

GOOGLE SEARCH VOLUME'S ABILITY TO EXPLAIN  
MARKET ACTIVITY OF PRECIOUS METAL ETFS IN THE  
US MARKET

Bachelor's Thesis  
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Finance  
Summer 2021

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<b>Title of thesis</b> Google search volume's ability to explain market activity of precious metal ETFs in the US market		
<b>Degree</b> Bachelor's degree		
<b>Degree programme</b> Finance		
<b>Thesis advisor(s)</b> Juha Joenväärä		
<b>Year of approval</b> 2021	<b>Number of pages</b> 32	<b>Language</b> English

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**Abstract**

Investor attention and its reflection to the stock market is a popular research topic in finance. One of the proxies for measuring this attention among retail investors is Google search volume, or more specifically a standardized figure provided by Google, a Google search volume index (GSVI). Unique features of GSVI include its direct nature and the popularity of Google among the common public.

The GSVI's ability to capture retail investor attention has been excessively studied in the stock market, but the research has not reached the commodity market to a large extent. Precious metals represent a commodity class, especially interesting during the COVID-19 pandemic due to the safe haven nature associated with them. Literature concerning GSVI in relation to precious metal exchange traded funds (ETFs) has so far been non existing.

This thesis contributes to the existing literature by studying Google search volume index's ability to explain market activity within the US precious metal ETF market, thus extending the GSVI literature to precious metal ETFs. More specifically, it is tested if GSVI has explanatory power over trading volume and total return index of selected precious metal ETFs. In addition, gold and silver ETFs are studied separately to spot differences between the metals. Special focus is given to silver ETFs due to the GME short squeeze in the beginning of 2021 and its attempted extension to the silver market. The research sample consist of 19 precious metal ETFs studied between 19.8.2018–31.5.2021 and analyzed with panel regressions.

To summarize the results, it is found out that GSVI has very high statistically significant explanatory power over both, trading volume and total return index. In addition, GSVI has a stronger effect on silver ETFs' trading volume, but a lower effect on silver ETFs' return index compared with the results obtained with all studied precious metal ETFs. This study opens the research on GSVI's explanatory power over precious metal ETFs in the US market, leaving multiple avenues for extended research in the future.

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**Keywords** Google search volume index, precious metals, ETFs, investor attention, attention theory, gold, silver

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# 1 Introduction

The financial research community has been increasingly interested in ways to measure investor attention and its reflection to the stock market. Although the efficient market hypothesis (EMH) states that market prices reflect all available information (Fama 1965), challenging arguments have been presented regarding the role of investor attention and its limitedness (Kahneman 1973, Merton 1987). Together with the interest towards measuring investor attention, a demand for efficient proxies has risen. The applied proxies have included e.g. the number of news articles and Wikipedia sites but with the rise of social media, new sources for these proxies have been found including for example Twitter and Google Trends.

Google is a quick and free of charge platform easily accessible by the general population. Google's worldwide market share within search engines such as Bing, Yahoo! and Baidu is approximately 90 % (Statcounter, 2021). Due to Google's popularity the quantity of Google searches has gained attention as a measure for investor interest. In fact, a variety of research exists on Google search volume's ability to explain and predict stock market activity, e.g. by Da, Engelberg & Gao (2011); Swamy, Dharani & Takeda (2019); Swamy, Dharani (2019) and Xu, Xuan & Zheng (2021), to name a few. Besides stock, the research has been applied to different commodities such as corn, oil and precious metals to some extent (Rao, Srivastava 2013; Ji, Guo 2015; Han, Lv & Yin 2017; Jain, Biswal 2019; Prange 2021).

Precious metals represent a commodity class that includes metals such as gold, silver, platinum and palladium. Investors can hold precious metals by purchasing the physical metals, related exchange traded funds (ETFs) or mutual funds, precious metal derivatives or by holding the shares of miner companies. Precious metals tend to serve investors as a safe haven in times of uncertainty (Li, Lucey 2017). The uncertainty caused by the global COVID-19 pandemic has been reflected to the pricing and volatility of precious metals (Umar, Aziz & Tawil 2021; Rajput et al. 2020).

So far there has been a variety of research on Google search volume index (GSVI) and its reflection to the stock market whereas research concerning commodities or ETFs has been limited, and research specifically on precious metal ETFs non existing. This thesis contributes to the existing literature by expanding the research on GSVI to precious metal ETFs in the US market. More specifically, the relationship between GSVI and the

trading volumes and returns of precious metal ETFs during the COVID-19 pandemic are studied. The research focuses on the US market as the availability of precious metal ETFs within Finland is limited and the GSVI can only be filtered within country level i.e. combined searches within Europe cannot be accessed. The precious metals included are gold, silver, platinum and palladium. The studied time period was chosen to be three years, due to the availability of data and timing of the COVID-19 pandemic. The pandemic provides a unique research setup as the number of publications from the time of the pandemic is still limited and especially precious metal market is likely to be affected by the COVID-19 outbreak.

The results of this thesis show that GSVI is able to explain trading volume and total return index with very high statistical significance in the precious metal ETF market within US. In addition, some metal specific differences are found as gold and silver ETFs are studied separately. It is shown that with silver ETFs an increase in GSVI has a stronger effect on trading volume but a weaker effect on total return index, compared with other metal ETFs. All in all, it is shown that besides the stock market GSVI can be utilized as a proxy for investor attention in a commodity ETF market as well.

This thesis answers the research question “does GSVI of precious metal ETFs capture investor attention in the US market?” The structure is as follows. The thesis begins with brief reviews of the existing literature on GSVI as a proxy for investor attention and precious metals as an investment class in chapter 2. The literature review is followed by the experimental part including an introduction of the used data and methods in chapters 3 and 4, respectively. The results found are presented in chapter 5. Chapter 6 ends the thesis with a discussion and conclusion.

## **2 Literature review and hypothesis**

The following sections provide a brief literature review on attention theory, used proxies for investor attention and especially GSVI as an attention proxy in section 2.1. Section 2.2. introduces precious metals as an investment class, focusing on the supply and demand aspects and the diversification, hedging and safe haven properties of the metals. The three main hypotheses tested in this thesis are presented in section 2.3.

### **2.1 The role and proxies for investor attention**

A challenging theory for the efficient market hypothesis has been introduced by Barber and Odean (2008) in the form of “price pressure hypothesis” also known as the “attention theory”. According to the attention theory retail investors are more likely to buy stocks that have caught their attention as their resources to examine all available stocks are limited. However, when selling stocks retail investors do not face the same problem with limited attention as they tend to sell the stocks already included in their portfolio, thus already acknowledged. As a result, the stocks gaining individual investors’ attention are more likely to have larger trading volumes and excess returns.

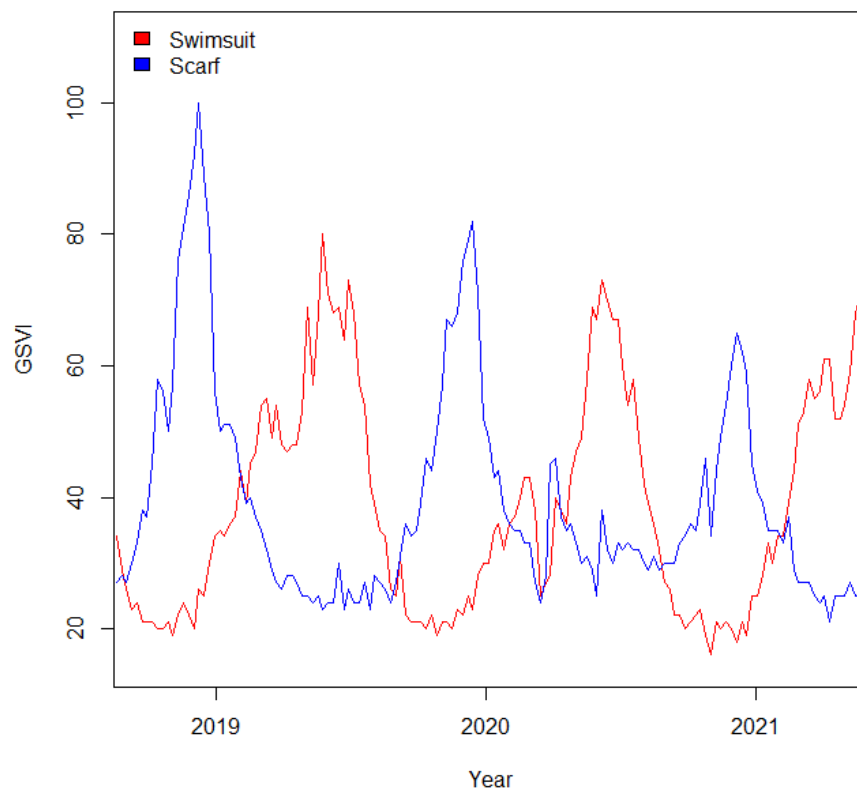
The proxies used for measuring investor attention through internet sources have been recently reviewed by Agarwal, Kumar & Goel (2019). The internet sources for attention data can be divided into two categories, internet news and social media. Within the internet news either the quality or quantity of the published news articles can be studied. In the case of quality i.e. content studies, text processing techniques can be used to determine whether the news is positive, negative or neutral, thus focusing on investor sentiment and its reflection to the stock market. In the quantity studies the number of published news can be used as a proxy for investor attention. Data sources within social media can be roughly divided into four groups: internet stock message boards, Twitter, Facebook and internet search volumes.

#### **2.1.1 Search volume indices as investor attention proxies**

The first study focusing on internet search volume as a proxy for investor attention was conducted by Mondria, Wu & Zhang (2010). They used the number of clicks on queries conducted through American Online (AOL), an US based internet search platform, as the attention proxy for equity investments to foreign countries by US investors. First Google based study on internet search volume as an attention proxy was introduced by

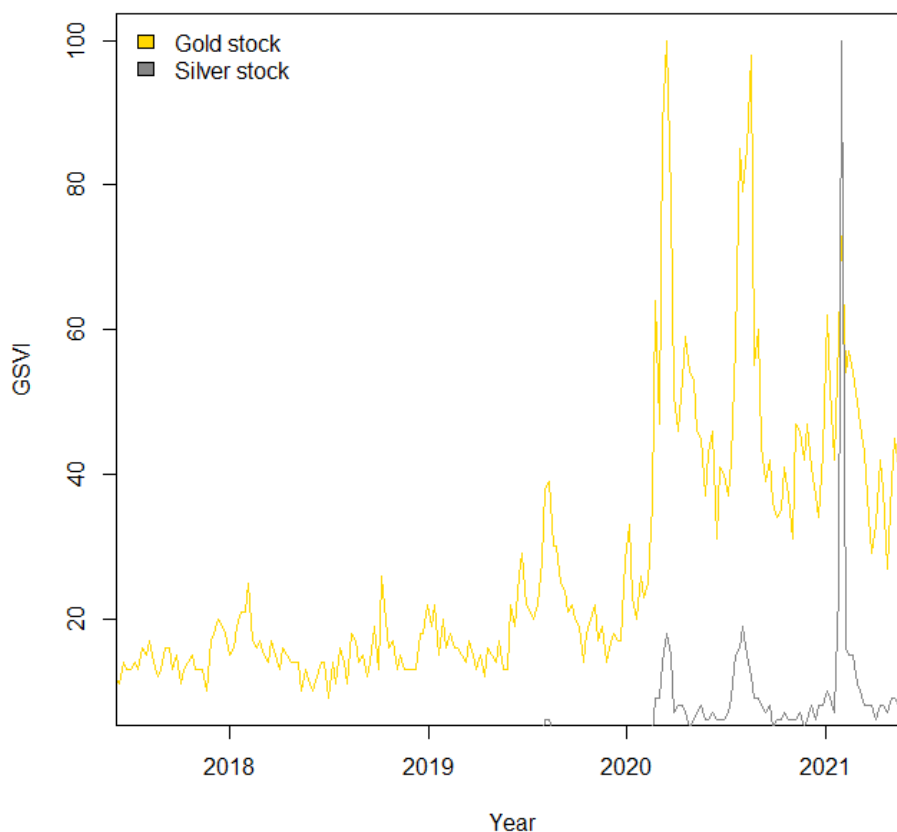
Da, Engelberg & Gao (2011). In their study Da et al. showed that GSVI is a better proxy for investor attention than trading volume, excess returns or news coverage. In addition, they showed that the GSVI is likely to measure the attention of retail investors. They also tested the attention theory and found out that an increase in GSVI predicted an increase in stock prices for the following two weeks and a price reversal within a year.

One especially novel feature of GSVI as an attention proxy is its direct nature. When an investor conducts a Google search, it is evident that he or she pays attention to the searched object. This is not the case when using indirect attention proxies such as the number of news articles, as the investors are not likely to read all the published articles. In addition to the direct nature of GSVI, one additional advantage is Google’s popularity. In the US market Google’s market share is 89 % (Statcounter, 2021). Google’s ability to grab attention is demonstrated in Figures 1 and 2. Figure 1 demonstrates how GSVI changes with searches that are intuitively seasonal. Swimsuits attract more search interest during summer season and scarfs during winter season. Figure 2 demonstrates search activity more relevant to this thesis, i.e. the searches for “gold stock” and “silver stock”.



**Figure 1.** Google search volume index for “swimsuit” and “scarf”. The word swimsuit is searched in the middle of the year during summer season and scarf at the end of the year during winter season.





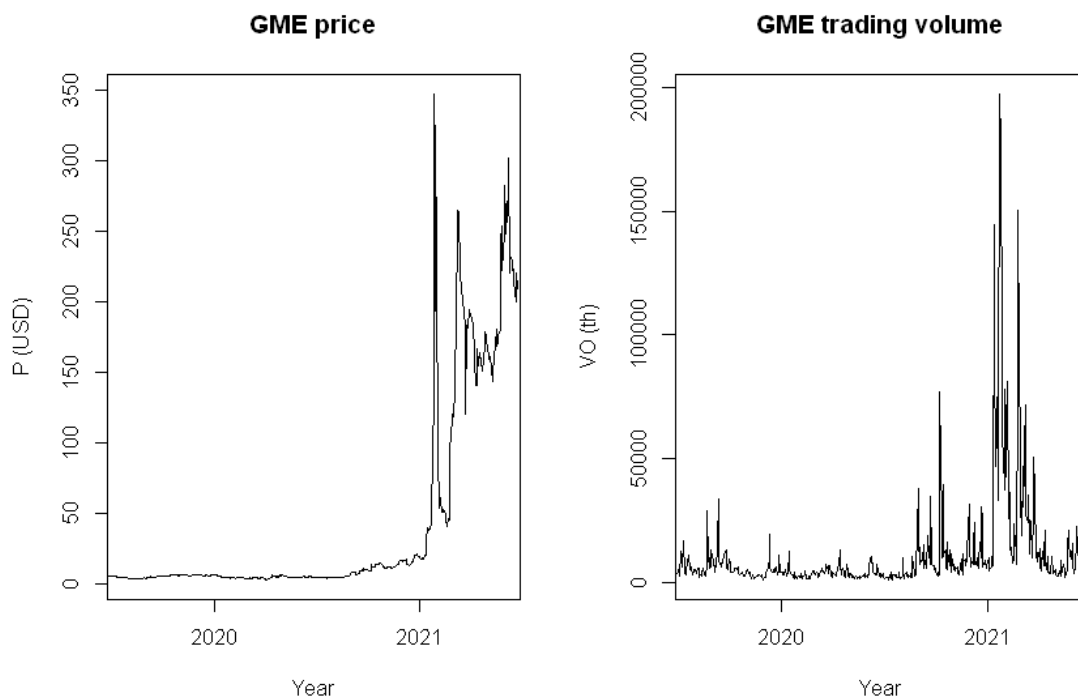
**Figure 2.** Google search volume index for “gold stock” and “silver stock” queries between 2018 and 2021.

### 2.1.2 Retail investors’ ability to affect the stock market – the GameStop short squeeze

One historically exceptional phenomenon initiated by retail investors through social media was witnessed in early 2021. Retail investor discussion through a social media platform, a Reddit cite [r/wallstreetbets](#), initiated a GameStop (ticker GME) short squeeze. A short squeeze occurs when a stock with a significant amount of short position holders unexpectedly and rapidly rises in price. The short sellers realize losses as they are obligated to buy the underlying stock to cover their short positions.

Reddit is an American social news website consisting of “subreddits” i.e. discussion platforms focusing on different topics. The short squeeze of GME was initiated through the [r/wallstreetbets](#) forum, a subreddit focusing on stock and option trading discussions. GameStop is an American video game retailer, operating mainly through physical videogame stores, thus suffering due to both, digitalization of gaming and the COVID-19 restrictions, making the stock appealing for short selling.

The idea behind the GME short squeeze was to induce excessive buying of GameStop shares by retail investors, to cause losses to major hedge funds holding the short positions. Other stocks besides GameStop such as AMC Entertainment Holdings, BlackBerry, Koss Corporation, Nokia and Eastman Kodak were included in the phenomenon as well. The short squeeze resulted in a significant increase in trading volume and stock price of GME (Figure 3). This eventually resulted in discontinued trading of GME, AMC, BlackBerry and Nokia on 28.1.2021 by Robinhood, one of the major online brokerages through which the short squeeze was executed.



**Figure 3.** Effect of GameStop short squeeze in January 2021 on the GME stock price and trading volume.

It has been analyzed that the COVID-19 pandemic and the impoverishment and misery it has brought to the general public was one of the motivators behind the sabotage towards Wall Street (Chohan 2021). After the GameStop short squeeze started to wear off, retail investors' attention was transferred to silver with similar attempt. However, the silver short squeeze by the Reddit community was not successful due to the larger, more liquid and more complex market with a lack of excessive short positioning. Nevertheless, the attention paid to silver through social media temporarily lifted the price to an eight-year high, 30 USD/oz. (Westbrook et al. 2021)

## 2.2 Precious metals as an investment class

The term precious metal is used for naturally occurring metallic elements that are rare and have high economic value. The best known precious metal is gold, but other precious metals, especially silver but also platinum and palladium are well known as well. These metals hold intrinsic value, which explains why they are considered a good store of value. Besides investment use, precious metals are used for example in jewelry and industrial applications.

### 2.2.1 Demand and pricing of gold, silver, platinum and palladium

Gold represents a precious metal that holds significant investment value for both individual and institutional investors. In addition to the investment value, gold has industrial and jewelry usage. It is approximated that the already mined, above ground stock of gold is around 200 000 tons. From this approximately 46 % is bound in jewelry, 22 % in private investments, 17 % in official holdings and 15 % in other usages. The main industrial uses for gold are electronics and dentistry. Typical forms of gold investments are gold bars, coins and ETFs. (World Gold Council, 2021)

One unique feature of gold is its popularity in government reserves. As stated above, approximately 17 % of world's all gold is tied in central banks' gold reserves. The top six largest governmental gold holders are presented in Table 1. As can be seen from the table, the US reserve of gold is significant compared to the others. Also, almost 80 % of the US' total reserve is stored as gold. The world's largest miner countries for gold in 2020 were China, Russia and Australia. (World Gold Council, 2021)

**Table 1.** Six largest gold reserves by country. Total holdings % describes gold's percentage of the total holdings of the government reserve.

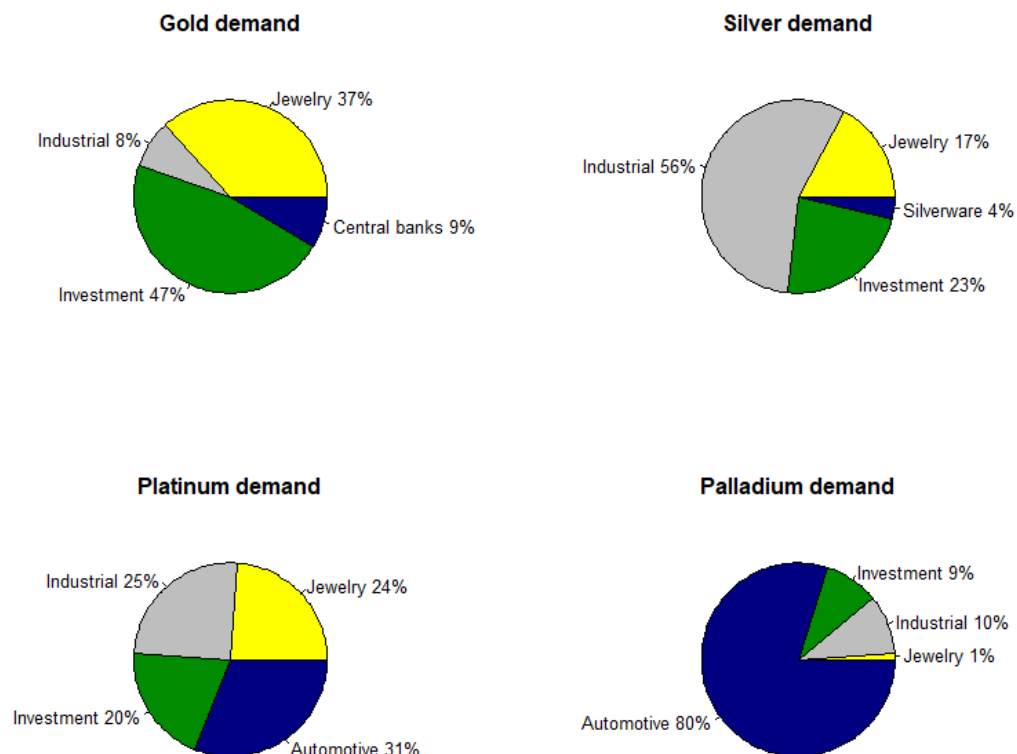
Country	Gold Reserves (1 000 k)	Gold Reserves (MUSD)	Total holdings %
US	8 100	494 000	79
Germany	3 400	204 000	76
Italy	2 500	149 000	71
France	2 400	148 000	66
Russia	2 300	139 000	23
China	1 900	118 000	4

Similarly to gold, also silver has demand in both, as an investment and in industrial use. The typical investment forms for silver are the same as with gold, coins and bullion. Industrial usages for silver include e.g. electronics, brazing alloys and photovoltaics. In addition, silver is used in jewelry and silverware. As with gold, government reserves include silver as well, but in smaller values. In 2020 the world's largest silver producers were Mexico, Peru and China. (Silver Institute, 2021)

One of the main applications for platinum is automotive catalysis. In addition to this, platinum is used in industrial and medical applications, jewelry and as an investment. The investment usage of platinum is more scarce than with gold and silver, and it can be speculated whether platinum should trade as a precious or industrial metal. The world's largest platinum producers in 2020 were South Africa, Russia, Zimbabwe and Canada. (World Platinum Investment Council, 2021)

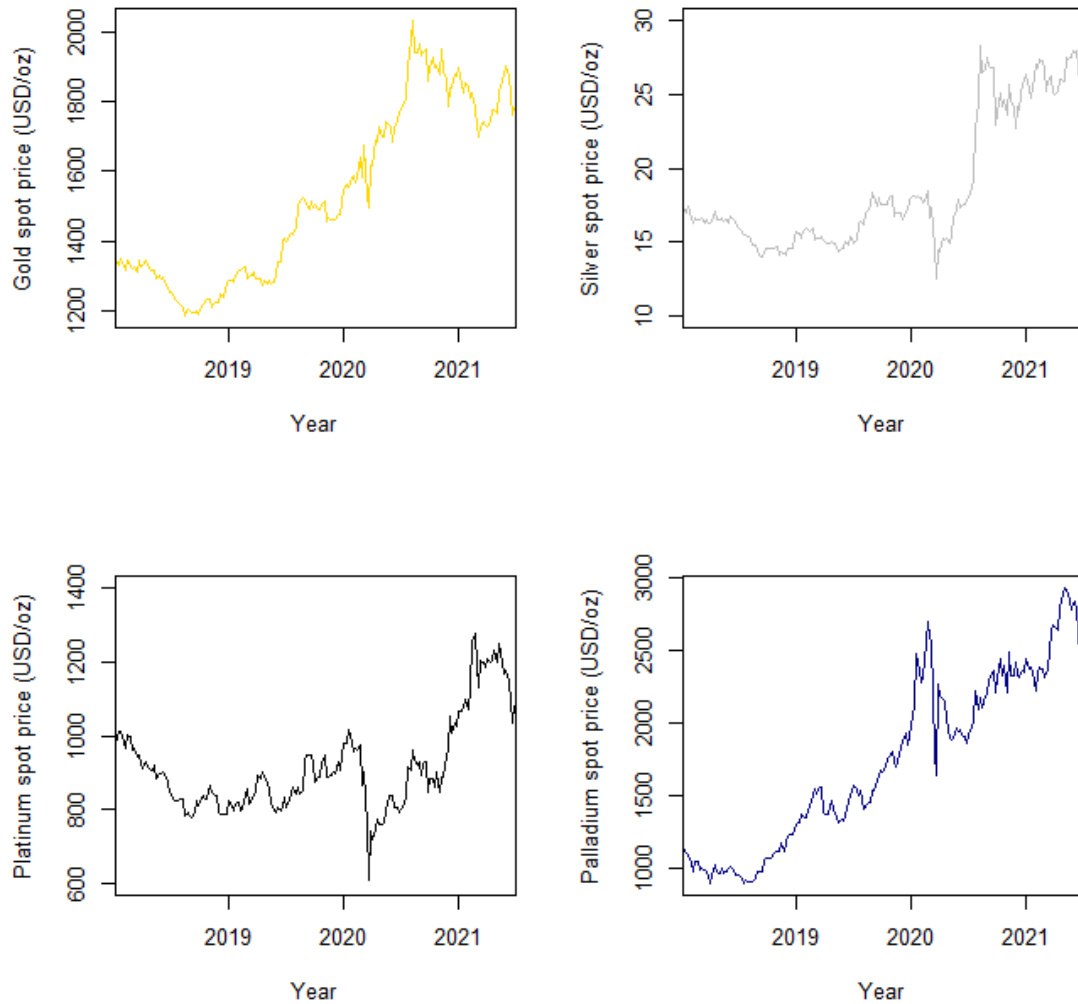
As with platinum, the automotive catalysis is also the main application for palladium. However, with palladium the automotive industry takes up to 80 % of the total demand, corresponding figure for platinum being approximately 30 %. In addition to the automotive applications, palladium is used in electronics, dentistry and jewelry. The world's largest producers of palladium in 2020 were Russia and South Africa.

As discussed in the previous paragraphs, all four precious metals are held as investments by retail investors, which implies that their price movements are affected by retail investor sentiment. This applies especially to gold, which is the best acknowledged investment class metal. Pricing of platinum and palladium is more dependent on the economy due to the high demand for automotive and other industrial applications. However, also these two have demand as investments. The demand for each of the four discussed precious metals is summarized in Figure 4.



**Figure 4.** Precious metal demand in 2020. Sources for the data: World Gold Council, Silver Institute, World Platinum Investment Council and Sprott USA (2021).

The spot prices of precious metals from 2018 to June 2021 are collected in Figure 5. The pricing of the metals is closely linked to their rareness. It can be seen from the graphs that pricing of silver is lower than the rest of the metals.



**Figure 5.** Spot prices for the studied precious metals. Prices are expressed as USD/oz. One oz converts to approximately 28 g. Source: Refinitiv Eikon, Multi-Contributor spot prices of XAU, XAG, XPT and XPD.

### 2.2.2 Precious metals as a safe haven investment

The diversification, hedging and safe haven properties of precious metals have gained research and investor attention especially after the financial crisis. As defined by Baur and Lucey (2010) a diversifier is “an asset that is positively (but not perfectly correlated) with another asset or portfolio on average”. A hedge is “an asset that is uncorrelated or negatively correlated with another asset or portfolio on average”. Whereas a safe haven instrument is “an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil”. In their study Baur and Lucey show that gold is a hedge and short term safe haven for stocks, but not for bonds.

The diversification, hedging and safe haven aspects of assets are important for investors that aim to reduce risk in their investment portfolios. When assets included within a portfolio are not perfectly correlated, they respond differently to market influences i.e. the negative performance of one investment can be compensated with a positive performance of another investment thus enhancing the performance of the whole portfolio. The safe haven property of an investment class is especially valuable in times of market stress, caused by e.g. the financial crisis or the more recent COVID-19 pandemic.

The safe haven property of precious metals and the related literature has been recently studied and reviewed by Ali et al. (2020) and Talbi et al. (2021). The safe haven property is most extensively studied with gold, but also silver, platinum and palladium are included in some studies (Li, Lucey 2017; Ali et al. 2020). According to the reviews, the more recent studies are in line with the previous literature on that gold expresses the strongest safe haven properties among the precious metals. However, also silver, platinum and palladium are considered safe havens in some markets. It is worth noticing that the results differ between markets and especially emerging and developed stock markets may express different results.

As gold and potentially also the other three precious metals are recognized as safe haven investments, changes in their trading activity and volatility should be expected during economic distress. In addition, as gold and the other three precious metals are owned by retail investors, it can be expected that retail investor sentiment potentially affects the demand and pricing of the metals.

## 2.3 Hypothesis

The first two hypotheses concern GSVI in relation to stock market variables in the US market. As GSVI is considered as a proxy for investor attention, it can be used to explain increases in ETF trading activity and returns. Retail investors can be expected to be more active in trading assets that they have been paying attention to. Also, attention towards the ETFs can be reflected to their returns. In addition to investigating how efficiently GSVI can explain the trading volume and return changes, special attention is paid to the silver ETFs with the third hypothesis. This is due to the social media induced buying spree of silver after the GameStop short squeeze discussed in subsection 2.1.2. It is tested whether the results are more strongly detected with silver ETFs due to the Reddit effect. The hypothesis is described in detail in Table 2.

**Table 2.** The three main hypotheses tested in this thesis, first two related to GSVI and market variables and the third one on silver ETFs in relation to other precious metal ETFs.

No.	The hypothesis
H1	Increase in GSVI of an ETF ticker increases the trading volume of the corresponding ETF.
H2	Increase in GSVI of an ETF ticker increases the return of the corresponding ETF in a short term.
H3	The effects described in H1 and H2 are stronger with silver ETFs.



### **3 Data**

This chapter presents the data and sample used to answer the research questions of this thesis. Formation and selection criteria for the sample used in this study is presented in section 3.1. followed by the introduction of the GSVI data obtained from Google Trends and stock market data obtained from Eikon Datastream in sections 3.2. and 3.3. respectively. Variable definitions and summary statistics are provided in section 3.4.

#### **3.1 Sample**

The initial sample for this study was gathered with the help of ETF database's precious metal ETF listing (<https://etfdb.com/etfs/natural-resources/precious-metals/>) and consisted of 28 precious metal ETFs. The list was extended with GDX and GDXJ ETFs to increase the sample size. From the initial sample of 30 ETFs, nine were excluded due to the lack of sufficient search data in Google Trends. In addition, one ETF was excluded as market data was not available in Datastream and one due to a late establishment year at the beginning of 2021. Thus, the remaining sample consisted of 19 precious metal ETFs. The initial sample is presented in detail in Appendix 1. The remaining 19 ETFs used as the study sample are presented in Table 3. ETFs with noisy tickers, i.e. such tickers that can be confused to mean something else than the ETF (BAR for example), are marked with an asterisk. The defined search term is the one used to obtain the GSVI from Google Trends.

**Table 3.** The selected ETFs used as the study sample with related information. PCQ = Nyse Arca Consolidated, BTQ = Cboe Consolidated.

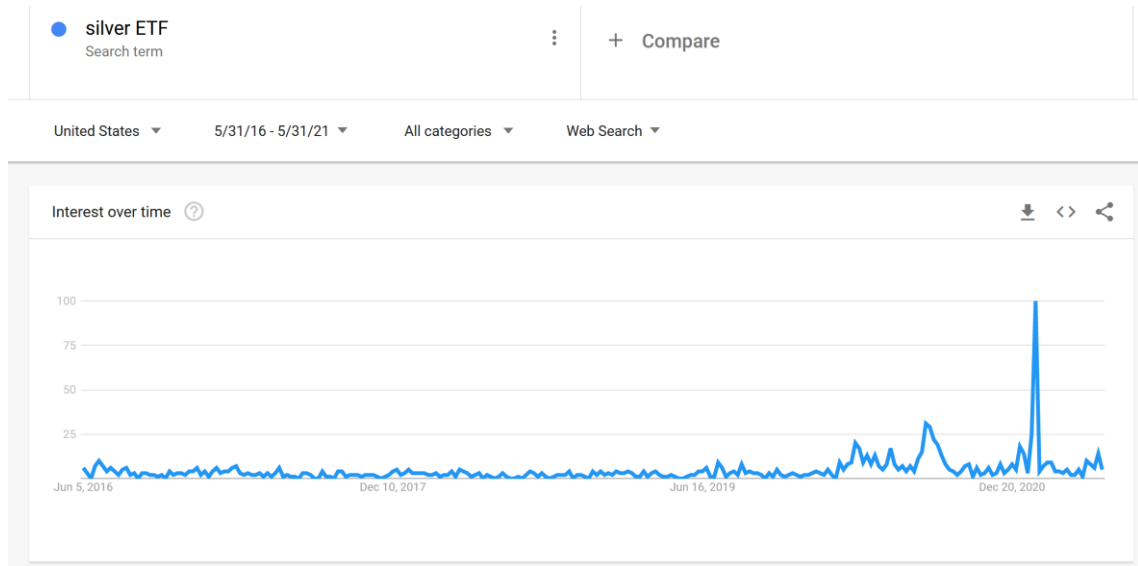
Ticker	ETF name	Noisy	Search term	Exchange	Market cap (MUSD)	Target metal	Instrument type	Currency
AAAU	Goldman Sachs Physical Gold ETF		AAAU	PCQ	376	Gold	Commodity ETFs	USD
AGQ	ProShares Ultra Silver		AGQ	PCQ	736	Silver	Commodity ETFs	USD
DBS	Invesco DB Silver Fund	*	DBS ETF	PCQ	27	Silver	Commodity ETFs	USD
DGL	Invesco DB Gold Fund	*	Invesco Gold Fund	PCQ	103	Gold	Commodity ETFs	USD
GDX	VanEck Vectors Gold Miners ETF		GDX ETF	PCQ	16 692	Gold	Equity ETFs	USD
GDXJ	VanEck Vectors Junior Gold Miners ETF		GDXJ Gold	PCQ	5 983	Gold	Equity ETFs	USD
GLD	SPDR Gold Shares		GLD ETF	PCQ	63 038	Gold	Commodity ETFs	USD
GLDM	SPDR Gold MiniShares Trust		GLDM	PCQ	4 574	Gold	Commodity ETFs	USD
GLTR	Aberdeen Standard Physical Precious Metals Basket Shares ETF		GLTR ETF	PCQ	1 057	All	Commodity ETFs	USD
IAU	iShares Gold Trust	*	IAU ETF	PCQ	30 358	Gold	Commodity ETFs	USD
IAUF	iShares Gold Strategy ETF		IAUF	BTQ	26	Gold	Equity ETFs	USD
OUNZ	VanEck Merk Gold Trust		OUNZ	PCQ	505	Gold	Commodity ETFs	USD
PALL	Aberdeen Standard Physical Palladium Shares ETF	*	PALL	PCQ	461	Palladium	Commodity ETFs	USD
PLTM	GraniteShares Platinum Trust		PLTM	PCQ	41	Platinum	Commodity ETFs	USD
PPLT	Aberdeen Standard Physical Platinum Shares ETF		PPLT	PCQ	1456	Platinum	Commodity ETFs	USD
SGOL	Aberdeen Standard Physical Gold Shares ETF		SGOL	PCQ	2 513	Gold	Commodity ETFs	USD
SIVR	Aberdeen Standard Physical Silver Shares ETF		SIVR	PCQ	1 123	Silver	Commodity ETFs	USD
SLV	iShares Silver Trust		SLV	PCQ	16 063	Silver	Commodity ETFs	USD
UGL	ProShares Ultra Gold	*	UGL ETF	PCQ	258	Gold	Commodity ETFs	USD

The studied time period was chosen to be 19.8.2018–31.5.2021 as a three-year time period was targeted and three of the 19 ETFs lacked data between 31.5.2019–18.8.2018. The time period was chosen to be rather narrow due to availability of the data and as the COVID-19 pandemic started at the beginning of year 2020 and this study focuses especially on the time of the pandemic.

### **3.2 Google search volume index data**

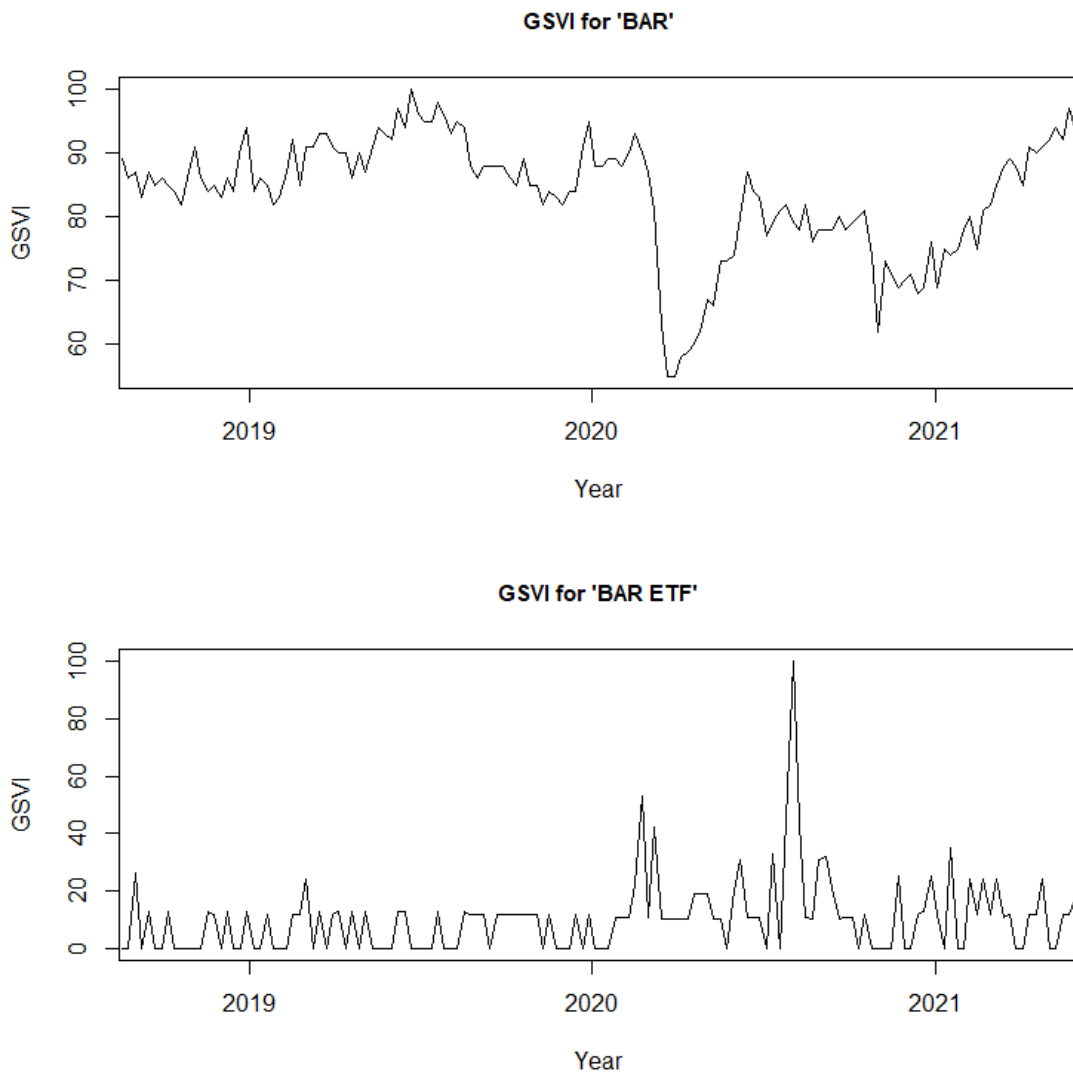
Google search volume indices for the selected ETFs were obtained from Google Trends (<https://trends.google.com/trends/>). The data provided by Google Trends is normalized and available with a varying frequency depending on the acquired timeframe. Normalization of the queries means that the absolute search volumes (e.g. 50 searches per day for a certain search term) are not presented, but the time point with the most queries within the acquired time frame will get the value of 100 and rest of the queries will be scaled accordingly between 0–100. The frequency of provided data points depends on the acquired period of time, a minute frequency is available for the past hour but when retrieving data from the past year or later, the data is provided with a weekly frequency. In case of a too small search volume for a specific search term, Google Trends provides no search data. The search data is available from 2004 onwards.

Google Trends contains filters that can be used to set selection criteria for the searches. These filters include country, timeframe, category and search type. The used filters in this study were United States as country, approximately three years custom time period, all categories and web searches. An illustrative Google Trends query is presented in Figure 6.



**Figure 6.** A Google Trends query for “silver ETF”. The query is filtered to show searches made from the United States between 31.5.2016 and 31.5.2021 with all categories using a web search.

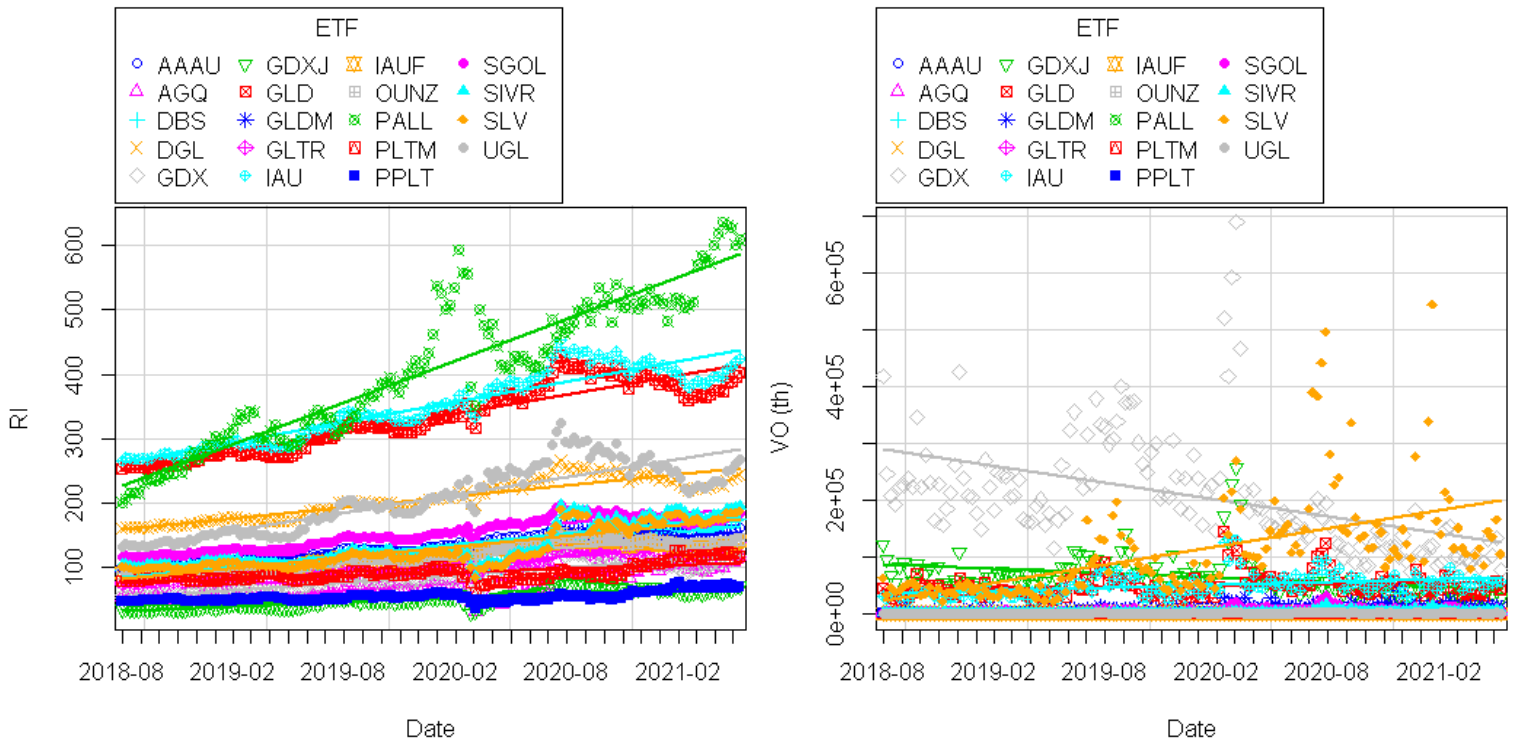
Two common practices within the literature on GSVI’s reflection to the stock market are to use either a company name or the ticker symbol as the search term for Google Trends data (Kim et al. 2019; Da, Engelberg & Gao 2011). In this research ticker symbols were selected over ETF names due to the relatively long and complicated names of the ETFs, in most cases not providing enough search data. The exact search terms used for the Google Trends queries were however selected individually for each ETF to ensure the availability of search data and to compensate for false results for noisy search terms, such as “BAR” as a ticker for GraniteShares Gold Trust Shares ETF. The ETF tickers were used as the primary search terms, but in case of a noisy ticker or lack of sufficient search volume, alternative search terms were used. In most cases addition of “ETF” after the ticker symbol was used if the ticker alone did not provide sufficient data. Detailed listing of the search terms is presented in Table 3 and Appendix 1. Different search volumes for alternative search terms for “GraniteShares Gold Trust Shares” ETF are demonstrated in Figure 7.



**Figure 7.** Google Trends search results with different search terms for the “GraniteShares Gold Trust Shares” ETF with the ticker BAR. Enough searches with the ETF name were not found and the ticker “BAR” resulted in noisy data due to the double meaning of the word. With “BAR ETF” there were enough queries, and the data was less noisy.

### 3.3 Stock market data

Stock market data for the selected ETFs was retrieved from Eikon Datastream. The selected data items included the ETF's trade volume, total return index, market capitalization and volatility on a weekly frequency to match the GSVI data. The returns and trading volumes for the studied time period and selected ETFs are presented in Figure 8.



**Figure 8.** Return index (RI) and trading volume (VO) development from August 2018 to May 2021 with the studied precious metal ETFs.

### 3.4 Variable definitions and summary statistics

List of the variables presented in the two previous sections together with their definitions are gathered in Table 4. Summary statistics for the variables are presented in Table 5.

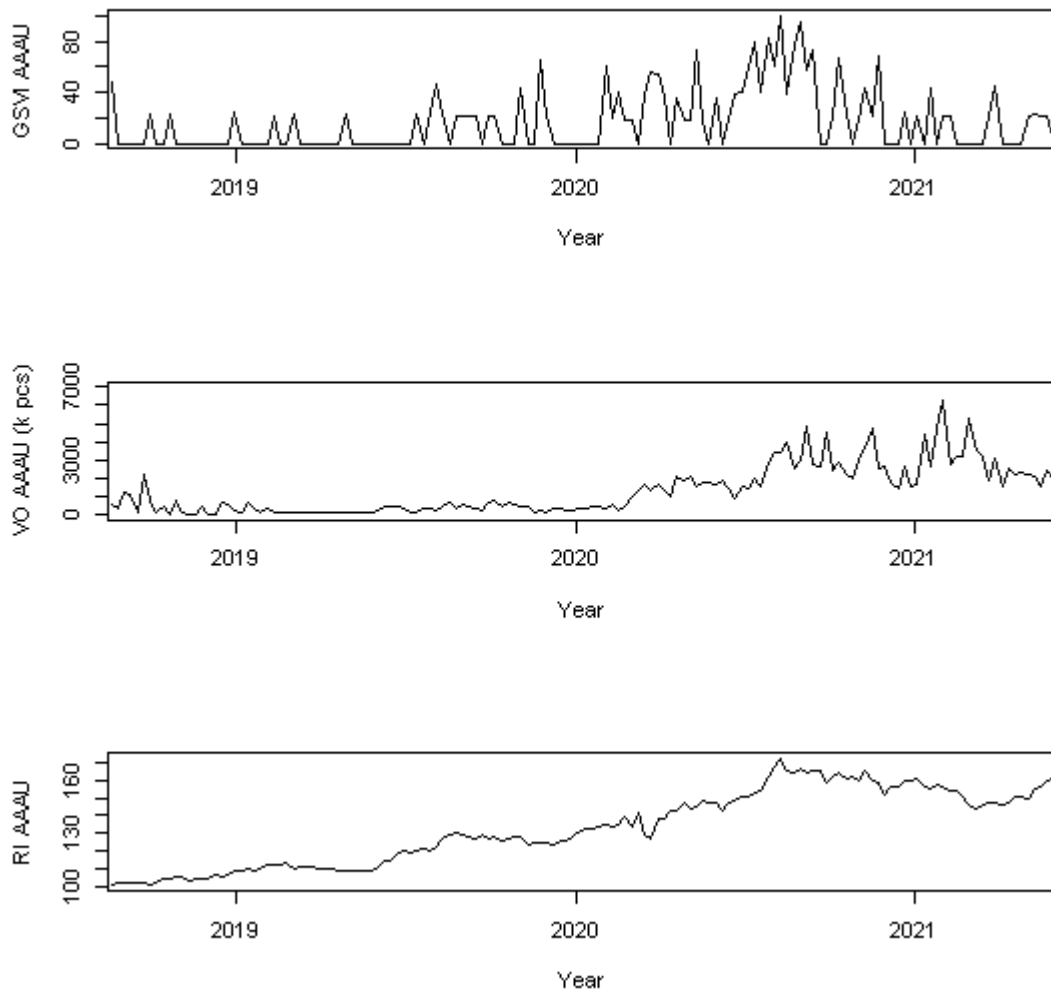
**Table 4.** List of variables and their definitions.

Variable	Definition
<b>Variables from Google Trends</b>	
Google search volume index (GSVI)	Standardized search volume for a search term within US.
<b>Variables from Datastream</b>	
Trading volume (VO)	Number of trades per week. Expressed in thousands.
Total return index (RI)	Weekly ETF return index.
Market capitalization (MC)	Weekly market capitalization expressed in MUSD.
Volatility ( $\sigma$ )	Weekly ETF volatility.
<b>Other</b>	
Gold	Dummy variable describing whether the ETF is a gold ETF (value 1) or other precious metal ETF (value 0).

**Table 5.** Summary statistics of the variables.

	N	Mean	STDEV	Median	Min	Max
GSVI	2 774	13	19	3	0	100
VO (k)	2 774	26 500	61 372	935	0	689 200
RI	2 774	157	106	122	28	636
MC (MUSD)	2 774	5 408	12 471	437	4	82 392
$\sigma$	2 774	0.222	0.112	0.192	0	0.580
Gold	2 774	0.579	0.494	1	0	1

The GSVI, trade volume and total return index for the Goldman Sachs Physical Gold ETF are presented in Figure 9 to give an example of the studied parameters. It can be seen from the graphs that all three parameters, search index, trading volume and total return index are increasing towards the year 2021.



**Figure 9.** Google search volume index, trading volume and total return index as a function of time for Goldman Sachs Physical Gold ETF (AAAU).



## 4 Methods

In order to investigate if GSVI has explanatory power over ETF trading volume and returns, multiple regressions with panel analysis were used. In a multiple regression more than one independent variable is used to explain the dependent variable, whereas in a panel regression the same entities (here ETFs) are measured at multiple points in time.

The regression equations for trading volume and ETF return are presented in Equations 1 and 2, respectively. Trading volume and ETF return represent the dependent variables. Related independent variables were GSVI, return, market capitalization and volatility for trading volume and GSVI, trading volume, market capitalization and volatility for ETF returns. In addition, a gold dummy variable was used in both equations to define whether the ETF in question was a gold ETF or not. The dummy variable was used because 11 of the studied 19 ETFs were gold ETFs.

$$VO_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 RI_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t} \quad (1)$$

$$RI_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 VO_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t} \quad (2)$$

Where VO = trading volume, GSVI = Google search volume index, RI = total return index, MC = market capitalization and  $\sigma$  = volatility for an ETF  $i$  at a time  $t$ . Gold is a dummy variable, obtaining value 1 for gold ETFs and 0 for others. Additionally,  $\alpha$  is the regression constant,  $\beta$  regression coefficient and  $\varepsilon$  the error term.

With panel regressions, either a fixed or a random model can be used. In a fixed effect model the correlation between the independent variables and corresponding regression constants ( $\alpha_i$ ) can be existent. In the fixed effect model the regression constants eventually get extracted from the model. In a random effect model, correlations between the independent variables and regression constants are evaluated separately for each entity. If a correlation exists the fixed effect model is used, and if not, an ordinary least squares model is used. To define which is preferable, fixed or random effect model, a Hausman test can be used. In a Hausman test the null hypothesis is that the preferred model is the fixed effects model.

## 5 Results

Panel regression results including all metal ETFs are presented in section 5.1. The hypothesis 1 and 2 can be tested based on these results. In order to test the third hypothesis, panel regressions were conducted for silver ETFs separately. In addition, same metal specific regressions were conducted for gold too. The metal specific regression results for gold and silver are presented in section 5.2.

### 5.1 Explanatory power of Google search volume index with precious metal ETFs

Correlation matrix for the studied variables is presented in Table 6. As can be seen from the table, GSVI has a positive correlation with both, the trading volume and total return index which suggests that more active Googling of the ETFs results in more trading and higher returns. The correlation is stronger with trading volume than the total return index. All other parameters are positively correlated with trading volume, expect for the total return index. In case of the total return index, both trading volume and volatility express a negative correlation. Intuitively, higher volatility is negatively reflected to the total return index. In addition to the total return index, volatility is negatively correlated with market capitalization and the dummy variable. This suggests smaller volatility for gold ETFs and ETFs with a higher market cap.

**Table 6.** Correlation matrix for the studied variables including all studied ETFs.

	VO	RI	GSVI	MC	$\sigma$	Gold
VO	1	-0.051	0.106	0.331	0.307	0.164
RI	-0.051	1	0.093	0.491	-0.179	0.149
GSVI	0.106	0.093	1	0.183	0.037	0.123
MC	0.331	0.491	0.183	1	-0.101	0.275
$\sigma$	0.307	-0.179	0.037	-0.101	1	-0.317
Gold	0.164	0.149	0.123	0.275	-0.317	1

All in all, correlations between the studied variables are very weak (absolute value of correlation coefficient 0–0.19) or weak (absolute value of correlation coefficient 0.20–0.39). Only market cap and total return index express a moderate correlation (absolute value of correlation coefficient 0.40–0.69). The weak correlations between the dependent variables and corresponding independent variables can be explained by the relatively simple regression models used and the fact that in reality multiple other factors affect the trading volume and total return index besides the ones considered here. Also, the strengths of the correlation coefficients shown here are in line with previous thesis on GSVI and the stock market (Rechartd 2019; Wuoristo 2012) and with Da, Engelberg & Gao (2011).

The panel regression results are presented in Tables 7 and 8 for trading volume and returns, respectively. In both cases p-value from the Hausman test was greater than 0.05, and thus random effect model was used in the analysis.

**Table 7.** Results from the panel data regression analysis of ETF trading volumes with random effect model.

$$VO_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 RI_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t}$$

Variable	Coefficient	Std Error	z-value	p	Significance
$\alpha$	798	17 300	0.0461	0.963	
GSVI	168	36.0	4.68	2.93e-6	***
RI	-12.4	19.7	-0.630	0.529	
MC	0.545	0.160	3.41	0.000660	***
$\sigma$	49 800	21 800	2.29	0.0220	*
Gold	19 700	21 700	0.909	0.364	
R <sup>2</sup>	0.0189				
Adj. R <sup>2</sup>	0.0172				

#### Hausman test

p-value      0.228 > 0.05      Random effect model preferred.

\*\*\*p<0.001, \*\*p<0.01, \*p<0.05, .p<0.1

**Table 8.** Results from the panel data regression analysis of ETF returns with random effect model.

$$RI_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 VO_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t}$$

Variable	Coefficient	Std Error	z-value	p	Significance
$\alpha$	29.4	33.8	0.869	0.385	
GSVI	0.219	0.0340	6.44	1.19e-10	***
VO	-6.54e-6	1.81e-5	-0.362	0.718	
MC	3.74e-3	1.36e-4	27.5	<2.2e-16	***
$\sigma$	387	19.8	19.6	<2.2e-16	***
Gold	32.7	44.0	0.743	0.458	
R <sup>2</sup>	0.345				
Adj. R <sup>2</sup>	0.344				

**Hausman test**

p-value      0.0809 > 0.05      Random effect model preferred.

\*\*\*p<0.001, \*\*p<0.01, \*p<0.05, .p<0.1

As can be seen from Table 7, GSVI has very high statistically significant explanatory power over the trading volume, confidence level being at 0.1 %. Same holds with market capitalization. Volatility has statistically significant explanatory power over the trading volume, confidence level being at 5 %. The total return index does not express statistically significant explanatory power over the trading volume. The R-squared value for trading volume is relatively low, implying that only approximately 2 % of trading volume's variance is explained by the variances of the independent variables.

According to the results presented in Table 7, increase of one standard deviation in GSVI results as an increase of 3.3 million more shares traded per week. Corresponding effect with market capitalization and volatility is 6.8 and 5.6 million more shares traded per week, respectively. Standard deviations used in the calculations were presented in Table 5. Results regarding the GSVI show that the correlation coefficient is different from zero at 0.1 % confidence level and the coefficient is positive. Thus, the first hypothesis stating that an increase in GSVI affects an increase in trading volume is accepted.

Concerning the results presented in Table 8, GSVI is again very highly statistically significant in explaining the total return index. In this case also market capitalization and volatility have explanatory power over total return index at 0.1 % confidence level. According to the regression model, trading volume has no statistically significant explanatory power over the total return index. In case of total return index, the model's R-squared value is moderate, implying that approximately 35 % from the variance of the total return index is explained by the independent variables.

In case of the total return index, an increase of one standard deviation in GSVI causes an increase of 4.2 in the total return index. One standard deviation increase in market capitalization results in an increase of 46.6 in the total return index, corresponding effect with volatility being 43.2. Standard deviations used in the calculations were presented in Table 5. As the correlation coefficient for GSVI is positive and different from zero at a 0.1 % confidence level, also the second hypothesis stating that an increase in GSVI affects an increase in the total return index is accepted.

When comparing the effects of one standard deviation increase to the dependent variables, it can be noted that the effect of GSVI to trading volume is approximately half of the effect of market capitalization or volatility. In case of total return index, the effect of GSVI is approximately one tenth of the effect of market capitalization or volatility. This seems logical as active Googling of the ETF tickers can intuitively be expected to transfer to trading volumes rather directly but the effect with returns is more complex.

## **5.2 Differences between gold, silver and all precious metal ETFs**

In order to investigate whether the third hypothesis on the market effects being stronger with silver ETFs holds, the silver ETFs were analyzed as a separate group. Separate analysis was also conducted with the gold ETFs. All in all, four silver and 11 gold ETFs were analyzed separately. Results from the panel regressions for all precious metal ETFs, gold ETFs and silver ETFs are collected in Table 9 for trading volume and Table 10 for total return index. In this case a fixed effect model was used in all analysis as problems occur with R when small datasets are analyzed with the random effect model.

**Table 9.** Regression results with fixed effect model for trading volume with all metal ETFs, and gold and silver ETFs separately.  $N_{ALL}=19$ ,  $N_{GOLD}=11$  and  $N_{SILVER}=4$ .

$$VO_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 RI_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t}$$

Variable	Coefficient			Std Error			p-value		
	All	Gold	Silver	All	Gold	Silver	All	Gold	Silver
GSVI	170	220	470	36	45	120	2.5e-6 ***	9.5e-7 ***	7.9e-5 ***
VO	-5.7	-25	-27	20	38	96	0.78	0.51	0.78
MC	0.50	-0.020	13.7	0.16	0.20	0.84	0.002 **	0.92	<2e-16 ***
$\sigma$	4.0e4	-2.3e5	-8.8e4	2.2e4	4.8e4	5.6e4	0.071 .	2.6e-6 ***	0.12
R <sup>2</sup>	0.018	0.027	0.40						
Adj. R <sup>2</sup>	0.010	0.018	0.39						

**Table 10.** Regression results with fixed effect model for total return index with all metal ETFs, and gold and silver ETFs separately.  $N_{ALL}=19$ ,  $N_{GOLD}=11$  and  $N_{SILVER}=4$ .

$$RI_{i,t} = \alpha_i + \beta_1 GSVI_{i,t} + \beta_2 VO_{i,t} + \beta_3 MC_{i,t} + \beta_4 \sigma_{i,t} + \beta_5 Gold_i + \varepsilon_{i,t}$$

Variable	Coefficient			Std Error			p-value		
	All	Gold	Silver	All	Gold	Silver	All	Gold	Silver
GSVI	0.22	0.24	0.15	0.34	0.029	0.051	2e-10 ***	2e-15 ***	0.004 **
VO	-5.1e-6	-1.1e-5	-5.1e-6	1.8e-5	1.7e-5	1.8e-5	0.78	0.51	0.78
MC	3.7e-3	3.7e-3	3.9e-3	1.4e-4	9.9e-5	4.1e-4	<2e-16 ***	<2e-16 ***	<2e-16 ***
$\sigma$	390	380	420	20	31	17	<2e-16 ***	<2e-16 ***	<2e-16 ***
R <sup>2</sup>	0.35	0.54	0.72						
Adj. R <sup>2</sup>	0.34	0.54	0.72						

\*\*\*p<0.001, \*\*p<0.01, \*p<0.05, .p<0.1

In case of trading volume, it can be seen from Table 9 that GSVI is positive and different from zero at a 0.1 % confidence level with gold, silver and all metal ETFs. The regression coefficient for silver ETFs is larger than with gold or all metal ETFs, i.e. an increase in GSVI affects a larger increase in the trading volume with silver ETFs. In case of the total return index presented in Table 10, the confidence level for silver ETFs' GSVI is 1 % compared to gold and all metal ETFs' 0.1 %. In addition, the corresponding regression coefficient is lower with silver ETFs than with gold or all metal ETFs, which implies that the GSVI's effect on the return index is lower with silver ETFs than others. This means that the third hypothesis is partially excepted as the GSVI with silver ETFs affects more strongly the trading volume but not the return index when compared to gold and all metal ETFs. Regarding the R-squared values, it is worth noticing that separating the metals enhances the goodness of fit. However, this is most likely affected by the small sample sizes, especially with the silver sample consisting only of four ETFs the R-squared value increases significantly.

## 6 Discussion and conclusions

The aim of this study was to test whether Google search volume can explain market activity in the US precious metal ETF market. More specifically, GSVI's effect on trading volume and total return index was studied. The sample consisted of 19 precious metal ETFs from which 11 were gold, four silver and four platinum, palladium and mixed precious metal ETFs. The studied timeframe was three years with a weekly frequency.

All in all, three hypotheses were tested. The first hypothesis concerned GSVI's ability to explain trading volume. It was concluded that GSVI does explain trading volume of precious metal ETFs with very high statistical significance, 0.1 %. It was also concluded that an increase in GSVI affects an increase in trading volume, i.e. more searched ETFs are traded more. The second hypothesis concerned the relationship between GSVI and ETF returns. It was found out that an increase in GSVI affects an increase in the total return index. Also in this case, the results expressed very high statistical significance, 0.1 %. In case of the third hypothesis, silver ETFs were tested separately in order to test whether the effects described in H1 and H2 were stronger with silver ETFs than other precious metal ETFs. It was found out that in case of trading volume, increase in GSVI affects the trading volume of silver ETFs more than with other precious metal ETFs. However, in case of the total return index, silver ETFs expressed a weaker effect, i.e. an increase in GSVI would affect the returns less with silver than other precious metal ETFs. Results from the hypothesis testing are summarized in Table 11.

**Table 11.** Summary of the results from hypothesis testing.

No.	The hypothesis	Result	Explanation
H1	Increase in GSVI of an ETF ticker increases the trading volume of the corresponding ETF.	Accepted	0.1 % confidence level
H2	Increase in GSVI of an ETF ticker increases the return of the corresponding ETF in a short term.	Accepted	0.1 % confidence level
H3	The effects described in H1 and H2 are stronger with silver ETFs.	Partially accepted	With H1 accepted, with H2 rejected



The results of this thesis imply that GSVI explains the trading volume and returns in a short period. However, it is worth noticing that the study was constructed using weekly data, and implications for longer time periods remained unstudied. Also, the exceptional time period of COVID-19 is likely to affect the results. As precious metals have the already discussed safe haven property the pandemic most likely increased interest towards the metals as an investment class. All in all, the results of this thesis show that Google search volume index captures the attention of retail investors also in the precious metal ETF market within the US. In practice this implies that retail investors use Google when making investment decisions on precious metal ETFs in the US market.

In this thesis the link between GSVI and market activity was studied and found in the US precious metal ETF market. To further utilize this relationship, one could try to develop a trading strategy for precious metal ETFs based on Google Trends data. However, in practice outperforming the market with such a trading strategy would most likely be challenging, one implication for this being the weak correlations between the variables as well as the low R-squared values of the models presented in Tables 6, 7 and 8.

The main limitations of this study include sample and data restrictions. This thesis focused on 19 precious metal ETFs, providing a relatively small sample size. The data limitations are related to the data provided by Google. Data obtained from Google Trends is always standardized and the frequency cannot be freely altered. Availability of non standardized data with no frequency limitations would provide major benefits for this and similar studies but problems with information privacy related to individuals' Google searches would be faced. Regarding the limitations, it is worth reminding that when discussing GSVI and investor attention, the attention of retail investors, not institutional investors is studied.

When it comes to the avenues for future research, multiple possibilities exist due to the lack of studies on GSVI with respect to precious metal ETFs. This thesis focused on the time of the COVID-19 crisis. The market conditions were exceptional due to the global pandemic, and it could be worthy to conduct a similar research outside COVID's timeframe and compare the results. In addition, the research could be expanded outside the US market, one interesting possibility being the European market. One additional avenue would be testing the effect of broader search terms besides the ETF tickers, such as "silver investment" and their effect on the precious metal market.

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## Appendices

### Appendix 1: Preliminary sample

Ticker	ETF name	Noisy	Search term	Included
AAAU	Goldman Sachs Physical Gold ETF		AAAU	X
AGQ	ProShares Ultra Silver		AGQ	X
BAR	GraniteShares Gold Trust Shares	*	BAR ETF	**
BGLD	FT Cboe Vest Gold Strategy Quarterly Buffer ETF		BGLD	***
DBP	Invesco DB Precious Metals Fund	*	-	
DBS	Invesco DB Silver Fund	*	DBS ETF	X
			Invesco Gold	
DGL	Invesco DB Gold Fund	*	Fund	X
DGP	DB Gold Double Long Exchange Traded Notes	*	-	
DGZ	DB Gold Short Exchange Traded Notes	*	-	
DZZ	DB Gold Double Short Exchange Traded Notes	*	-	
GDX	VanEck Vectors Gold Miners ETF		GDX ETF	X
GDXJ	VanEck Vectors Junior Gold Miners ETF		GDXJ Gold	X
GLD	SPDR Gold Shares		GLD ETF	X
GLDM	SPDR Gold MiniShares Trust		GLDM	X
GLL	ProShares UltraShort Gold	*	-	
GLTR	Aberdeen Standard Physical Precious Metals Basket Shares ETF		GLTR ETF	X
IAU	iShares Gold Trust	*	IAU ETF	X
IAUF	iShares Gold Strategy ETF		IAUF	X
IGLD	FT Cboe Vest Gold Strategy Target Income ETF	*	-	
	iPath Series B Bloomberg Precious Metals Subindex Total			
JJP	Return ETN	*	-	
OUNZ	VanEck Merk Gold Trust		OUNZ	X
PALL	Aberdeen Standard Physical Palladium Shares ETF	*	PALL	X
PGM	iPath Series B Bloomberg Platinum Subindex Total Return ETN	*	-	
PLTM	GraniteShares Platinum Trust		PLTM	X
PPLT	Aberdeen Standard Physical Platinum Shares ETF		PPLT	X
SGOL	Aberdeen Standard Physical Gold Shares ETF		SGOL	X
SIVR	Aberdeen Standard Physical Silver Shares ETF		SIVR	X
SLV	iShares Silver Trust		SLV	X
UGL	ProShares Ultra Gold	*	UGL ETF	X
WGLD	Wilshire wShares Enhanced Gold Trust		-	

\* Noisy ticker

\*\* Not available at Datastream

\*\*\* Established in January 2021

- Not enough search data available at Google Trends

X Included into the final sample