Big Data in Financial Markets: Using Search Volume Data for Market Trading Strategies

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Abstract

This paper examines the relationship between Big Data and two financial assets. This is achieved through replication of the portfolio method proposed by Preis, Moat and Stanley (2013) which examines and tests the relationship between search engine query volumes and financial markets. Collecting data from 98 different search terms, this paper extends the study by applying the strategy to two new financial assets, gold and the United States dollar, through the use of exchange traded funds. The results show statistically significant and positive returns for domestic United States search volumes and statistically insignificant results for global search volumes.

Key Words: Big Data, Google Trends, Gold, United States Dollar, Exchange Traded Funds

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1. Introduction

The internet has been at the forefront of the information age, fostering economic growth and development throughout the world. One such development has been the mass accumulation and access to data, referred to in this paper as "Big Data". This is defined as "extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions" (Oxford Dictionary, 2014). Due to the complexity and size of the data, its collection and management requires unique and individualised software solutions, something which has only become accessible to the general population in recent years (Snijders, Matzat Reips, 2012). One platform which is freely available and has harnessed the use of Big Data is Google Trends. Launched in September 2012, Google Trends maps and manages search term query data (Matias, Y. 2012). It provides the search volume of a given word, relative to the total volume of all words searched on Google for any given week.

This paper and others (Snijders et al. 2012; Varian, & Choi, 2009) propose that search volume data can be interpreted as an indication of the amount of research conducted in relation to the particular search term. As information gathering is performed before individuals make decisions (Simon, 1955), changes in the volume of particular search terms can suggest changes in levels of research and hence decision making. This was originally proposed by Preis, Moat and Stanley (2013) in their report "*Quantifying Trading Behaviour in Financial Markets Using Google Trends*". Preis, Moat and Stanley investigate the relationship between search volume data from Google Trends and the Dow Jones Industrial Average (DJIA) stock index. Using 98 search terms tested to be financially relevant, the change in the weekly search volume of each term was calculated over an eleven year time horizon. Each term was then used to construct an individual portfolio such that the changes in weekly search term volume determined the position taken in the DJIA the following week. Preis, Moat and Stanley (2013) find that the Google Trends data can be used to forecast both current and future states of economic activity, resulting in a profitable and statistically significant trading strategies.

This thesis replicates and extends the portfolio strategy used in "*Quantifying Trading Behaviours in Financial Markets using Google Trends"* (Preis et al. 2013). It applies the strategy to two new financial assets, gold and the United States dollar, through the use of exchange traded funds (ETFs). This paper aims to further test the robustness of this relationship between Google Trends data and financial markets to see if it can be profitably applied to other financial assets with statistical significance. It also investigates whether the results differ between the users of the search engines, by collecting different data sets for users in the United States of America (USA) only, and the total number of users globally.

This study finds varied results, providing statistically significant and positive returns for search volumes based on United States users and statistically insignificant results for search volumes from total global users. The study is restricted to two assets due to the significant time and computational power needed for data collection and manipulation. The data set time periods of nine and ten years are limited due to the inception dates of the assets used.

The thesis contains eight sections: section two provides a background and summary of existing research; section three offers the relevant theory; section four outlines the use, collection and application of data; section five discusses the methods used to construct the portfolios and conduct statistical analysis; section six provides the results; section seven offers discussion; and section eight contains the conclusion.

2. Background and Previous Research

There have been numerous studies investigating a variety of relationships involving Big Data (Ginsberg, Mohebbi, Patel, Brammer, Smolinski, Brillian, 2009; Seifter, Schwarzwalder, Geis, & Aucott, 2010; & Pelat, Turbelin, Bar-Hen, Flahault & Valleron, 2009). Whilst these have focused on forecasting current and future disease patterns, there has been limited research investigating the relationship between Big Data and economic and financial outcomes.

In the paper *"Complex dynamics of our economic life on different scales: insights from search engine query data"*, Preis, Reith and Stanley (2010) investigate the relationship between Google Trends data and financials markets. Using the companies from the S&P 500 stock market index, the study finds Google Trends weekly search volume of company names is correlated with weekly transaction volumes. Whilst the study establishes this relationship with search term volume, it cannot differentiate between buying and selling transaction volumes.

"Predicting the Present with Google Trends" by Hyuntoung Choi and Hal Varian (2009) uses Google Trends search term query data to predict economic indicators. The study investigates relationships using examples of motor vehicles and arts, initial claims for unemployment benefits, travel and consumer confidence. The study finds that Google Trends can be used to predict current economic indicators. Whilst this may appear unnecessary and redundant, the forecasts produced using Google Trends are available weeks before the lagged economic indicators are released by government agencies.

Wu and Brynjolfsson have investigated a similar relation in their study titled *"The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales"* (2009). They establish predictive capabilities from Google Trends in forecasting underlying economic activity. Using housing sales, they find a correlation between Google Trends search terms and future prices and sales in selected United States housing markets.

Preis, Moat, and Stanley's study *"Quantifying Trading Behaviours in Financial Markets using Google Trends"* is the first and only paper to utilise the data to both forecast and trade on the financial markets (Preis et al. 2013). This paper uses the largest data set and a complex and sophisticated portfolio technique to exploit the relationships. The positive and statistically significant results from this strategy prompted the extension of their study to my thesis.

3. Theory

The principles explored in this paper revolve around behavioural finance. Before investors make decisions, they perform research in order to find information to either support or reject the decision at hand (Simon, 1955). As the largest and most easily accessible source of information, the internet has become a key tool to gather knowledge to help make decisions. To ease access and navigate through the vast array of information, search engines have been developed, the most popular of which is Google (Comscore, 2013). Google Trends collects all search term data used on the Google search engine and makes it easily accessible on its website (Preis et al. 2013). It provides the search volume of a given word, relative to the total volume of all words searched on Google for any given week back to 2004.

Through the use of Google Trends, this study suggests that changes in the relative search volume of particular financial words indicate changes in the levels of information gathering and decision making. This was originally proposed by Preis, Moat and Stanley (2013) who not only confirmed and tested the relationship, but also exploited it to produce a profitable trading strategy.

The study by Preis, Moat and Stanley (2013) which this thesis replicates, had varied results. It found that the majority and best performing portfolios had a negative relationship between the change in relative search volume and weekly movement in the DJIA. This relationship is consistent with Herbert Simons Decision Making model (Simon, 1955) in that "trends to sell on the financial market at lower prices may be preceded by periods of concern" in which people gather information (Preis et al. 2013). This suggests that people engage in more information gathering when they are worried or concerned, resulting in the sale of stocks on the DJIA. This suggests the higher the relative search term, the more negative the connotations are for financial markets.

This study builds on this proposition by investigating the relationship between changes in the relative search term volume and the price of two additional investment assets, gold and the United States dollar (USD), through the use of exchange traded funds (ETFs). ETFs are

securities “backed by a pool of assets whose return is expected to track a specific Benchmark as closely as possible” (Kosev, Williams, 2011). The benefits of ETFs over alternative forms of investment deem it the most suitable investment asset for the portfolio strategy. There are many alternatives to gain exposure for investment in gold and the USD. Whilst the use of ETFs has some limitations, their capability to hold long and short positions, relatively low transactions and holding costs, and ability to trade intraday make them highly suitable for a trading strategy. Both of the ETFs examined in this thesis have 0.40% management expense fees, which are incorporated in the price of the ETFs. Other specific advantages of ETFs over the other forms of exposure are outlined below.

Gold

Gold as a financial asset holds value as a commodity and as a means of monetary exchange. It maintains characteristics as being both a safe haven asset and a hedge. During times of economic uncertainty and concern, investors flock to “safe haven” assets like gold as a means of retaining or even increasing portfolio value (Baur & Lucey, 2010 & Baur, & McDermott, 2010). Economic volatility increases the default risk of other assets making gold a safer and more liquid option. It also maintains protective value against inflationary consequences from a weak dollar (Betashares, 2012). Gold is also used as a hedge due to its lack of correlation with stocks and bonds (Baur, et al. 2010). These properties make gold highly dissimilar to the DJIA index tested by Preis, Moat and Stanley (2013). These differences offer the possibility of a different signed relationship, such that changes in search volumes could be positively related to the gold price. Examining this will further test the robustness of the proposed theory whilst also providing an invaluable insight into the applicability of the trading strategy to other financial assets.

The most common ways to gain investment exposure to gold are direct ownership, mutual funds, exchange traded funds, stocks, and through options and futures (Wiggin, A. 2007). Direct ownership is relatively illiquid and has associated handling, holding and storage costs. Mutual funds are also illiquid, making them harder to trade and hence to implement a dynamic portfolio strategy. Gold stocks can be too uncorrelated to the gold price and often are speculative in nature. As the equity prices reflect more than just the gold price and

include the company's fundamental value and performance. Options and futures are easy and liquid to trade, however the price movements of the option are not representative of the fluctuations in gold. Whilst each method has advantages and disadvantages, gold ETFs are the most suitable for this strategy. Gold ETFs hold 100% physical gold bullion and track the value of the gold price. ETFs also have the ability to be short sold, are available to both sophisticated and novice investors, and have low management fees in comparison to mutual and other managed funds (Kosev & Williams, 2011). Whilst some ETFs can be subject to trading liquidity issues, the ETF selected in this report were all traded intraday and are highly liquid.

The ETF used for the portfolio is the SPDR Gold Trust, ticker symbol GLD. This is the largest gold exchange traded product in the USA (ETF Database, 2014) representing over 25 million ounces of gold with value in excess of $34 billion at 10 July 2014 (SPDR Gold Shares, 2014). It is highly liquid and traded intraday on the New York Arca stock exchange, with one holding representing one "share" in the SPDR Gold Trust (GLD). The gold bullion holdings of the ETF are maintained such that one share is valued at one tenth of an ounce of gold (SPDR Gold Shares, 2014), hence the GLD shares move closely in line with the gold price. This relation can be seen in Figure 1 below.

Figure 1: GLD vs. Gold Spot Price (NASDAQ, 2014)

As seen above, the GLD ETF closely tracks one tenth the price of gold. Differences are primarily due to the 0.40% management expense fee and other transaction costs associated

with the ETF relative to holding other positions in gold. The predicted relationship between gold, GLD and the selected search words should be substantially different to that of the negative association presented by Preis, Moat and Stanley (2013). As both a safe haven and hedge, a positive relation between the two variables is expected.

United States dollars

The second investment asset is the United States dollar (USD). The USD is the most used and traded currency in the world (Bank for International Settlements, 2013), with a daily volume average of one trillion USD (Investopedia, 2014). Similar to gold, the USD also contains the characteristics of being both a safe haven asset and a hedge as a means of retaining and increasing portfolio value over times of volatility (Beck, R. & Rahbari, E. 2008). In periods where the USD is high, people flock to the dollar due to expected inflation (Betashares, 2012). However, unlike gold, the USD holds a higher correlation with stocks and bonds making the USD similar to the DJIA index tested by Preis, Moat and Stanley (2013). As such, we expect a different relationship to that of the GLD ETF. As currencies are a medium of exchange, a currency pair is required to track the relative movements of the USD. For this study, we have selected the Euro, as it the second most used and traded currency in the world (Bank for International Settlements, 2013).

Exposure to the USD can be gained through many avenues, including direct ownership, exchange traded funds, swaps, options, futures and a large range of other financial derivatives. For the same reasons as gold, ETFs are the most suitable for this strategy. ETFs are liquid, have no holding or storage costs, have low management expense fees, and track the price of the underlying asset.

The ETF used for the portfolio is the Currency Share Euro Trust, ticker symbol FXE. Since its inception in September 2005, Currency Share Euro Trust (FXE) has been the fourth largest currency exchange traded product in the world with a value over $17 million as at October 2014 (ETF Database, 2014 & Euro Shares, 2014). It is highly liquid and traded intraday on the New York Stock Exchange Arca. This ETF is designed to track the price of the Euro, such that one share is roughly equal to 100 Euros expressed in USD. As we are interested in the effect

on the USD, it is the inverse price and performance of the trust that we are interested in. Whilst a specific USD ETF could have been selected, users of the FXE are more likely to be from the USA and hence are aligned with the Google Trends data set of users from the USA. The relation between the Currency Share Euro Trust (FXE) and the Euro/USD currency can be seen in Figure 2 below. The price differences can be attributed to the 0.40% management expense fee, the interest income earned on the Euro holdings, and other transaction costs associated with the ETF relative to holding other positions in the USD/Euro.

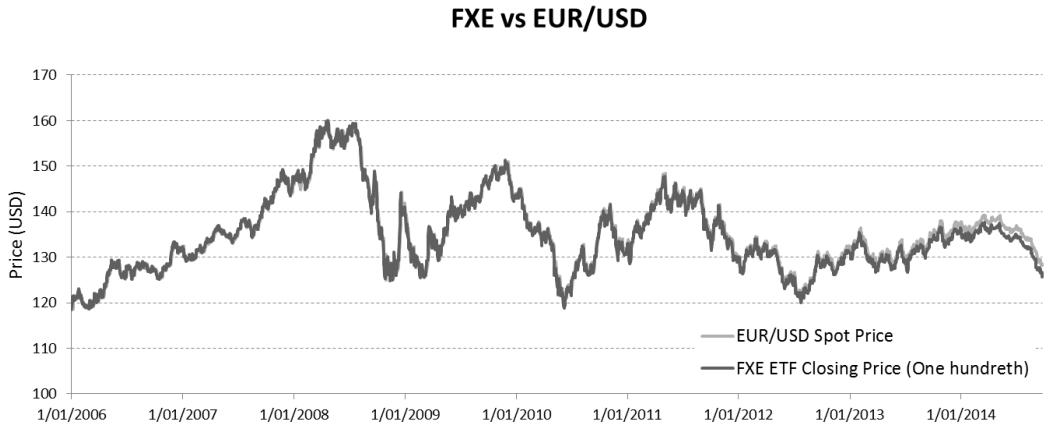


Figure 2: FXE vs. EUR/USD Spot Price (NASDAQ, 2014)

The relationship between GLD, FXE and the DJIA will be varied. Based on the characteristics of the assets mentioned above and the results of the study by Preis, Moat and Stanley (2013), one would expect the DJIA and the inverse of FXE (to represent the USD) to be negatively related to search term volumes, and GLD to be positively related to search term volumes (Betashares, 2012). Transaction and brokerage costs are excluded from this study. As the portfolio strategy only completes two trades per week, there is a maximum of only 104 trades per year. Whilst this cost is material, a specific trading and brokerage platform must be specified to truly quantify this number, something which is out of the scope of this thesis.

4. Data

The ETF price data was obtained from the NASDAQ website (NASDAQ Historic Data, 2014). The data ranges from both the GLD and FXE trust inception dates of November 2004 and September 2005, respectively, up until the portfolio close of June 1, 2014 (SPDR Gold Shares, 2014 & Euro Shares, 2014). Data verification tests were performed by cross checking prices with both the GLD and FXE websites (SPDR, 2014 & Euro Shares, 2014). The price per holding used in this study's portfolio is the closing market price of the GLD and FXE shares. This is the closing market value and actual real time trade price of the ETF which can differ to the Net Asset Value (NAV). The NAV is calculated as the total value of the gold holdings divided by the total number of shares issued. These two measures can slightly differ, as the NAV is often delayed in reflecting the current market and holdings of the ETF as the quantity of holdings fluctuates to maintain its price relative to the asset.

The search volume data was collected from the Google Trends website (Google Trends, 2014). The service provides weekly search volume data for any search word since 2004. The data week spans from Sunday to Saturday and is outputted as a normalised index between 1 and 100. It is normalised by the total number of searches for each country; hence the relative search volume differs from region to region. For this study, search volume data is collected for users from the USA only, denoted "USA GLD" and "USA FXE", as well as an aggregated data set of the total global number of users, denoted as "Global GLD" and "Global FXE". These differing data sets allow for a more in depth analysis of the anticipated results.

Preis, Moat and Stanley noted that the search volume data changed marginally over time at different access periods due to "Google's extraction procedure" (Preis et al. 2013). This was overcome by taking the average of the data over three independent searches over three consecutive weeks, a procedure which was replicated in this study. Data consistency and the immateriality of the differences was tested separately as per the supplementary Appendix of the study by Preis, Moat and Stanley (Figure S1, 2013).

A total of 98 search terms were selected in this study and were taken directly from

"Quantifying Trading Behaviours in Financial Markets using Google Trends" (Preis et al. 2013). Preis, Moat and Stanley selected these words for their financial relevance. The word selection process initially started with certain words associated with the stock market and then expanded through the use of another Google service called Google Sets. Given any word or number of words, Google Sets produces sets of suggested related search terms. In utilising this service, the authors were able to create a list of search terms which were not arbitrary chosen, but suggested due to their search relevance on Google Sets.

The financial relevance of the suggested search terms was then examined by investigating the usage of each word in a financial context. This was done by calculating the frequency of occurrence of each search term in the online edition of the Financial Times from August 2004 to June 2011, and then normalising each word by the number of Google hits. Preis, Moat and Stanley (2013) found that this normalised number was highly correlated with the return for each search term portfolio, with results of Kendalls Tau equal to 0.275, $Z = 4.01$ and $p < 0.01$ for all 98 search terms (Preis et al. 2013). The test confirmed the strong financial relevance of each word.

As gold and the USD are financial assets, the words selected are highly relevant to the assets selected. This is highlighted by the inclusion of the words "gold" and "dollar" in the 98 search terms.

5. Method

The method of this study involves two parts, construction of the portfolio and tests of significance, using one and two sided t tests, both of which required the use of Microsoft Excel and Stata. The method is replicated from the study *"Quantifying Trading Behaviour in Financial Markets Using Google Trends"* by Preis, Moat and Stanley (2013).

Portfolio Construction

Each search term has its own portfolio, consisting of one transaction per week over the designated time horizon. As there are two assets, GLD and FXE, and two data types, USA and Global, this resulted in four portfolio forms: USA GLD, Global GLD, USA FXE and Global FXE.

Each form was applied to the 98 search terms, resulting in 392 portfolios in total.

Each portfolio was constructed individually. The Google Trends data capturing the weekly number of searches "n" was collected, with the changes in search term volume, Δn, calculated as:

$$\Delta n(t, \Delta t) = n(t) - N(t-1, \Delta t)$$

where

$$N(t-1, \Delta t) = (n(t-1) + n(t-2) + \cdots + n(t-\Delta t))/\Delta t$$

To determine the optimal time horizon for recognising changes in search volumes, the change in time horizon Δt was tested from one up to six weeks, such that:

1 Week: $\Delta n(t, 1) = n(t) - n(t-1)$

2 Weeks: $\Delta n(t, 2) = n(t) - \left[\frac{n(t-1) + n(t-2)}{2}\right]$

3 Weeks: $\Delta n(t, 3) = n(t) - \left[\frac{n(t-1) + n(t-2) + n(t-3)}{3}\right]$

4 Weeks: $\Delta n(t, 4) = n(t) - \left[\frac{n(t-1) + n(t-2) + n(t-3) + n(t-4)}{4}\right]$

5 Weeks: $\Delta n(t, 5) = n(t) - \left[\frac{n(t-1) + n(t-2) + n(t-3) + n(t-4) + n(t-5)}{5}\right]$

6 Weeks: $\Delta n(t, 6) = n(t) - \left[\frac{n(t-1) + n(t-2) + n(t-3) + n(t-4) + n(t-5) + n(t-6)}{6}\right]$

The search volume data was then used in the investment strategy designed by Preis, Moat and Stanley titled the "Google Trends Strategy" (Preis et al. 2013). The strategy was implemented at the closing price (P_t) on the first trading day or week t. If the search volume decreased, such that:

$$\Delta n(t-1, \Delta t) < 0$$

Then a long position in GLD and FXE was held, such that the ETF was purchased at the closing price on the first trading day of week t at price (P_t), and sold at the closing price on the first trading day of following week t+1 at price (P_{t+1}). If the search volume increased, such that:

$$\Delta n(t-1, \Delta t) > 0$$

Then a short position in the GLD and FXE was held, such that the ETF is sold at the closing price on the first trading day of week *t* at price (P_t), and repurchased at the closing price on the first trading day of following week *t+1* at price $(\mathrm{P_{t+1}})$.

The weekly log returns of each transaction were then calculated, such that the long position was equal to:

$$\mathrm{r_t} = \ln(\mathrm{P_{t+1}}) - \ln(\mathrm{P_t})$$

And the short position

$$\mathrm{r_t} = \ln(\mathrm{P_t}) - \ln(\mathrm{P_{t+1}})$$

The log returns were used as they are time additive and can be summated to form the cumulative return. Log returns also adjust long and short positions to have "symmetric impacts" on the cumulative return, providing a better basis for evaluating and comparing the trading strategy (Preis et al. 2013 & Svard, 2014). The weekly returns, $\mathrm{r_t}$, were calculated for all time horizons, $\Delta\mathrm{n(t,1)}$, $\Delta\mathrm{n(t,2)}$, $\Delta\mathrm{n(t,3)}$, $\Delta\mathrm{n(t,4)}$, $\Delta\mathrm{n(t,5)}$ and $\Delta\mathrm{n(t,6)}$ to form portfolios $r_{p,t}$. They were then aggregated to form the mean return, $\bar{r}_{\mathrm{p}}$, over the six time horizons such that:

$$\bar{\mathrm{r}}_{\mathrm{p}} = \frac{\Delta\mathrm{n(t,1)}+\Delta\mathrm{n(t,2)}+\Delta\mathrm{n(t,3)}+\Delta\mathrm{n(t,4)}+\Delta\mathrm{n(t,5)}+\Delta\mathrm{n(t,6)}}{6}$$

The mean returns, $\bar{\mathrm{r}}_{\mathrm{p}}$, for each portfolio were then aggregated into their forms: USA GLD, Global GLD, USA FXE and Global FXE, resulting in 98 portfolios per form, and 392 in total. Each form and its associated portfolios were then tested for statistical significance.

T tests of significance

To implement the t-test, a random investment strategy was created for the two ETFs. This strategy would buy and sell the ETFs, creating random long and short positions in the portfolio in an uncorrelated manner. This was simulated 10,000 times in order to achieve the true values of uncorrelated random investment strategies. The random strategies for the GLD and Euro trust produced mean returns of 0 and standard deviations of 0.2% and 0.4%, respectively (see descriptive statistics of results in Appendix 1).

This portfolio was generated as a means to compare and test the statistical significance of the Google Trends strategy. With a mean return of effectively zero, the random investment strategy gives the basis in which to conduct a two tailed t-test. This is created to determine whether the return from the Google Trends investment strategy for each search term was significantly different from the mean of 0, the mean return achieved by the random investment strategies. Two additional benchmarks were also created for comparison, consisting of a single "buy and hold" positions in both GLD and FXE over the entire duration of the study, summary statistics of these strategies are outlined in Appendix 1.

A two tailed t-test was then performed on the mean returns, $\bar{r}_p$, to test the statistical significance in that the returns were different from 0, the return from the random strategy. The t-test was used due to the data symmetry and the efficiency of the test, see Appendix One. A two tailed hypothesis test was then performed at the 99% level of significance on each portfolio across USA GLD, Global GLD, USA FXE and Global FXE. Given 97 degrees of freedom, *n -1*, the null and alternative hypothesis was given by;

$$\mathrm{H_0}: \bar{r}_\mathrm{p} = 0$$
$$\mathrm{H_A}: \bar{r}_\mathrm{p} \neq 0$$

Given an absolute T statistic smaller than the T critical value, the null hypothesis would be accepted, and the mean of the average portfolios for the specific form would not be statistically different from the random strategy return of 0. Given an absolute T statistic larger than the T critical value, the null hypothesis would be rejected and that the returns would be statistically different from the random strategy return of 0, and hence would be deemed statistically significant.

6. Results

The returns and statistical significance of portfolios and forms varied significantly. The statistical significance of mean returns $\bar{r}_p$ at 99% is outlined in the Table 1.

	USA GLD	Global GLD	USA FXE	Global FXE
Alpha	*0.01*	*0.01*	*0.01*	*0.01*
Mean	-0.16049	0.007269	-0.0935007	0.03287398
Variance	0.217596	0.217556	0.0443974	0.04305095
t Stat	-3.40593	0.154284	-4.3928785	1.56846184
P(T<=t) two-tail	0.000961	0.877706	2.857E-05	0.12002992
t Critical two-tail	2.627468	2.627468	2.6274678	2.62746777

Table 1: Results of T Test

Given the results, we can deduce the following:

- USA GLD: T stat = 3.40593 > 2.627468 = T critical

  We reject Ho, the results are statistically different from 0

- Global GLD: T stat = 0.154284 < 2.627468 = T critical

  We accept Ho, the results are not statistically different from 0

- USA FXE: T stat = 4.3928785 > 2.6274678 = T critical

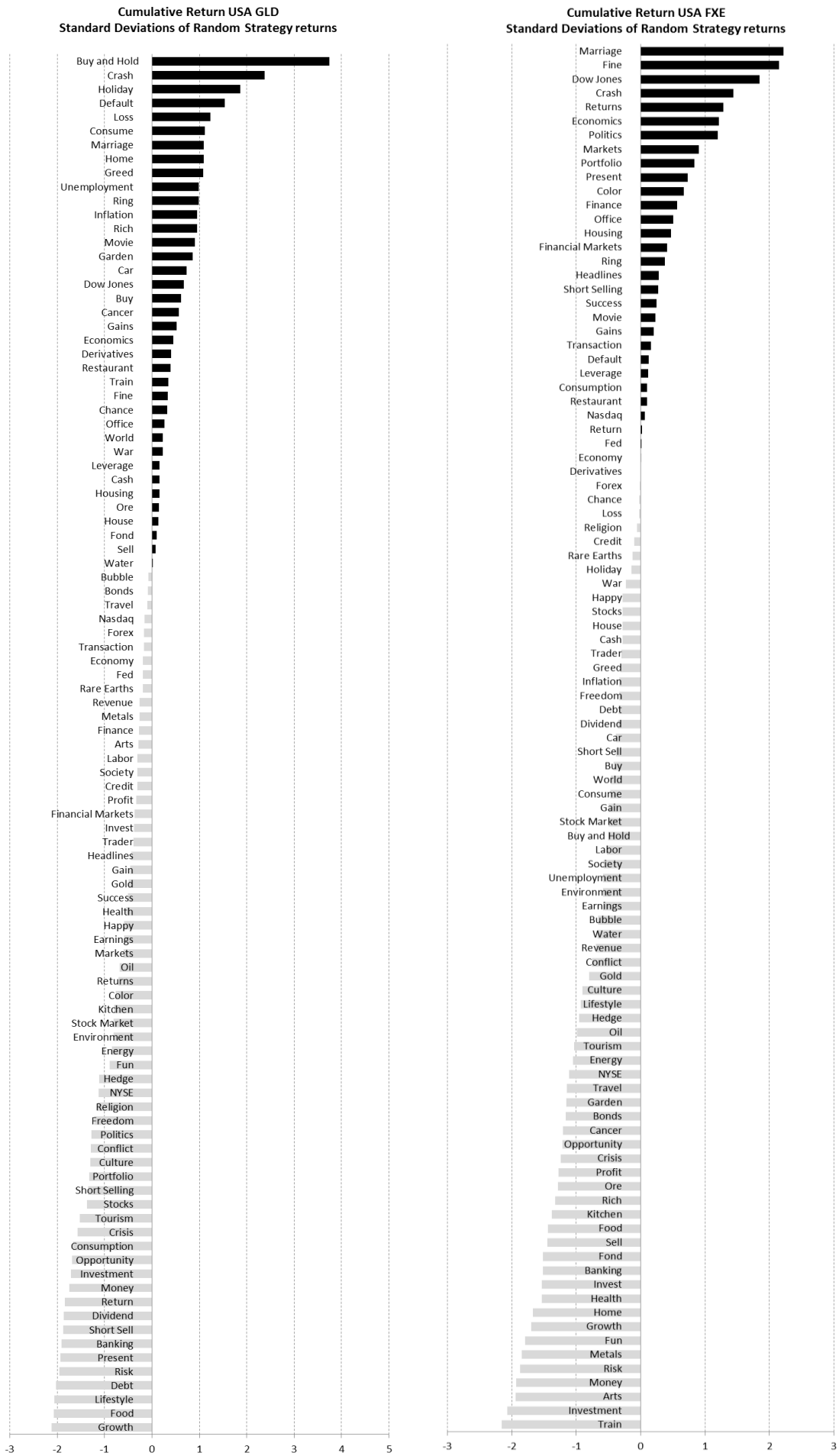
  We reject Ho, the results are statistically different from 0

- Global FXE: T stat = 1.56846184 < 2.627468 = T critical

  We accept Ho, the results are not statistically different from 0

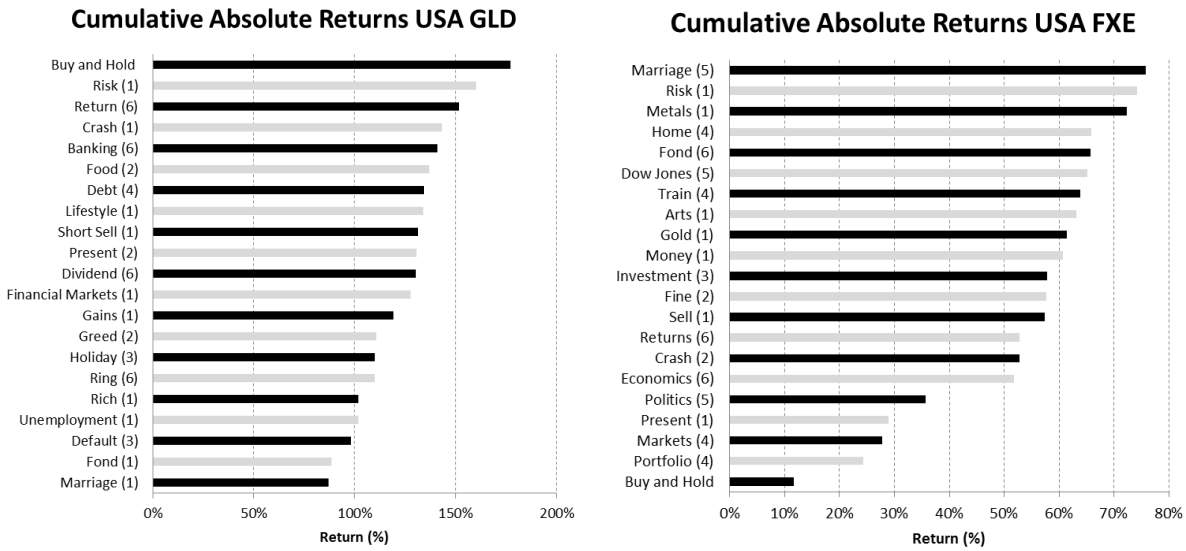
These results are also confirmed by the p value such that USA GLD and USA FXE forms have p values less than 0.005 (0.01 /2). This indicates the portfolios of the two Global forms of search volumes are statistically insignificant.

The performance of the two significant investment strategies for the mean value $\bar{r}_p$ over the six returns for each search term as well as the single buy and hold strategy can be seen in Figures 3 and 4. It shows the cumulative returns of each portfolio in standard deviations from the mean return of uncorrelated random investment strategies. These returns are for the entire testing period, November 2004 to June 2014 for GLD, and September 2005 to June 2014 for FXE.



Figures 3 and 4: Returns for USA GLD and USA FXE

As shown, each portfolio for the mean value of the six returns is varied. These portfolios can be further divided to show the best performing time horizons $r_{p,t}$. The Buy and Hold and top 20 portfolios adjusted for their relationship and time horizon (in weeks) over the entire testing period are illustrated in Figures 5 and 6 below.



Figures 5 and 6: Top 20 Cumulative Returns for USA GLD and USA FXE

7. Discussion

The results vary greatly in comparison to Preis, Moat and Stanley (2013). The first point of interest is the statistical insignificance of the global forms on both the GLD and FXE portfolios. This differs to their study, which showed significant results for the Global forms on the DJIA. This study offers three explanations which explain the causation of the insignificance, individually or aggregated together.

The first reason was proposed by Preis, Moat and Stanley (2013). They suggest the poor performance of the Global portfolios could be due to the fact that the population of USA internet users contains a higher proportion of traders compared to the global population of internet users. This was supported by their results in that the returns from global hits were significantly less than that of USA hits. This reason is highly plausible and can be used individually or in conjunction with the two additional explanations this paper offers.

Another explanation could be that the global data contains conflicting search patterns. The global data collects 100% of the users, which indicates that it could be capturing the search

volume data from both sides of the transaction. This could mean that in aggregating these movements they are capturing the opposing forces, and hence nullifying the changes in search term volume. Whilst this argument could also be applied to the domestic USA hits, there is the possibility that there would be a consensus among USA users to hold positions, with users in different countries holding opposing positions.

Another reason could be that the selected words are not financially relevant to global users. The different languages and cultures could make the words financially unrelated in a global context. The words were tested using an English source, the Financial Times (Preis et al. 2013), meaning that they may not be best suited to English markets. Although the USA market is the largest, this explanation seems highly plausible. There is also the possibility that the search terms are not specific enough for the assets tested. By adding further bias to the selected search terms, it may be possible they could better reflect the underlying assets tested, resulting in better performance.

The next point of discussion involves the statistically significant results. The relationship discussed by Preis, Moat and Stanley (2013) suggest a negative relationship between the number of searches, and the position taken on the DJIA index, such that an increase in *"n"* would indicate a short position in stocks, and a decrease in *"n"* would direct a long position.

The same positions were taken for our portfolio with differing results. Investigating the returns in Figures 3 and 4, we can see the highest mean returns $\bar{\mathrm{r}}_{\mathrm{p}}$ are achieved by the current strategy using a negative relationship between the search volume and the positions held in the portfolio. However, when examining the descriptive statistics in Appendix 1, it is evident that the mean and median returns are negative. The negative results can be inverted to form positive returns by inversing the relationship between the search volume and the positions held in the portfolio. In inverting the relationship to be positive, the portfolios offer higher returns on the individual time horizons $r_{p,t}$, as shown in Figures 5 and 6. This indicates that the relationship between the search volume and the positions held in the portfolio are word specific. To take advantage of the positively related search terms, all negatively performing search terms as outlined in Figures 3 and 4 would have to be reversed, such that an increase in a search volume, $\Delta\mathrm{n}(\mathrm{t}-1,\Delta\mathrm{t})>0$, would foster a long

position and a decrease in search volume, $\Delta n(t-1, \Delta t) < 0$, would foster a short position. In reversing the relationship for the specific words, all portfolios would return positive gains, with a higher mean. The final adjusted returns for the mean portfolios, $\bar{r}_p$,are illustrated in Appendix 2.

Although the relationships appear to be word specific, further analysis can be performed. Examining the results of Preis, Moat and Stanley (2013), who found a negative relationship between the DJIA and the search volumes, the positive relationship between USA GLD and the search volumes is consistent with theory and can be explained by its hedge and safe haven properties. The fact that many of the words, such as risk, debt and crisis, have negative connotations also supports this positive relationship from GLD's safe haven properties. Given that the 2007 Global Financial Crisis occurred within the data set, this further increased the performance of this portfolio. However, in analysing its performance, a comparison with the buy and hold strategy must be made. From Figure 3, it must be noted that the buy and hold strategy outperforms all USA GLD portfolios with a return of 177% over the entire period. Whilst this severely dampens the results, it must be noted that the gold price encountered the largest price growth experienced in 40 years, including an abnormal sustained increase after the Global Financial Crisis (Macro trends, 2014). This does not nullify the results of the study, but merely indicates that further investigations must be made with larger time and data sets.

The performance and relationship of the USA FXE form portfolios is more complex. As the shares in FXE represent holdings in the Euro, any positive change in the FXE exchange rate would represent an appreciation of the Euro relative to the USD. Given that the mean and median returns are negative, any negative results can be inverted to form positive returns by inversing the relationship between the search volume and the positions held in the portfolio. By changing the relationship to positive, the search volume relative to the USD is negative. Hence, changing the relationship between the search volume and FXE to positive changes the relationship between the search volume and the USD/EUR currency pair to be negative. The relative asset relationships are outlined in Table 2 with an included reference to the original results provided by Preis, Moat and Stanley (2013).

Asset	Negative relationship	Positive Relationship
DJIA	Increase Δn, Decrease in DJIA	Not Applicable
GLD	Increase Δn, Decrease in GLD	Increase GLD, Increase in Δn
FXE	Increase Δn, Decrease in EUR/USD and FXE, Increase in USD/EUR (depreciation of USD)	Increase Δn, Increase in EUR/USD and FXE, Decrease in USD/EUR (appreciation of USD)

Table 2: Relative Asset relationship (DJIA from Preis et al. 2013)

Using the table, it is evident that the majority of the USA FXE portfolios have a positive relationship with search volumes, Δn, which indicate a negative relation with the USD/EUR currency pair. This is consistent with theory in that the USD is positively related to the DJIA, and negatively related to GLD (Reference 12). This relationship is confirmed by the success of this strategy relative to the buy and hold portfolio. With a negative return of 12%, the buy and hold strategy is outperformed by the majority of USA FXE portfolios.

8. Conclusion

From this analysis, it is clear that most of the relationships between search volumes and asset returns can be explained and supported by theory. The performance of portfolios that do not adhere to the theory can be explained by nature of the relationships, in that they are word specific; different words have different relationships with the portfolios using the same asset. In spite of this, three general results can be ascertained:

- The majority of portfolios tested performed best using a positive relationship
- The highest returns were achieved by using portfolios with individual time horizons, $r_{p,t}$, and a positive relationship
- The mean return over the time horizons, $\bar{r}_p$, performed best using a negative relationship

Using these relationships, profitable and statistically significant results were produced on completely new assets. It demonstrates how the portfolio strategy used in *"Quantifying Trading Behaviours in Financial Markets using Google Trends"* can be successfully applied to other financial assets. Only one asset outperformed the benchmark strategy, however both

produced higher mean and median returns than the portfolio created by Preis, Moat and Stanley (2013). Whilst this study confirms the robustness and majority of findings on the base study in which this replicates; it differs in producing different results for users in the USA only, and the total global number of users. It also offers the suggestion that different words have different effects on the same assets, something which can be exploited through reversing the strategy. This study opens the door for further investigation into these areas as well as differing asset classes, time horizons and risk adjusted returns.

In conclusion, this study confirms the findings of Preis, Moat and Stanley (2013). As information gathering is performed before individuals make decisions, changes in the volume of particular search terms can suggest changes in levels of research and hence decision making. As the changes in search volume data can reflect both current and future states of the economy, these can be used to gain positive returns profitably and with statistical significance.

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Appendix 1: Descriptive Statistics of Portfolio Forms and Random Strategies

	USA GLD	*Global GLD*	*Random GLD*	*USA FXE*	*Global FXE*	*Random FXE*
Mean	-0.1605	0.0073	0.0006	-0.0935	0.0329	0.0021
Standard Error	0.0471	0.0471	0.0150	0.0213	0.0210	0.0023
Median	-0.1389	-0.0571	0.0029	-0.0838	0.0162	0.0023
Standard Deviation	0.4665	0.4664	0.4732	0.2107	0.2075	0.2290
Sample Variance	0.2176	0.2176	0.2241	0.0444	0.0431	0.0525
Kurtosis	-0.3903	0.1733	0.0056	0.3120	0.1250	-0.0240
Skewness	0.0920	0.4757	-0.0492	0.4503	0.4306	-0.0004
Range	2.1243	2.3415	3.0804	1.0009	0.9536	1.8381
Minimum	-1.0016	-1.0073	-1.5917	-0.4940	-0.3620	-0.8920
Maximum	1.1227	1.3342	1.4887	0.5069	0.5916	0.9462
Count	98	98	10000	98	98	10000

Appendix 2: Returns in Absolute Terms