0.154073 | 1.000000 |

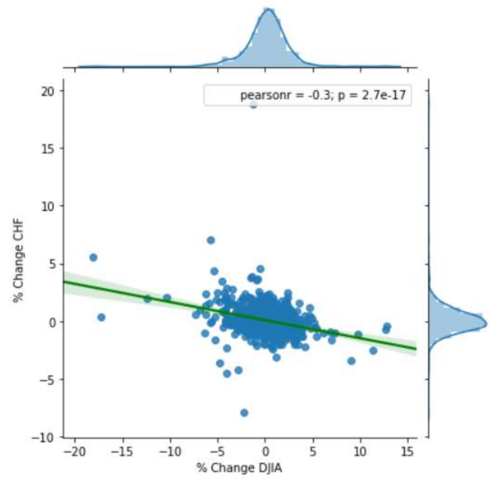
DJIA versus JPY Basket shows the most promise for analysis while surprisingly there is slightly positive correlation between DJIA and Gold. While the relationship is extremely week it is nevertheless surprising because negative relationship was expected.

# 4. Results

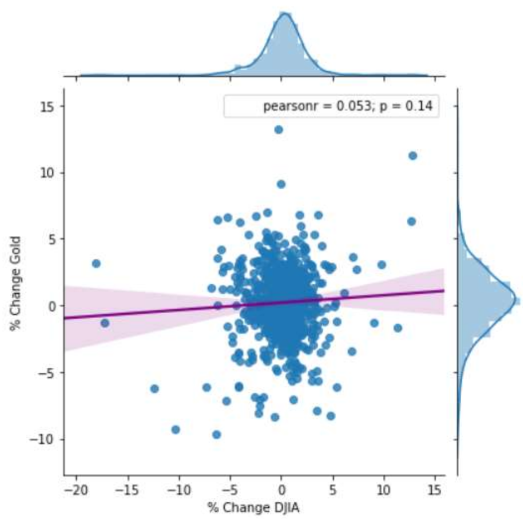
## 4.1 Linear Regression Risk Assets (DJIA) vs Safe Havens

Once the data was explored the question was posed – is it possible to determine the safe havens value based on the DJIA returns. If this was the case then in accordance with the common understanding of “safe haven flight” if an investor thought DJIA was going to decline for the week they could then move funds into one of the safe havens. The Linear regression results are presented below.




***DJIA vs JPY Basket*** ***DJIA vs CHF Basket***




***DJIA vs Gold***

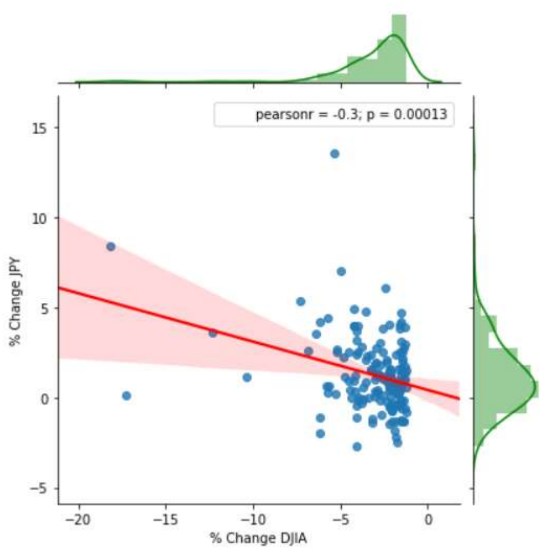
Based on the results none of the Linear regression have produced a strong result. Particularly unexpected result came from Gold that appears to suggest a positive relationship where a negative one was expected. The most promising candidate for further investigation was DJIA versus JPY Basket.

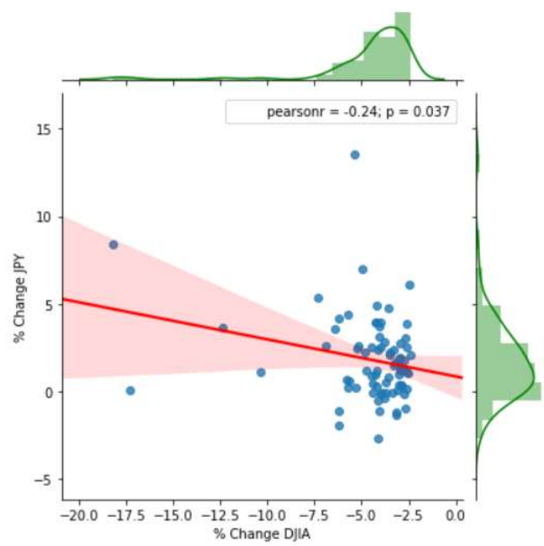
| | ***R Squared*** | ***MSE*** |
|---|---|---|
| *DJIA vs JPY* | -0.04 | 2.87% |
| *DJIA vs CHF* | -0.28 | 2.15% |
| *DJIA vs Gold* | -0.12 | 7.28% |

Furthermore examining the R-Squared and MSE showed that none of the methods had significant reliability. In fact a negative R squared indicated that simply taking the mean would be a better option.

## 4.2 Worst Performing Risk Assets

A possible explanation for the weak negative correlation and predictive capabilities between the Risk assets and Safe Havens was the data used for analysis encompassed all of the weeks for the last 15 years. Going back to the phrase "flight to safe havens" a possible explanation was that a clear relationship only exists during the times of market turmoil. Therefore, the data was cut to check if there was a clearer relationship during the worst performing weeks for DJIA. Two cuts were prepared – bottom 20% and bottom 10%. The results are presented below.



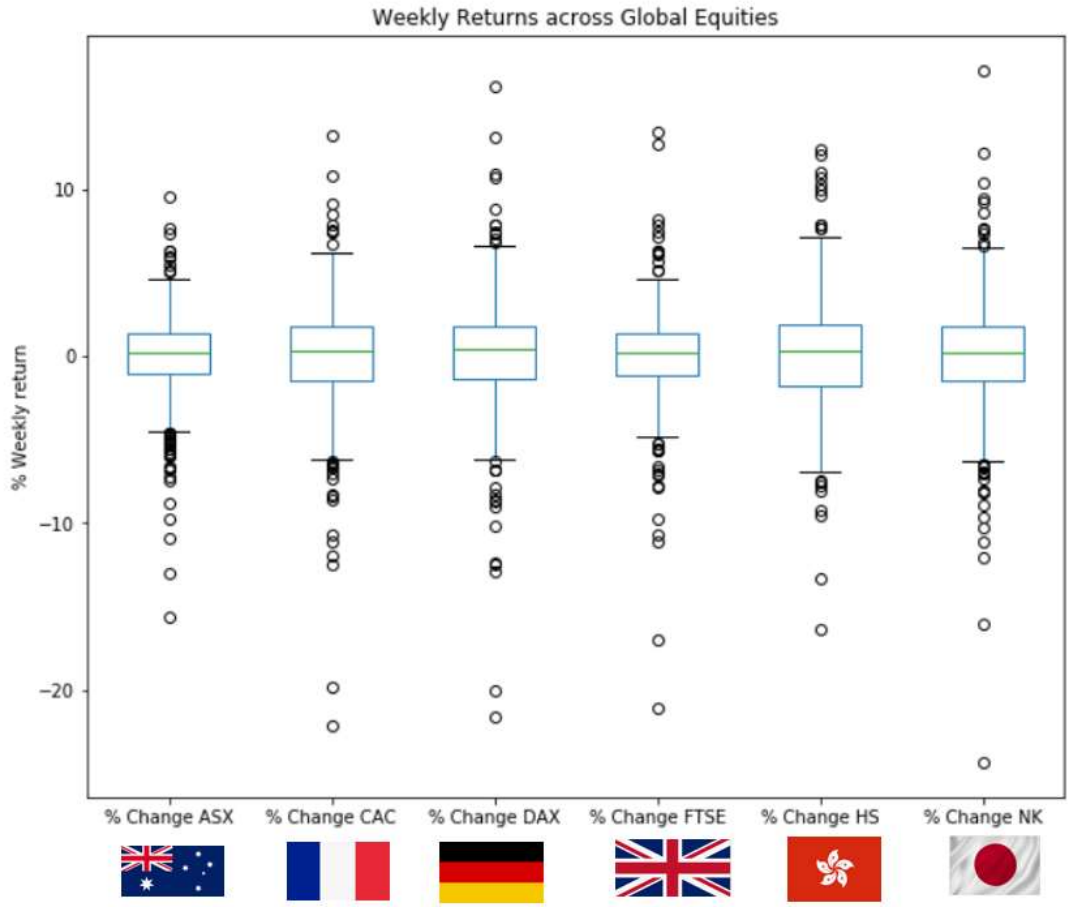




***Worst 20% DJIA Weeks vs JPY*** ***Worst 10% DJIA Weeks vs JPY***

Based on the modelling above slicing by taking the worst week produces worse result than taking the data as a whole. It is important to note the right skew in distribution of DJIA data in both cases versus a more symmetric distribution of JPY Basket returns.

## 4.3 Classification Models

The results of regression modelling indicated very limited relationship between DJIA performance and safe haven performance and also suggested that it would not be possible to predict the outcome for a safe haven based on an assumption of DJIA performance. As the result more options were explored. Specifically is it possible to classify when a safe haven would appreciate and when depreciate. Furthermore, as this simplified the possible outcomes for safe havens it was decided to add additional equity indices to Risk assets.



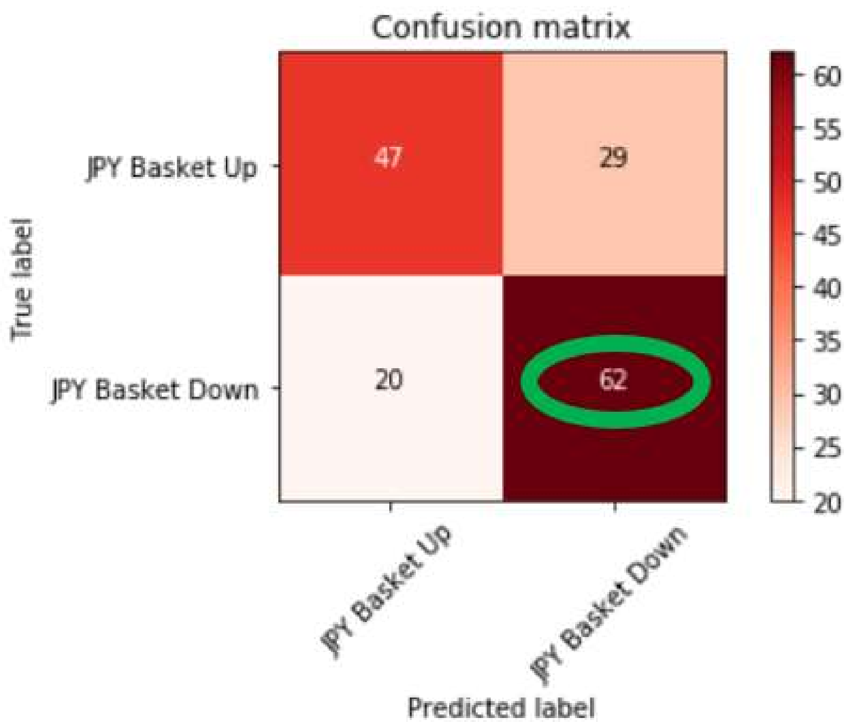

The box plots indicate that Hong Kong generally has the most volatility while Australia has the lowest volatility within the IQR range. Another assessment was to check the correlation between the indicies and DJIA to confirm that the risk assets belonged to be grouped together.

| | % Change ASX | % Change CAC | % Change DAX | % Change FTSE | % Change HS | % Change NK | % Change DJIA |
|---|---|---|---|---|---|---|---|
| **% Change ASX** | 1.000000 | 0.685373 | 0.654485 | 0.719033 | 0.651803 | 0.654329 | 0.660579 |
| **% Change CAC** | 0.685373 | 1.000000 | 0.937898 | 0.902829 | 0.624477 | 0.701172 | 0.789862 |
| **% Change DAX** | 0.654485 | 0.937898 | 1.000000 | 0.868527 | 0.610848 | 0.690315 | 0.793365 |
| **% Change FTSE** | 0.719033 | 0.902829 | 0.868527 | 1.000000 | 0.639064 | 0.667276 | 0.801065 |
| **% Change HS** | 0.651803 | 0.624477 | 0.610848 | 0.639064 | 1.000000 | 0.649736 | 0.567548 |
| **% Change NK** | 0.654329 | 0.701172 | 0.690315 | 0.667276 | 0.649736 | 1.000000 | 0.660708 |
| **% Change DJIA** | 0.660579 | 0.789862 | 0.793365 | 0.801065 | 0.567548 | 0.660708 | 1.000000 |

As expected there was a positive correlation between the stock market indices as they are similar class of assets and are considered risk assets. The lower correlation between Japanese Nikkei and Hong Kong Hang Seng was also expected as the companies listed there are of a different profile. Higher correlation between the European indices (UK, France, Germany) was also expected. Highest correlation of 0.938 was observed between CAC & Dax and lowest between DJIA and HK HS.

### 4.3.1 Logistic Regression

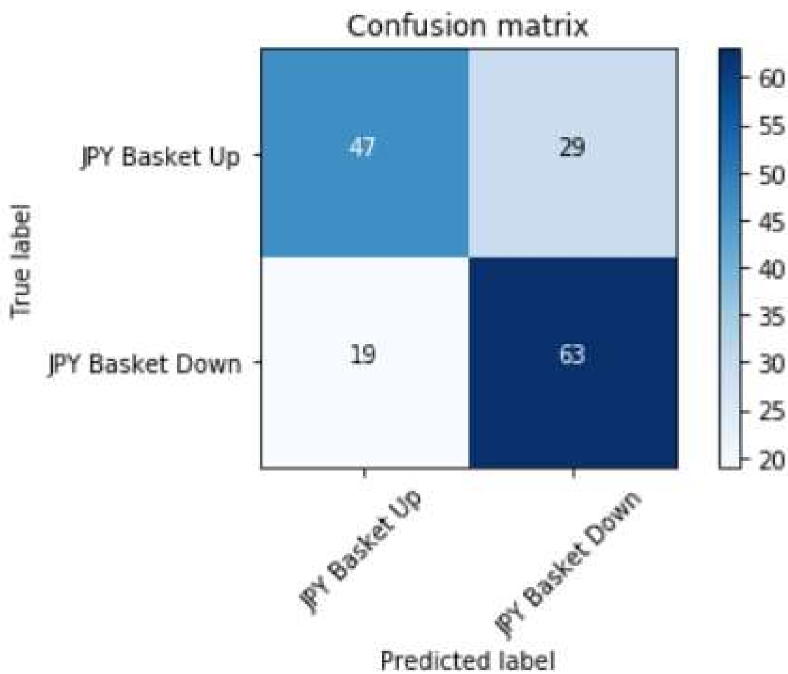
The first classification that was investigated was the Logistic regression. As the decision was taken to take the JPY Basket data and convert it into a binary outcome with 1 if it ended a week above 0% return and 0 if it ended up in the negative territory. In addition as multiple indices were used to determine the question this was one of the classification algorithms best suited for the problem. Below is the evaluation of the model through the confusion matrix.




The confusion matrix clearly shows that in the logistic regression model was generally correct in predicting whenever the JPY Basket will end the week higher or lower based on the behaviour of the stock market indices. Of the particular importance is the prediction of JPY basket being up within the precision metrics (0.7) =47/(47+20) which provided that the model was slightly more robust in determining when the JPY would likely to appreciate (I.e. when should the investors flee risky assets to JPY).

### 4.3.2 Support Vector Machine

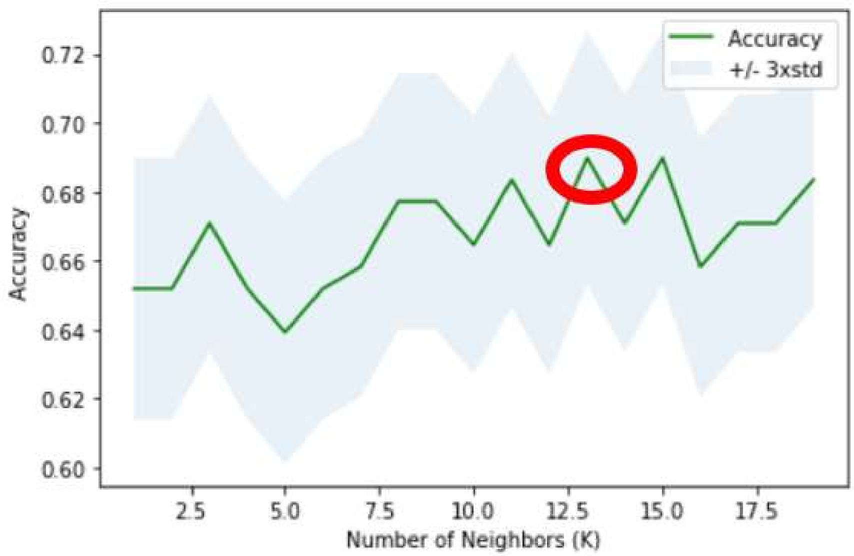
SVM is one of the most robust classification algorithms and it was decided to use it because of its ability to utilize the kernel engineering to solve the classification problem for JPY. Like for logistics regression the confusion matrix was used to evaluate the results.



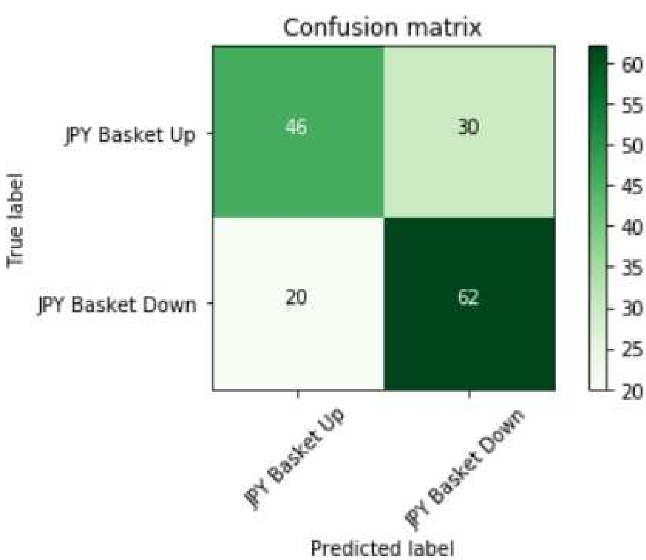

The results produced were slightly better for the SVM than those seen for Logistic regression however the improvement came from the True Negative classification rather than the true positive. Nevertheless this is still an important asset that a savvy investor could take advantage of.

### 4.3.2 K-Nearest Neighbour

The advantages of using this algorithm is that it is generally easy to implement and furthermore the classes do not have to linearly inseparable which had potential application in the current case. The results are presented below




The data indicated that using 13 neighbours to determine whether JPY was going to be up or down was the most robust way to approach the problem.




While at the initial look the result looks similar to the previous ones this turned out to be the poorest performing algorithm. In particular it had one less True Positive and one less True Negative than the SVM.

# 5 Discussion

## 5.1 Safe Havens and regression

The results have clearly raised a lot of questions as to the veracity of the claim that during the times of crisis money flees to the safe havens. This was highlighted by the safe havens of JPY, CHF and Gold not having a significant positive correlation. In particular gold was found to have almost no correlation to other assets. That is it suggests that looking at a price of an asset it is nearly impossible to predict the direction and the size of the move for Gold. There was however evidence of week negative correlation between JPY and CHF versus DJIA. The most promising out of the options was the basket of the JPY currencies. Interestingly when looking at the subset of the data at the worst 20% and worst 10% performing weeks in DJIA the correlation and depressional models broke down even further.

This would suggest that there is almost no way to predict the direction or the size of the move based on an investors view about DJIA performance.

The possible limitation of the current study are that not all safe havens were explored for example money markets and bond markets were omitted from the study and it is possible that there is a much stronger link between them. In addition while DJIA is a good indicator of the stock market as it is the most well known index other more risker indices such as NASDAQ which is based predominantly of technology companies could have been utilized.

## 5.2 Classification Models

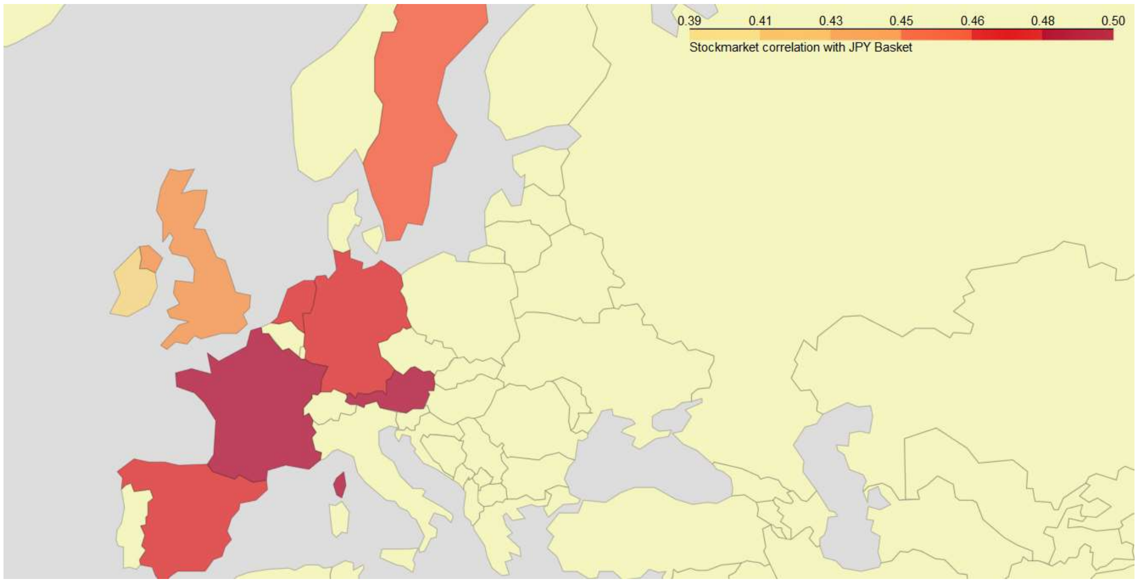
The classification models showed more promise in being able to predict the where the JPY basket might end up based on the inputs from the multiple markets the below table provides a deeper dive into the model performance across the three models that were utilized – Logistic regression, Support Vector Model and k Nearest.

| | ***Jaccard Score*** | ***F1 Score*** | ***Log Loss*** |
|---|---|---|---|
| *Logistic Regression* | 0.6899 | 0.6882 | 0.6 |
| *Support Vectors Machine* | 0.6962 | 0.6942 | N/A |
| *k-Nearest* | 0.6835 | 0.6815 | N/A |

As the evaluation indicates the Support Vector Machine has provided the best evaluation. In fact a score of 69 shows that it using this algorithm it is possible to predict 7/10 where the JPY will end for the week based on the stock market indices performance. This does have the potential application for investor as a win of 70% of the trades would be considered significant.

## 5.3 Individual Markets Consideration

While not part of the overall framework an expoloration was made regarding if there were differences and how significant they were between JPY Basket and the markets in terms of correlation. The results are presented below




The data indicates that Austria and France stock indices warrant further research vs JPY Basket in terms of their negative correlational strength. Please note that this shows the strength of the correlation rather than the direction (which is negative)

# 6 Conclusion & Further Research Direction

While there is limited relationship between the Safe Havens and the Risk assets that were uncovered in this study and therefore it disproves the commonly held notion that money flows from risk assets into safe havens of JPY, CHF and Gold it does provide some interesting learnings. Specifically it is possible to look at the individual indices versus the safe havens. Other safe havens can also be investigated such as the bond markets.

An additional piece of research can be looking at a different time frame for example daily returns with the time decay (where the newer data has more weight to the older data).

Another interesting learning was that using multiple indices from around the world it was possible to determine a relatively accurate model of where the Japanese Yen would end up higher or lower for the week. The shortcoming with the model is that the time parameters are of the same time and therefore one would have decide where the markets would close to make any use of it for practical purposes.