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"Google Trends as a predictive tool for the sales of the Apple."

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I hereby declare that the work submitted is mine and that where I have made use of another's work, I have attributed the source(s) according to the Regulations set in the Student's Handbook.

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Abstract

This dissertation was written as part of the MSc in Management at the International Hellenic University –intake 2014-2015. In this paper I am trying to find causal relationship between the sales of three Apple products, Ipod, Ipad, Iphone and the Google Trends search queries by using as keywords the name of every product. All data for the sales were downloaded from Statista.com as they were complete there, but crosschecked by the SEC Fillings posted by Apple quarterly. Apple is publishing the sales of all products in a quarterly basis only and without special clarifications about each product and model. For the data downloaded from Google Trends I needed to transform them from weekly to quarterly range. In all data I applied Seasonality Tests and Velocity Tests as it was expected from theory to have evidence of existence of both of them. After the appropriate transformations, when Seasonality and Velocity existed I continued with Unit root testing, in order to decide the level of Integration of my data. For Unit Root testing I used the Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller GLS (ERS), the Phillips-Perron Test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test. After conducting all Unit Root tests I ended up that all data were in zero level of integration I (0) so I could proceed with them without any further transformation. The most crucial test for my work was the Granger Linear Causality test between the Google Trends Index and the actual sales of every product. The results showed that there is linear causality relationship between the two variables. As for the conclusions, a full causal relationship was revealed. Indeed, I can suppose that there is the possibility to make forecasts in the sales of Apple products by examining the search queries in Google of the three keywords "Ipod", "Iphone", "Ipad".

Keywords: Google Trends, Innovation, Apple, Forecasting, Granger Causality

Dedicated to my family

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Contents

Tables

Graphs

1 Introduction

A major problem that all managers and retail businesses face, is the predictions of the sales of their products. There are several techniques that are used from professionals in order to forecast the actual sales of a specific product. Some of these techniques are only qualitative and are based on the experience and the knowledge of a specific person, like a manager or an expert on the sales. There are also quantitative techniques[1] that can provide safe forecasts. The quantitative methods are separated into time series models and causal models. In a time series model we assume that the future will follow same patterns ofthe past. Some examples of time series models are: i) Naïve method, ii) Simple Mean, iii) Moving Average, iii) 3-month Simple Moving Average iv) 5 month Simple Moving Average v) Weighted Moving Average vi) Exponential Smoothing. In the Causal Models researchers are exploring cause-and effect relationships between dependent and independent variables by using leading indicators to predict the future. Major factors that are helping us to choose which is the best forecasting technique, are:

- The amount and type of available data
- Degree of accuracy required for every forecast
- Length of forecast horizon
- Presence of data patterns

During recent years it came out another tool that experts could use in order to track consumers' wills and trends. This is the Google Trends tool, which was released

[1] All the information about the forecasting techniques were taken by the lecture notes provided by prof. Katsaliaki K. for the course Operations/Information Management

from Google in 2009 but includes data since 2004. This service provides to users free data about the online queries that Google's search engine users did, through the years. Data about a specific keyword or a combination of keywords can be categorized between countries or wider regions and between different periods of time. It uses a special Index from 0 to 100. The more a specific keyword is being searched, the higher is getting the value of the Index. The recent previous years other search engines like Yahoo or Bing started providing data about the search queries of their users, but Google is the leader search engine and facilitates the biggest amount of data. Data extracted from Google Trends can be regarded representative of the search queries globally and to be regarded trustworthy for econometric analysis, as Google has a market share over 68%.

Since 2009 many academics used the search queries to examine whether there is specific correlation between search activity and different social phenomena. Some of the previous researches are focusing in the topics of finance like stock returns and currencies volatility, others in medicine like epidemiology and many more in unemployment rate, real estate prices, tourist arrivals and political elections results. Moreover, there have been conducted several analysis about the private consumption. Researchers examined whether the sales of movies, video games and music songs, or even sales of cars can be predicted by using the data from Google Trends. However, I couldn't find in the literature any specific research that was done about the sales of technological products like mobile phones or tablets or personal computers. With the rapid evolution of technology consumers spend more and more every year for buying new technology products, either for first time or to replace older models and keep ahead of the curve.

In their paper Wu and Brynjolfsson (2009) examined whether Google searches could forecast the housing prices. This study is one of the first at the field of using data from Google Insights, as it was called the service before 2012, in order to make forecasts. On the end of the paper they proposed that in the future should be examined whether the sales of Mac computers could be predicted by the online queries. So, I decided to work on the sales of Apple products and to examine if there is correlation between the Google Trends data and the actual sales of three major products of Apple, the Ipod, the Iphone and the Ipad. I chose these three products as they are popular to consumers and they are being sold for many years globally with great success. Regarding the fact that, Apple releases data about these three products only on a global basis I have to work also on a global level. Good

My work follows the mainstream techniques to indicate the power of using accurate data coming from Google Trends service to indicate their predictive power on the actual sales of Ipod, Iphone, Ipad. In my methodology I used the Granger Causality test, proposed by Granger (1969), which is a simple hypothesis testing statistical test widely used to predict the future values of a linear time series by using prior values of another series. Before reaching to this point, my data got tested for every possible problem that could lead to wrong results and they got transformed several times to take the best accuracy level.

The results that are represented below can have a wide implementation around many different technology products. Big firms or even SMEs should use Google Trends in order to track the consumers' activity and receive signs or even clear messages about the consumers' needs and preferences about technology products. Nonetheless, the more famous is a product and the more are the web searches about this, the more accurate can be the forecasts that will be done about future sales. It should be also mentioned that in some cases it is important to be extracted the "noise" that is provoked when a new innovative product is released to the market, in order to take safer results. The hypothesis that I make about my dissertation, by having studied the literature, is that the data from Google Trends can Granger cause the actual sales of the three products. This can be translated to the research question whether Google Trends can forecast the actual sales of Ipod, Iphone and Ipad.

My dissertation is structured as follows. In the next section there is an extensive review for all the previous literature. Section 3 includes information about the methodology I used and the tests that were conducted and Section 5 presents the results. In Section 4 there are presented the data and the last Section 6 concludes my whole research.

2 Literature Review

During the previous years many studies have been conducted to examine the relationship between the web search activity and many sectors of economic activity. One of the first researches on this topic, which was the basis for many future studies, conducted by Ginsberg *et al.* (2009), who used the Google search queries to track influenza-like illness in U.S. By assuming that in areas with a large community of Internet users, when a human gets a flu, then is searching via the Google search engine for online information about the flu or a doctor to visit for cure. They claimed upon their study that the flu related online search queries have strong correlation with the visits to doctor with flu symptoms and can be used to monitor the level of weekly influenza activity in every state of U.S.

On the same range, the paper from Carneiro and Mylonakis (2009), who used the Google Flu Trends tool as a surveillance system of epidemics and diseases with high pervasiveness to the population. Off course, their assumption is, that this system is referring to the developed world, where web search engines are widely used. The authors propose that Google Flu trends should be used in cooperation with traditional surveillance systems, in order to track the outbreak of diseases and to set the authorities in high surveillance. In addition, their findings showed that Google Trends can present the epidemics seven to ten days earlier than the conventional systems that were used till then.

Wu and Brynjolfsson (2009) in a preliminary period examined whether Google trends can foreshadow the housing prices and the demand for home appliances in USA. By using simple autogressive models, which included lagged variables, they resulted in strong evidence about positive correlation between actual home sales and the online searches of the housing prices and the house price index. Their study was one of the first studies that examined this topic and took place on the period of the global economic recession. That's the reason why they believe that their results are just a sign and they suggest further studies on the field after the end of the recession and on a period of economic expansion. Moreover, they proposed that Google Trends should be tested whether they can predict the sales of Mac Laptops and the expansion of the Macintosh software against Windows. This paper was really innovative for the period that was written and led the way to the use of Google Trends as a new forecasting technique.

Another early study from Askitas and Zimmermann (2009) tried to prove correlation between "Google econometrics", as called in their paper and the unemployment rate in Germany. The methodology they used was the error correction model (Engle and Granger, 1987; Greene, 2008). Their results showed that there is strong relationship between the searches of specific keywords and the unemployment rates. The research was held also at 2009, the years of the economic recession, when the flow of the traditional economic data was too slow. Indeed, they proposed that their work can be used just as a basis for further research during the years of normal economic evolution in order to fill in the blanks of this study. The same period, D'Amuri and Marcucci (2009) worked into the correlation between the Google Trends Index and the US unemployment. Their findings showed that the Google Index is very accurate with "superior predictive ability" in respect to the unemployment dynamics. The models that included this Index were outperforming by far any other Index that was used to their model and their forecasts showed to be even more accurate than the forecasts that were released in the Survey of Professional Forecasts, conducted by the Philadelphia Fed.

On their report, Choi and Varian (2009), find that simple AR models and fixed-effects models which include as variables data from the Google Trends facility can deliver better forecasting results than models without Google Trends data. In their report, they examined the predictive power of Google Trends series in many different fields like Retail Sales, Automotive sales, Home sales and Travel. The strongest prediction effect was happening to the category "Motor Vehicles and Parts" and it was followed by the "New Housing Starts". On the other categories the effect was very slight but still could be translated as a sign of predictability.

Kholodilin *et al.* (2010) examines whether Internet search activity can be used in order to forecast real private consumption in US. They compare using the same model, different sentiment indicators and financial variables with the data coming from the Google Trends. The results show that the model in which it was included as independent variable the Google Trends Index outperformed to the other indices and was providing more accurate nowcasting power than some other variables and indicators that were tested. Nonetheless, their conclusion was that some of the sentiment indicators and the financial variables seem to have the same predictive power with the Google Trends for nowcasts to the real private consumption in US.

Goel *et al.* (2010) with the empirical tests they conducted, they ended up to the conclusion that Internet search activity can have predictive power into the consumer activities and especially watching movies or buying music or video games. However, there are differences on the power of the prediction between the three different categories of consuming goods. The factors that are influencing the search queries as are settled by the authors are, firstly the different relevant audiences that every consuming good has, secondly the fact that in goods like films, consumers may search straight for the cinemas where they can watch it and not specifically for the name of the film and finally the difficulty to examine relevant search queries for every of the three products.

The first step in the financial economics field was done by Da *et al.* (2011), who tried to measure investor attention by using the Google Trends Index (and also the same period a similar paper was done from Modria, Wu, Zhang 2010). Da *et al.* (2011) despite the existence of many indirect proxies like turnover, stock returns, news and advertising by examining a sample of Russell 3000 of 2004 to 2008, they managed to provide evidence that there is strong correlation between the Internet search queries and the real activity in the stock markets. In addition, they justified that the Google Trends can capture also the attention of retail investors. So, the general conclusion was that search volume can be used to measure the interest of investors and to create the potential for further research.

On the same field, Kissan *et al.* (2011) examine whether "the evidence from online search can forecast abnormal stock returns and trading volume". They used online searches of the relevant ticker as a proxy for the investor sentiment. For their research they used a sample of S&P 500 firms for the period 2005-2008. Their findings conclude that the search intensity can forecast the abnormal stock returns and the high trading volumes. Specifically, they managed to prove that the "sensitivity of returns to the search intensity is lowest for easy-to-arbitrage, low volatility stocks and highest for difficult difficult-to-arbitrage, high volatility stocks". In the end, they proposed that in order to make more precise predictions about the stock returns, investors should include also data coming social networking sites like Facebook or Twitter.

Vosen and Schmidt (2011), in order to find the best indicator for forecasting the private consumption, they compared the data from Google Trends and the Survey-based Indicators like the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. By using simple autoregressive models they ended up that data from Google Trends outperform by far the Survey-based indicator when used for forecasting purposes at the private consumption field. Guzman (2011) compared the forecasting performance of Google Inflation Search Index (GISI), which is constructed from data coming from Google Trends with other 37 indicators which derive their data from survey based techniques. Results were really impressive. GISI seems to surpass the old-used indicators in accuracy, rationality and predictive power. The

Granger Causality test showed that the GISI is capable of forecasting the Inflation rate by 12-months in the future.

Ortiz-Cordova and Jansen (2012), worked on how online businesses can use search queries provided by search engines in order to classify customers according to their online behavior. They used several keywords, which were categorized by an algorithm, and they managed to prove that website owners by using the big data coming from tools like Google Analytics or Google Trends can cluster their customers according to their spending behaviors and other ecommerce factors "to engage the user at a more personalized level upon arriving at the landing page". The most important implementation of this study is that website owns-administrators can use all these data for creating more effective and profitable online advertisements.

Again on the field of finance, Siganos (2012) investigates how the share prices of firms react after the announcement of a merger in relation to the Google activity. He assumed that when investors learn about a potential firm merger they use Google to gain information and this follows to run ups to the share prices of these firms. The results of his research showed that the price run ups are not explained from the Google Trends Indexes on a percentage more than 36%, and there are other stronger factors that influence the share prices. Smith (2012) on his paper tried to predict volatility of 7 currencies by studying the Google internet searches. The keywords they are using are: "economic crisis" and "financial crisis", "inflation" and "recession". On his (i suppose one author) research, he is using a GARCH Model, with parameters that are trying to cover both the "short term" and the "long term" predictions. After conducting his empirical analysis, he resulted firstly that "the hypothesis that the conditional variance of a GARCH, is an unbiased predictor of exchange rate volatility is rejected and secondly the hypothesis that Google search volume data has no predictive volume beyond the GARCH is also rejected". It is concluded from this research that, when the correct keyword is chosen, it can be proven strong correlation between the Google searches and the currencies volatility.

Beracha and Wintoki (2013) on their paper examined whether the data from Google Trends can be used a proxy for the housing sentiment and if the housing prices can be predicted from this proxy. The results revealed that there is strong relationship between the change in housing prices and the Google search volume activity in a specific city. The findings of the empirical analysis are in compliance with the economic situation, the housing market strength and the growth of the population of that period in these cities.

Vaughan and Romero-Frias (2014) investigated the correlation of Google Trends and the "unexplored' field of academic fame. For their study, they selected the top 50 U.S. universities from the QS World Universities Rankings of 2011 and the "Shanghai Ranking Expanded" of 2011 for the Spanish and Latin American universities. Concerning the U.S. universities the output of the study was that there is significant correlation between the search volume and their academic fame, even after several methods were used in order to distract the "noise" that is provoked due to the strong reputation of these universities. On the other side, the evidence for the Spanish universities was not the same. It was very difficult to be extracted the same conclusions for the Spanish universities like the American, but this is attributed more to the lack of data for the search queries and the fact that Spanish language is used much less than English on the Internet. The researchers, set as limitation for their study that they worked only in universities from just two countries with much different culture, language and learning approaches and also these two countries may not be the best representative sample for all the universities globally. Indeed, further research on this specific field is proposed.

Jun *et al.* (2014) pursued to prove that search activity, which is captured by Google Trends can be used in order to evaluate the adoption of new technologies. Rogers (2003) introduced the consumer adoption model for innovative products which included the five stages of Awareness, Interest, Evaluation, Trial and Adoption. The second stage of Interest is the one that can be monitored by the web search activity. For the research purposes, they focused on the sales of the Hybrid cars and specifically on the Toyota Prius, as it is the market leader in the Hybrid cars. The findings showed that search activity index surpassed the other indices that had been used before in order to predict demand of new technology products, like the hybrid cars. Moreover, this paper finds that "the traffic for the searches in which price is simultaneously included has a highly significant correlation to sales"

Das *et al.* (2014) examine the connection between the prices of the apartments that were for rent or for sale and online search activity. Using several models they conclude that search activity cannot provide evidence about the vacancy rates, but asset pricing decisions and net demand for residents are related to the internet queries. In addition, the authors ended up to the results that there is strong association between online rental searches and future Real Estate Investment Trusts (REIT) returns. This means that investors always investigate the online search data before proceeding to investments in Real Estate. However, there are some limitations to this study, like the use of other search engines apart from Google and also the existence of websites that are specialized in listings of flats or houses for sale or rent could provide more secure data. In any case, this study should be considered a good representation of the relationship between online search activity and the real estate market.

Bangwayo-Skeete and Skeete (2014) use data from Google Trends as forecasting tool for the arrivals in touristic regions. Specifically, they examined whether the search queries for "hotels and flights to" the 5 main vacation destinations of Caribbean from three source countries US,UK and Canada can predict the arrivals of tourists for the next years. They tested three different models, the simple Auto Regressive model (AR), the

Seasonal Autoregressive Integrated Moving Average (SARIMA) and the Auto-Regressive Mixed-Data Sampling (MIDAS). The results show that MIDAS was outperforming by far the other two models and it was able to offer accurate forecasts for the arrivals of tourists in a year's horizon. The authors suggest that Google search queries can safely be used for planning and policy making purposes by the touristic industry for predicting the next year's arrivals in every destination all over the world.

One of the most recent studies uses web search data to prove that voter registration procedure which was undertaken before the presidential elections of 2012 in U.S., deducted from many U.S. civilians the right to vote, as they lost the deadline for the registration process. Street *et al.* (2015) by measuring the web search activity after the deadline for the "voter registration" they estimated that about 3-4 million more Americans would have the opportunity to vote for the President of U.S in case of extension for the deadline for the voter enrollment till the previous day of the elections.

3 Methodological Framework

3.1 Seasonality

Time-series data may have several frequencies such as daily, weekly or quarterly. It is common to this type of data and especially for data that measure sales to exhibit seasonal patterns. In order to detect and confirm the existence of seasonality we use the dummy variable technique. If we suspect a quarterly seasonal pattern we use the following model:

$$Y_t = \mathrm{B}_1 + \mathrm{B}_2 D_{2t} + \mathrm{B}_3 D_{3t} + \mathrm{B}_4 D_{4t} + u_t \qquad (1)$$

where Y_t the dependent variable (in my case is the sales of Apple products in millions devices), and D_{2t}, D_{3t}, D_{4t} are the dummies representing the second, third and fourth quarter of the year, that receive 1 for the relevant quarter and 0 for the base category. As base category we consider the first quarter and we exclude it from the model in order to avoid the dummy variable trap. The base category could be any quarter.

After estimating this model we check the results. The seasonal dummies that are statistically significant indicate the existence of seasonality. In case of no statistical significance (jointly) we may argue in favor of no seasonality and therefore to proceed with our raw data. In order to obtain the de-seasonalized time series we have to subtract the fitted values Y_t from the actual values Y_t or in other words to recover the residuals. At the final stage, we have to add to the residuals the mean value of Y_t . The new series that we acquired is the seasonally adjusted series.

3.2 Velocity

High tech products usually present a diffusion process in the shape of an S-Shaped curve that captures 4 different phases: the introductory phase, the growth phase, the maturity phase and the decline phase. The two commonly used curves to describe the diffusion process are the Logistic curve and Gompertz curve.

In my data in order to identify the existence of a quantratic pattern (velocity), I regress the sales variable and the google trends variable (for all three products) against t (time) and t2 and then I check the significance through the usual t-statistic. If velocity can be characterized as a deterministic process (significant trends), in order to get rid of it, I extract the residuals from the above regression. As a result the new series is free of deterministic patterns (seasonality and velocity).

3.3 Unit Root Tests-Stationarity Tests

In regressions with time-series data the delivered results many times can be characterized as spurious. This means that the results may look significant but if we examine further the validity of the regression (specification testing) we will realize that several assumption of the standard regression model are violated. In spurious regressions the R^2 is principally extremely high. According to Granger and Newbold (Granger & Newbold, 1974) a rule of thumb to detect spurious regressions is when the R^2 is greater than the *d*-statistic. Stationary series is the series that has constant mean and constant variance and at the same time the auto-covariance is independent of time. The time series that are non-stationary are transformed to stationary by differentiating them. In order to conduct our empirical analysis, we need first to find the order of integration that the series. Integrated series of order d (denoted as I(d)) is the number of times that we need to differentiate a non-stationary series in order to become stationary. In other words, to transform a series of order $I(2)$ to stationary we need to take the differences of the series twice. Stationary series are denoted as $I(0)$.

After extracting all the deterministic components sales are expected to be $I(0)$. There are several Unit Root Tests in order to examine the order of integration of the involved series. In my analysis I will conduct the following 4 tests:

- Augmented Dickey-Fuller test (ADF)
- GLS Dickey-Fuller (GLS-DF)
- Phillips-Perron (PP)
- Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

3.3.1 Augmented Dickey-Fuller (ADF)

The Augmented Dickey-Fuller test (Said & Dickey, 1984) is an augmented version of the simple Dickey-Fuller test for larger and more complicated time-series models. Moreover, the simple Dickey-Fuller test is valid only for AR (1) process, the ADF test is valid when higher-order correlations are observed in the series. The test estimates the following specification:

$$\Delta y_t = \sim + \ _t + \text{¥}\, y_{t-1} + \ldots + \text{¢}_{\circ -1} + \Delta y_{t-1-\circ} + \text{£}_t \tag{2}$$

where $\sim$ is a constant, $\ _t$ is the coefficient of the time trend, ° is the selected lag order, ¥ is the coefficient for the first order lag, and £_t is the error term.

The null hypothesis under of the ADF test is that there is a unit-root and the alternative hypothesis is that there is no a unit-root. These 2 hypothesis are written as:

$$H_0 : \text{¥} = 0$$

$$H_1 : \text{¥} < 0$$

when the value of the test statistic

$$DF_t = \frac{\hat{\text{¥}}}{SE(\hat{\text{¥}})} \tag{3}$$

Is calculated, then it can be compared with the relevant critical value of the Dickey-Fuller Test. When the test statistic is smaller from the negative critical value, in the selected level of significance (which should be larger), not in absolute values, then the Null Hypothesis $H_0 : \text{¥} = 0$ can't be rejected and there is a unit root.

3.3.2 Dickey-Fuller test with GLS Detrending (ERS)

The Dickey-Fuller test with GLS Detrending (Elliott *et al.,* 1996) is a pretty similar test to the ADF test. Elliott *et al* (1996) proposed an improvement for the ADF Test using the Generalized Least Squares rationale (GLS). The test that they created has better performance comparing to ADF, especially in small sample-sizes.

3.3.3 The Phillips-Perron (PP) Test

The Phillips-Perron (Phillips and Perron, 1988) test is a more developed test, introduced in 1988 and is has the same Null Hypothesis with ADF tests and also uses the same critical values with it. The PP test makes a non-parametric correction to the *t*-statistic. The PP test involves the equation coming from Dickey-Fuller test:

$$\Delta y_t = \text{«} y_{t-1} + \text{¬} + \text{ª}_t + \text{£}_t \tag{4}$$

Where £_t is $I(0)$ and it can be heteroscedastic. For this reason, the test estimates the equation :

$$y_t = y_{t-1} + \text{¬} + \text{ª}_t + \text{£}_t \tag{5}$$

The PP method estimates the non-augmented DF test equation and modifies the *t*-ratio of the coefficient, so that serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\bar{t}_{\text{«}} = t_{\text{«}} \left(\frac{\text{¥}_0}{f_0} \right)^{1/2} - \frac{\mathrm{T}(f_0 - \text{¥}_0)\left[se\left(\text{«}\right) \right]}{2 f_0^{1/2} s} \tag{6}$$

3.3.4 The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS)

In the KPSS test (Kwiatkowski *et al.,* 1992) the Null Hypothesis assumes that the series Y_t is stationary. The alternative Hypothesis assumes that there is no stationarity in the series. The test statistic of the KPSS test is defined as:

$$LM = \sum_t \frac{S(t)^2}{\mathrm{T}^2 f_0} \tag{7}$$

Where f_0 is an estimator of the residual spectrum at zero frequency.

$$S_{(t)} = \sum_{r=1}^{t} u_t \tag{8}$$

3.4 The Granger Causality

Coming to this point means that my data have been checked for seasonality and got de-seasonalized, checked for velocity and kicked off the velocity and finally, I have concluded about the order of integration of the involved variables (implementing four different tests). The unit-root and stationarity tests described above suggest that the order of integration of the involved variables is *I*(0). The standard Granger Causality Test (Granger, 1969) examines if there is a causal relationship between two variables. On my case I am testing for Causality that runs from the web search activity for three apple products (the activity is obtained by the relevant Google Trends web site) to the actual sales of these three products.

A variable X is said to Granger-cause the variable Y within a VAR framework, after an *F*-testing on the lagged values of X rejects the null hypothesis of the joined insignificance. This way X can be seen as a significant information source about the future values of Y . In order to decide the optimal number of lags that will be included in the VAR model, an information criterion, called Schwarz, is used.

4 Data

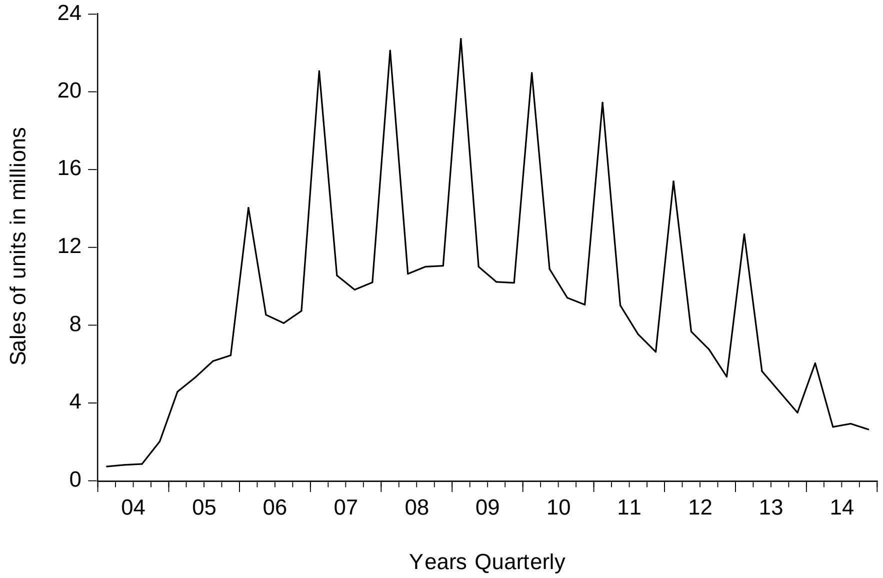
For my research I used two different kind of data. First, was the actual sales of the three Apple products Ipod, Iphone, Ipad. On the other side, I downloaded the series with the values given by the Google trends for the keywords “Ipod”, “Iphone”,”Ipad”,. Google Trends Index measures the frequency that a keyword is searched online to the Google search engine during the time, with the criterion of a specific geographic area. Below will be extensively described the whole process of gathering, transforming and using the data for my empirical analysis.

4.1 Sales of Ipod, Iphone, Ipad

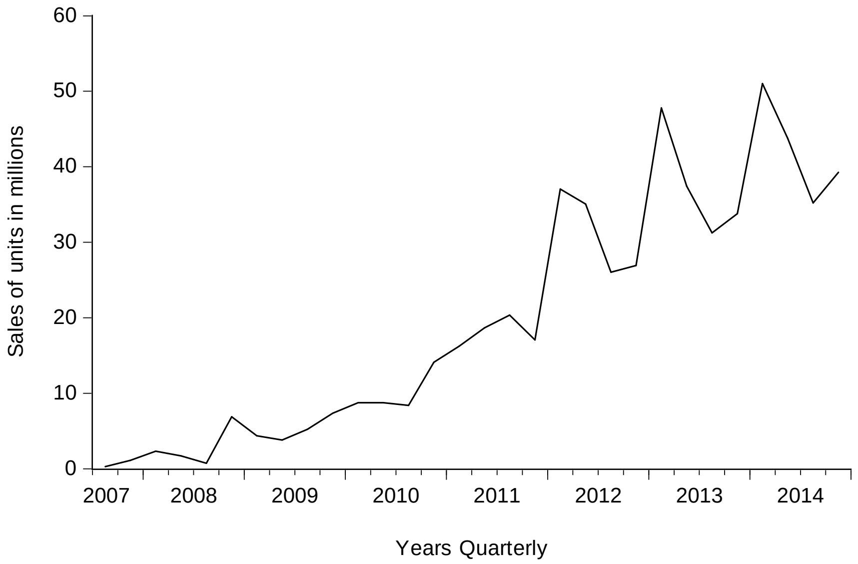
The three products of Apple where chosen as they are pretty popular all over the world and they had great sales all over the world. Apple’s policy is to publish the sales of each product quarterly in the SEC Fillings for every year. My intention was to find the sales weekly by contacting to Apple online, but their reply was that “it’s our policy to publish sales quarterly, and there is no chance to send you the data in weekly basis”. For convenience reasons, I downloaded all data about sales for all three products from the website www.statista.com. All the data was checked twice with the data given by the SEC Fillings of Apple Inc. The sales of the three products were provided in millions of units

The sales of Ipod which is the oldest product from the three, where starting from the first Quarter of 2002 and were published till the first quarter of 2015, but for my research I used the data of sales from the first Quarter 2004 till last Quarter of 2014. Iphone sales were starting from the third Quarter of 2007 till the last of 2014. Finally, Ipad ’s first published sales were in the third quarter of 2010 till the last quarter of 2014. Below you can see the graphs of the sales of the three products before any transformation. With a first glance at the data is obvious that we have seasonality and velocity, which is expected from the theory to exist.

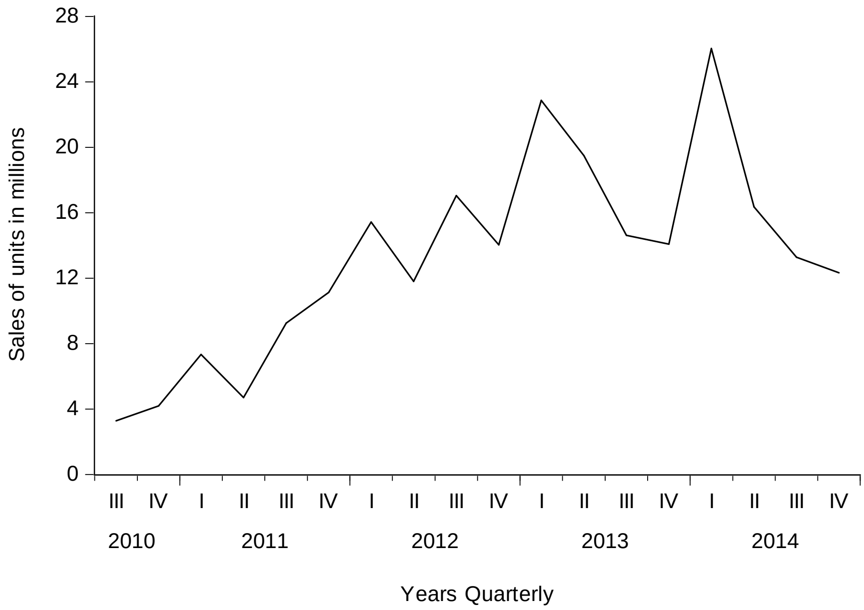
Graph 1 Ipod Sales-Raw Data



Graph 2 Iphone Sales-Raw Data



Graph 3. Ipad Sales-Raw Data

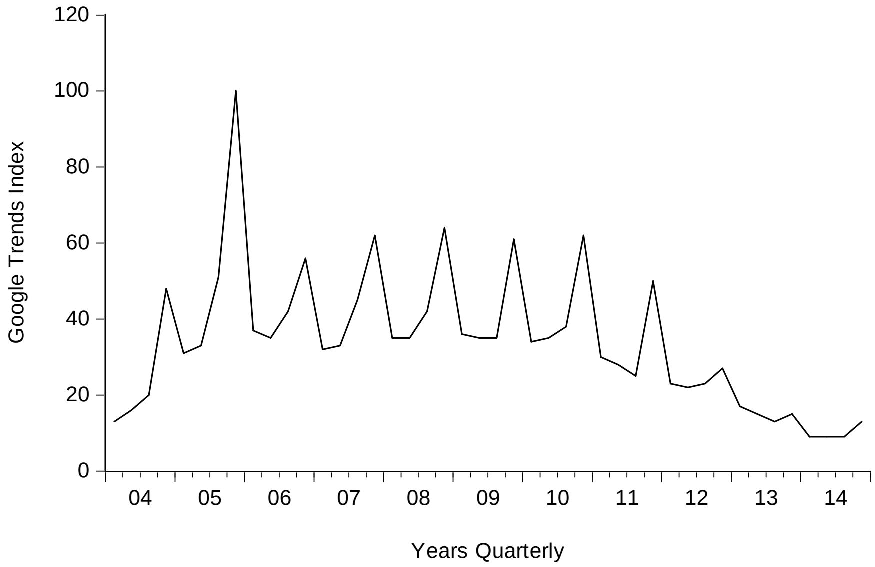


4.2 Google Trends Index

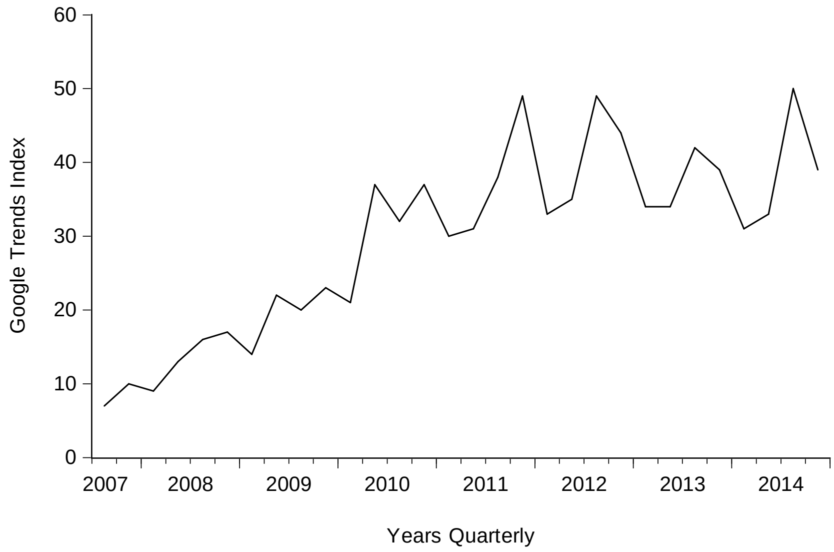
The independent variable that I use in my study is a series coming from queries from Google Trends. Google Trends is a tool offered by Google which allows to the users to download data about the queries of a specific keyword. Google Trends is using an index from 0-100 according to the amount of queries. The last years, Google trends is used by experts for forecasting in economic data or retail products.

The reason why I have chosen Google is because is the leader search engine with more than 3 billion searches per day, according to BBC. According to www.netmarketshare.com the total market share of Google globally, till September 2015 was up to 67.49%, followed by Yahoo with 10.77%. From the market share it can be easily justified my preference in using Google Trends and not them provided by other search engines like Yahoo or Bing.

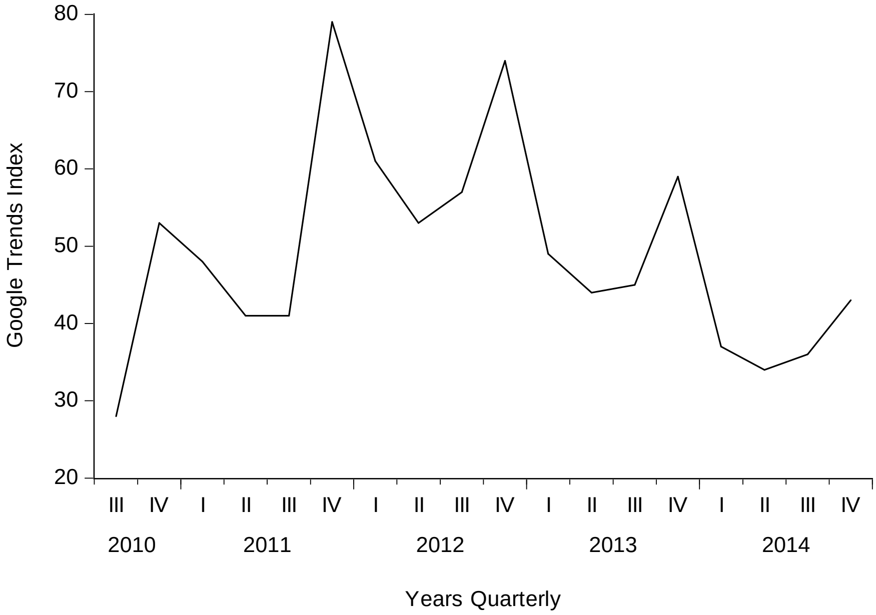
Graph 4 Google Trends for Ipod- Quarterly



Graph 5 Google Trends for Iphone- Quarterly



Graph 6 Google Trends for Ipad- Quarterly



4.3 Selection of Keywords

For my paper I used the keywords "Ipod", "Iphone", "Ipad" in order to extract the relevant time series from the Google trends facility. I preferred to use just the name of the products avoiding adding also the model of every product in order to have wider range of results. My purpose was to gain data about the queries generally about every product without paying attention to which specific model Google users were focusing on their searches. Also, my data about the sales were not specifying the model of each product. The Google Trends tool provides data only on a weekly basis.

For Ipod the first queries took place a couple of months before January 2003, when Ipod first launched to the market. I downloaded the data given for the period January 2003 till December 2014. For Iphone also the first evidence of searches for the keyword "Iphone" were starting on a low level one month ago before the initial launch on July 2007. My chosen time span was July 2007 till December 2014. In the data for the Ipad it happened the same, just a few searches of the keyword "Ipad" before the first launch, but the real queries start on July 2010 when Ipad was announced by Apple. My download for Ipad includes the time July 2010 till December 2014. All the data were downloaded in CSV, after transformed in .xls file and used to build my model and start my work on Eviews. For the final model that was analyzed in Eviews I had to transform the data I retrieved from Google Trends from weekly to quarterly in order to match with the actual sales of the three products.

5 Empirical Analysis and Results

5.1 Seasonality

5.1.1 Ipod

In order to check seasonality for the Ipod sales I regressed the three dummies Q2, Q3,Q4 to Ipod sales, and I received the following results:

Table 1. Ipod Sales regression withwith seasonal dummies

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q2	-7.000455	2.052369	-3.410913	0.0015
Q3	-7.495273	2.052369	-3.652009	0.0007
Q4	-7.640545	2.052369	-3.722792	0.0006
C	14.52936	1.451244	10.01166	0.0000

As we can conclude from the table, the *t*-Statistic of the 3 dummies in absolute values are greater than 2. This is a solid evidence of seasonality, which I have later to correct. The results of the table show a decreasing trend between the base category of Q1 and the other 3 Quarters. The same procedure I follow in order to control the Google Trends data for seasonality. I regress the Q2, Q3, Q4 dummies to the Google Trends data and I receive the following table:

Table 2.Ipod Trends regression with seasonal dummies

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q2	-0.090909	6.781233	-0.013406	0.9894
Q3	4.181818	6.781233	0.616675	0.5409
Q4	23.72727	6.781233	3.498961	0.0012
C	27.00000	4.795056	5.630800	0.0000

From the table, by looking at the *t*-Statistic of 2 out of 3 the dummies, which are less than 2, I conclude that there is no significance and this is strong evidence of lack of seasonality.

5.1.2 Iphone

By following the same procedure as described above, I control the data of Sales of Iphone and the Google Trends data for Iphone. The results that I received for both, show no seasonality. Indeed, I proceed with my data as they are.

Table 3. Iphone Sales-Seasonality test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q4	-5.615179	8.562363	-0.655798	0.5177
Q3	-8.005179	8.562363	-0.934926	0.3584
Q2	-2.631429	8.843171	-0.297566	0.7684
C	23.93143	6.253066	3.827151	0.0007

Table 4. Iphone Trends-Seasonality Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q2	4.714286	6.766224	0.696738	0.4921
Q3	7.178571	6.551368	1.095736	0.2832
Q4	7.678571	6.551368	1.172056	0.2518
C	24.57143	4.784443	5.135693	0.0000

5.1.3 Ipad

By following the same procedure as described above, I control the data of Sales of Ipad and the Google Trends data for Ipad. The results that I received for both, show no seasonality. Indeed, I proceed with my data as they are.

Table 5. Ipad Sales-Seasonality Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q2	-4.835000	4.290802	-1.126829	0.2788
Q3	-6.423000	4.070612	-1.577896	0.1369
Q4	-6.765000	4.070612	-1.661912	0.1187
C	17.91500	3.034055	5.904639	0.0000

Table 6. Ipad Trends-Seasonality Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Q2	-5.750000	8.069232	-0.712583	0.4878
Q3	-7.350000	7.655145	-0.960139	0.3533
Q4	12.85000	7.655145	1.678610	0.1154
C	48.75000	5.705808	8.543925	0.0000

5.1.4 Seasonal Adjustment

The Ipod sales data and the Ipod Trends after the seasonality test showed evidence of seasonality. In order to correct this, I obtain the residuals which are giving me the de-seasonalised series So, I receive the seasonal adjusted data for Ipod sales and Ipod Trends and I continue using them.

5.2 Velocity

5.2.1 Ipod

In my data I expected before that I would face the Velocity effect, because the data address to innovation-technology products which are following the diffusion process.

Table 7.Ipod Sales-Velocity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	1.237088	0.099852	12.38925	0.0000
TIME^2	-0.028375	0.002245	-12.63783	0.0000
C	-8.905526	0.928208	-9.594323	0.0000

The de-seasonalised data from the Ipod sales show strong evidence of velocity in respect to the *t*-statistic of the two independent variables.

Table 8.Ipod Trends-Velocity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	2.019499	0.422641	4.778289	0.0000
TIME^2	-0.062744	0.009503	-6.602285	0.0000
C	-4.298155	3.928809	-1.094010	0.2803

The de-seasonalised data from the Ipod google trends show strong evidence of velocity in respect to the *t*-statistic of the two independent variables

5.2.2 Iphone

Table 9.Iphone Sales-Velocity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	1.237367	0.486754	2.542081	0.0171
C	-2.686532	3.049299	-0.881033	0.3861
TIME^2	0.015535	0.016219	0.957851	0.3466

The data from the sales of Iphone devices show the existence of Velocity. Here the evidence are not strong because the Iphone product is relatively new and still the sales are in growth. In the near future we expect also the sales of the Iphone to slow down and later decline.

Table 10.Iphone Trends-Seasonality Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	2.913078	0.459107	6.345096	0.0000
C	4.477419	2.876105	1.556765	0.1312
TIME^2	-0.059908	0.015297	-3.916227	0.0006

The data from the Iphone Google Trends show the existence of Velocity

5.2.3 Ipad

Table 11.Ipad Sales-Velocity Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	2.846801	0.615805	4.622891	0.0003
C	1.006316	2.257522	0.445761	0.6621
TIME^2	-0.121280	0.034957	-3.469435	0.0034

The Ipad sales variable show evidence of Velocity, as the-statistics are greater than 2 in absolute values.

Table 12.Ipad Sales-Velocity Test

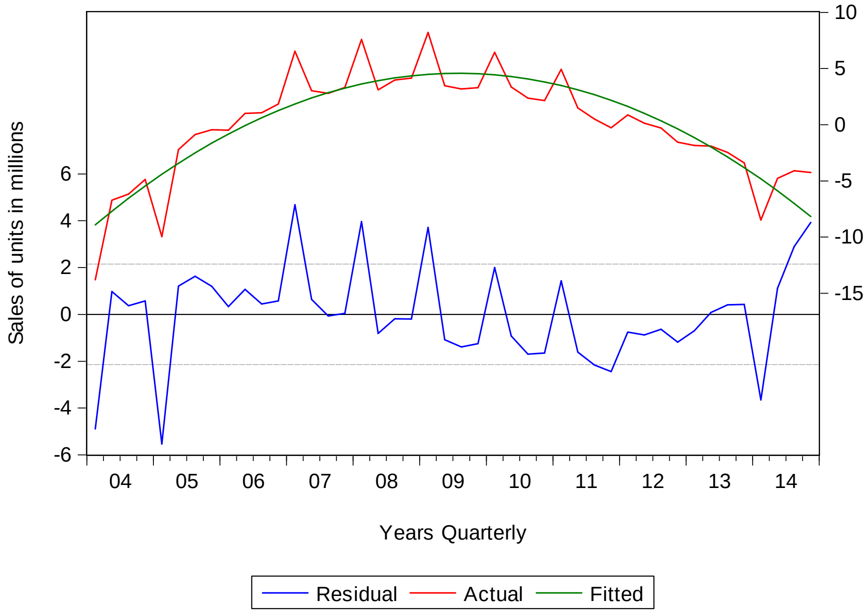
Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIME	5.063016	1.955065	2.589692	0.0205
C	37.79825	7.167204	5.273779	0.0001
TIME^2	-0.321014	0.110981	-2.892523	0.0112

5.2.4 Velocity-off

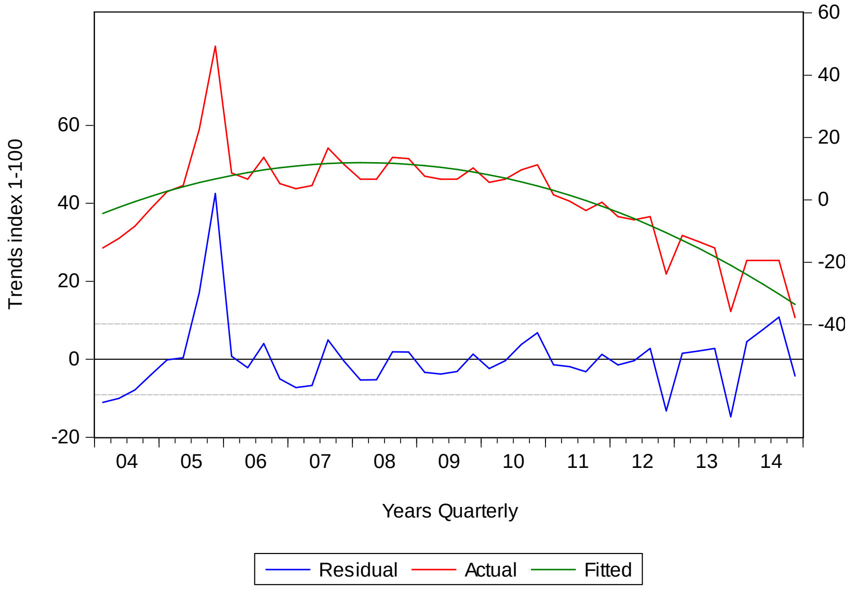
In order to get rid-off the velocity I take the residual series. I use the graph from the velocity test and I realize that the quantradic trend describes in a great extent the actual series. Indeed, we can substract the quantradic trend and to continue working with the residuals.

5.2.5 Velocity-off Ipod

Graph 7 Ipod Sales Residuals

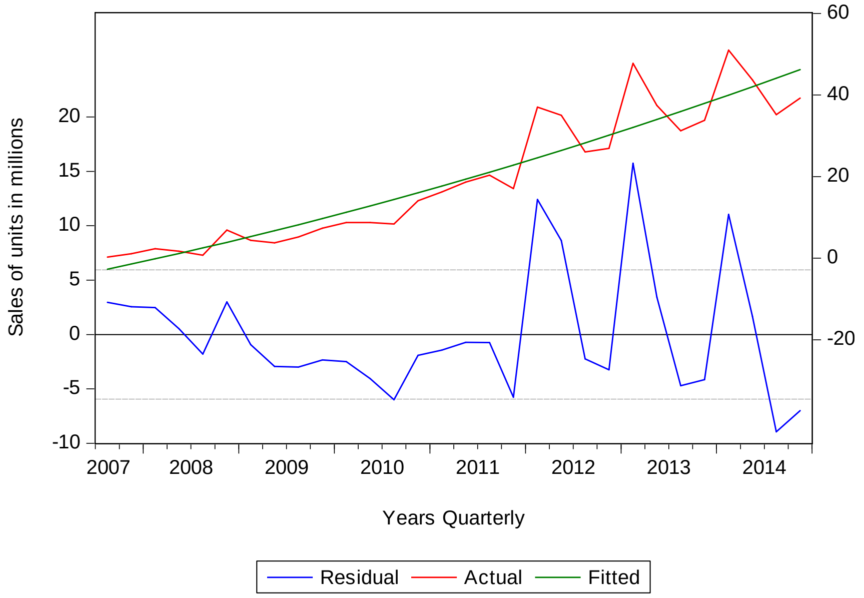


Graph 8 Ipod Trends Residuals



5.2.6 Velocity off Iphone

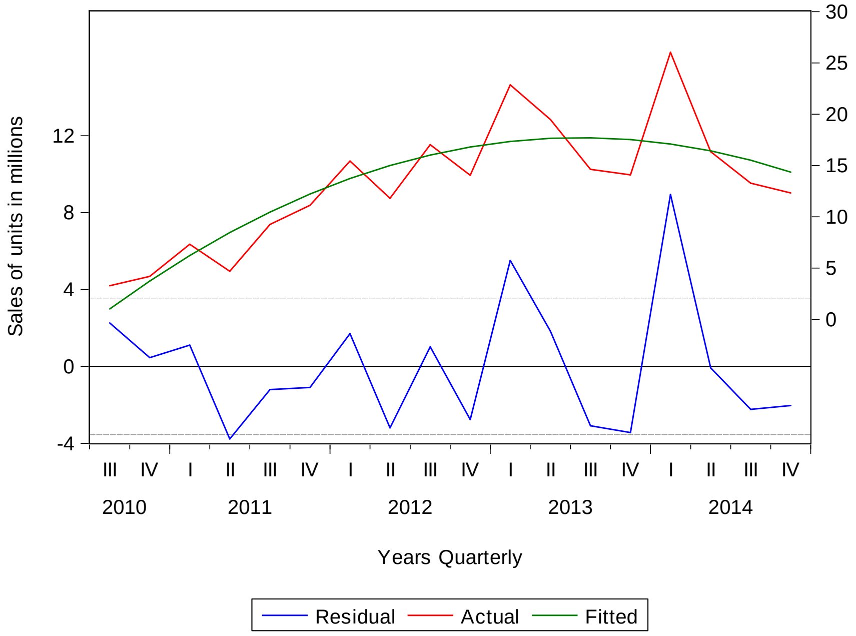
Graph 9 Iphone Sales Residuals



Graph 10 Iphone Trends Residuals

5.2.7 Velocity-off Ipad

Graph 11 Ipad Sales residuals



Graph 12 Ipad Trends residuals

5.3 Unit Root Tests

5.3.1 ADF Test

I conduct the test for both the two variable, Sales and Google Trends, for every of the three products. In Table 19 are presented the results from the ADF Test to the Sales of the products and in in Table 20 are presented the results of the test at the Google Trends Index variable.

Table 13. ADF Test Sales

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-2.061275	-2.945842	I(0)
Iphone	-2.836101	-2.998064	I(0)
Ipad	-1.031348	-3.098896	I(1)

Table 14. ADF Test Trends

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-4.839570	-2.931404	I(0)
Iphone	-5.700544	-2.971853	I(0)
Ipad	-0.952708	-3.098896	I(1)

From the Dickey –Fuller test we can claim stationarity at I(0) only for the variables of both the Ipod and Ipod. We can't claim stationarity in Ipad's both Sales and Trends vareiables.. For this reason I proceed in stronger tests.

5.3.2 DF GLS (ERS)

The DF GLS Test is conducted also for both Sales and Google Trends variables for all three products. In Table 21 are presented the results from the DF GLS Test to the Sales of the products and in Table 22 are presented the results of the test at the Google Trends Index variable.

Table 15. DF GLS Test Sales

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-0.542516	-1.950394	I(0)
Iphone	-2.889774	-1.956406	I(0)
Ipad	-1.55566	-1.948630	I(1)

Table 16. DF-GLS Test Trends

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-3.965800	-1.948686	I(0)
Iphone	-5.348966	-1.953381	I(0)
Ipad	-0.964122	-1.968430	I(1)

The results show the same with the previous test. Ipod's and Iphone 's both sales and trends are showing to be in $I(0)$, but the variables of Ipad both are in Order one of Integration. So, we proceed with the next test.

5.3.3 Phillips- Perron Test

PP test is conducted also for both, Sales and Google Trends variables for all three products. In Table 23 are presented the results from the PP Test to the Sales of the products and in in Table 24 are presented the results of the test at the Google Trends Index variable.

Table 17. PP Test Sales

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-6.199980	-2.931404	I(0)
Iphone	-4.205121	-2.967767	I(0)
Ipad	-7.953142	-3.052169	I(0)

Table 18.PP Test Trends

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	-4.704542	-2.931404	I(0)
Iphone	-8.074404	-2.967767	I(0)
Ipad	-6.569513	-3.052169	I(0)

From the Phillips-Perron test I can claim stationarity in all variables. All three products seem to be in zero order of Integration in both variables. Nonetheless, in order to confirm this I proceed to KPSS test, which is the most complicated and secure test.

5.3.4 KPSS Test

The KPSS Test is conducted also for both, Sales and Google Trends variables for all three products. In Table 25 are presented the results from the DF GLS Test to the Sales of the products and in in Table 26 are presented the results of the test at the Google Trends Index variable.

Table 19. KPSS Test Sales

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	0.128026	0.463000	I(0)
Iphone	0.121558	0.463000	I(0)
Ipad	0.500000	0.463000	I(1)

Table 20. KPSS Test Trends

Product	*Test-statistic*	*Critical values 5%*	*Order of Integration*
Ipod	0.071412	0.463000	I(0)
Iphone	0.385676	0.463000	I(0)
Ipad	0.445158	0.463000	I(0)

The results from the KPSS Test show stationarity in most variables. Only the Ipad's sales variable is in I (1), but this result is to the limit.

Concluding I may argue in favor of stationarity for all three Apple products sales and the Google Trends. Some series illustrate to be stationary in all 4 tests.

Other series, like the Ipad sales and Trends are showing stationarity only from 1 test. But this is still enough in order to claim stationarity and continue working on the data without any further transformation

5.4 The Granger Causality Test

The Granger Causality linear test (Granger 1969) is the most important test for my dissertation. GC test is the test that will either confirm or not my initial hypothesis that the Google Trends series for every product Granger cause the sales series for the respective product. Granger Causality is a powerful tool on my effort to prove the strength of the causality between the main variables, the Google Trends and the actual sales of a product.

In order to decide whether the Null Hypothesis is rejected or not I can use the "rule of thumb" that, when the p-value is less than the level of significance that I am working (0,05% in my case), then the Null Hypothesis can be rejected.

In Table 27 are reported the results from Ipod, at Table 28 the results from Iphone and at Table 29 the results from Ipad.

5.4.1 Ipod

Lag length: 5 Observations: 39

Table 21. Granger Causality Test Ipod

Null Hypothesis	F-statistic	Prob.
Trends ↛ Sales	9.68308	2.E-05
Sales ↛ Trends	0.52875	0.7525

Note: the sign ↛ represents the Null Hypothesis, doesn't Granger Cause

5.4.2 Iphone

Lag length: 2 Observations: 28

Table 22. Granger Causality Test Iphone

Null Hypothesis	*F-statistic*	*Prob.*
Trends ↛ Sales	11.3794	0.0004
Sales ↛ Trends	2.70472	0.0881

Note: the sign ↛ represents the Null Hypothesis, doesn't Granger Cause

5.4.3 Ipad

Lag length: 1 Observations: 17

Table 23. Granger Causality Test Ipad

Null Hypothesis	*F-statistic*	*Prob.*
Trends ↛ Sales	4.23221	0.0588
Sales ↛ Trends	0.86967	0.3669

Note: the sign ↛ represents the Null Hypothesis, doesn't Granger Cause

From the results above I can securely conclude that there is strong Granger causality evidence between the Google Trends and the actual sales of Ipod and Iphone. For the Ipad I can't claim Granger Causality as I am working at the 0,05% level of significance but the difference is very slight and the observations are not so many as the Ipad came out to the market in 2010. I am quite ambitious that in a couple of years with more data it will be possible to prove Granger Causality relationship also in Ipad.

On the other side, the Null Hypothesis that the Sales of the Products Granger does not cause the Google Trends Index can't be rejected as the p-value is much greater than

0,05% for all three products. But this result is the expected one from the theory and confirms my initial expectations from the research.

6 Conclusions

As it was shown from the literature, Google Trends data are widely used for forecasting reasons in many different fields. There have been made several researches that have proved already correlation between the search queries and different social phenomena. My research can be regarded as an extension to the literature, as it was proposed from Wu and Brynjolfsson (2010).

This study can have many implications in firms that are selling retail technology products and help them to make forecasts for the sales in the future. I managed to provide evidence , that there is significant predictive power from the Google Trends data that are delivered after carefully selecting a relevant key-word and the actual sales. By using the search queries in Google somebody could make improved forecasts about the sales of the three Apple products in the future.

However, there are some limitations about my research. First of all, my observations that were used in the analysis are not so many. This is because of the fact that Apple has a very strict policy in announcing sales of products just in a quarterly basis. Moreover, I was not able to study specifically for a single model for every year. Indeed, I couldn't have a clear picture of the sales of every model of every product. In case this was possible, then I could extract even safer results and conclusions. In addition, I used data downloaded only from Google, as it is the market leader. In an even more extensive research it could be used the search queries provided by Yahoo or Bing for more representative results.

My proposal for future studies would be to work on every single model of every product, in case this will be possible to the future and also to try also to find correlation between Google Trends and the products that are produced by the biggest competitor of Apple and market leader in Asia, Samsung.

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