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SEARCHING FOR RETURN: HOW GOOGLE SEARCH ENGINE QUERY DATA CAN BEAT THE MARKET

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Abstract

Throughout the last years technologic improvements have enabled internet users to analyze and retrieve data regarding Internet searches. In several fields of study this data has been used. Some authors have been using search engine query data to forecast economic variables, to detect influenza areas or to demonstrate that it is possible to capture some patterns in stock markets indexes. In this paper one investment strategy is presented using Google Trends' weekly query data from major global stock market indexes' constituents. The results suggest that it is indeed possible to achieve higher Info Sharpe ratios, especially for the major European stock market indexes in comparison to those provided by a buy-and-hold strategy for the period considered.

Keywords: Financial Markets, Google Trends, Search Engine Query Data, Info Sharpe ratio

Introduction

After the advent of Internet a wide range of new possibilities arose in the contemporary society. Through Internet it is possible to access to a wide range of documents in the World Wide Web such as texts, videos, images and other multimedia using an Internet Browser. Throughout the last years Internet has become more and more imperative and its developments allowed the general public to replace preceding sources of information with the data present in Internet. Consequently this platform has become the prevailing information system. On one hand, the size of Internet according to the number of sites across all domains has significantly increased over the last years. In 2013 solely, 328 million new domains were registered (Factshunt, 2014). Furthermore it is also predicted that the size of Internet will double every 5,32 years (Zhang, Yang, Cheng & Zhou, 2008). On the other hand, the number of Internet users has been increasing clearly in the last years. In 2004 there were 914 million of Internet users globally whilst in 2014 this value is estimated to be 2923 million of Internet users (Statista, 2014).

This increase in internet size has contributed to the rising importance of Internet search engines. These websites comprise nearly all of the information uploaded in Internet and provide its users with a rapid and easy access to the data they are looking for. Fallows (2005) concluded that “searching is becoming a daily habit for about a third of all internet users” in U.S., one of the most representative countries in Internet global share.

Moreover it is also argued that consumers use Internet searches to “gather information about products they intend to buy” (Horrigan, 2008; Brynjolfsson, Hu and Rahman, 2013). Furthermore it is expected that searches can display some patterns and purchase intentions and their study helps to decide which goods people are more likely to buy.

Google Trends is, as its name suggests, a Google service that identifies the search volume for given terms throughout a time period as well as the global regions where the terms are searched the most or even related searches for the term entered. It might be argued that since Google Trends exclusively focuses on Google searches it wouldn't be accurate in determining the global search volume because searches could be done in other search engines. However, since "Google.com" was registered as a domain on September 15 1997, this U.S. website has been positioning itself as the global search engine with the highest market share. In fact, between January 2010 and August 2014, Google searches account for approximately 90% of all Internet searches (Statista, 2014). Additionally, Google Chrome global market share has been increasing since the release of this Internet browser in September, 2008. In that month Google Chrome represented 0,3% whilst in August 2014 this browser accounted a remarkable 38% of internet browsers global market share (W3Counter,2014). This is also pertinent for the relevancy of Google searches since any terms entered in Google Chrome address bar are by default searched in Google.

The main motivation with the elaboration of this paper is to exploit new sources of information in order to build an easy to implement investment strategy. After backtesting the strategy its returns will be used to understand if it is possible to construct a positive alpha strategy using weekly changes in search volume of stock market index's constituents.

Literature Review

During the past years many academics have tried to exploit Internet search query data. Designated as the first paper to study search engine query data, (Mondria et al., 2007) explored the relationship between attention allocation and home bias. Rather than using

Google Trends or its ancestor, Google Insights, authors have used an AOL's (America Online) release of internet search data from 657426 users during March 2006.

In the past there were authors that tried to build investment strategies using Google Trends data. In fact, (Preis et al., 2013) found patterns that authors argue that might be "interpreted as early warning signs of shifts in stock market". There were considered 98 search terms such as "risk", "inflation" or "stocks" e.g. and then positions in Dow Jones Industrial Average (DJIA) index were taken taking into account the comparison between the search volume of a given search term at week t and its moving average value in the last Δt weeks. The most successful search term in this analysis is "debt" which yielded a 326% cumulative return between January 2004 and February 2011. In the discussion of results the authors argued that "strategies based on search volume of U.S. users are more successful for the U.S. market than strategies using global search volume data" and that these results "suggest that Google Trends data and stock market data may reflect two subsequent stages in the decision making process of investors". (Challet & Ayed,2013) used SPY ETF to confirm this intuition claiming that "data from Google Trends contains enough information to predict future financial index return". In this paper there are presented some limitations to the approach taken in (Preis et al., 2013) however similar conclusions about the validity of search engine query data to build profitable investment strategies are reached.

Google Trends data has been used also to analyze some characteristics of financial markets. Moreover, (Da, Engelberg & Gao, 2011) demonstrated how Google Search Volume Index captures investor attention beyond other measures such as advertising expense or extreme price movements. Smith (2012) investigated whether the volume of Google searches for particular keywords can "predict volatility in the market for foreign currency" finding that the number of searches for keywords such as “economic crisis”, “financial crisis” and “recession” have “higher incremental predictive power than GARCH (1,1) models”. (Drake & Thornok, 2012) suggested that it is possible to partially anticipate the information content of the earnings announcement by taking into account the Google search volume of data demanded by investors. (Bank et al., 2011) showed that increases in trading activity and stock liquidity can be associated with an increase in search queries’ volume. (Preis et al., 2010) established a relationship between financial market fluctuations and search volume data. The authors found “clear evidence that weekly transaction volumes of S&P 500 companies are correlated with weekly search volume of corresponding company names”. (Beer et al., 2012) created an innovative measure of French investor sentiment taking into account internet search volume data from Google Trends. The authors found that this “sentiment indicator correlates well with alternative sentiment measures often used in literature” as well as “evidence about short-run predictability in return”.

With the technologic improvements that permit to capture internet search engine data there are also new trends in the way firms are managed. (McAfee and Brynnjolfsson, 2012) enumerated how the collection of more firm’s information in a faster way can help executives to decide more effectively. Moreover, (Davenport, 2006) also aimed at highlighting the importance of collecting and interpreting data and showed the importance of analytic data. According to the author there is a direct relationship between the amount of data firms collect and their position in their markets since aggressive analytics competitors companies tend to be the leaders in their markets.

Internet search data is also applicable to forecasting models. In fact, there are models including this data as a variable that tend to outperform models that do not consider search engine query data. (Choi & Varian, 2009a) built models to predict retail, automotive and home sales in U.S. as well as travel destinations using Google Trends data in their models. The authors concluded that the gains of including GT data variables can “sum up to 18% in predictions for Motor Vehicles and Parts”. (Choi & Varian, 2009b) displayed the improvements that can be reached by using Google Trends data in predicting initial claims for unemployment benefits in the U.S. Moreover, (D’Amuri & Marcucci, 2010) stated that US unemployment rate was best predicted using an “Internet job-search indicator”. Similar conclusions are pointed out to Israel and Germany in (Suhoy, 2009) and (Askitas & Zimmerman, 2009) respectively. (Schmidt & Vossen, 2009) introduced Google Trends search volume data as a new indicator to forecast private consumption. Results suggest that “Google indicator outperforms the survey-based indicators”. (Dzielinski, 2011) established a peculiar indicator of economic uncertainty based on the search volume of the term “economy” in Google Trends which is convenient when predicting stock returns. Moreover, (Goel et al., 2010) found that it is possible to predict the behavior of online searching consumers in different areas such as box office ticket sales, videogames’ sales or even the rank of songs on Billboard Hot 100 chart. In all cases “search counts are highly predictive of future outcomes”.

There are also studies in other scientific areas that used internet search query data. (Kuruzovich et al., 2008) found that consumers are differentiated in the way they collect information through online information sources and consequently, as the results in this study suggest, different business models are recommended to different consumers with different abilities in collecting online information. Ripberger (2010) contributed and demonstrated the potential gains by considering Internet search data to measure public attractiveness which plays a critical role to political scientists. Lazer et al. (2009) enumerated several examples on how internet and networks' data are transforming social network research as well as some challenges that developments in this area may face especially regarding internet users' privacy. (Baker & Fradkin, 2014) developed a model using Google search data to study the effects of Unemployment Insurance (UI) finding that "unemployed individuals not in UI search 30% more than unemployed individuals in UI". (Ginsberg et al., 2009) used Google Search data to improve early detection of disease activity. In this paper, the authors recorded influenza-like illness in a population by accessing changes in search queries' volume. They conclude that this approach is "accurate in areas with large population of web users" and that there is a reporting lag of one day which is significantly lower than the 1-2 weeks that traditional systems require to "gather and process surveillance data".

Data

Google Trends data consists in a query index rather than in the absolute search levels. This index is constructed by analyzing a percentage of Google web searches to determine how many searches have been done with the terms considered compared to the total number of Google searches done during that time and location. The data is normalized between 100, the maximum value regardless the time period considered and 0, the minimum possible value, for each time series. Since all the values are rounded to integers very small changes in search query values can be unperceived. Moreover, Google Trend exclusively analyzes data for popular search terms and thus, when the terms have a search volume below a certain threshold their time series will not be available. At the same time, Google Trends in order to provide robust data does not consider repeated searches from the same users over a short period of time.

Google Trends data is available from January 2004 and therefore the time range considered in this paper relies on the data between January 2004 and August 2014. For this time range the values are generally presented in a weekly periodicity. However, when their search volume is low but higher than the availability threshold values are presented in monthly terms. In this paper, monthly data was not considered and was simply ignored.

The query data is considered among a wide range of 25 first-level categories and 288 second-level subcategories in Google Trends to filter the results. However, there were no search queries filtered by category since there would be no relevant benefit in comparing search query values from different categories.

In addition, there were also analyzed 20 stock market indexes geographically distributed across the world such as AEX 25 (Netherlands), CAC 40 (France), DAX 30 (Germany), IBEX 35 (Spain), ISEQ 20 (Ireland), KFX 20 (Denmark), OMX 30 (Sweden), OSEBX 53 (Norway), PSI 20 (Portugal) and SMI 20 (Switzerland) in Europe, HSI 50 (Hong Kong), KLCI 30 (Malaysia), SENSEX 30 (India), STI 30 (Singapore) and TA 25 (Israel) in Asia, IBOV 70 (Brazil), INDU 30 (United States of America) and TSX 60 (Canada) in Americas, FTSE TOP 40 in Africa and NZX 50 (New Zealand) in Oceania.

Furthermore, the Google Trends weekly search queries were retrieved on the September 1st 2004 using the constituents of these stock market indexes in that day. Moreover, when the Google Trends data was available in a weekly frequency to all of the companies belonging to a specific market index the terms were also searched using filtering searches exclusively done in that stock market index's country.

The name of the companies entered in Google Trends was the service's first suggestion after typing company's name as it appears in the Bloomberg's security description. For instance, for BMW the name entered in Google Trends would be "Bayerische Motoren Werke AG" and then one would choose the term "BMW" which is the first suggestion and is labeled as "Automobile Company". However, when the popularity of the term searched is low Google Trends does not recognize it as a company. In these cases, the term is entered without the firms' legal description. For example, Google Trends does not associate the Spanish company "Viscofan SA" with any suggestion. In this case one would simply search for "Viscofan" removing the "SA" part of its name (refer to Appendix 1 for a detailed description of the terms entered in Google Trends for some stock market indexes).

In addition, weekly closing price of the constituents of the 20 stock market indexes analyzed were also retrieved. It should be mentioned that there is a slight mismatch between Stock Market Indexes and Google Trends' data since the former considers only trading days while Google Trends' weeks begin on Sundays and finish on Saturdays. Weekend days should not be neglected from this analysis, in fact searches done on weekends are more influential and beneficial on future stock price than searches done on weekdays and an increase of searches done on weekends rather than weekdays predicts a higher stock price in the next week (Ye & Liu, 2014). However, weekend days are considered in this approach because weekly positions taken on Monday depend on Google Trends' data comprised until the previous Saturday. Sunday's data for a given week will be considered in the week afterwards.

Methodology

In order to determine if Google Trends data can anticipate subsequential changes in the stock prices of the 20 stock market indexes' constituents a model was built. After collecting the Google Trends data for all constituents, slight changes to the data need to be performed to ensure that investors buy the 10% most searched and sell the 10% least searched companies. Consequently, a percentage change between search query for company *i* at week *t+1* and search query for company *i* at week *t* needs to be computed since Google Trends data is relative rather than absolute. Furthermore it is important to state that it is not accurate to buy the 10% shares with the highest search query volume and sell the 10% shares with the lowest search query volume because the absolute values are commonly different and Google Trends search volume scores may not reflect that. Moreover, by using the 10% highest percentage changes to buy and the 10% lowest percentage changes to sell it is being ensured that the investor goes long on the 10% shares which search volume has increased the most and goes short on the 10% shares which search volume has decreased the most from one week to the following one.

Consequently, after computing the percentage changes at week t+1 each observation needs to be ranked to define which stocks to buy or sell (refer to Figure I to a description of the investment procedure from week *t* (denoted as 0 in x-axis) throughout the return at week *t+3*).

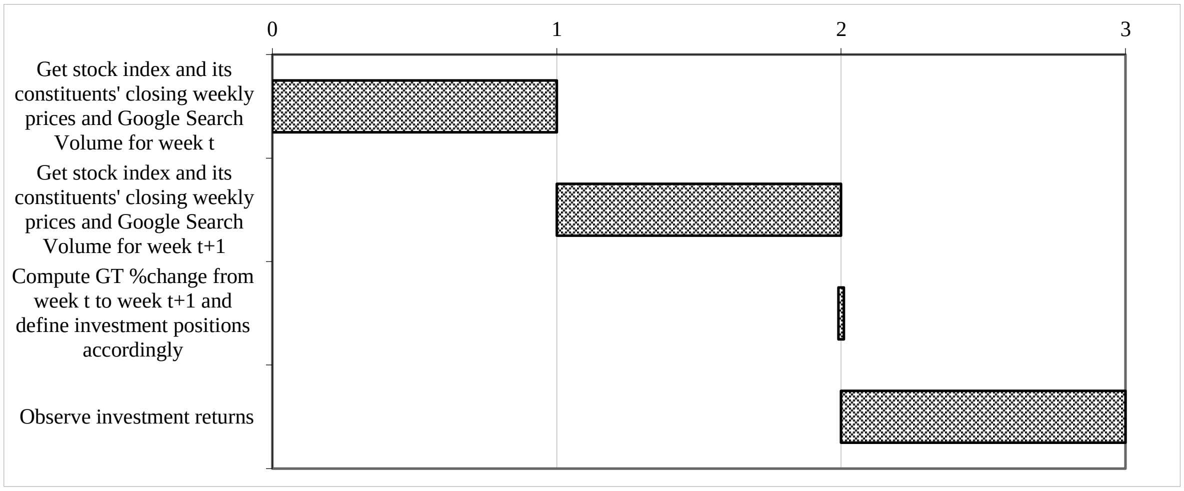

Figure I - Chronogram of the investment procedure (in weeks)

In this model it is assumed that investors will hedge their positions by buying or selling the market index to become market-neutral. It might be expected that since investor are taking the same proportion of long and short positions its weekly position would not be long nor short biased. However, depending on the data this may not be the case (refer to Table I to observe the methodology using some companies from PSI 20 from the two weeks between 2004-01-04 and 2004-01-17)[1].

	BPI PL Equity	BCP PL Equity	BES PL Equity	EDP PL Equity	NOS PL Equity	PTC PL Equity	
	GOOGLE TRENDS SEARCH VOLUME						
2004-01-04/10	16	19	22	23	29	66	
2004-01-11/17	16	13	22	22	28	89	
	GOOGLE TRENDS RETURNS						
2004-01-11/17	0,0000	-0,3795	0,0000	-0,0445	-0,0351	0,2990	
	RANK						
2004-01-11/17	2	6	2	5	4	1	
	POSITIONS						SUM
	1	-1	1	-1	0	1	1

Table I - Methodology description using some of PSI 20's constituents.

[1] The remaining constituents of PSI 20 Index are purposely not displayed in Table I since it is not possible to retrieve its Google Trends Search Volume or its Google Trends Return is not defined.

In the example shown in Table I investors would be net long in the positions for PSI 20 in the week from 11th to 17th January 2004. In this case, as in all of the other cases for all stock indexes considered where the sum of positions for a given week is different from zero investors it is assumed that investors will hedge their positions. Consequently, financiers buy the index *x* times if the sum of positions is *x* and *x* is negative and short the index *y* times if the sum of positions is *y* and *y* is positive. Therefore, in the example described in Table 1, investors would short one time PSI 20 index in the week from 11th to 17th January 2004.

Moreover the weekly return for a given week *t* is given by:

$$r_t = \frac{position_{i,t} * ln\left(\frac{last\ price_{i,t}}{last\ price_{i,t-1}}\right) - \sum_{i=1}^{N} position_{i,t} * ln\left(\frac{market\ last\ price_t}{market\ last\ price_{t-1}}\right)}{max(\#\ long\ positions_t, \#long\ positions_t)}$$

Where $position_{i,t}$ denotes position for company *i* in week *t*, $last\ price_{i,t}$ express company *i* weekly closing price for week *t* whereas $market\ last\ price_t$ represents market closing price for week *t* and max($\#\ long\ positions_t, \#long\ positions_t$) stands for the maximum number between long or short positions taken in week *t*. This number is always 10% of the number of constituents for every stock market considered.

The benchmark used to compare the results from Google Trends strategy is a strategy of buy-and-hold the stock market index considered during January 2004 and August 2014.

Results

1. Main European Indexes

The main objective with this paper is to elaborate an investment strategy which would be easy to implement. The strategy is firstly backtested in two European major markets, CAC 40 and DAX 30 in France and Germany respectively and afterwards other stock market indexes around the world were also considered. By starting to analyze the investment strategy in Europe it is ensured on one hand that diversity is guaranteed since there are a significant number of stock market indexes in this zone and on other hand that the investment strategy is backtested in a region where there is a remarkable percentage of worldwide internet Google search engine users.

When Google search data for the companies in these indexes is filtered to exclusively include searches done in France and Germany, Google Trends' (GT) strategy outperforms the benchmark in terms of Info Sharpe (IS). Simultaneously, in these two markets GT strategy also exhibits investor favorable characteristics in terms of skewness and kurtosis, since it provides lower kurtosis and higher skew than the benchmark. Regarding standard deviation (std), GT strategy provided a lower value in CAC 40 and a quite similar value in DAX 30 considering exclusively searches in France and Germany respectively (refer to Table II where descriptive statistics are summarized).

DAX 30 Germany	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	0,0989	0,0783
ann.std	0,2293	0,2223
IS	0,4314	0,3523
%neg weeks	0,4567	0,4368
skew	-0,0289	-1,1240
kurtosis	2,9071	9,5067
Max	0,1472	0,1494
Q3	0,0201	0,0182
Med	0,0023	0,0049
Q1	-0,0139	-0,0140
Min	-0,1373	-0,2435

CAC 40 France	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	0,0317	0,0166
ann. std	0,1638	0,2169
IS	0,1938	0,0764
%neg weeks	0,4838	0,4513
skew	0,2697	-1,3585
kurtosis	1,0401	10,1202
Max	0,0961	0,1243
Q3	0,0127	0,0179
Med	0,0010	0,0030
Q1	-0,0133	-0,0151
Min	-0,0678	-0,2505

Table II - Descriptive Statistics for for DAX 30 and CAC 40 using exclusively local searches.

However, when considering global searches GT strategy underperforms both in CAC 40 and DAX 30 its benchmark in terms of IS (refer to Table III where descriptive statistics are summarized). Nonetheless, again in both stock market indexes GT strategy delivers favorable characteristics in terms of kurtosis and skewness that actually underestimates the GT Info Sharpe for CAC 40 and DAX 30 using global searches (Kat & Brooks, 2001).

DAX 30 global	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	-0,0360	0,0783
ann. std	0,2159	0,2223
IS	-0,1669	0,3523
%neg weeks	0,5415	0,4368
skew	0,1533	-1,1240
kurtosis	3,9405	9,5067
Max	0,1359	0,1494
Q3	0,0137	0,0182
Med	-0,0027	0,0049
Q1	-0,0166	-0,0140
Min	-0,1707	-0,2435

CAC 40 global	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	0,0000	0,0166
ann. std	0,1919	0,2169
IS	0,0000	0,0764
%neg weeks	0,4982	0,4513
skew	-0,0306	-1,3585
kurtosis	2,2546	10,1202
Max	0,1115	0,1243
Q3	0,0157	0,0179
Med	0,0001	0,0030
Q1	-0,0153	-0,0151
Min	-0,1064	-0,2505

Table III - Descriptive Statistics for DAX 30 and CAC 40 using global searches

2. Testing Fama-French Factors

After acknowledging the potential of this investment strategy it was also tested if GT monthly returns for CAC 40 and DAX 30 using exclusively country-level searches displayed statically significant positive alpha. In order to understand if alpha is created these returns were regressed in an excess market return variable, denoted as the difference between market and risk-free returns in these two countries[2] as in Fama-French three factor (Fama & French, 1992) and Carhart four factor models (Carhart, 1997). In both cases alpha is positive, however it is associated with a large p-value which evidenciates that alpha is not statistically significant different from zero (refer to Appendix 2 for a detailed description of the regressions). Since for these two markets GT strategy outperforms the market it is possible to conclude that the excess return displayed in GT strategy for DAX and CAC using country-level has to be explained by another factor rather than market risk factor.

3. Other indexes

The investment strategy was also analyzed in European peripheral stock markets such as IBEX 35, AEX 25, PSI 20 and ISEQ 20 among others.

Regarding IBEX 35, the Spanish stock market index, conclusions are similar to those from CAC 40 and DAX 30. Google Trends strategy's Info Sharpe is lower than the benchmark when considering global searches but higher when considering exclusively searches done in Spain. Since 10% of the 35 constituents is not an integer number in Spain there were

[2] Data was retrieved from Stefano Marmi personal website (http://homepage.sns.it/marmi/) on the December 18th, 2014. Moreover it should be noted that the time series of factors was available from January 2004 but only comprises data until March 2013.

considered two cases: when investors go long and short 3 stocks and when they go long and short 4 stocks (refer to Table IV).

IBEX 35 Spain	**GOOGLE TRENDS**		**BUY AND HOLD**
	3/3	4/4	
ann. ret	0,0433	0,0390	0,0278
ann. std	0,2266	0,1916	0,2370
IS	0,1910	0,2035	0,1172
%neg weeks	0,4621	0,4856	0,4332
skew	-0,1428	0,0567	-1,1121
kurtosis	2,2337	1,7259	6,3319
Max	0,1453	0,1276	0,1110
Q3	0,0185	0,0155	0,0191
Med	0,0019	0,0006	0,0044
Q1	-0,0162	-0,0144	-0,0151
Min	-0,1238	-0,0912	-0,2383

Table IV - Descriptive Statistics for IBEX 35 using local searches

AEX 25 is one of the markets where Google Trends' strategy profitability, evaluated by Info Sharpe, is more noticeable. Again, due to the number of constituents there were considered two cases (refer to Table V where descriptive statistics are summarized).

AEX 25 global	**GOOGLE TRENDS**		**BUY AND HOLD**
	2/2	3/3	
ann. ret	0,0865	0,0659	0,0136
ann. std	0,2653	0,2094	0,2162
IS	0,3260	0,3147	0,0627
%neg weeks	0,4892	0,5018	0,4585
skew	0,6064	0,3829	-1,8063
kurtosis	2,8638	2,1232	16,5041
Max	0,1837	0,1252	0,1248
Q3	0,0192	0,0151	0,0159
Med	0,0005	-0,0004	0,0022
Q1	-0,0203	-0,0156	-0,0146

Min	-0,1327	-0,1138	-0,2875

Table V - Descriptive Statistics for AEX 25 using global searches

PSI 20 and ISEQ 20, the Portuguese and Irish stock market indexes respectively were also considered to backtest GT strategy (refer to Table VI where descriptive statistics are summarized). There are similar results to the two indexes. Both exhibit higher IS as well as less kurtosis and higher skewness than both benchmarks. In fact, in these two indexes benchmark's the Info Sharpe ratio is negative whilst GT IS is positive (refer to Appendices 3 to 8 to understand the differences in cumulative return between GT strategy and correspondent benchmarks for the stock markets aforementioned).

ISEQ 20 global	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	0,0001	-0,0205
ann. std	0,3774	0,2539
IS	0,0003	-0,0807
%neg weeks	0,4585	0,3899
skew	0,2537	-1,9364
kurtosis	5,1056	16,3231
Max	0,2603	0,1447
Q3	0,0224	0,0165
Med	0,0000	0,0003
Q1	-0,0233	-0,0140
Min	-0,2612	-0,3290

PSI 20 global	**GOOGLE TRENDS**	**BUY AND HOLD**
ann. ret	0,0232	-0,0149
ann. std	0,2401	0,2018
IS	0,0967	-0,0738
%neg weeks	0,4928	0,4549
skew	-0,0518	-1,3837
kurtosis	1,6196	6,9314
Max	0,1483	0,0851
Q3	0,0178	0,0160
Med	0,0006	0,0017
Q1	-0,0159	-0,0127
Min	-0,1172	-0,2057

Table VI - Descriptive Statistics for ISEQ 20 and PSI 20 using global searches

The strategy was also backtested in other stock market indexes globally (refer to Appendix 9 for general characteristics of all markets analyzed). In none of these indexes analyzed Google Trends strategy outperformed the benchmark. There is also one characteristic that should be pointed out. In BSE SENSEX 30 (India), INDU 30 (USA) and SMI 20 (Switzerland), when searches are filtered to consider exclusively those done in these countries, GT strategy's IS values are higher in absolute value than those from benchmark implying that if decision rule was inverted, i.e., go long the 10% less searched and go short the 10% most searched stocks, from one week to the following one, GT strategy would be profitable. Same conclusion can be drawn from TSX 60 (Canada) when using global searches.

4. Hit Ratio

In order to study how distributed and independent are weekly returns in the stock market indexes analyzed a new measure to evaluate GT strategy denoted as "Hit Ratio" was created. This value was computed by aggregating weekly returns into monthly returns and assessing whether, for a given month t, the sum of the Google Trends strategy's returns in the previous 12 months is higher than those from the benchmark. For that month t a value of 1 is assigned if GT returns in the previous 12 months are higher than those from benchmark, otherwise it will be assigned a value of 0. Hit Ratio is consequently the sum of these values divided by the number of total months where it was possible to analyze the 12 previous observations. Naturally, the value of this Hit Ratio tends to be higher in stock index markets where the GT strategy outperforms its benchmark. In fact, for the 8 cases where GT strategy outperforms in 4 of them Hit Ratio is higher than 0,5[3] which ensures some consistency and robustness (refer to Figure II to observe the relationship between GT's and Benchmark's IS difference and Hit Ratio values)[4].

[3] For AEX 25 2/2, IBEX 35 Spain 3/3, IBEX 35 Spain 4/4 and PSI 20 Hit Ratio is higher than 0,5.

[4] In Appendix9 it is presented a Table where it is possible to observe the difference between GT's and Benchmark's IS value and Hit Ratio value for all stock markets analyzed.

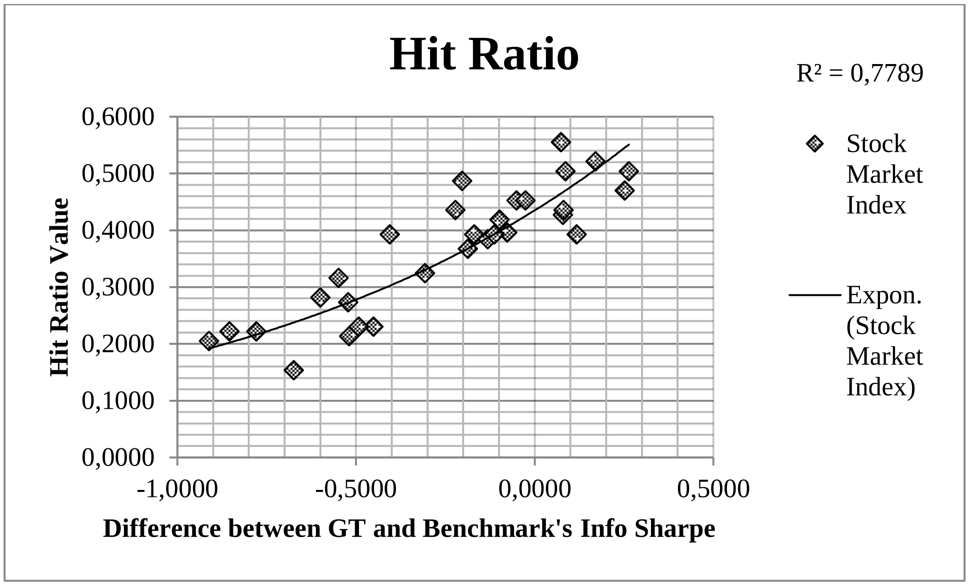

Figure II – Analysis of Hit Ratio for all of the stock market indexes considered

Conclusion

In this paper it is possible to conclude that the potential of using Internet search engine data to build profitable investment strategies is notable. In the main European stock markets index it is possible to build a strategy that outperforms a conventional buy-and-hold strategy. Google Trends strategy generally reduces the kurtosis and increases the skewness of the returns, even when the strategy does not outperform the benchmark. These characteristics may underestimate the Info Sharpe since investors demand and prefer to have returns with lowest kurtosis and highest skewness possible (refer to Appendices 10 and 11 to a detailed description of kurtosis and skewness for the markets where GT strategy outperforms benchmark).

The results tend to be better when considering exclusively Google searches specific to the country analyzed which confirms the intuition presented in (Preis et al., 2013). Moreover, Google Trends service has been developed in the last years to better capture local searches in countries with less search volume. It may be also expected that in the future service developments will allow to retrive data with different periodicities, e.g., daily instead of weekly for large time periods.

On the negative side of this strategy it should be taken into account that transaction costs were not considered. Since positions are taken as a percentage of the number of constituents this might be critical in indexes with more securities. However, CAC 40 is the index with largest stocks where Google Trends strategy is profitable which has a number of constituents lower than TSX 60 or IBOV 70 e.g.

All in all, Google Trends provides a reliable and a promising source of data that can be used to build profitable investment strategies. Even if transaction costs were not considered the gains in terms of Info Sharpe are particularly remarkable. Moreover, it is expected that developments in Google Trends platform will continue which will ultimately open even wider opportunities in the future.

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Appendices

Appendix 1 – List of Google Trends terms searched for all markets where GT strategy outperformed benchmark[5].

AEX 25 (Netherlands)

AEX Index

Company Name	Ticker	Google Trends
Aegon NV	AGN NA Equity	Aegon
Akzo Nobel NV	AKZA NA Equity	AkzoNobel
ArcelorMittal	MT NA Equity	ArcelorMittal
ASML Holding NV	ASML NA Equity	ASML Holding
Corio NV	CORA NA Equity	Corio
Delta Lloyd NV	DL NA Equity	Delta Lloyd Group
Fugro NV	FUR NA Equity	Fugro
Gemalto NV	GTO NA Equity	Gemalto
Heineken NV	HEIA NA Equity	Heineken
ING Groep NV	INGA NA Equity	ING Group
Koninklijke Ahold NV	AH NA Equity	Ahold
Koninklijke Boskalis Westminster NV	BOKA NA Equity	Royal Boskalis Westminster
Koninklijke DSM NV	DSM NA Equity	DSM
Koninklijke KPN NV	KPN NA Equity	KPN
Koninklijke Philips NV	PHIA NA Equity	Philips
OCI*	OCI NA Equity	OCI
Randstad Holding NV	RAND NA Equity	Randstad Holding
Reed Elsevier NV	REN NA Equity	Reed Elsevier plc
Royal Dutch Shell PLC	RDSA NA Equity	Royal Dutch Shell
SBM Offshore NV	SBMO NA Equity	SBM Offshore
TNT Express NV*	TNTE NA Equity	TNT Express
Unibail-Rodamco SE	UL NA Equity	Unibail-Rodamco
Unilever NV	UNA NA Equity	Unilever
Wolters Kluwer NV	WKL NA Equity	Wolters Kluwer
Ziggo NV	ZIGGO NA Equity	Ziggo

CAC 40 (France)

CAC Index

Company Name	Ticker	Google Trends
Accor SA	AC FP Equity	Accor
Air Liquide SA	AI FP Equity	Air Liquide
Airbus Group NV	AIR FP Equity	Airbus
Alcatel-Lucent	ALU FP Equity	Alcatel-Lucent
Alstom SA	ALO FP Equity	Alstom
ArcelorMittal	MT NA Equity	ArcelorMittal

[5] *monthly data
** monthly data when searched at country-level
*** insufficient search volume to retrieve Google trends data
**** insufficient search volume to retrieve Google trends data when searched at country-level

AXA SA	CS FP Equity	AXA
BNP Paribas SA	BNP FP Equity	BNP Paribas
Bouygues SA	EN FP Equity	Bouygues Telecom
Cap Gemini SA	CAP FP Equity	Capgemini
Carrefour SA	CA FP Equity	Carrefour
Cie de St-Gobain	SGO FP Equity	Saint-Gobain
Cie Generale des Etablissements Michelin	ML FP Equity	Michelin
Credit Agricole SA	ACA FP Equity	Crédit Agricole
Danone SA	BN FP Equity	Groupe Danone
Electricite de France SA	EDF FP Equity	Électricité de France
Essilor International SA	EI FP Equity	Essilor
GDF Suez	GSZ FP Equity	GDF Suez
Gemalto NV	GTO NA Equity	Gemalto
Kering	KER FP Equity	Kering
L'Oreal SA	OR FP Equity	L'Oréal
Lafarge SA	LG FP Equity	Lafarge
Legrand SA	LR FP Equity	Legrand
LVMH Moet Hennessy Louis Vuitton SA	MC FP Equity	LVMH Moet Hennessy
Orange SA	ORA FP Equity	Orange
Pernod Ricard SA	RI FP Equity	Pernod Ricard
Publicis Groupe SA	PUB FP Equity	Publicis Groupe
Renault SA	RNO FP Equity	Renault
Safran SA	SAF FP Equity	Safran
Sanofi	SAN FP Equity	Sanofi
Schneider Electric SE	SU FP Equity	Schneider Electric
Societe Generale SA	GLE FP Equity	Société Générale
Solvay SA	SOLB BB Equity	Solvay
Technip SA	TEC FP Equity	Technip
Total SA	FP FP Equity	Total S.A.
Unibail-Rodamco SE	UL NA Equity	Unibail-Rodamco
Valeo SA	FR FP Equity	Valeo
Veolia Environnement SA	VIE FP Equity	Veolia Environnement
Vinci SA	DG FP Equity	Vinci
Vivendi SA	VIV FP Equity	Vivendi

DAX 30 (Germany)
DAX Index

Company Name	Ticker	Google Trends
adidas AG	ADS GY Equity	Adidas
Allianz SE	ALV GY Equity	Allianz
BASF SE	BAS GY Equity	BASF
Bayer AG	BAYN GY Equity	Bayer
Bayerische Motoren Werke AG	BMW GY Equity	BMW
Beiersdorf AG	BEI GY Equity	Beiersdorf
Commerzbank AG	CBK GY Equity	Commerzbank
Continental AG	CON GY Equity	Continental AG
Daimler AG	DAI GY Equity	Daimler AG
Deutsche Bank AG	DBK GY Equity	Deutsche Bank
Deutsche Boerse AG	DB1 GY Equity	Deutsche Börse
Deutsche Lufthansa AG	LHA GY Equity	Lufthansa
Deutsche Post AG	DPW GY Equity	Deutsche Post
Deutsche Telekom AG	DTE GY Equity	Deutsche Telekom
E.ON SE	EOAN GY Equity	E.ON
Fresenius Medical Care AG & Co KGaA	FME GY Equity	Fresenius Medical Care
Fresenius SE & Co KGaA	FRE GY Equity	Fresenius SE
HeidelbergCement AG	HEI GY Equity	HeidelbergCement

Henkel AG & Co KGaA	HEN3 GY Equity	Henkel
Infineon Technologies AG	IFX GY Equity	Infineon Technologies
K+S AG	SDF GY Equity	K+S
LANXESS AG	LXS GY Equity	Lanxess
Linde AG	LIN GY Equity	The Linde Group
Merck KGaA	MRK GY Equity	Merck KGaA
Muenchener Rueckversicherungs AG	MUV2 GY Equity	Munich Re
RWE AG	RWE GY Equity	RWE AG
SAP SE	SAP GY Equity	SAP SE
Siemens AG	SIE GY Equity	Siemens
ThyssenKrupp AG	TKA GY Equity	ThyssenKrupp
Volkswagen AG	VOW3 GY Equity	Volkswagen Passenger Cars

IBEX 35 (Spain)
IBEX Index

Company Name	Ticker	Google Trends
Abengoa SA	ABG/P SM Equity	Abengoa
Abertis Infraestructuras SA	ABE SM Equity	abertis
Acciona SA**	ANA SM Equity	Acciona
ACS Actividades de Construccion y Servicios **	ACS SM Equity	Grupo ACS
Amadeus IT Holding SA	AMS SM Equity	Amadeus IT Group
ArcelorMittal**	MTS SM Equity	ArcelorMittal
Banco Bilbao Vizcaya Argentaria SA	BBVA SM Equity	Banco Bilbao Vizcaya Argentaria
Banco de Sabadell SA	SAB SM Equity	Banco Sabadell
Banco Popular Espanol SA**	POP SM Equity	Banco Popular Español
Banco Santander SA	SAN SM Equity	Santander Group
Bankia SA	BKIA SM Equity	Bankia
Bankinter SA**	BKT SM Equity	Bankinter
Bolsas y Mercados Espanoles SA	BME SM Equity	Bolsas y Mercados Españoles
CaixaBank SA	CABK SM Equity	Caixabank
Distribuidora Internacional de Alimentacion SA**	DIA SM Equity	Dia
Enagas SA	ENG SM Equity	Enagás
Ferrovial SA**	FER SM Equity	Ferrovial
Fomento de Construcciones y Contratas SA	FCC SM Equity	Fomento de Construcciones y Contratas
Gamesa Corp Tecnologica SA	GAM SM Equity	gamesa
Gas Natural SDG SA	GAS SM Equity	Gas Natural
Grifols SA	GRF SM Equity	Grifols
Iberdrola SA	IBE SM Equity	Iberdrola
Inditex SA**	ITX SM Equity	Inditex
Indra Sistemas SA	IDR SM Equity	Indra Sistemas
International Consolidated Airlines Grou	IAG SM Equity	International Airlines Group
Jazztel PLC	JAZ SM Equity	Jazztel
Mapfre SA****	MAP SM Equity	Mapfre
Mediaset Espana Comunicacion SA****	TL5 SM Equity	Mediaset España Comunicación
Obrascon Huarte Lain SA**	OHL SM Equity	Obrascón Huarte Lain
Red Electrica Corp SA	REE SM Equity	Red Eléctrica de España
Repsol SA	REP SM Equity	Repsol YPF S.A.
Sacyr SA**	SCYR SM Equity	Sacyr Vallehermoso
Tecnicas Reunidas SA	TRE SM Equity	Técnicas Reunidas
Telefonica SA**	TEF SM Equity	Telefónica
Viscofan SA	VIS SM Equity	viscofan

ISEQ 20 (Ireland)
ISEQ20P Index

Company Name	Ticker	Google Trends
Aer Lingus Group plc	AERL ID Equity	Aer Lingus
Aryzta AG	YZA ID Equity	Aryzta
Bank of Ireland	BKIR ID Equity	Bank of Ireland
C&C Group PLC*	GCC ID Equity	C&C Group
CRH PLC	CRH ID Equity	CRH plc
Dragon Oil PLC	DGO ID Equity	Dragon Oil
FBD Holdings PLC***	FBD ID Equity	FBD Holdings
Fyffes PLC	FFY ID Equity	Fyffes
Glanbia PLC	GLB ID Equity	Glanbia
Green REIT plc	GRN ID Equity	Green Reit
Hibernia REIT plc	HBRN ID Equity	Hibernia Reit
Irish Continental Group PLC	IR5B ID Equity	Irish Ferries
Kenmare Resources PLC	KMR ID Equity	Kenmare Resources
Kerry Group PLC	KYG ID Equity	Kerry Group
Kingspan Group PLC	KSP ID Equity	Kingspan Group
Origin Enterprises PLC*	OGN ID Equity	Origin Enterprises
Paddy Power PLC	PWL ID Equity	Paddy Power
Ryanair Holdings PLC	RYA ID Equity	Ryanair
Smurfit Kappa Group PLC	SKG ID Equity	Smurfit Kappa Group
Total Produce PLC	TOT ID Equity	Total Produce

PSI 20 (Portugal)
PSI20 Index

Company Name	Ticker	Google Trends
Altri SGPS SA	ALTR PL Equity	Altri
Banco BPI SA	BPI PL Equity	Banco Português de Investimento
Banco Comercial Portugues SA	BCP PL Equity	Banco Comercial Português
Banco Espirito Santo SA	BES PL Equity	Banco Espírito Santo
BANIF - Banco Internacional do Funchal SA	BANIF PL Equity	Banif Financial Group
Cofina SGPS SA*	CFN PL Equity	Cofina
EDP - Energias de Portugal SA	EDP PL Equity	Energias de Portugal
EDP Renovaveis SA	EDPR PL Equity	EDP Renováveis
Espirito Santo Financial Group SA*	ESF PL Equity	Espírito Santo Financial Group
Galp Energia SGPS SA	GALP PL Equity	Galp Energia SGPS
Jeronimo Martins SGPS SA	JMT PL Equity	Jerónimo Martins
Mota-Engil SGPS SA	EGL PL Equity	Mota-Engil
NOS SGPS	NOS PL Equity	NOS Comunicações
Portucel SA	PTI PL Equity	Portucel Soporcel
Portugal Telecom SGPS SA	PTC PL Equity	Portugal Telecom
REN - Redes Energeticas Nacionais SGPS*	RENE PL Equity	Redes Energéticas Nacionais
Semapa-Soci.de Inv., e Gestao SGPS SA*	SEM PL Equity	Semapa
Sonae Industria SGPS SA	SONI PL Equity	Sonae Indústria
Sonae SGPS SA	SON PL Equity	Sonae SGPS SA
Sonaecom - SGPS SA*	SNC PL Equity	sonaecom

Appendix 2 –Alpha analysis Output for CAC 40 and DAX 30 using country-level searches.

Dependent Variable: CAC_40_FRANCE_4_4
Method: Least Squares
Date: 01/04/15   Time: 11:47
Sample: 2004M01 2013M03
Included observations: 111

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002095	0.004475	0.468058	0.6407
RM_RF_FRANCE	-0.002198	0.000931	-2.359985	0.0201

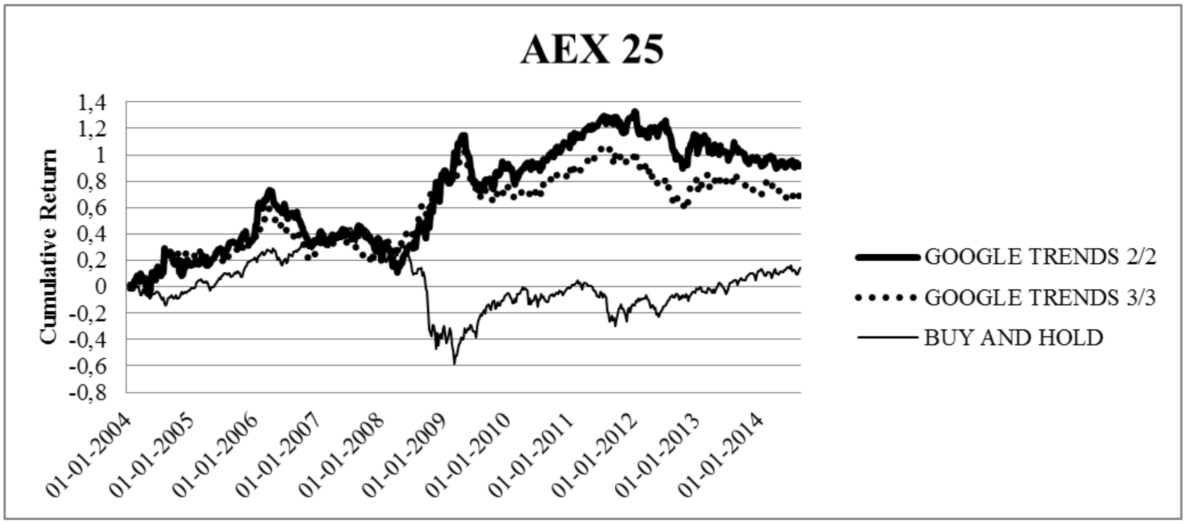
R-squared	0.048613	Mean dependent var	0.001256
Adjusted R-squared	0.039884	S.D. dependent var	0.047965
S.E. of regression	0.046999	Akaike info criterion	-3.259521
Sum squared resid	0.240772	Schwarz criterion	-3.210701
Log likelihood	182.9034	Hannan-Quinn criter.	-3.239716
F-statistic	5.569528	Durbin-Watson stat	2.096987
Prob(F-statistic)	0.020054		

Dependent Variable: DAX_30_GERMANY_3_3
Method: Least Squares
Date: 01/04/15   Time: 11:48
Sample: 2004M01 2013M03
Included observations: 111

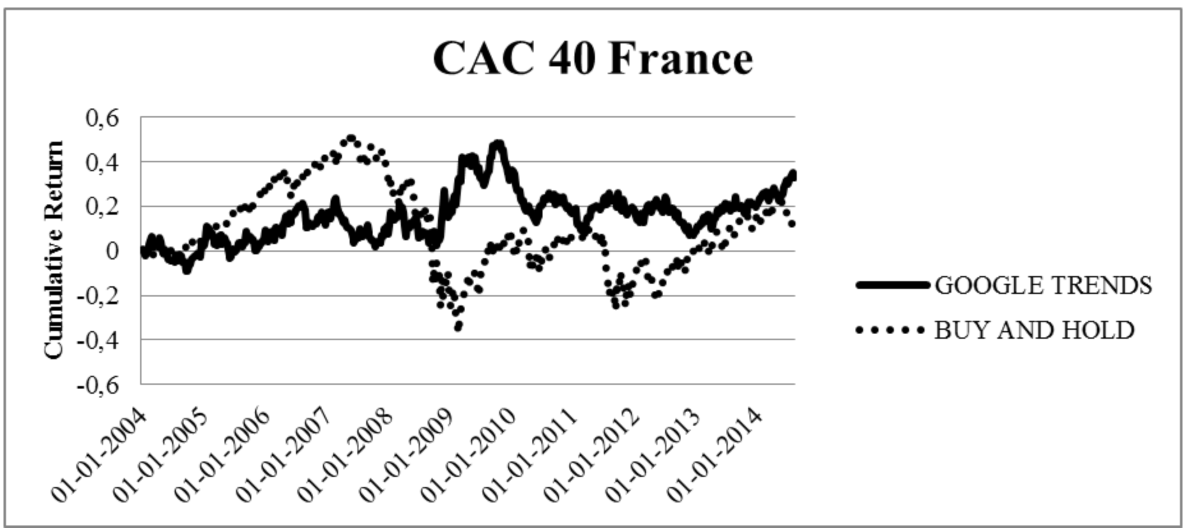
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007324	0.007219	1.014529	0.3126
RM_RF_GERMANY	-0.000429	0.002125	-0.202095	0.8402

R-squared	0.000375	Mean dependent var	0.007096
Adjusted R-squared	-0.008796	S.D. dependent var	0.074796
S.E. of regression	0.075124	Akaike info criterion	-2.321497
Sum squared resid	0.615156	Schwarz criterion	-2.272676
Log likelihood	130.8431	Hannan-Quinn criter.	-2.301692
F-statistic	0.040842	Durbin-Watson stat	2.098729
Prob(F-statistic)	0.840220		

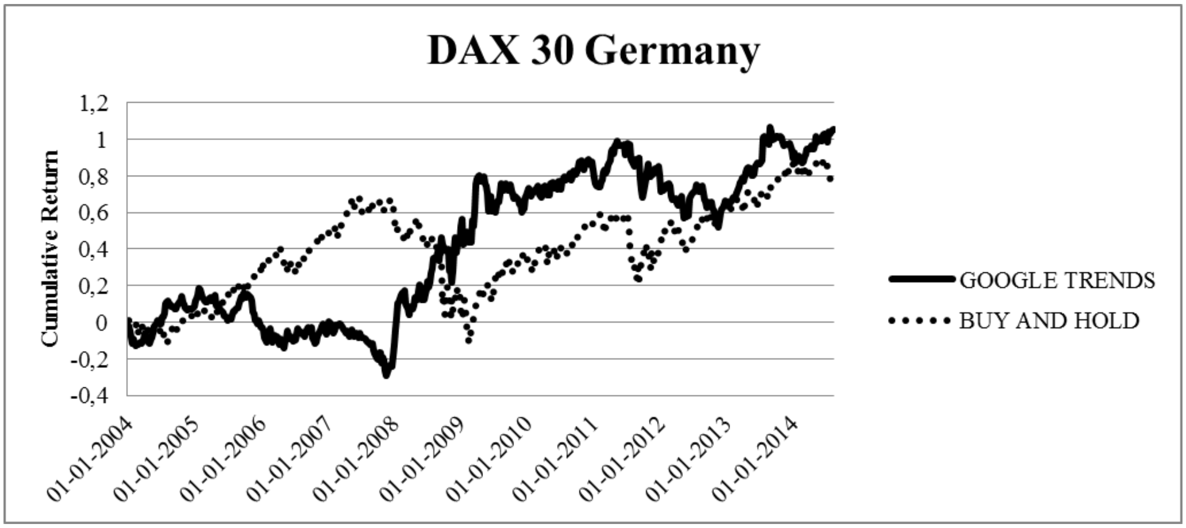
Appendix 3 – Comparison between GT strategy's for AEX 25 and benchmark's cumulative return using global searches.



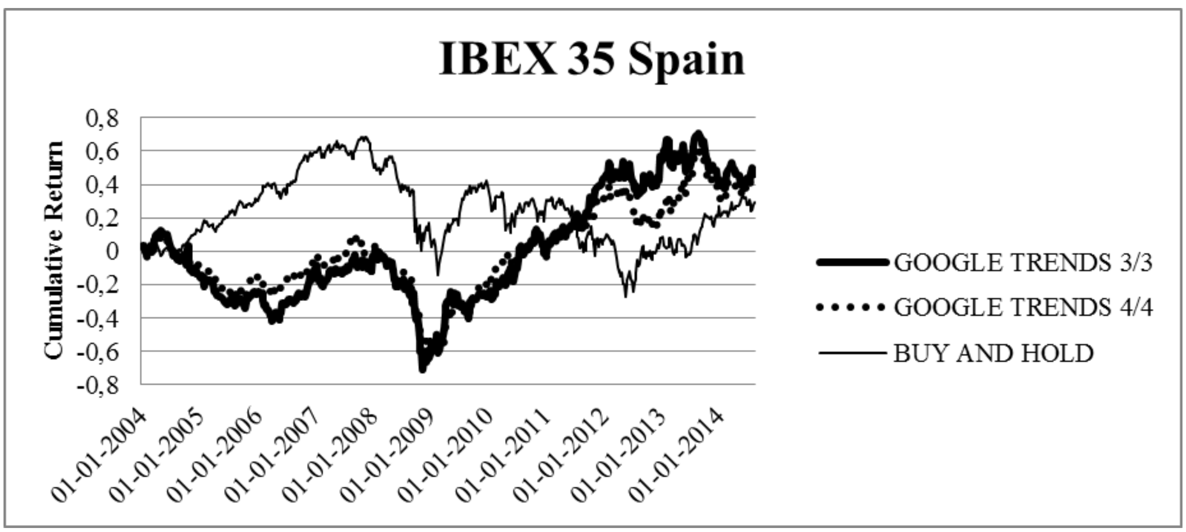
Appendix 4 – Comparison between GT strategy's for CAC 40 and benchmark's cumulative return using exclusively searches done in France.



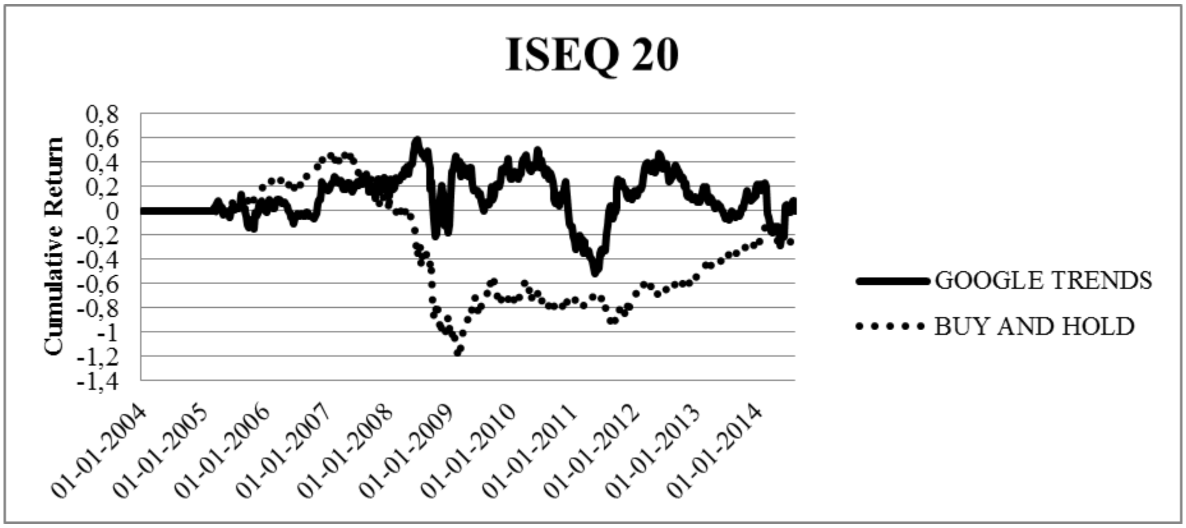
Appendix 5– Comparison between GT strategy's for DAX 30 and benchmark's cumulative return using exclusively searches done in Germany.



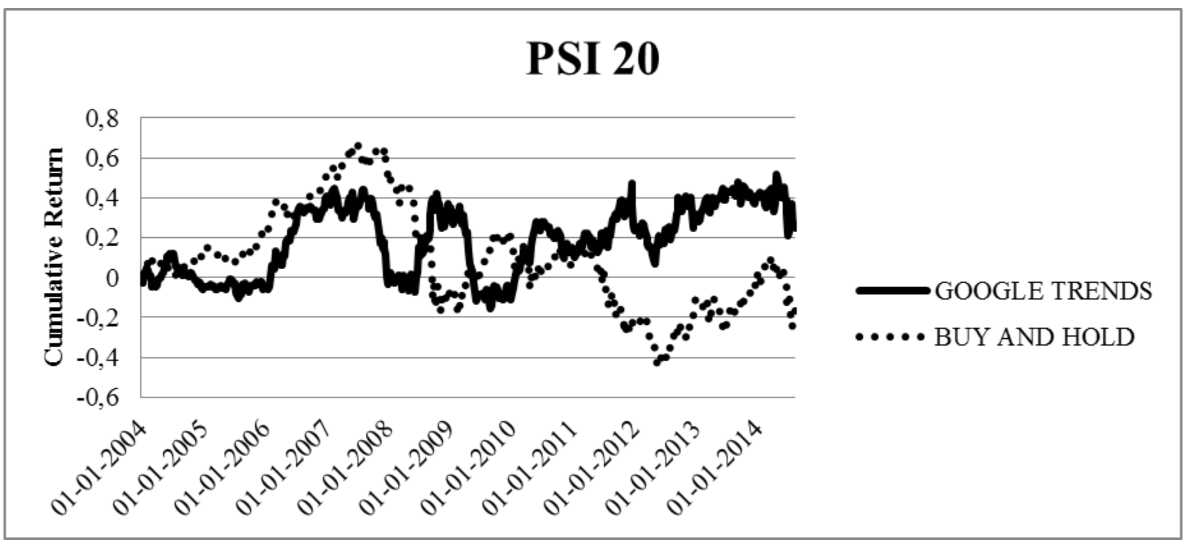
Appendix 6 – Comparison between GT strategy's for IBEX 35 and benchmark's cumulative return using exclusively searches done in Spain.



Appendix 7 – Comparison between GT strategy's for ISEQ 20 and benchmark's cumulative return using global searches.[6]



Appendix 8 – Comparison between GT strategy's for PSI 20 and benchmark's cumulative return using global searches.



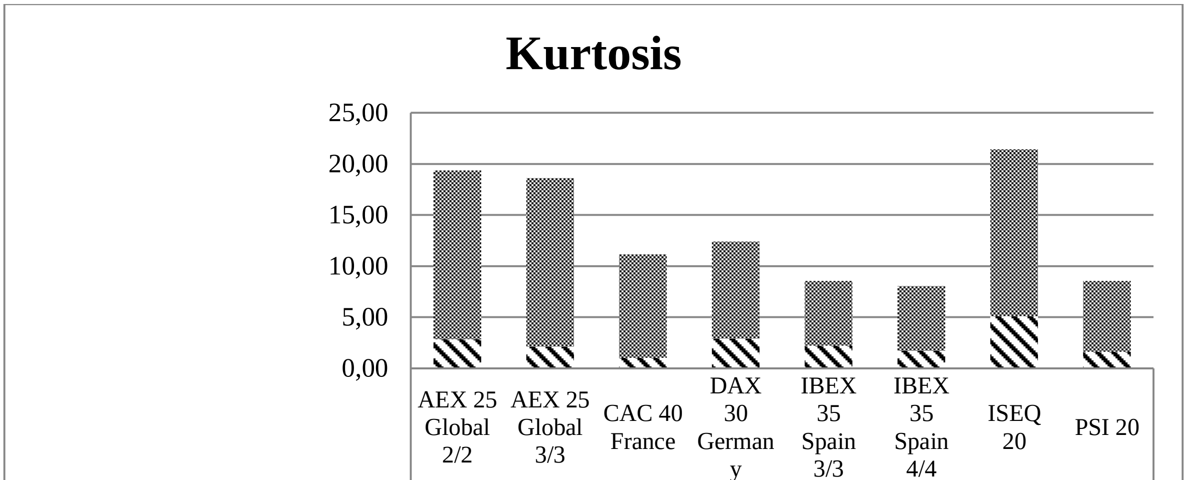
6 ISEQ 20's weekly last price is only available from the week ending in 18-03-2005 afterwards.

Appendix 9 – General statistics for all markets analyzed.[7]

Index	Search	(#long/#short)	% GT	GT IS	BENCHMARK IS	Difference	Hit Ratio
AEX 25	**Global**	**2/2**	**92%**	**0,3260**	**0,0627**	**0,2633**	**0,5043**
	Global	**3/3**	**92%**	**0,3147**	**0,0627**	**0,2520**	**0,4701**
BSE SENSEX 30	Global	3/3	100%	0,0453	0,3523	-0,3070	0,3248
	India	3/3	100%	-0,4267	0,3523	-0,7790	0,2222
CAC 40	Global	4/4	100%	0,0000	0,0764	-0,0765	0,3966
	France	**4/4**	**100%**	**0,1938**	**0,0764**	**0,1174**	**0,3932**
DAX 30	Global	3/3	100%	-0,1669	0,3523	-0,5192	0,2137
	Germany	**3/3**	**100%**	**0,4314**	**0,3523**	**0,0790**	**0,4274**
HSI 50	Global	5/5	60%	-0,4083	0,2656	-0,6739	0,1538
IBEX 35	Global	3/3	100%	0,0668	0,1172	-0,0504	0,4530
	Global	4/4	100%	0,0188	0,1172	-0,0984	0,4188
	Spain	**3/3**	**63%**	**0,1910**	**0,1172**	**0,0738**	**0,5556**
	Spain	**4/4**	**63%**	**0,2035**	**0,1172**	**0,0863**	**0,5043**
IBOV 70	Global	7/7	90%	0,2155	0,3465	-0,1310	0,3846
INDU 30	Global	3/3	100%	-0,1846	0,2661	-0,4507	0,2308
	U.S.	3/3	100%	-0,2830	0,2661	-0,5490	0,3162
ISEQ 20	**Global**	**2/2**	**85%**	**0,0003**	**-0,0807**	**0,0810**	**0,4359**
JSE FTSE TOP 40	Global	4/4	83%	0,1651	0,6873	-0,5222	0,2735
KFX 20	Global	2/2	95%	0,2528	0,4558	-0,2029	0,4872
KLCI 30	Global	3/3	77%	0,1140	0,6061	-0,4921	0,2308
NZX 50	Global	5/5	62%	0,4058	0,5923	-0,1865	0,3675
OMX 30	Global	3/3	93%	0,2965	0,3221	-0,0256	0,4530
OSEBX 50	Global	5/5	70%	-0,3900	0,4640	-0,8540	0,2222
PSI 20	**Global**	**2/2**	**75%**	**0,0967**	**-0,0738**	**0,1704**	**0,5214**
SMI 20	Global	2/2	100%	0,0465	0,2159	-0,1694	0,3932
	Switzerland	2/2	65%	-0,3839	0,2159	-0,5998	0,2821
STI 30	Global	3/3	80%	0,2019	0,3146	-0,1127	0,3932
TA 25	Global	2/2	76%	0,1343	0,5395	-0,4051	0,3932
	Global	3/3	76%	0,3176	0,5395	-0,2219	0,4359
TSX 60	Global	6/6	98%	-0,5787	0,3325	-0,9112	0,2051

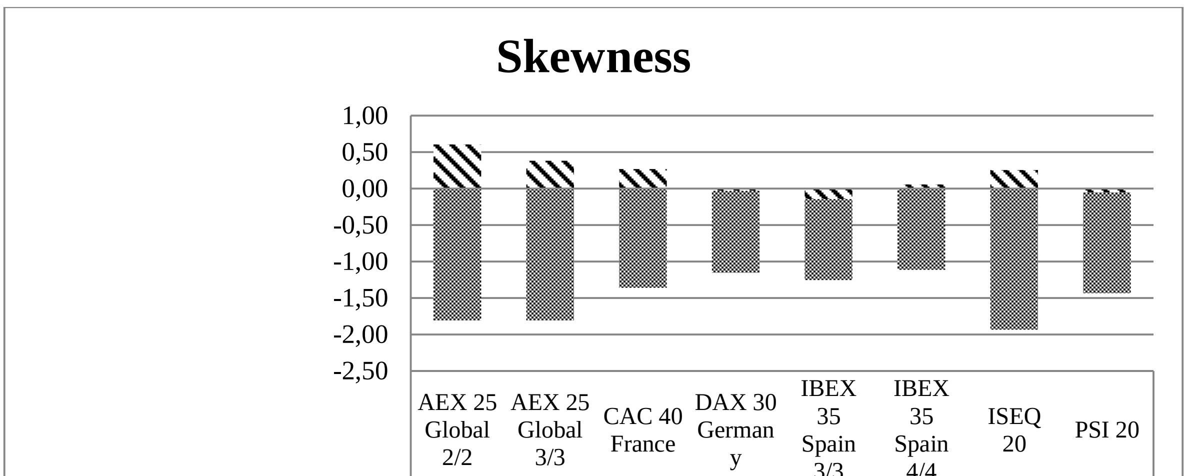
[7] "Search" denotes the type of search considered in Google Trends Data, "(#long/#short)" represents the number of short and long positions taken in each week, "% GT" accounts for the percentage of the index constituent which have weekly search volume data available, "GT IS" and "BENCHMARK IS" stand for Google Trends strategy and correspondent benchmark Info Sharpe ratios.

Appendix 10 – Kurtosis analysis for all markets where GT strategy outperformed benchmark.



	AEX 25 Global 2/2	AEX 25 Global 3/3	CAC 40 France	DAX 30 Germany	IBEX 35 Spain 3/3	IBEX 35 Spain 4/4	ISEQ 20	PSI 20
BENCHMARK	16,50	16,50	10,12	9,51	6,33	6,33	16,32	6,93
GOOGLE TRENDS STRATEGY	2,86	2,12	1,04	2,91	2,23	1,73	5,11	1,62

Appendix 11 – Skewness analysis for all markets where GT strategy outperformed benchmark.



	AEX 25 Global 2/2	AEX 25 Global 3/3	CAC 40 France	DAX 30 Germany	IBEX 35 Spain 3/3	IBEX 35 Spain 4/4	ISEQ 20	PSI 20
BENCHMARK	-1,81	-1,81	-1,36	-1,12	-1,11	-1,11	-1,94	-1,38
GOOGLE TRENDS STRATEGY	0,61	0,38	0,27	-0,03	-0,14	0,06	0,25	-0,05