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RELATIONSHIP BETWEEN GOOGLE SEARCH VOLUME AND STOCK RETURNS IN FINLAND

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Abstract

Can investor recognition or attention affect stock prices? The attention theory suggests that investors are net buyers of attention-grabbing companies. However, finding a fitting proxy for attention is in a key position to when studying the attention theory empirically.

The aim of this thesis is to use Google search volume as a proxy for investor attention and study whether there is a relationship between investor attention and stock returns in Finland. The thesis uses weekly data from 2018 to 2022. To study the investor attention, Fama-French three-factor model with an additional Google search volume -factor (GSV-factor) is used in stock-based OLS-regressions. Multiple models are built with different lags and different adjustments on GSV-factor data. Two different datasets for the Google search volume are tested to determine the better keyword for empirical analysis. Thesis uses companies from OMXH25 as stock data for the regressions.

The findings of this thesis suggest that there is no meaningful connection between Google search volume and stock returns in Finland. Individual stocks have statistically significant regression results in different models, but the overall effect of attention on stock returns is meaningless. Furthermore, the results suggest that GSV-factor has no predictive power in Finland. Since GSV-factor is a proxy for attention, the findings show that attention has no effect on the most traded stocks in Helsinki stock exchange.

Keywords
Factor investing, Finnish stocks, Attention effect

Additional information

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1 INTRODUCTION

Can one measure attention, and more importantly, can it affect stock returns? According to the efficient market hypothesis (Fama, 1970), stock prices reflect all available information immediately. Therefore, there should not be room for a concept like attention or recognition to alter prices in the long term. However, markets are not always perfect, and there are often phenomena that can be utilized in asset pricing. This paper aims to test the idea of attention or recognition having long-term pricing effect.

Merton (1987) introduces the model of capital market equilibrium under incomplete information, in which investor recognition may affect asset prices and liquidity. This means that stocks that investors know about are priced higher and enjoy better liquidity. Vice versa, companies that are not recognized by investors may be priced lower and have poor liquidity. The key idea behind Merton's model is that investors only use securities they know when creating their optimal portfolios. Later, behavioral finance introduces the attention theory, that suggest that attention may also have pricing power. These ideas are worth studying, but how can you measure this "investor recognition" or "investor attention"

Past studies on this subject have used multiple methods to capture investor recognition. For example, Lehavy and Sloan (2008) use the number of institutional investors owning a security as a proxy for recognition. They argue that an increase in the number of owners must also mean an increase in the number of investors who know about security. Obviously, this sort of assumption has its shortcomings, and it most likely does not reflect the whole truth. In reality, there is no way of telling if individual investors know anything about the security even though the number of institutional owners increases. Other measures used for investor recognition, such as a number of published news articles on the security, analyst coverages, or advertisement expenditures, also have similar shortcomings. However, there is an alternative method proposed by Da, Engleberg and Gao (2011), and that is Google search volumes.

Google is the most popular and used search engine in the world. Google searches indicate trending and general excitement around the searched subject. Those subjects that are most frequently searched tend to be the ones that grab the attention of the public. Searching for a keyword requires active participation from an individual, and the search terms provide actual proof of recognition. Therefore, Google searches provide an excellent tool for studying investor recognition and attention and their effect on stocks.

This study investigates the relationship between Google search volumes and stock returns in Finland. This is done by utilizing Google Trends, Google's own tool that provides relative datasets for any keyword's search volume for a freely selectable sample period. Google search volume (GSV) is then used in OLS regression with the Fama-French three-factor model to form a four-factor model. The meaningfulness and explanatory power of the GSV factor are then critically assessed to conclude if GSV and, therefore, attention affect stock returns in Finland. Stock data of this study consist of OMXH25, the most traded companies in the Helsinki stock exchange. The study uses weekly data, and the sample period is from the beginning of January 2018 to the end of December 2022.

The main research question of this study is:

- Is there a meaningful relationship between GSV and stock returns in Finland?

Additional research questions are:

- Is GSV a leading, lagging, or contemporaneous factor?

- Do adjustments in GSV data affect results?

- Is GSV a good proxy for attention?

Finland is an exciting country to study this phenomenon for two reasons: 1) Finland has an internet penetration rate of 95-97%, depending on the source. This leads to a high number of internet users and high search volumes in relation to the population.

2) Small market. Finland is a very small market. This can magnify the effect of attention and spikes in search activity. Low liquidity and smaller volumes should lead to a more apparent result if there is a movement caused by an increase in search volume.

The rest of this paper is structured as follows: Chapter two is the literature review. Theoretical framework, related concepts, and the most important earlier studies are introduced. Chapter three introduces all the datasets used in the study and explains the study method in detail. Chapter four presents the empirical results. Results are then discussed thoroughly, and important notions on possible factors affecting the results are also presented. Chapter five concludes.

2 LITERATURE REVIEW

This literature review will go through the theoretical framework and the most important asset pricing theories that this paper relies upon. Additionally, the past studies on the same subject are introduced.

2.1 Theoretical framework

While studying the connection between Google search volume and stock returns is a fascinating subject per se, there is finance theory behind the idea. The theoretical framework of this study relies heavily on a phenomenon in finance called investor attention or investor recognition. Merton’s model of capital market equilibrium under incomplete information and the attention theory introduced by behavioral finance are critical theories behind this study.

Merton’s (1987) model of capital market equilibrium under incomplete information suggests that investor recognition does affect security prices and liquidity. The 2-period model assumes that investors have incomplete information about available securities. There are no taxes, transaction costs, or restrictions on borrowing or short selling. The key takeaway from the theory for this study is the “Investor recognition hypothesis”. The hypothesis states that when the company's visibility increases, new information is conveyed to new investors. This new information then persuades some of the new investors to buy the stock. Therefore, investor recognition alone can affect stock prices and returns. Since then, this model and theory have been tested in multiple ways, founding different proxies for “investor recognition”. For example, such proxies as “number of institutional owners” or “amount of analyst coverage” have been suggested.

More recent studies in the field of behavioral finance suggest that public attention alone is enough to cause stock price movements. This would not even require any new information. The so-called “attention theory” suggests that individuals tend to buy stocks that attract their attention. This is because individual investors do not have enough time or resources to examine thousands of assets. When it comes to selling, investors do not have a similar problem. All stocks in the portfolio are already familiar.

This leads to a situation where investors are net buyers of attention-grabbing stocks. (Barber & Odean, 2008).

The importance of attention has been discussed in the earlier literature as well. Kahneman (1973) suggests that attention requires effort and is, therefore, a scarce resource. Individuals have limited resources, so attention cannot be focused everywhere. Simon (1978) also discusses the scarcity of attention. He points out that if attention is a scarce resource, information may be an expensive luxury since it can divert one's attention from important issues towards unimportant issues. This means that individuals may be unable to identify relevant information and divert towards unimportant issues. Fischhoff, Slovic, & Lichtenstein (1978) show that if individuals are unavailable to retrieve relevant information, they underweight the importance of that information. On the other hand, the information that is available and known by the individuals can be overweighted. This may lead to irrational and unbalanced decision-making. These papers are not explicitly directed toward finance, but their information can be utilized in the field of finance as well. The traits of attention can be seen as anomalies in investor behavior. An average retail investor can easily have the abovementioned issues while making investment decisions, especially concerning buying new assets.

The difficulty of studying either investor recognition or attention theory lies in the measurability of these variables. How can you measure recognition or attention? This study uses arguably one of the better ways of measurement. Google search volume reflects recognition and attention better than many other proxies. Searching with a specific keyword requires that the individual has recognized the company, and active searching is a proof of attention. However, even this proxy is not perfect. Google searches may very well reflect the attention of individual investors or the general public but might not be able to represent the attention of institutional investors.

2.2 Factor investing

The study method of this paper relies heavily on the modern portfolio theory and on the asset pricing methods that are at the heart of finance. This chapter introduces the main concepts and ideas behind risk factors and asset pricing, which are essential for this paper.

Markowitz (1952) created the framework for the modern portfolio theory and asset pricing. He introduces methods of selecting assets in a portfolio in a way that maximizes returns for a specific level of risk. Another key idea that Markowitz introduces is diversification. A portfolio that is constructed from assets that do not correlate perfectly with each other is less risky. These ideas are then refined and built upon in the next decade, most famously by Sharpe (1964), Lintner (1965), and Mossin (1966). The result is the famous capital asset pricing model, also known as CAPM. Like other standard asset pricing models, CAPM assumes that expected returns of assets can be explained by their sensitiveness to pervasive economic state variables. In the case of CAPM, this pervasive economic state variable is the market risk. Additionally, CAPM divides risk into specific risk and systematic risk. Specific risk is a quality of an individual asset that can be diversified away. Taking specific risk is not compensated according to the model. Systematic risk, on the other hand, is unavoidable and present in all assets. Therefore, CAPM assumes that all agents hold a combination of the market portfolio and risk-free assets. This leads to a situation where the only risk factor is market risk.

For an individual asset, CAPM states that its expected return equals the risk-free rate plus beta times market risk premium. Beta represents the asset's sensitivity to the changes in risk factor. In the case of CAPM, beta is the asset's sensitivity to the movements of the market portfolio. CAPM is criticized for making unrealistic assumptions that do not reflect real life. Nevertheless, it is still a fundamental concept in the history of asset pricing since it can form a linear relationship between systematic risk and return.

However, later study shows that market risk is not the only risk factor that affects stock prices. For example, Banz (1981) shows that small companies outperform their beta, meaning that their return is better than CAPM suggests. Smaller companies, therefore, have higher risk-adjusted returns than large companies. This shows that market risk alone can not explain stock returns and other factors are needed to complement the equation. Ross (1976) introduces the first multifactor model as an alternative to the

CAPM. The idea of a multifactor model is that systematic risk can not be explained by using one factor alone but instead by using multiple factors. This famous model and theory are called Arbitrage pricing theory (APT), and it is the basis for many future multifactor models. APT does not require as strict assumptions and restrictions as CAPM. However, Ross does not specify what factors should be used in the APT model. This leaves room for later studies to create a fitting set of factors for specific asset classes.

Arguably the most famous extension to the capital asset pricing model and to the APT model is proposed by Fama and French (1993). Their three-factor model (FF3) introduces two additional factors to the CAPM model. These factors are related to company-specific traits that market risk premium can not explain. The first factor is related to company size and is known as Small-Minus-Big (SMB). This factor means that small companies outperform large companies in the long run. As mentioned earlier, the size factor was actually discovered earlier by Banz (1981), who was to first to show that small companies have higher risk-adjusted returns than big companies. The second additional factor in FF3 is the value factor, known as High-Minus-Low (HML). This factor represents the outperformance of high book-to-market companies to low book-to-market companies. Empirical study shows that the explanatory power of FF3 is better than the explanatory power of CAPM. However, Griffin (2002) shows that the risk factors of FF3 are regional. This means that the factors work best when calculated country- or region-specifically. Fama and French (2015) expand their own three-factor model with two additional factors to a five-factor model. They suggest a factor related to investment behavior, known as Conservative-Minus-Aggressive (CMA) and a factor related to operating profitability, known as Robust-Minus-Weak (RMW).

Jagadeesh & Titman (1993) introduce another famous factor known as the momentum factor. They show that assets that have performed better in the past will perform better in the future. Therefore, a strategy where one sells assets that have performed poorly and buys ones that have performed well generates abnormal returns. The momentum effect lasts for three to twelve months from the portfolio construction. However, the effect disappears and reverses after that. In 24 months, half of the excess return disappears. Daniel & Moskowitz (2016) point out that momentum strategies can experience persistent times of negative returns resulting from the panic states of the market. After a market decline and during a market rebound momentum effect reverses, and the momentum strategy gives negative returns. The momentum effect strengthens when investors exploit momentum strategies: stock prices move temporarily further away from their fundamental values. Stock prices react more aggressively to new information, making the momentum effect even stronger. Therefore, there are similarities between the momentum effect and the attention theory.

The momentum factor is often added to different versions of Fama-French factor models. Throughout the years, multiple additional risk factors and different risk factor models have been suggested by other authors. For example, Amihud and Mendelson (1986) suggest a liquidity factor, and Hou Xue & Zhang (2015) introduce their own 4-factor model.

2.3 Factor investing in practice

Factor investing is an essential part of finance literature. Thousands of authors have developed and expanded the theoretical framework for factor investing, and new risk factors are constantly developed. There are multiple implementations of factor investing in the practice. For example, many ETFs are formed based on risk factor exposure. This part of the literature review examines how risk factors and factor investing perform in practice.

Dimson, Marsh and Staunton (2017) study how factor investing and different factor models perform in the very long term. They point out that up until 2017, researchers have identified at least 316 different factors. However, the robustness of the factors is questioned by multiple authors. For example, Green, Hand and Zhang (2017) note that even though factors may show promising in-sample results that seem exploitable, the out-of-sample results are often non-robust. Novy-Marx and Velikov (2016) express similar concerns about seemingly profitable factor strategies that show robust results in-sample. Therefore, finding the factors that hold their explanatory power in the long term is essential for both finance theory and practical portfolio management. Dimson, Marsh and Staunton (2017) conclude that these kinds of factors are at least size, value, income, momentum and volatility factors. Therefore, at least the conventional risk factors are proven to have pricing power in the very long term.

Kim (2023) also studies the implementation of risk factors in portfolios. In the study, Kim forms so-called enhanced factor portfolios. This is achieved by examining the asset's level of exposure to a set of factors collectively and then forming the enhanced factor portfolios from conventional single-factor models. This method increases the factor risk premium for the portfolio. These enhanced portfolios are then tested and compared to the conventional multifactor models. The study results show that the conventional multifactor model formed by using signal-blending performs best throughout the 50-year sample period. The factors used in the study are size, value, momentum, profitability, and low beta.

Fama and French (2012) study how their empirical asset pricing models hold internationally. Regions considered in the study are North America, Europe, Japan, and Asia Pacific. They test CAPM, FF3, and FF4 on value- and momentum portfolios to see if the models can explain value and momentum patterns on a global scale. Their results suggest that integrated, global models cannot explain regional portfolio returns. Therefore, for regional returns, local models should be used. However, even local models have trouble explaining momentum portfolios, especially in Europe and Asia Pacific. From the tested models, FF4 shows the most promising results. Authors, however, note that, in the study, the left-hand side assets of the models are constructed specifically for the value and momentum. Therefore, the results may differ if portfolios are constructed in other ways. Additionally, Fama and French (2017) test their five-factor model internationally in a similar manner. The results are similar; global models perform poorly on tests on the regional portfolios. Local models are again recommended for regional studies.

Grobys and Kolari (2022) continue with international testing of asset pricing models. They extend the studies of Fama and French on international factors by testing nested and non-nested asset pricing models in multiple equity markets. Their results show that a six-factor model dominates other models internationally. Six-factor model of the study consists of the Fama-French five-factor model with an additional momentum factor. Surprisingly, the findings of the study suggest that the often-used benchmark model, the Fama-French three-factor model, does not outperform CAPM in terms of pricing equities in North America, Europe and Japan.

As mentioned earlier, Fama and French (2012) and Griffin (2002) show that Fama-French risk factors work best when calculated country- or region specifically. Since the functionality of factors seems to be regional, it is justified to study which models perform best in specific geographical areas and different markets. The target market of this thesis is Finland, so the factor models that perform well in Europe and in Finland are of interest. Zaremba and Czapkiewicz (2017) test the explanatory power of four famous models on emerging European markets. They focus specifically on the models' ability to explain anomalies. The models tested in the study are the CAPM, Fama-French three-factor model, Fama-French five-factor model and the four-factor model (C4) introduced by Carhart (1997) with momentum factor expansion. Their results suggest that the FF5 is the best model to explain anomalies in emerging markets in Europe. Additionally, FF5 is the most useful model in pricing assets in emerging European markets compared to the three other tested models.

Bauer, Cosemans and Schotman (2010) focus specifically on the Fama-French three-factor model on European markets. They test how static and dynamic versions of the three-factor model perform in Europe. The study shows that there is a strong time variation in factor risk loadings. Adding conditional specifications to the three-factor model improves the model's ability to explain time variation in expected returns. Additionally, the study shows that the size effect, which has vanished in the USA after its discovery, is still present in Europe. Finally, the authors point out that FF3 is unable to completely capture cross-sectional variations in returns since the model is unable to explain the momentum effect.

2.4 Past studies

This study is not the first that attempts to find a connection between Google search volume and stock characteristics. Da, Engleberg and Gao (2011) are the first to investigate this relationship and study the Google search volume (GSV) as a proxy for investor attention. Their results suggest that GSV captures investor attention (or recognition) more in-time than other proxies. They also study GSV and its correlation with Russell 3000 stocks. Findings indicate that GSV has a short-term affect on stocks: higher GSV predicts higher stock prices in the next two weeks. Da, Engleberg and Gao focus on the search volume of stock-specific ticker symbols.

Bank, Larch, & Peter (2011) study how Google search results affect stock returns and liquidity in Germany. Their stock data consist of all the stocks traded on Xetra. In Google search data, they use company names instead of ticker symbols. Their results suggest that higher search volumes cause a rise in trading activity and, therefore, improved liquidity. Moreover, they also find evidence that an increase in search volume is associated with higher future returns but only temporarily.

Vlastakis and Markellos (2012) also use Google search data in their study of information demand and stock market volatility. Although the focus of their research is not exactly the same, their results provide valuable information for this paper. They find that search volume is positively related to trading volume and return volatility. Their study focuses on the 30 largest stocks traded on the NYSE and NASDAQ, and they use the company name as a keyword for search volumes.

According to these studies, a clear connection exists between Google search volumes and stock liquidity, trading volumes and return volatility. These studies have different sample sizes, markets, and timeframes, but the results do not contradict. Studies above also suggest that there is a short-term connection between search volumes and stock returns. However, stock returns have not been the main focus of those studies. Therefore, papers that focus more on stock returns are reviewed next.

Bijl, Kringhaug, Molnár, & Sandvik (2016) study if Google search data can be used to forecast stock returns. Their stock data consist of all the companies in the S&P 500 index, and the sample period of their study is from 2008 to 2013. For Google search data, they use company names and focus only on searches inside the United States. Their results suggest that high Google search volumes lead to negative returns. However, building a trading strategy around that idea (selling those with high and buying those with low search volumes) did not yield any meaningful results after transaction costs. The relationship is weak but robust and statistically significant.

These results contradict with earlier findings which suggest that the relationship would be positive but only in the short term.

Takeda and Wakao (2014) study Google search intensity and its relationship with stock returns in Japan. Their data consist of 189 Japanese stocks searched between 2008 and 2011. Company names and abbreviations are used when capturing the Google search data. They find only a weak positive correlation between search intensity and stock returns. However, like in earlier studies, their results suggest that an increase in search activity is associated with increased trading activity.

The connection between stock market activity and Google searches has also been studied in the Norwegian markets by Kim, Lučivjanská, Molnár & Villa (2019). They study if Google search results can explain current and predict future abnormal returns. Stock data of their study consists of the 28 biggest companies in Norway's stock exchange from 2012 to 2017. For Google search data, they use company names. Their results indicate that Google searches do not correlate with abnormal returns. There is no connection between Google search results and stock returns. Search results do not have any predictive power. However, they also found that increased searches indicate increased trading volume and volatility in the future, which is in line with the earlier results.

Ekinci & Bulut (2021) study the relationship between stock returns and Google searches in Turkey's stock index BIST 100. Timeframe of the study is 2012-2017, and for Google search data, they use ticker symbols. Their results indicate that Google searches are associated with positive stock returns, especially in small-cap stocks. Furthermore, the relationship is more robust with specific business areas such as sports and real estate but weaker with commercial and banking. However, they found no predictive power in Google search results. Quite the contrary, they suspect that abnormal returns cause higher search numbers.

Finally, Akarsu & Süer (2022) provide international evidence for the relationship between investor attention and stock returns. This study also uses Google search volume to capture investor attention. Authors study 31 different countries using stock specific panel data regressions. Their findings are in line with the earlier studies, since they find that the impact of investor attention is not consistent throughout the world. Both the sign and the significance of the impact vary from country to country. However, the research shows that there is predictive power in investor attention in developed, individualistic countries. Additionally, Finland is one of the countries studied in the paper. According to the results, investor attention does not have statistically significant predictive power on stock returns.

The connection between stock returns and Google search volume seems to differ in these past studies. Some results show a weak positive relationship which is too small to utilize, while some studies find a weak negative relationship, also too small to exploit. Additionally, some studies see no connection between stock returns and Google search results. Even though the results of these studies vary from positive to negative, the relationship has often been statistically significant. Explanations for this phenomenon could be different timeframes of these studies, different markets, and different study methods.

Also, different methods are used when collecting the Google search volume data. Finding a relevant keyword that reflects investors' interest towards the company is crucial. Some studies suggest that the ticker symbol is the best option because it is short and points directly towards company stock. However, other studies argue that the more common approach of using the simple version of the company name reflects better actual search behavior of investors. All studies agree that whatever the keyword, it should be very simple and short. Using multiple words as a keyword may be problematic since the more complicated keyword may result in a search volume being zero for smaller companies. Weekly stock data and Google search data are the most used data density.

To conclude the literature review, there is a reasonable amount of past literature dedicated to the subject of Google search activity and stock characteristics. Google search volume is used as a proxy for investor recognition or, more recently, for investor attention. Past studies provide contradicting results on the connection between Google search volumes and stock returns. However, all studies focusing on volatility and trading volumes agree that an increase in Google search activity results in an increase in stock volatility and trading volume. Liquidity also increases. Few research papers on this subject are left outside of this literature review. Even though those papers do study the same phenomenon and could provide useful insight for this paper, they lack the peer review status.

3 DATA & METHODOLOGY

Data is collected from three different sources. Refinitiv Datastream is used to obtain stock market data, Google search results are collected from Google Trends, and Fama & French factor data is obtained from Kenneth R. French data library. The sample period is from the 1st of January 2018 to the 30th of December 2022. However, some additional data points are gathered to study lagged effects. The following chapters specify different dataset traits and necessary adjustments made to the raw data.

3.1 Stock market data

Stock market data of this study is gathered using the Refinitiv Datastream Excel add-in. This thesis aims to study the effect of Google search volume on individual stock returns in Finland. Therefore, the stocks in OMX Helsinki 25 are very fitting for the purposes of this study. OMX Helsinki 25 (OMXH25) is a stock index that consists of the 25 most traded stocks on the Helsinki stock exchange. Stocks that are part of the index in January 2023 are used in this study. Finland and Helsinki stock exchange is quite a small market with multiple individual stocks with very low trade volumes and visibility. For the purposes of this study, it makes sense to delimit the stock data to OMXH25 because these stocks will have consistent Google search volume. Some smaller stocks in the Helsinki stock exchange have long periods without any searches.

Stocks that are listed on the stock exchange in the middle of the sample period are eliminated from the dataset. This is done to ensure that the studied regressions are comparable. In addition, eliminating these companies should not lead to survivorship bias since removed companies are listing, not declaring bankruptcy during the sample period. In this case, only one company, Kojamo, is listed in the middle of the sample period. Therefore, there are 24 companies in our final sample.

For the purposes of this study, weekly stock returns are required. Weekly total returns for the 24 companies are gathered straight from the Refinitiv datastream. Total returns adjust for the dividends paid during the sample period. The sample period starts from the beginning of January 2018 (the first week of the year) and ends on the last week of December 2022. Therefore, the sample period is five years long and has 261 data points for all 24 stocks. Total returns are then adjusted into the excess total return. That is done by deducting the weekly risk-free return from the weekly total return. Excess returns are needed in the regressions of this study. How the risk-free rate is gathered and adjusted is explained in Chapter 3.3.

3.2 Google search volume

From here on, Google search volume (GSV) means the amount that a particular keyword has been searched for in a specific period. As mentioned earlier, GSV stands as a proxy for recognition and attention. GSV can be gathered from Google Trends, a website by Google that analyzes the popularity of search queries across various regions and languages. The sample period can be adjusted freely starting from 2004. However, the length of the period decides how frequent the data is. For example, a sample period that is longer than five years is automatically given monthly. For the purposes of this study, weekly data is needed. Therefore, a five-year sample period is used. This is in line with other similar studies mentioned in the literature review.

The most important characteristic of Google Trends data is that they are not absolute. Google Trends provides relative data, which means that, for example, in weekly data, the week with the highest number of searches within the selected time frame takes the value of 100 and other weeks are proportionally scaled. If the weekly search volume is <1% of the peak volume, that week is scored 0. This leads to a situation where the same week can have different score depending on time interval adjustments. For this reason, in this study, once GSV is collected, no additional data is gathered, or intervals changed for different models or study methods.

Finding a suitable Google search keyword is crucial for this kind of research. Past studies have tested multiple different keywords to capture a relationship between stock returns and GSV. For example, company names and company ticker symbols are suggested and used in studies. Bijl et al. (2016) conclude that a company name has a stronger relationship with stock returns than a ticker symbol. This intuitively makes sense since ticker symbols are not as well-known as company names. Ticker symbol data also has more 0-values, indicating that tickers are not commonly searched. Ekinci & Bulut (2021) challenge the use of company names and argue that sometimes the company name can be too general and have nothing to do with the company stock. They use ticker symbols instead because tickers are often meaningless and can easily distinguish companies. Takeda and Wakao (2014) aim to specify the method of using a company name by eliminating unrelated information associated with the keyword by using a minus sign. This, however, is a very unfamiliar feature of Google. Eliminating keyword results is also subjective and challenging.

This paper uses two different keywords that should reflect Finnish search patterns. The first one is the company name. Most company names in OMXH25 are very distinguishable and easily associated with the company. However, a few company names could be searched in a very different context. To find the most fitting version of the keyword, an additional Google feature is utilized. While searching for a company, Google predicts your keyword after a few letters and gives suggestions. If the suggestion is a company, this information is provided in a footnote without changing the keyword. This study uses search results of these keywords with the footnote for two reasons: 1) usually, it is the simplest form of the company's name, and 2) these keywords can easily be combined with the company. Testing keywords with and without the footnote reveals that there is very little difference in search volume.

The second keyword is company name + "osake" (Finnish for "stock"). This keyword is chosen over the ticker symbol for a few reasons. As mentioned earlier, ticker symbols are very rarely searched on Google. Datasets for ticker symbols have many 0 values. Also, it seems that when Finnish investment service companies optimize their Google search visibility, they often use similar keyword patterns. Using this keyword combination refers directly to the company's stock. However, using combinations of two words or more often leads to lower search volumes and many 0-values. Using OMXH25 helps with this issue since these companies should have the highest visibility and search volumes in Finland.

All the keywords are collected in the same manner. The sample period starts from the last week of December 2017 and ends after the first week of January 2023. GSV dataset, therefore, has 263 data points for all 48 keywords. Google allows limiting the geographical area of the searches to a specific country. In this study, these kinds of limitations are not used since the keyword selection should refer specifically towards the company. GSV is captured from the whole world.

As mentioned earlier, GSV is a relative measure with values between 0 and 100. 100 is the maximum search volume of the sample period. This causes some problems since different times of retrieval or different sample period may lead to the same week getting different values. Also, strong peaks may cause scale problems since other periods will then have very low values. For these problems, earlier studies have suggested alternative versions of GSV. For example, both Takeda &Wakao (2014) and Ekinci & Bulut (2021) use two adjusted versions of GSV in addition to the original raw data.

This study follows the same methods to adjust GSV. The first adjusted version of GSV is a difference in GSV (ΔGSV). This adjustment aims to make search volumes of individual stocks more comparable in case large shocks affect some stocks but not others (Takeda & Wakao, 2014). The formula for ΔGSV is following:

$$\Delta GSV_{t-j} = GSV_{t-j} - GSV_{t-j-1} \tag{1}$$

where t is the time component and j = 1,0,-1 describes the time lag. ΔGSV is, therefore, the difference between the GSV of the current period and the last period. This variable can have both positive and negative values.

The second adjusted version of GSV is abnormal GSV (AGSV). As mentioned earlier, Google search data may vary depending on the time of retrieval. This means that Google Trends calculates search volumes based on a random subset of historical data search activities, which may lead to search volume for the same keyword being different when it is downloaded at different times (Takeda & Wakao, 2014). In order to eliminate this time of retrieval bias, abnormal GSV is suggested. The formula for AGSV is following:

$$AGSV_{t-j} = GSV_{t-j} - median\ (GSV_{t-j-1}, GSV_{t-j-2}, \dots, GSV_{t-j-7}) \tag{2}$$

where t is the time component and j=1,0,-1 describes the time lag. AGSV is therefore, the GSV of current period minus the median value of the last seven periods.

3.3 Factor data

This paper uses Fama & French's (1993) three-factor model in the study method. Factors are control variables in the regressions. Three factors in the model try to capture market-wide phenomena that explain stock returns. Therefore, it is fitting to use them as a control variable when studying the effect of GSV on returns. Three factors in the model are market excess return (Mkt-RF), small minus big (SMB), and high minus low (HML). Market excess return is the return of the market portfolio minus the risk-free rate. Small minus big is the difference in returns of small-cap stocks and large-cap stocks in the market. Finally, high minus low is the difference in return of high book-to-market stocks versus low book-to-market stocks.

Fama & French factor data is collected from Kenneth R. French data library. The library provides daily, weekly, and monthly returns for the most common asset pricing models. Factor data is also available for different markets and geographical locations. However, European FF3 factor data is available daily and monthly in the library. For this study, weekly data is required, so daily data is transformed into weekly. The daily factor data that Kenneth R. French Library provides is already compounded, so the data adjustment is straightforward. The weekly factor value is the sum of its daily values.

The risk-free rate is also collected from the Kenneth R. French Library. Like the factor data, the risk-free rate is only available in daily or monthly form. The risk-free rate is, therefore, also manually adjusted into weekly data. The risk-free rate is then used to calculate excess return from stock market data by subtracting the risk-free rate from the total return.

3.4 Method

The Fama-French three-factor model is utilized in the empirical analysis of this study. The study method is inspired heavily by past studies where already-recognized risk factors were used as control variables. Google search volume component is then added to the existing model as an additional factor. FF3 is chosen because past studies show that its explanatory power is better than the CAPM. Additionally, the FF3 is a simple but effective way to create a baseline for further analysis. As mentioned in the literature review, multiple other models could be utilized in the empirical research. However, FF3 provides a sufficient framework for the purposes of this study.

This study follows a similar method to Ekinchi & Bulut (2021). First, stock-based OLS regression is run for all 24 stocks. In these regressions, only FF3 factors are used as explanatory variables. The dependent variable is the excess return. These regression results form the baseline to which future regression results are compared. The formula for these baseline regressions is following:

$$ER_{i,t} = a_i + \beta_{1i}\left(R_{m,t} - R_{f,t}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t \tag{3}$$

where $ER_{i,}$ is the excess return of stock i, a is the abnormal return, $R_{m,t} - R_{f,t}$ is the market risk premium, *SMB* is the difference in returns of small cap stocks and large cap stocks, *HML* is the difference in return of high book-to-market stocks versus low book-to-market stocks. Subscript *t* stands for the time component and $\beta_1, \beta_2, \beta_3$ are the coefficients of FF3 factors. Once regressions are run, coefficients and $R^2$of each regression are gathered for later comparisons.

Second, Google search volume components are added to all OLS regressions. As mentioned earlier Google data consists of two sets of keyword search volume data. First on is the simple form of company name. This set is called GSV1 from now on. The second keyword data is the same company name + “osake”. This set is GSV2 from now on. Two sets of regressions are run for each individual stock using both keywords. The regression formula is following:

$$ER_{i,t} = a_i + \beta_{1i}\left(R_{m,t} - R_{f,t}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}GSV(X)_{i,t-j} \tag{4}$$

where *GSV*, is the search volume of the stock *i*, *X*=1,2 represents the different keyword set, *t* is the time component and *j*=1,0,-1 is the time lag. Other parts of the formula are the same. Adding the new GSV component means that we create a search volume factor and study the "search volume"-beta (β_4). This formula can be called a four-factor model, or FF3 with an additional search volume factor.

Additionally, lagged regressions are also run for both keywords. This is to study the direction of the relationship between the excess returns and search volume. Regressions where the GSV is the leading regressor (j=1) and where the GSV is the lagging regressor (j=-1) are run again for all individual stocks using both keywords. If regressions, where GSV is leading, give more robust results, meaning better p-values and R^2, this would suggest that search volume has a prediction value. On the other hand, if regressions with lagging GSV give better results, then search volume is more likely the result of return movement.

After running the abovementioned regressions, the better GSV keyword data will be additionally tested with two other models. Differences in GSV (ΔGSV) and abnormal GSV (AGSV) are calculated for better GSV data and regressed once again with all the stocks and with the same lags. The regression model is the same, but GSV is replaced with ΔGSV and AGSV. In total, this study will have one model without GSV as a baseline model and 12 models with different versions of Google search volume as explanatory variables.

Finally, different models are compared with each other. Coefficients, signs, and p-values of GSV factor terms (β_4) are studied to assess if GSV affects stock returns. Furthermore, this study aims to determine if GSV can predict stock returns. This would suggest that public attention and recognition are factors that affect stock prices since GSV is used as a proxy for those phenomena. Adjusted R^2 is collected from all the regressions and compared to the baseline model and other four-factor models. The aim is to find the model with the best explanatory power. With all these factors in mind, this paper assesses if GSV is a significant and valuable factor to consider in the Finnish market.

4 EMPIRICAL RESULTS

This chapter displays the most important descriptive statistics for the data selected for this study. After that, all different regression results are introduced, and the results of diagnostic checks are presented. Finally, results are discussed, analyzed and compared to earlier studies.

4.1 Descriptive statistics

Table 1 shows the final list of stocks selected for the study. Stocks are listed in the first column, and the most important descriptive statistics are listed in the following columns. For each stock, the table shows mean and median values for total excess return as well as standard deviation (SD), minimum, and maximum values for the sample period. Total excess return is calculated by subtracting the weekly risk-free rate from the weekly total return. In the last two columns are the GSV1 and GSV2 keywords that are used for each stock in the data gathering. GSV1 is the simple form of the company name with the Google footnote that ties the keyword to the company. GSV2 is the company name in the simple form + “osake”. The dataset has 261 data points for each stock.

Table 2 shows the descriptive statistics for the explanatory variables used in the study. Explanatory variables are the three factors from FF3: market risk premium (Mkt-RF) Small-Minus-Big (SMB), and High-Minus-Low (HML). Two additional explanatory variables are the Google search volume factors GSV1 and GSV2. Every stock has its individual GSV1 and GSV2 data. In order to capture an overview of GSV1 and GSV2 statistics across the dataset, the weekly average value between all keywords is calculated for each week. Then the following statistics are gathered from the average weekly value. While this method does not give a comprehensive description of the whole GSV data, it helps to highlight the differences between the two Google search volume keywords. GSV can have values between 100 and 0.

Table 1. Descriptive statistics of stock data

	Mean	*Med.*	*SD*	*Min*	*Max*	*GSV1**	*GSV2***
Cargotec b	0.17	-0.26	6.17	-23.77	31.16	Cargotec	cargotec osake
Elisa	0.26	0.48	3.08	-18.12	20.53	Elisa	elisa osake
Fortum	0.19	0.32	4.84	-28.18	25.52	Fortum	fortum osake
Huhtamäki	0.08	0.05	4.27	-17.40	16.15	Huhtamäki	huhtamäki osake
Kesko b	0.36	0.47	3.94	-17.51	12.12	Kesko	kesko osake
Kone b	0.12	0.43	3.16	-11.09	10.77	Kone	kone osake
Konecranes	0.10	0.28	5.69	-26.20	19.36	Konecranes	konecranes osake
Metsä Board b	0.23	0.34	4.69	-15.28	17.46	Metsä Board	metsä board osake
Metso Outotec	0.36	0.04	6.81	-36.93	31.75	Outotec	outotec osake
Neste	0.48	0.31	5.12	-20.06	26.71	Neste Oyj	neste osake
Nokia	0.17	0.02	5.06	-26.86	16.91	Nokia	nokia osake
Nokian Renkaat	-0.30	-0.05	5.59	-33.64	20.67	Nokian Renkaat	nokian renkaat osake
Nordea Bank	0.19	0.13	4.23	-26.80	15.08	Nordea	nordea osake
Orion b	0.35	0.21	4.68	-17.70	29.77	Orion	orion osake
Outokumpu	0.08	0.07	7.05	-26.22	36.48	Outokumpu	outokumpu osake
QT Group	1.06	0.39	7.34	-24.28	31.28	Qt Group	qt group osake
Sampo a	0.19	0.43	3.54	-26.82	12.46	Sampo-konserni	sampo osake
SSAB b	0.34	0.05	5.58	-21.58	19.09	SSAB	ssab osake
Stora Enso	0.13	0.22	4.65	-17.54	12.68	Stora Enso	stora enso osake
Telia Company	0.02	0.02	3.11	-17.34	11.82	Telia Company	telia osake
Tietoevry	0.14	0.32	3.59	-16.44	12.20	Tieto-Evry	tietoevry osake
UPM-Kymmenen	0.25	0.44	3.77	-16.34	15.40	UPM	UPM osake
Valmet	0.30	0.36	4.42	-16.61	23.28	Valmet	valmet osake
Wärtsilä	-0.14	-0.08	5.07	-21.32	19.82	Wärtsilä	wärtsilä osake

Notes: Descriptive statistics are for the total excess returns of each stock during the sample period. Total excess return is calculated by subtracting weekly risk-free rate from the weekly total return. * = Google search volume dataset 1, where the keyword is company name in a simple form and tied to company by Google suggestion footnote. ** = Google search volume 2, where the keyword is company name + “osake”

Table 2. Descriptive statistics of explanatory variables

	Mkt-RF	*SMB*	*HML*	*GSV1**	*GSV2**
Mean	0.062	-0.035	-0.034	45.618	22.525
Median	0.250	0.000	-0.160	45.625	24.667
Std.dev	2.993	0.882	1.627	4.148	13.910
Min	-20.150	-5.670	-5.390	33.167	0.708
Max	10.970	2.150	7.300	58.292	63.375
N	261	261	261	263	263

* = weekly average search volume across the 24 stocks

GSV2 is the more complicated keyword which immediately lowers the statistic values. There are multiple 0 values for individual keywords, even for longer periods, especially at the beginning of the sample period. This is most likely because of the turbulent times at the end of the sample period. Since GSV is a relative measure, times of very high search volumes may push lower search volumes very near to 0 values. Table 2 shows that GSV1 is smoother series throughout the sample period.

It is also worth noting that GSV1 and GSV2 have two data points more than other variables. This is for the purposes of lagged regressions. As mentioned earlier, changing or altering the sample period for later parts may result in different weekly values since GSV is a relative measure. Therefore, the same GSV dataset is used throughout this study without altering the sample period.

As mentioned earlier, an empirically better dataset of the two search volume measures is additionally adjusted for the differences in GSV (ΔGSV) and abnormal GSV (AGSV). During the empirical research, GSV1 turned out to be a more fitting keyword set for further analysis. Table 3 introduces the descriptive statistics for the two additional adjusted datasets.

Table 3. Statistic for the adjusted search volume factors

	ΔGSV1	*AGSV1*
Mean	0.015	0.425
Median	0.100	0.640
Std.dev	3.129	3.698
Min	-13.320	-13.920
Max	9.160	12.320
N	262	256

Weekly average search volume across all 24 stocks

Compared to the other GSV datasets, these two can have negative values, and the mean value settles around zero. The difference in search volume has 262 data points because the calculation method retracts one data point from the beginning of the set. Similarly, AGSV has 256 data points because of the calculation method of the variable. As mentioned earlier, later adjustments for the dataset are not made because changing the sample period may change all the set values and because of the time of retrieval bias. It is essential to notice that the regressions that use either of these variables may have fewer data points. Therefore, the adjusted R^2 is an important measure when comparing different models.

4.2 Regression results

The empirical part of this paper starts by creating the control series. As mentioned earlier, this is done by running OLS regressions for all 24 individual stocks. The dependent variable is the total excess return, and the explanatory variables are the factors in the Fama-French three-factor model. Table 4 presents the results of control series regressions. Individual coefficients, p-values, and explanatory power are captured in the table. The bottom row represents the average of each column. These averages are then used in further analysis. The p-values and coefficient of FF3 variables are not likely to adjust very much, but the R^2 and the adjusted R^2 are monitored closely when conducting the regressions with the GSV component.

When focusing on the average p-values, the only consistently significant variable is the excess market return (Mkt-RF). The p-value of the excess market return is statistically significant in every regression. On the other hand, the average p-values of SMB and HML are insignificant. There are multiple individual regressions, where SMB and HML are statistically significant, but the overall effect of these variables is less impactful. However, after some additional testing, the explanatory power of the three-factor model is significantly better than the explanatory power of simple CAPM in this sample. The FF3 model has an average R^2 of 0.334 and an adjusted R^2 of 0.326.

Table 4. Control series results

	a	p-value	Mkt-RF	p-value	SMB	p-value	HML	p-value	R^2	Adj R^2
Cargotec b	0.122	0.685	1.267	2.93E-28	0.616	0.0738	0.225	0.233	0.394	0.387
Elisa	0.190	0.276	0.307	4.06E-07	-0.966	2.27E-06	-0.334	0.003	0.175	0.165
Fortum	0.129	0.613	0.796	1.43E-17	-0.516	0.0795	0.278	0.086	0.283	0.275
Huhtamäki	0.023	0.916	0.825	3.57E-24	-0.082	0.7408	0.055	0.685	0.341	0.333
Kesko b	0.305	0.156	0.646	1.06E-16	-0.049	0.8404	-0.385	0.005	0.240	0.231
Kone b	0.040	0.798	0.548	9.03E-21	-0.750	4.86E-05	-0.620	1.91E-09	0.354	0.346
Konecranes	0.051	0.853	1.211	1.67E-30	0.601	0.0548	0.050	0.768	0.412	0.405
Metsä Board b	0.200	0.444	0.697	8.30E-14	0.130	0.6627	0.130	0.426	0.206	0.197
Metso Outotec	0.305	0.355	1.396	2.66E-28	0.631	0.0958	0.334	0.109	0.398	0.391
Neste	0.429	0.118	0.886	1.11E-18	0.111	0.7232	-0.078	0.649	0.264	0.256
Nokia	0.103	0.708	0.808	5.29E-16	-0.526	0.0963	-0.053	0.762	0.239	0.230
Nokian Renkaat	-0.374	0.184	1.065	6.21E-24	-0.456	0.1569	0.213	0.228	0.352	0.344
Nordea Bank	0.141	0.426	0.919	5.33E-38	-0.408	0.0456	0.610	1.05E-07	0.549	0.543
Orion b	0.288	0.300	0.428	7.93E-06	-0.646	0.0430	-0.455	0.010	0.099	0.088
Outokumpu	0.031	0.927	1.341	1.58E-25	0.205	0.5975	0.917	2.41E-05	0.407	0.400
QT Group	1.017	0.011	1.046	1.44E-13	1.703	0.0002	-1.133	7.79E-06	0.256	0.247
Sampo a	0.141	0.335	0.805	2.25E-41	-0.296	0.0782	0.433	3.96E-06	0.563	0.558
SSAB b	0.293	0.284	1.079	1.48E-25	0.073	0.8163	0.518	0.003	0.386	0.379
Stora Enso	0.079	0.728	0.926	1.20E-26	-0.184	0.4801	0.243	0.090	0.384	0.377
Telia Company	-0.045	0.791	0.353	4.49E-09	-1.095	6.11E-08	-0.035	0.743	0.220	0.211
Tietoevry	0.100	0.571	0.735	1.97E-27	0.265	0.1925	-0.007	0.952	0.375	0.367
UPM-Kymmenen	0.198	0.292	0.712	5.03E-24	-0.354	0.0994	0.263	0.026	0.368	0.360
Valmet	0.231	0.326	0.785	9.41E-20	-0.225	0.4032	-0.258	0.081	0.278	0.270
Wärtsilä	-0.189	0.412	1.124	7.20E-35	0.226	0.3917	0.292	0.045	0.469	0.463
AVERAGE	**0.159**	**0.479**	**0.863**	**3.48E-07**	**-0.083**	**0.278**	**0.050**	**0.246**	**0.334**	**0.326**

The regression results of Fama & French three-factor model for the individual stocks.

The results of the control series are then compared to the results of different four-factor models with GSV components. Similar tables are constructed for all the remaining regression models. The specific results of all regressions of this thesis can be found in appendix 1.

First, the better keyword set needs to be determined. The more fitting keyword set is then used in the additional regressions. Table 5 compares the regression results of the two different keyword sets, GSV1 and GSV2. There are three regression models per keyword set.

Table 5. GSV1 and GSV2 comparison

	GSV1			GSV2		
	t = 0	t - 1	t + 1	t = 0	t - 1	t + 1
R^2	**0.3394**	0.3360	0.3359	0.3383	0.3356	0.3380
Adj. R^2	**0.3290**	0.3257	0.3188	0.3280	0.3253	0.3276
average p-value	0.4044	0.5392	0.5395	0.4159	0.5402	**0.4039**
Sig. p-values	**5**	1	0	3	0	2
5 %	**3**	1	0	2	0	1
1 %	**2**	0	0	1	0	1

R^2 and Adj. R^2 represent the explanatory power of the model. Average p-value is the average of all 24 regressions. Sig. p-values show the number of significant individual p-values for the GSV factor among all 24 regressions. Additionally, significant p-values are also divided in the groups of 5% confidence interval and 1% confidence interval.

Table 5 shows that in contemporaneous models, GSV1 is the better variable. It has the best explanatory power, and there are most individual regressions with significant p-values for the GSV factor. The results for the regressions where the GSV factor is leading (t-1) are quite similar for both keyword sets. GSV2 seems to work better as a lagging (t+1) factor.

The results suggest that GSV1 could work better in the study. GSV2 has better results when the factor is lagging, but that is not necessarily better for the study. Lagging significance signals that the factor is the effect instead of the cause. In the study, the aim is to find out if GSV can explain or predict returns. Therefore, GSV1 is selected for further analysis. The difference in GSV and abnormal GSV is calculated using the GSV1 dataset.

Finally, regression models where differences in GSV and abnormal GSV are used as explanatory variables are run. Like the other models, there are three different models per variable: leading, contemporaneous, and lagging GSV. Results from individual regressions are gathered similarly, and averages are calculated. Table 6 introduces the results of each model. There are 13 regression models in total, and the results in the table are average values from all 24 individual regressions.

Changes in the coefficients of original Fama & French factors are not in the interest of this study. Instead, signs of the GSV variable coefficient, p-values and explanatory power of each model are the key takeaway of the table. There are six models with positive coefficients for GSV and six with negative. However, in most models, the average coefficient of the GSV variable is very close to zero. In addition to that, the average p-value of every model is clearly statistically insignificant.

When studying the explanatory power of each model, adjusted R^2 is the best measure. Models have different amounts of variables, and some models also have fewer data points in their regressions. Models with the best adjusted R^2 are FF3 + ΔGSV1, FF3 + AGSV1 (t+1), and FF3 + AGSV1. The models are best by a fine margin, but it seems that adjusted GSV variable creates better models. The adjusted R^2 of the control series with only FF3 factors is 0.326, and for the best model with the GSV variable, it is 0.335. There is no significant improvement.

Table 6. Regression results summary

	a	*p-value*	*Mkt-RF*	*p-value*	*SMB*	*p-value*	*HML*	*p-value*	*GSV*	*p-value*	*R^2*	*Adj R^2*
FF3	0.159	0.479	0.863	3.477E-07	-0.083	0.278	0.050	0.246	-	-	0.334	0.326
FF3 + GSV1	-0.728	0.402	0.863	3.945E-07	-0.088	0.275	0.045	0.253	0.022	0.404	0.339	0.329
FF3 + GSV1 (t-1)	0.196	0.551	0.864	3.615E-07	-0.079	0.276	0.049	0.253	-0.006	0.539	0.336	0.326
FF3 + GSV1 (t+1)	-0.249	0.562	0.863	3.556E-07	-0.087	0.272	0.052	0.257	0.007	0.540	0.336	0.319
FF3 + GSV2	-0.014	0.518	0.863	3.560E-07	-0.084	0.277	0.048	0.248	0.006	0.416	0.338	0.328
FF3 + GSV2 (t-1)	0.135	0.568	0.861	5.062E-07	-0.086	0.276	0.051	0.251	-0.001	0.540	0.336	0.325
FF3 + GSV2 (t+1)	0.117	0.432	0.863	3.175E-07	-0.090	0.278	0.046	0.260	-0.001	0.404	0.338	0.328
FF3 + ΔGSV1	0.158	0.478	0.867	3.769E-07	-0.086	0.272	0.041	0.240	0.032	0.471	0.338	0.335
FF3 + ΔGSV1 (t-1)	0.156	0.480	0.864	4.792E-07	-0.087	0.285	0.053	0.236	-0.014	0.465	0.336	0.326
FF3 + ΔGSV1 (t+1)	0.160	0.477	0.863	3.767E-07	-0.085	0.287	0.047	0.245	-0.019	0.477	0.339	0.328
FF3 + AGSV1	0.144	0.498	0.868	1.934E-06	-0.087	0.275	0.044	0.232	0.027	0.413	0.342	0.332
FF3 + AGSV1 (t-1)	0.160	0.475	0.868	3.330E-06	-0.079	0.289	0.056	0.249	-0.015	0.540	0.336	0.326
FF3 + AGSV1 (t+1)	0.164	0.460	0.864	3.819E-07	-0.087	0.269	0.053	0.243	0.005	0.462	0.343	0.333

Coefficients and p-values for each model are the average for all 24 regressions.

Table 7 focuses purely on the GSV factor. The table is formed using all 12 regression models where the GSV factor is part of the equation. It explores the amount of significant GSV coefficients among all 24 regressions per model. The results are divided into two different columns to represent the sign of the coefficient. The third column combines the results of the first two. Additionally, each column is divided into 1% and 5% confidence levels to study the p-values further.

Models are divided into three groups based on the lags. This is done to highlight the effect of each lag. Additionally, it helps to study if GSV is a leading or lagging factor. If GSV were to have explanatory power or predictive power, the leading and contemporaneous sets should have the most significant results. On the other hand, if lagging models are the most significant, this would suggest that GSV does not have explanatory power, but instead, it reacts to the total excess return movements.

Table 7. Significant GSV coefficients across 12 regression models

	>0		<0		All	
	1 %	5 %	1 %	5 %	1 %	5 %
FF3 + GSV1	2	3	0	0	2	3
FF3 + GSV2	0	2	1	0	1	2
FF3 + ΔGSV1	4	2	1	0	5	2
FF3 + AGSV1	2	3	0	0	2	3
FF3 + GSV1 (t-1)	0	0	0	1	0	1
FF3 + GSV2 (t-1)	0	0	0	0	0	0
FF3 + ΔGSV1 (t-1)	0	0	0	2	0	2
FF3 + AGSV1 (t-1)	0	0	0	1	0	1
FF3 + GSV1 (t+1)	0	0	0	0	0	0
FF3 + GSV2 (t+1)	0	1	1	0	1	1
FF3 + ΔGSV1 (t+1)	0	0	2	1	2	1
FF3 + AGSV1 (t+1)	0	1	1	1	1	2

Table shows the number of stocks for which the coefficient is significant at 1% or 5% confidence interval. Additionally, positive and negative coefficients are displayed in their own columns (>0, <0) and "All" column represents all positively and negatively significant coefficients. Different regression models are grouped by the lag,

Table 7 shows that the contemporaneous regression models have the most statistically significant GSV factors. The model using the difference in GSV (ΔGSV1) is the most successful in this regard: it has 7/24 (25%) significant GSV values. The contemporaneous set of models gives better results than their counterparts in leading and lagging model sets. The results of the leading (t-1) set suggest that GSV has no predictive power whatsoever. There are only a few individual significant results among regressions. Similarly, the lagging (t+1) set has only a few individual regressions that provide statistically significant results. Overall, the results of Table 7 suggest that Google search volume has very little effect on total returns, even though contemporaneous models give some promising results and significant coefficients.

4.3 GSV factor data analysis

This study uses three different versions of Google search volume data: Raw GSV, the difference in GSV, and abnormal GSV. Following graphs visually represent three different datasets for three individual stocks. The aim is to demonstrate how adjustments affect the datasets. The first graph is for the raw, unadjusted GSV1 for the whole sample period.

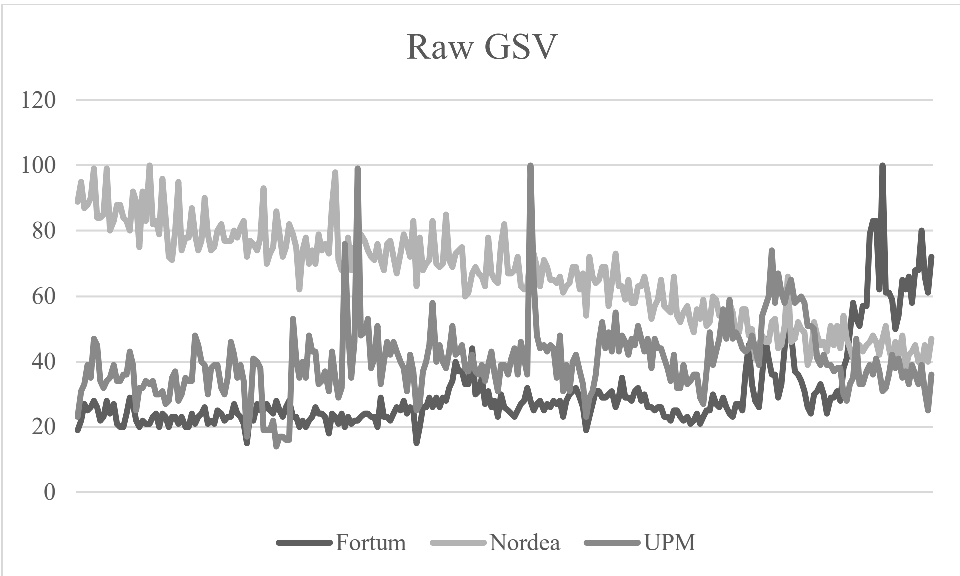

Figure 1: Raw GSV for three stocks before any adjustments

Data has strong spikes and clear trends. The graph presents the most significant issues in using the raw data. If the search volume for a keyword is normally low, times of higher search volume appear as sharp spikes. This is not that big of an issue with OMXH25 since stocks are well-known and often searched. However, a dataset of UPM is an example of this kind of problem. On the other hand, the graph of Nordea shows a clear trend that is problematic for regressions. Visual inspection reveals that raw datasets are not stationary, and adjustments are necessary. The following graph is for the difference in GSV.

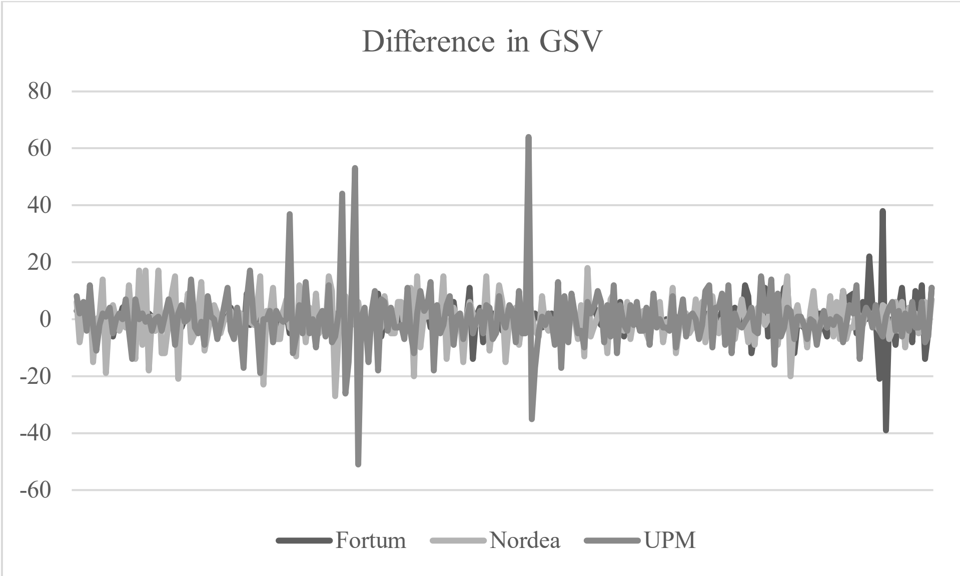

Figure 2. Difference in GSV for three stocks

Using the difference in GSV clears all trends from the data. This is better for time-series regressions than the raw data. However, using this simple adjustment does not eliminate spikes from the data. For example, in the UPM data, there are still clear spikes: a sharp increase in search volume and a strong decrease immediately after that. From a purely empirical point of view, this data is better for regressions. There are no trends in the data which is essential for time series regressions. Finally, the following graph presents the dataset for abnormal GSV for the same stocks.

Like the difference in GSV, abnormal GSV seems stationary after visual inspection. However, the graph for Nordea shows a pattern that looks very seasonal. There is no similar effect on the two other test subjects. However, there are still strong spikes in data. Without any further adjustments, the difference in GSV seems to be the best dataset in visual inspection.

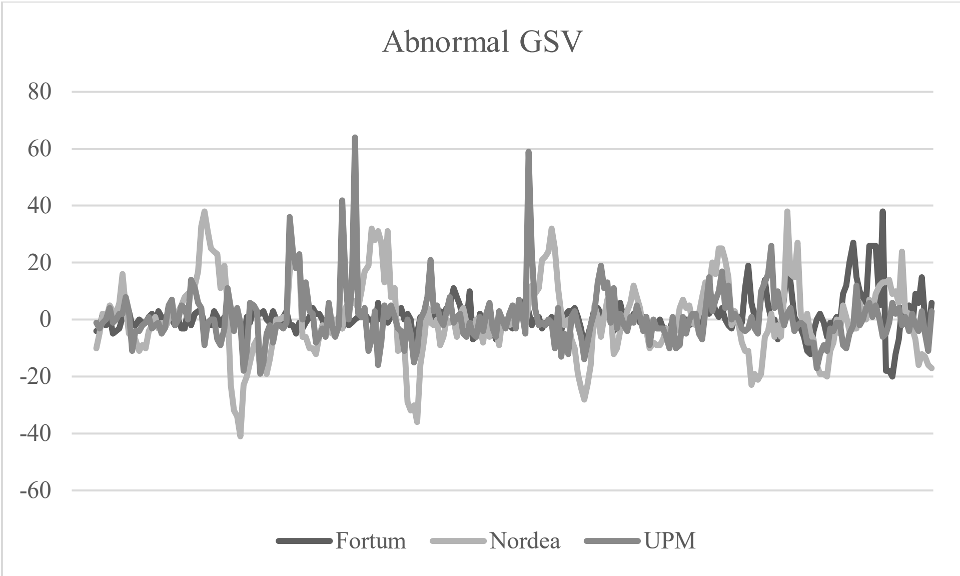

Figure 3. Abnormal GSV for three stocks

4.4 Discussion on results

The results of this study are less significant than expected. The two most important measures of the study are adjusted R^2 and the p-values of GSV factors in regressions. Adjusted R^2 improved very little, even in the best model. Table 6 presents the average values for adjusted R^2. There are some limitations in using averages as a presentation method. However, in this case, averages give a fair and fitting image of the impact of adding GSV in the FF3 model. The improvements in explanatory power are minimal, even in best individual regressions.

Additionally, there is very little consistency in the GSV factor when considering the p-values of the GSV factor. Individual regression that shows promising results turns meaningless by adjusting the lag, keyword, or GSV data. There are often individual regressions where the p-value of the GSV factor is statistically significant just in one model on some specific lag, and on every other model, the results are always insignificant. Statistically significant results for the p-values are random. There are only a few individual stocks that have multiple significant p-values across the different models.

This study also aims to answer if there is any predictive power in GSV. The results presented in Table 7 are constructed in a way that predictive power is easy to examine. The most robust results of the GSV factor are in the contemporaneous models. This suggests that search volumes for the keywords and stock returns change almost simultaneously. This study uses weekly data, so the effect often happens during the same week. However, in the contemporaneous models, it is difficult to estimate the direction of the effect. Are GSV causing the reaction to the stock returns, or is it the other way around, and search volumes react to stock returns? Therefore, the results of the leading and lagged models are in the key position.

Models where the GSV is a leading factor show very poor results. There is a maximum of one significant p-value per model, and in every leading model, it is for a different stock. Therefore, the results of this study suggest that Google search volume has no predictive power. Similarly, the lagging results are also quite poor. Only individual regressions have significant p-values for the GSV factor. The result results are only slightly better than for the leading models. Therefore, results suggest that GSV is not a lagging factor either.

Overall results of this study suggest that GSV has very little explanatory power. Google search volume is not a fitting additional factor for asset pricing since the regression results are significant only for individual stocks. Adding the GSV factor in regressions improves the explanatory power of the classic FF3 very little at best. There is no consistent relationship between GSV and stock returns. GSV is used as a proxy for investor recognition and investor attention. Therefore, this study concludes that investor recognition or attention does not affect stock returns in Finland in a meaningful and consistent way. The results of this study are in line with earlier results. The earlier studies on the same subject suggest that there is either a very small negative or positive connection between stock returns and GSV. Additionally, some studies show that there is no connection at all. This study gives stronger confirmation for the consensus.

As always, there are factors in the research method that could be improved and limitations that should be discussed. First, this study uses GSV as a proxy for investor recognition and attention. It should be discussed if GSV is somehow inadequate and if a better proxy exists. As discussed earlier, GSV is a relative measure. Spikes in search activity during the sample period may render the dataset useless, especially for keywords with low average search volume. This problem is well recognized, and different adjustments to the data are made to fix this issue. However, these adjustments do not remove the problem completely. Additionally, Google is the most used search engine in Finland (Statista, 2022), but investors can and do use other means to search for information on companies as well. For example, active investors are likely to use their broker's platform or some social platform to study new companies. Regardless of these facts, Google search volume is still one of the better proxies suggested in similar studies.

Another issue related to GSV that should be discussed is that search volume tends to react to good and bad times. Intuitively, it does not matter if the company is surrounded by good or bad news; the search volume will increase. This is not a problem when GSV is used to study variables such as the volume or volatility of stocks. However, this poses a problem for stock returns if only raw data is used. It can be argued that the adjusted versions of GSV (difference in GSV and adjusted GSV) are better for regressions. Also, the raw GSV could likely explain squared returns better.

The summary Table 6 shows that average p-values for the control variables HML and SMB are statistically insignificant. Using the average p-values from 24 regressions has its issues, but it represents the results of individual regressions quite well. HML is statistically significant in 10 or 11 individual regressions depending on the model, and SMB is significant in six out of 24. This is quite poorly compared to the market factor, which is significant in every individual regression. One issue regarding the HML and SMB factors may be that the dataset used in this study is calculated from the European Fama & French factor data. It is possible that the factor values would have been better if they were explicitly calculated for the Finnish market. However, after some additional testing, FF3 has better explanatory power among OMXH25 than the simple CAPM. The adjusted R^2 is better for FF3 in the sample used in this study. Often FF3 was very clearly the better model of the two. However, poor HML and SMB values throughout the empirical part of the study raise the question of whether the control variables chosen in this paper are the best possible. For example, the momentum factor could have been an interesting addition to the model since the intuition behind the factor is somewhat similar to the GSV factor.

The study method of this paper is quite straightforward and simple. A similar approach has been used in other research papers, but alternative methods are also available. For example, portfolio groupings based on GSV could be done and studied. Some studies use panel data, and in some cases, abnormal returns are used as the dependent variable. However, it is likely that the results would not change substantially even with different methods. This assessment is based on the results of earlier studies, where the results are either a very small positive or negative relationship between stock returns and GSV or no connection at all. For example, Kim et al. (2019) studied the same subject on the Norwegian stock market by using panel data and abnormal returns as the dependent variable. However, the results regarding stock returns are exactly the same. There is no connection between GSV and stock returns.

This study uses two different keyword sets in order to find the more fitting version. However, there are different keywords suggested by other studies. For example, the company ticker symbol is a popular keyword used in many papers. The ticker symbol is clearly connected to the company stock, but the problem is that, at least in Finland, the search volumes for tickers are very low. Therefore, the keywords used in this study should be very fitting in the Finnish environment.

This paper focuses only on the OMXH25 companies. Companies are, therefore, the most traded in Finland. This means that stocks in this study have the best liquidity and highest volumes possible. It can be argued that investor recognition or attention has a smaller effect on these companies than, for example, on the smallest companies on the Helsinki stock exchange. When trade volumes are low, even small spikes in activity can cause a more significant effect. In other words, the imperfections in the market could show better results for the GSV factor. Therefore, using a wider stock pool in this study could have provided better results.

Finally, the sample period of this study contains some very important events that should be mentioned. The COVID-19 pandemic began in the middle of the sample period, and the war in Ukraine started towards the end of the period. Both events have had a significant effect on the Finnish stock market. The crisis could distort the results of even better models, so these important events are worth mentioning. However, it can be assumed that these crises did not render the effect of the GSV factor non-existence.

5 CONCLUSION

The results of this study suggest that there is no meaningful connection between Google search volume and stock returns. Some individual regressions show statistical significance for the GSV factor, but the overall effect across the sample is meaningless. The findings align with the spectrum of earlier studies, which suggest either a very small negative or positive relationship between Google search volume and stock returns. The consensus among the research on the subject is that the GSV factor can not be utilized in stock pricing effectively. GSV factor is used as a proxy to measure the effect of investor recognition and attention to stock returns. Therefore, the results suggest that recognition or attention has no pricing power or that the GSV is ineffective as a proxy.

This study focuses only on the biggest and most traded stocks in the Helsinki stock exchange. While the search volume data for these stocks is the most consistent, it can be argued that attention and recognition factors for these companies are hindered because of the already existing popularity. Smaller companies that lack trade volume and liquidity could show more potent results. In other words, imperfections in the market could work for the GSV factor. On the other hand, this kind of factor analysis aims to find pricing factors that are market-wide and work in all conditions. Additionally, this paper focuses only on the relationship between stock returns and GSV. Other stock characteristics could work better with the GSV factor. For example, earlier studies have found a stronger relationship between GSV and volatility and trade volume.

Further studies on the subject should be conducted, especially on the relationship between GSV and trade volume or volatility in Finland. Past studies on other markets have shown promising results for GSV, volume, and volatility. Also, market-wide research on the relationship between Google search volume and stock returns could be conducted to gain further confidence in the results of this paper. Additionally, the GSV factor focuses only on one search engine activity. Investors search and study companies using many other services in addition to Google. Combining search activity from multiple sources, such as Twitter or stockbroker platforms, could prove fruitful into one proxy to represent attention and recognition.

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Appendix 1

INDIVIDUAL REGRESSION RESULTS FOR DIFFERENT MODELS

Bolded values are statistically significant at 5% level.

FF3 + GSV1

	a	Mkt-RF	SMB	HML	GSV	R^2	Adj R^2
Cargotec b	**-2.677**	**1.239**	0.533	0.225	**0.143**	0.425	0.416
Elisa	-1.760	**0.308**	**-1.013**	**-0.330**	0.029	0.183	0.170
Fortum	-0.421	**0.804**	-0.497	0.265	0.018	0.285	0.274
Huhtamäki	-1.242	**0.826**	-0.057	0.057	0.019	0.343	0.333
Kesko b	0.474	**0.645**	-0.046	**-0.384**	-0.003	0.240	0.229
Kone b	0.129	**0.548**	**-0.751**	**-0.621**	-0.006	0.354	0.344
Konecranes	-0.591	**1.214**	0.614	0.053	0.014	0.412	0.403
Metsä Board b	0.045	**0.699**	0.134	0.133	0.003	0.206	0.194
Metso Outotec	-1.142	**1.406**	0.649	0.317	0.050	0.403	0.394
Neste	-1.731	**0.890**	0.152	-0.044	0.045	0.271	0.260
Nokia	**-2.678**	**0.814**	-0.553	-0.050	**0.086**	0.254	0.242
Nokian Renkaat	0.803	**1.061**	-0.449	0.235	-0.029	0.360	0.350
Nordea Bank	0.452	**0.918**	**-0.403**	**0.606**	-0.005	0.549	0.542
Orion b	0.419	**0.428**	**-0.644**	**-0.455**	-0.002	0.099	0.085
Outokumpu	**-2.786**	**1.338**	0.234	**0.883**	**0.054**	0.417	0.408
QT Group	1.288	**1.042**	**1.692**	**-1.110**	-0.014	0.256	0.245
Sampo a	-0.087	**0.806**	-0.298	**0.429**	0.005	0.564	0.557
SSAB b	**-2.245**	**1.103**	0.068	**0.446**	**0.052**	0.402	0.393
Stora Enso	0.575	**0.922**	-0.191	0.244	-0.013	0.385	0.375
Telia Company	-1.272	**0.353**	**-1.123**	-0.032	0.019	0.225	0.213
Tietoevry	0.135	**0.734**	0.264	-0.006	-0.001	0.375	0.365
UPM-Kymmenen	**-1.608**	**0.728**	-0.387	0.223	**0.045**	0.384	0.375
Valmet	-2.618	**0.787**	-0.250	-0.281	0.037	0.281	0.270
Wärtsilä	1.059	**1.111**	0.205	**0.291**	-0.019	0.470	0.462

FF3 + GSV1 (t-1)

	a	Mkt-RF	SMB	HML	GSV	R^2	Adj R^2
Cargotec b	1.283	**1.278**	0.625	0.218	-0.060	0.400	0.390
Elisa	0.357	**0.308**	**-0.962**	**-0.334**	-0.002	0.175	0.162
Fortum	-0.411	**0.796**	-0.498	0.268	0.018	0.285	0.274
Huhtamäki	-1.436	**0.832**	-0.085	0.052	0.022	0.344	0.334
Kesko b	0.800	**0.647**	-0.033	**-0.383**	-0.010	0.241	0.229
Kone b	0.178	**0.548**	**-0.760**	**-0.622**	-0.009	0.354	0.344

Konecranes	2.165	**1.208**	0.596	0.021	-0.048	0.416	0.407
Metsä Board b	-0.132	**0.697**	0.151	0.135	0.007	0.207	0.195
Metso Outotec	0.513	**1.397**	0.629	0.332	-0.007	0.399	0.389
Neste	-0.601	**0.880**	0.131	-0.059	0.021	0.266	0.255
Nokia	**3.175**	**0.821**	-0.499	-0.075	**-0.095**	0.258	0.246
Nokian Renkaat	-0.176	**1.066**	-0.454	0.217	-0.005	0.352	0.342
Nordea Bank	0.422	**0.920**	**-0.405**	**0.606**	-0.004	0.549	0.542
Orion b	0.197	**0.428**	**-0.647**	**-0.455**	0.002	0.099	0.085
Outokumpu	0.624	**1.342**	0.209	**0.923**	-0.011	0.407	0.398
QT Group	**1.670**	**1.038**	**1.689**	**-1.087**	-0.033	0.260	0.249
Sampo a	-0.173	**0.801**	-0.296	**0.428**	0.007	0.564	0.558
SSAB b	-0.708	**1.081**	0.086	**0.502**	0.021	0.389	0.379
Stora Enso	0.408	**0.924**	-0.196	0.243	-0.009	0.385	0.375
Telia Company	-0.710	**0.351**	**-1.099**	-0.032	0.011	0.221	0.209
Tietoevry	0.168	**0.734**	0.264	-0.006	-0.002	0.375	0.365
UPM-Kymmenen	-0.145	**0.714**	-0.346	**0.258**	0.009	0.368	0.358
Valmet	-2.909	**0.789**	-0.225	-0.267	0.041	0.282	0.271
Wärtsilä	0.154	**1.123**	0.222	**0.289**	-0.005	0.469	0.461

FF3 + GSV1 (t+1)

	a	Mkt-RF	SMB	HML	GSV	R^2	Adj R^2
Cargotec b	-0.037	**1.268**	0.614	0.227	0.008	0.394	0.379
Elisa	-1.045	**0.305**	**-0.989**	**-0.332**	0.018	0.178	0.157
Fortum	0.716	**0.790**	-0.538	0.293	-0.019	0.286	0.267
Huhtamäki	-0.442	**0.825**	-0.079	0.059	0.007	0.341	0.324
Kesko b	-0.032	**0.647**	-0.057	**-0.387**	0.007	0.241	0.221
Kone b	0.363	**0.547**	**-0.754**	**-0.625**	-0.020	0.355	0.339
Konecranes	-0.788	**1.221**	0.609	0.057	0.019	0.413	0.398
Metsä Board b	0.559	**0.698**	0.125	0.125	-0.008	0.207	0.187
Metso Outotec	0.024	**1.397**	0.625	0.333	0.010	0.399	0.383
Neste	-1.199	**0.896**	0.124	-0.045	0.034	0.268	0.250
Nokia	-1.426	**0.807**	-0.549	-0.040	0.048	0.244	0.224
Nokian Renkaat	0.281	**1.065**	-0.471	0.221	-0.016	0.354	0.338
Nordea Bank	0.427	**0.920**	**-0.406**	**0.604**	-0.004	0.549	0.537
Orion b	-0.025	**0.429**	**-0.648**	**-0.459**	0.006	0.099	0.076
Outokumpu	-2.501	**1.341**	0.181	**0.898**	0.049	0.415	0.400
QT Group	1.180	**1.047**	**1.700**	**-1.123**	-0.008	0.256	0.237
Sampo a	0.294	**0.805**	-0.293	**0.433**	-0.004	0.563	0.552
SSAB b	-1.266	**1.081**	0.125	**0.491**	0.032	0.392	0.377
Stora Enso	0.416	**0.925**	-0.189	0.245	-0.009	0.385	0.369
Telia Company	-1.816	**0.354**	**-1.127**	-0.023	0.028	0.230	0.211
Tietoevry	0.231	**0.734**	0.261	-0.004	-0.003	0.375	0.359
UPM-Kymmenen	-0.301	**0.714**	-0.346	**0.258**	0.012	0.369	0.353
Valmet	-0.073	**0.785**	-0.226	-0.261	0.004	0.278	0.260

Wärtsilä	0.478	**1.122**	0.229	**0.292**	-0.010	0.469	0.456

FF3 + GSV2

	a	**Mkt-RF**	SMB	**HML**	GSV2	R^2	Adj R^2
Cargotec b	-0.282	**1.252**	0.558	**0.218**	0.024	0.398	0.389
Elisa	-0.030	**0.311**	-0.958	**-0.330**	0.010	0.178	0.165
Fortum	-0.103	**0.801**	-0.521	**0.280**	0.014	0.285	0.274
Huhtamäki	-0.029	**0.823**	-0.086	**0.054**	0.002	0.341	0.331
Kesko b	0.437	**0.647**	-0.051	**-0.381**	-0.006	0.241	0.229
Kone b	0.198	**0.541**	-0.758	**-0.615**	-0.007	0.356	0.345
Konecranes	-0.313	**1.207**	0.597	**0.045**	0.018	0.416	0.407
Metsä Board b	0.090	**0.694**	0.133	**0.135**	0.005	0.207	0.194
Metso Outotec	-0.359	**1.415**	0.625	**0.324**	0.028	0.404	0.395
Neste	0.345	**0.888**	0.112	**-0.078**	0.003	0.265	0.253
Nokia	-0.446	**0.819**	-0.560	**-0.068**	0.049	0.247	0.235
Nokian Renkaat	0.373	**1.029**	-0.415	**0.212**	-0.086	0.385	0.375
Nordea Bank	-0.606	**0.930**	-0.375	**0.593**	0.020	0.559	0.552
Orion b	0.156	**0.428**	-0.639	**-0.452**	0.006	0.099	0.085
Outokumpu	-0.893	**1.341**	0.194	**0.884**	0.025	0.415	0.406
QT Group	1.275	**1.039**	1.682	**-1.103**	-0.017	0.257	0.246
Sampo a	0.022	**0.805**	-0.296	**0.431**	0.005	0.564	0.557
SSAB b	-0.329	**1.106**	0.107	**0.475**	0.032	0.400	0.390
Stora Enso	-0.072	**0.923**	-0.185	**0.252**	0.008	0.385	0.376
Telia Company	0.272	**0.349**	-1.110	**-0.023**	-0.010	0.227	0.215
Tietoevry	0.089	**0.735**	0.266	**-0.008**	0.001	0.375	0.365
UPM-Kymmenen	-0.002	**0.713**	-0.349	**0.263**	0.007	0.369	0.359
Valmet	0.247	**0.786**	-0.225	**-0.257**	-0.001	0.278	0.267
Wärtsilä	-0.380	**1.124**	0.224	**0.291**	0.006	0.470	0.461

FF3 + GSV2 (t-1)

	a	Mkt-RF	SMB	HML	GSV2	R^2	Adj R^2
Cargotec b	-0.134	**1.257**	0.583	0.218	0.015	0.396	0.387
Elisa	0.079	**0.304**	**-0.968**	**-0.331**	0.005	0.176	0.163
Fortum	0.027	**0.793**	-0.522	0.276	0.006	0.283	0.272
Huhtamäki	0.003	**0.825**	-0.083	0.055	0.001	0.341	0.331
Kesko b	0.405	**0.647**	-0.043	**-0.386**	-0.005	0.241	0.229
Kone b	0.104	**0.547**	**-0.757**	**-0.620**	-0.003	0.354	0.344
Konecranes	0.198	**1.214**	0.602	0.051	-0.007	0.413	0.403
Metsä Board b	0.458	**0.698**	0.134	0.131	-0.012	0.209	0.197
Metso Outotec	-0.019	**1.386**	0.631	0.342	0.014	0.400	0.390

Neste	0.587	**0.890**	0.117	-0.080	-0.006	0.265	0.253
Nokia	0.704	**0.821**	-0.503	-0.041	-0.054	0.249	0.237
Nokian Renkaat	-0.314	**1.066**	-0.459	0.215	-0.007	0.352	0.342
Nordea Bank	-0.156	**0.914**	**-0.402**	**0.609**	0.008	0.550	0.543
Orion b	0.051	**0.423**	**-0.668**	**-0.450**	0.011	0.100	0.086
Outokumpu	-0.225	**1.340**	0.199	**0.909**	0.007	0.407	0.398
QT Group	**1.475**	**1.038**	**1.671**	**-1.088**	-0.031	0.261	0.249
Sampo a	-0.159	**0.797**	-0.309	**0.426**	0.012	0.568	0.561
SSAB b	-0.191	**1.079**	0.110	**0.490**	0.025	0.395	0.385
Stora Enso	0.175	**0.927**	-0.185	0.244	-0.005	0.385	0.375
Telia Company	0.031	**0.354**	**-1.099**	-0.030	-0.003	0.220	0.208
Tietoevry	0.165	**0.735**	0.266	-0.002	-0.003	0.375	0.365
UPM-Kymmenen	0.235	**0.712**	-0.355	**0.263**	-0.001	0.368	0.358
Valmet	0.150	**0.786**	-0.228	-0.262	0.003	0.279	0.267
Wärtsilä	-0.409	**1.120**	0.213	**0.286**	0.007	0.470	0.462

FF3 + GSV2 (t+1)

	a	Mkt-RF	SMB	HML	GSV2	R^2	Adj R^2
Cargotec b	-0.121	**1.256**	0.606	0.232	0.014	0.396	0.386
Elisa	0.241	**0.306**	**-0.962**	**-0.335**	-0.002	0.175	0.162
Fortum	0.575	**0.787**	-0.514	0.284	-0.026	0.290	0.279
Huhtamäki	0.181	**0.826**	-0.077	0.060	-0.007	0.343	0.332
Kesko b	0.467	**0.647**	-0.053	**-0.384**	-0.008	0.242	0.230
Kone b	0.273	**0.539**	**-0.765**	**-0.620**	-0.010	0.358	0.348
Konecranes	-0.244	**1.222**	**0.619**	0.045	0.014	0.414	0.405
Metsä Board b	0.262	**0.698**	0.129	0.129	-0.003	0.207	0.194
Metso Outotec	-0.243	**1.396**	0.553	0.339	0.023	0.402	0.393
Neste	0.787	**0.881**	0.107	-0.092	-0.014	0.267	0.256
Nokia	-0.025	**0.809**	-0.538	-0.054	0.011	0.240	0.228
Nokian Renkaat	0.328	**1.069**	-0.494	0.145	**-0.081**	0.381	0.371
Nordea Bank	-0.256	**0.925**	-0.398	**0.606**	0.011	0.551	0.544
Orion b	-0.122	**0.431**	**-0.661**	**-0.465**	0.018	0.103	0.089
Outokumpu	-0.823	**1.341**	0.175	**0.893**	0.023	0.414	0.405
QT Group	**1.303**	**1.043**	**1.683**	**-1.097**	-0.019	0.258	0.246
Sampo a	0.165	**0.805**	-0.295	**0.433**	-0.001	0.563	0.556
SSAB b	-0.319	**1.101**	0.106	**0.471**	**0.031**	0.399	0.390
Stora Enso	-0.047	**0.927**	-0.186	0.242	0.007	0.385	0.375
Telia Company	0.338	**0.350**	**-1.088**	-0.008	-0.012	0.230	0.218
Tietoevry	0.231	**0.734**	0.267	0.000	-0.006	0.376	0.367
UPM-Kymmenen	0.251	**0.711**	-0.355	**0.263**	-0.002	0.368	0.358
Valmet	0.149	**0.787**	-0.227	-0.263	0.003	0.279	0.267
Wärtsilä	-0.537	**1.125**	0.215	**0.290**	0.011	0.471	0.463

FF3 + ΔGSV

	a	Mkt-RF	SMB	HML	DGSV	R^2	Adj R^2
Cargotec b	0.117	**1.266**	0.556	0.207	**0.143**	0.438	0.429
Elisa	0.190	**0.318**	**-0.961**	**-0.348**	**0.080**	0.200	0.187
Fortum	0.129	**0.797**	-0.516	0.277	0.002	0.283	0.272
Huhtamäki	0.023	**0.826**	-0.086	0.055	-0.003	0.341	0.331
Kesko b	0.304	**0.648**	-0.044	**-0.387**	0.008	0.241	0.229
Kone b	0.040	**0.549**	**-0.752**	**-0.621**	0.002	0.354	0.344
Konecranes	0.051	**1.216**	**0.636**	0.031	0.044	0.417	0.408
Metsä Board b	0.200	**0.696**	0.135	0.130	-0.002	0.206	0.194
Metso Outotec	0.301	**1.414**	0.638	0.309	0.049	0.403	0.394
Neste	0.425	**0.911**	0.111	-0.087	0.066	0.270	0.258
Nokia	0.117	**0.864**	-0.532	-0.112	**0.280**	0.342	0.332
Nokian Renkaat	-0.383	**1.014**	-0.491	0.202	**-0.148**	0.385	0.375
Nordea Bank	0.141	**0.918**	**-0.407**	**0.610**	-0.002	0.549	0.542
Orion b	0.288	**0.427**	**-0.648**	**-0.455**	-0.005	0.099	0.085
Outokumpu	0.030	**1.345**	0.303	**0.910**	**0.113**	0.432	0.423
QT Group	**1.014**	**1.049**	**1.718**	**-1.146**	0.040	0.259	0.247
Sampo a	0.142	**0.802**	-0.294	**0.434**	-0.005	0.563	0.557
SSAB b	0.285	**1.102**	0.028	**0.480**	**0.060**	0.397	0.388
Stora Enso	0.079	**0.925**	-0.181	0.243	-0.004	0.384	0.375
Telia Company	-0.043	**0.356**	**-1.115**	-0.038	0.020	0.222	0.210
Tietoevry	0.100	**0.735**	0.265	-0.007	0.001	0.375	0.365
UPM-Kymmenen	0.194	**0.716**	**-0.428**	**0.247**	**0.043**	0.380	0.371
Valmet	0.231	**0.786**	-0.221	-0.256	-0.005	0.278	0.267
Wärtsilä	-0.188	**1.118**	0.223	**0.298**	-0.012	0.469	0.461

FF3 + ΔGSV (t-1)

	a	Mkt-RF	SMB	HML	DGSV	R^2	Adj R^2
Cargotec b	0.102	**1.269**	0.577	0.228	-0.048	0.398	0.388
Elisa	0.190	**0.308**	**-0.961**	**-0.323**	-0.018	0.176	0.163
Fortum	0.139	**0.798**	-0.513	0.271	-0.061	0.288	0.276
Huhtamäki	0.040	**0.828**	-0.072	0.101	**-0.043**	0.359	0.349
Kesko b	0.306	**0.647**	-0.046	**-0.383**	-0.005	0.240	0.228
Kone b	0.035	**0.547**	**-0.748**	**-0.621**	0.003	0.353	0.343
Konecranes	0.034	**1.210**	**0.619**	0.045	-0.047	0.416	0.407
Metsä Board b	0.203	**0.699**	0.160	0.130	0.008	0.208	0.195
Metso Outotec	0.301	**1.404**	0.643	0.333	-0.026	0.399	0.389
Neste	0.445	**0.888**	0.070	-0.094	-0.041	0.269	0.257
Nokia	0.091	**0.814**	-0.506	-0.055	-0.050	0.241	0.229
Nokian Renkaat	-0.371	**1.063**	-0.492	0.210	0.039	0.354	0.344
Nordea Bank	0.144	**0.920**	**-0.408**	**0.609**	0.002	0.548	0.541
Orion b	0.270	**0.422**	**-0.664**	**-0.452**	0.019	0.100	0.086

Outokumpu	0.038	**1.362**	0.155	**0.952**	**-0.074**	0.417	0.408
QT Group	**0.991**	**1.038**	**1.709**	**-1.131**	-0.015	0.255	0.243
Sampo a	0.144	**0.810**	**-0.345**	**0.439**	-0.023	0.568	0.561
SSAB b	0.292	**1.080**	0.073	**0.518**	0.013	0.386	0.377
Stora Enso	0.078	**0.922**	-0.184	0.246	-0.007	0.384	0.374
Telia Company	-0.054	**0.351**	**-1.097**	-0.032	-0.006	0.219	0.207
Tietoevry	0.101	**0.734**	0.271	-0.005	-0.008	0.374	0.365
UPM-Kymmenen	0.198	**0.713**	-0.349	**0.261**	0.009	0.368	0.358
Valmet	0.221	**0.788**	-0.211	-0.263	0.022	0.278	0.267
Wärtsilä	-0.205	**1.123**	0.227	**0.296**	0.027	0.470	0.462

FF3 + ΔGSV (t+1)

	a	Mkt-RF	SMB	HML	DGSV	R^2	Adj R^2
Cargotec b	0.121	**1.238**	0.577	0.200	**-0.096**	0.414	0.405
Elisa	0.188	**0.312**	**-0.977**	**-0.333**	-0.027	0.178	0.165
Fortum	0.164	**0.814**	-0.541	0.301	**-0.186**	0.332	0.322
Huhtamäki	0.023	**0.826**	-0.074	0.052	-0.009	0.342	0.331
Kesko b	0.304	**0.646**	-0.051	**-0.383**	0.013	0.242	0.230
Kone b	0.040	**0.550**	**-0.751**	**-0.622**	-0.012	0.354	0.344
Konecranes	0.050	**1.212**	0.600	0.051	0.003	0.412	0.403
Metsä Board b	0.200	**0.700**	0.132	0.130	-0.007	0.207	0.195
Metso Outotec	0.308	**1.398**	0.664	0.323	-0.034	0.401	0.392
Neste	0.430	**0.880**	0.128	-0.085	-0.032	0.266	0.254
Nokia	0.098	**0.813**	-0.517	-0.067	-0.060	0.244	0.232
Nokian Renkaat	-0.364	**1.051**	-0.364	0.235	0.079	0.361	0.351
Nordea Bank	0.142	**0.919**	**-0.407**	**0.610**	0.002	0.549	0.542
Orion b	0.287	**0.427**	**-0.644**	**-0.463**	0.009	0.099	0.085
Outokumpu	0.032	**1.341**	0.215	**0.915**	-0.010	0.407	0.398
QT Group	**1.017**	**1.042**	**1.698**	**-1.128**	0.011	0.256	0.244
Sampo a	0.142	**0.806**	-0.288	**0.418**	-0.020	0.567	0.560
SSAB b	0.290	**1.096**	0.003	**0.496**	-0.040	0.391	0.382
Stora Enso	0.079	**0.925**	-0.184	0.242	0.004	0.384	0.375
Telia Company	-0.043	**0.353**	**-1.088**	-0.030	0.020	0.222	0.210
Tietoevry	0.100	**0.735**	0.265	-0.006	-0.002	0.375	0.365
UPM-Kymmenen	0.195	**0.719**	-0.408	**0.243**	**-0.038**	0.378	0.368
Valmet	0.231	**0.787**	-0.235	-0.253	-0.032	0.281	0.270
Wärtsilä	-0.190	**1.121**	0.216	**0.292**	0.007	0.469	0.461

FF3 + AGSV

	a	Mkt-RF	SMB	HML	AGSV	R^2	Adj R^2
Cargotec b	0.043	**1.277**	0.626	0.228	**0.148**	0.432	0.422
Elisa	0.162	**0.315**	**-1.013**	**-0.341**	0.034	0.192	0.179
Fortum	0.098	**0.804**	-0.530	0.267	0.014	0.280	0.268
Huhtamäki	0.053	**0.834**	-0.080	0.063	-0.003	0.342	0.331
Kesko b	0.284	**0.661**	-0.064	**-0.389**	-0.004	0.246	0.234
Kone b	0.054	**0.538**	**-0.735**	**-0.608**	-0.017	0.351	0.340
Konecranes	0.086	**1.193**	**0.657**	0.061	0.035	0.405	0.395
Metsä Board b	0.219	**0.687**	0.124	0.125	-0.016	0.205	0.193
Metso Outotec	0.275	**1.436**	0.621	0.329	0.017	0.411	0.401
Neste	0.378	**0.925**	0.107	-0.081	0.030	0.285	0.274
Nokia	-0.022	**0.859**	**-0.645**	-0.097	**0.189**	0.307	0.296
Nokian Renkaat	-0.374	**1.064**	-0.463	0.207	-0.026	0.353	0.343
Nordea Bank	0.164	**0.928**	-0.405	**0.613**	0.000	0.550	0.543
Orion b	0.340	**0.389**	-0.563	**-0.419**	0.015	0.085	0.071
Outokumpu	0.035	**1.328**	0.348	**0.872**	**0.081**	0.423	0.414
QT Group	**0.982**	**1.060**	**1.716**	**-1.164**	0.046	0.262	0.251
Sampo a	0.161	**0.808**	-0.297	**0.445**	-0.013	0.567	0.560
SSAB b	0.257	**1.082**	-0.018	**0.464**	**0.070**	0.398	0.389
Stora Enso	0.100	**0.919**	-0.165	0.256	-0.020	0.383	0.373
Telia Company	-0.052	**0.340**	**-1.121**	-0.044	0.019	0.217	0.205
Tietoevry	0.069	**0.746**	0.250	-0.009	-0.004	0.381	0.371
UPM-Kymmenen	0.157	**0.721**	-0.376	**0.251**	**0.046**	0.381	0.371
Valmet	0.212	**0.779**	-0.252	-0.282	0.023	0.272	0.261
Wärtsilä	-0.227	**1.143**	0.197	**0.306**	-0.018	0.489	0.481

FF3 + AGSV (t-1)

	a	Mkt-RF	SMB	HML	AGSV	R^2	Adj R^2
Cargotec b	0.183	**1.292**	0.581	0.214	-0.081	0.410	0.400
Elisa	0.159	**0.307**	**-0.983**	**-0.325**	-0.034	0.188	0.175
Fortum	0.078	**0.795**	-0.524	0.273	0.027	0.278	0.266
Huhtamäki	0.031	**0.820**	-0.067	0.075	0.001	0.336	0.326
Kesko b	0.299	**0.671**	-0.042	**-0.394**	-0.019	0.252	0.240
Kone b	0.040	**0.530**	**-0.749**	**-0.601**	-0.019	0.344	0.333
Konecranes	0.068	**1.196**	**0.637**	0.044	-0.027	0.403	0.393
Metsä Board b	0.208	**0.692**	0.120	0.129	-0.005	0.200	0.188
Metso Outotec	0.326	**1.436**	0.596	0.336	-0.039	0.410	0.400
Neste	0.394	**0.920**	0.098	-0.086	0.021	0.285	0.273
Nokia	0.064	**0.857**	-0.551	-0.040	**-0.120**	0.277	0.266
Nokian Renkaat	-0.384	**1.072**	-0.449	0.213	0.008	0.348	0.338
Nordea Bank	0.170	**0.932**	**-0.408**	**0.609**	0.001	0.550	0.543
Orion b	0.350	**0.378**	-0.535	**-0.428**	-0.021	0.085	0.070

Outokumpu	0.143	**1.351**	0.274	**0.947**	-0.040	0.414	0.405
QT Group	**1.063**	**1.067**	**1.726**	**-1.121**	-0.025	0.262	0.250
Sampo a	0.154	**0.817**	-0.298	**0.442**	-0.009	0.565	0.558
SSAB b	0.278	**1.074**	0.054	**0.512**	0.015	0.381	0.371
Stora Enso	0.067	**0.909**	-0.162	0.269	-0.011	0.377	0.367
Telia Company	-0.067	**0.334**	**-1.111**	-0.023	-0.014	0.213	0.200
Tietoevry	0.061	**0.743**	0.255	-0.005	-0.003	0.377	0.367
UPM-Kymmenen	0.179	**0.705**	-0.339	**0.280**	-0.001	0.363	0.353
Valmet	0.208	**0.781**	-0.231	-0.273	0.034	0.271	0.259
Wärtsilä	-0.236	**1.148**	0.216	**0.306**	-0.001	0.485	0.477

FF3 + AGSV (t+1)

	a	Mkt-RF	SMB	HML	Ab.GSV	R^2	Adj R^2
Cargotec b	0.144	**1.276**	0.637	0.234	0.001	0.401	0.391
Elisa	0.152	**0.317**	**-1.009**	**-0.340**	0.018	0.195	0.182
Fortum	0.280	**0.754**	**-0.612**	0.292	**-0.176**	0.335	0.324
Huhtamäki	0.055	**0.833**	-0.075	0.062	-0.004	0.345	0.335
Kesko b	0.305	**0.647**	-0.057	**-0.384**	0.017	0.241	0.229
Kone b	0.032	**0.555**	**-0.755**	**-0.617**	-0.028	0.364	0.354
Konecranes	0.066	**1.221**	0.615	0.056	0.039	0.413	0.404
Metsä Board b	0.215	**0.700**	0.115	0.125	-0.023	0.214	0.201
Metso Outotec	0.369	**1.401**	0.664	0.342	-0.029	0.403	0.394
Neste	0.427	**0.899**	0.126	-0.071	0.020	0.270	0.258
Nokia	0.024	**0.826**	**-0.621**	-0.044	**0.120**	0.277	0.265
Nokian Renkaat	-0.369	**1.062**	-0.445	0.215	-0.003	0.349	0.339
Nordea Bank	0.166	**0.927**	-0.397	**0.617**	0.014	0.553	0.546
Orion b	0.276	**0.429**	-0.610	**-0.449**	0.014	0.098	0.084
Outokumpu	0.066	**1.326**	0.274	**0.910**	0.056	0.416	0.407
QT Group	**0.982**	**1.032**	**1.682**	**-1.142**	0.057	0.265	0.254
Sampo a	0.190	**0.799**	-0.300	**0.434**	**-0.028**	0.576	0.569
SSAB b	0.288	**1.073**	0.088	**0.509**	0.024	0.387	0.377
Stora Enso	0.082	**0.929**	-0.169	0.251	-0.007	0.387	0.377
Telia Company	-0.070	**0.358**	**-1.137**	-0.047	0.045	0.234	0.222
Tietoevry	0.084	**0.738**	0.256	-0.002	-0.007	0.379	0.369
UPM-Kymmenen	0.179	**0.719**	-0.347	**0.269**	0.006	0.375	0.365
Valmet	0.208	**0.781**	-0.253	-0.263	-0.020	0.278	0.266
Wärtsilä	-0.208	**1.137**	0.230	**0.307**	0.002	0.484	0.476