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Do Google Search Indicators explain CDS spreads?

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Management Summary

Over the last decade, technological development has allowed us to retrieve large economic data sets from various sources such as social media, internet search engines, and electronic transaction sources. Economists have constructed methods to use this new alternative data to monitor macroeconomic conditions in almost real time. Including these alternative data was found to improve the nowcast performance in many macroeconomic cases. In addition, a considerable number of successful attempts have been made to predict financial markets with data collected from online search engines. However, there is a lack of literature covering the relevance of internet search statistics for the assessment of credit risk.

The purpose of this thesis is to determine if Google-based indicators exhibit predictive power on Credit Default Swaps spreads of large Swiss companies. Credit Default Swaps prices reflect the perceived credit or default risk of the underlying entity. A quantitative analysis is conducted by running multiple OLS regression models to answer the research question. Credit Default Swap spread changes of large Swiss companies are regarded as the dependent variable. The independent variables of the regression analyses are three Google-based indicators from the website *trendEcon* and three control variables. The three independent variables from *trendEcon* are the index of Perceived Economic Situation, the index of Mobility, and the Clothing and Shoes indicator. The three control variables are the SMI returns, the two-year Swiss Government Bond Yields, and the stock market volatility index VSTOXX. In a first step, multiple regression models are run on a panel data set of the overall sample. The period of the analysis lasts from August 2, 2017, to August 29, 2022, with a total of 19'110 observations. In a second step, individual OLS regressions are run on the series of each company in the sample.

The results of the panel data regression show that the Google-based indicators from *trendEcon* perform well in capturing developments in Credit Default Swap spread changes on the whole sample. The coefficient of determination (R^2) of the regression models increases when *trendEcon* variables are included. Especially the index of Perceived Economic Situation and Clothing and Shoes exhibit significant results, and the directions of relation show the expected negative signs. However, the coefficients are rather low, indicating that the relationship between the two *trendEcon* variables and

Credit Default Swaps is rather weak. The Mobility indicator is also statistically significant, but the nature of the relationship is not in accordance with theoretical assumptions.

The results of the single-company regression models are, however, somewhat mixed across the companies. The coefficient of determination (R^2) of the single company regression models is indeed slightly higher when the *trendEcon* variables are included. However, some regression models show poor results with regard to the coefficient of determination (R^2) for certain companies, which seems to be related to the industry the company is operating in. Among the three *trendEcon* variables, the indicator of Clothing and Shoes (CS) shows the best capability to explain CDS spread changes of Swiss companies in the sample. None of the estimated coefficients of the Mobility indicator exhibit significance in the single-company regression models.

The results of the quantitative analysis imply that the Google-based indicators from *trendEcon* have the ability to explain CDS spread changes of Swiss companies, however, the impact is rather small. In that regard, this thesis lays the foundation for further empirical research in this field. The expansion of the analyses by including Google-based indicators using other keywords to examine credit risks contains great potential. Further, over time, more data will be available for certain keywords and areas, which increases the ability to create even better representations of sentiments captured from Google search volumes.

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List of Abbreviations

API	Application Programming Interface
CDS	Credit Default Swap
CH	Switzerland
CS	Clothing and Shoes
CSV	Comma-separated values
GDP	Gross Domestic Product
GIIPS	Greece, Ireland, Italy, Portugal, Spain
Mob	Mobility
OLS	Ordinary Least Squares
OTC	over-the counter
PES	Perceived Economic Situation
ROA	Return on Asset
ROE	Return on Equity
SMI	Swiss Market Index
UK	United Kingdom
US	United States
USA	United States of America

1. Introduction

Macroeconomic indicators are usually published with a delay of several weeks and might be revised a few months later (Choi and Varian, 2012). In a stable environment this delayed release of preliminary information may be a sufficient indicator of the current state of the economy. However, in times of an unstable and changing economy, the preliminary estimates may be a poor prediction of the actual state of the economy (Castle et al., 2013). It is crucial for policymakers to monitor the economic in real time to make informed economic and policy decisions and to recognise turning points in business cycles on time (Ashwin et al., 2021; Chen et al., 2015).

In recent years, economists and researchers have begun to use the term nowcasting to address the issue of delayed releases of information and macroeconomic indicators. The concept of nowcasting has its origin in meteorology and is a conjunction of the terms 'now' and 'forecasting'. It refers to the prediction of the present, the very near future, and the very recent past by exploiting early and highly frequent published information (Banbura et al., 2013).

With these first lines and an initial definition of the term nowcasting, the present thesis is introduced. This section provides a solid foundation for this study, reflects on the initial situation, points out the aim and research question of the thesis, and outlines the approach and data used to answer the research question.

High-frequency financial data, sales, production data, and consumer and business opinion surveys, which are published more frequently, have generally been used to track the current economic condition. This type of obtaining data can already be categorised as nowcasting as it explains a current situation (Consoli et al., 2021; McLaren and Shanbhogue, 2011). For example, Giannone et al. (2009) use monthly data from qualitative business surveys to compute early estimates of quarterly Gross Domestic Product (GDP) in the Euro Area. And, for instance, Siliverstovs (2012) uses real-time data at a weekly frequency to produce a forecast of quarterly GDP growth in Switzerland.

However, in recent years, nowcasting with new large alternative databases, which are available at very high frequency, such as social media, the internet, satellites, sensors, or texts, has emerged (Consoli et al., 2021). Several economic studies have been conducted using data from the internet, in particular, keyword searches by Google users, so-called Google Trends (Combes and Bortoli, 2016).

Google Trends is an online application launched by Google retrievable over https://trends.google.com/trends/?geo=CH. The tool provides data in real time on what people are searching for on the Google search engine (*Google Trends*, 2022). Since the launch of Google Trends in 2006, various economic studies have been conducted based on Google Trends data. Predominantly in macroeconomic papers, Google Trends data have been used extensively (Buono et al., 2017).

Choi and Varian (2009a) illustrated how to use Google Trends data to predict various economic metrics such as retail sales, automotive sales, housing sales, and travel behaviour. The same authors examined the initial claims for unemployment with Google search volumes (Choi and Varian, 2009b). Other authors followed and investigated the correlation between Google search activities and unemployment rates (Askitas and Zimmermann, 2009; D'Amuri and Marcucci, 2010). Guzmán (2011) inspected inflation expectation derived from Google search queries. Another paper revealed how to better predict the macroeconomic indicator Gross Domestic Product (GDP) with Google Trends (Kohns and Bhattacharjee, 2022).

Several studies have investigated the use of Google Trends data for finance-related topics, particularly the interaction with the stock market. For example, Perlin et al. (2017) showed that Google Trends data could be used to predict the behaviour of equity markets, as the search frequency of the word 'stock' can indicate increased volatility and decreased equity prices. Similar results were unveiled by the work of Preis et al. (2013), who additionally constructed a trading strategy defined by trading rules with the search frequency of certain keywords. Another paper analysed the impact of Google search queries on stock trading volumes (Moussa et al., 2017).

Limited academic literature is available covering the application of Google search data for the debt market. Dergiades et al. (2015) analysed the impact of Google search activity on the sovereign bond market of GIIPS states (Greece, Ireland, Italy, Portugal, and Spain) during the Greek debt crisis. The paper demonstrates that there is a short-run causality between Google search volume and the Greek and Irish government bond yield spreads. Other authors conducted a study to predict the evolution of the sovereign debt market in Europe with a created Google Sovereign-Risk Sentiment Index using Google Trends data and found that the index is positively correlated with Credit Default Swaps and mirrors investor sentiment regarding sovereign risk (González-Fernández and

González-Velasco, 2020b). It was also found that there is a strong negative relationship between rating changes and Google search volumes (Rose and Spiegel, 2012).

1.1. Objective and Research Question

The use of big data to improve predictions in various fields has a reasonable appeal. Several studies have been conducted using Google Trends data to predict macroeconomic indicators. Further researchers used Google Trends to analyse the financial markets and investors' attention.

However, there is a lack of literature addressing the link between Google search query volumes and Credit Default Swap (CDS) spreads in the private sector. CDS spreads measure the credit risk of a company and are early indicators for future changes in creditworthiness. Further, despite the growing literature using Google Trends data, there is no related work in this area available for Switzerland. The aim of this thesis is to find out whether Google search trends have predicting power on CDS spreads in Switzerland's private sector and are able to indicate a decline in the solvency of Swiss companies. Thereby, a selection of three economic indicators based on Google searches in Switzerland will be analysed to address the following research question:

Do Google Search Indicators explain CDS spreads?

The three economic indicators based on Google searches in Switzerland are provided by the website *trendEcon* (https://www.trendecon.org/). Finding that these Google-based indicators have significant predicting power on CDS spreads could also lead to the utilization of this alternative data in other contexts. Further, identifying additional determinants and understanding their effects on CDS spreads could be beneficial for investors, analysts, and other financial decision-makers. It would allow them to make better-informed decisions when buying or selling credit risks in the form of Credit Default Swaps.

1.2. Methodology

The thesis first completes a literature review of previous studies concerning the idea of nowcasting and the use of alternative data, particularly Google search data, in economics to understand the current state of research. Further, the literature review gives a brief explanation of CDSs and their determinants. Towards the end, the literature review connects the two topics, the use of Google search data and CDSs, to identify the current theories, methods, and gaps in the existing research.

Thereafter, a quantitative analysis is conducted to conclude the research question. This is done by regressing daily CDS spread log-returns against economic indicators based on Google search trends in Switzerland provided by the website *trendEcon*. The empirical analysis is conducted with, first, a pooled OLS regression on a panel data set for the overall sample and, second, with multiple OLS regressions for each company in the sample. The programming language Python is used over the Jupyter Notebook platform to conduct the quantitative analysis. Jupyter Notebook is an open-source and web-based tool that enables users to perform scientific data analysis and calculations in various programming languages.

1.3. Data

The data used for the empirical analysis will consist of two sets. First, three daily economic sentiment indicators based on Google search trends in Switzerland provided by the website *trendEcon* (https://www.trendecon.org/) as the independent variables. The three independent variables from *trendEcon* for this study are the index of Perceived Economic Situation, the index of Mobility, and the Clothing and Shoes indicator. The second data set used in the analysis as the dependent variable comprises daily five-year CDS spreads of Swiss companies. CDS spreads are measures of perceived default risk associated with the reference entity of the CDS contract (Alessi et al., 2019). The CDS spreads are retrieved directly from Refinitiv Eikon API to Jupyter Notebook. The analysis covers a period from August 2, 2017, to August 29, 2022. Non-trading days in Switzerland are omitted. The origin of both datasets, the data processing, the descriptive statistics, and visualised charts are found in section three of this paper.

1.4. Limitations

In order to clarify the objective of this paper, it has the following limitations. This paper exclusively focuses on three economic indicators based on Google search trends in

Switzerland provided by the website *trendEcon* (https://www.trendecon.org/). The three utilised *trendEcon* indicators are the indicator of Perceived Economic Situation (main *trendEcon* indicator), the indicator of Mobility, and the indicator for Clothing and Shoes. Further, as the indicators are based on Google searches in Switzerland, the empirical analysis focuses on Swiss companies only. Usually, CDS contracts are written on the debt of very large companies with high market capitalisation. Therefore, the empirical study is limited to Swiss companies with available CDS contracts written on their bonds, which are liquid and traded on the market.

1.5. Structure of the Work

The thesis is organised as follows. This first section introduces the topic, defines the research question and objective of the work, outlines the relevance, and briefly highlights the data set and methodology used for the empirical analysis. Section two covers the literature review, which presents the current state of research based on previous studies. Section three explicitly addresses the data used for the analysis and reveals the origin of the data and how it was processed. The descriptive statistics of the data are also presented in section three. A detailed description of the methodology applied to answer the research question is highlighted in section four. Section five reveals the findings of the quantitative analysis and discusses them. Section six concludes and interprets the results and provides an answer to the research question. The thesis concludes with implications and recommendations for further studies and an outlook.

2. Literature Review

This chapter discusses the current state of research through literature and past studies and mainly connects two fields of research. First, the literature review covers the literature and empirical studies around nowcasting in general. It also reviews studies incorporating internet search data for nowcasting purposes. After that, the literature review progresses to the second field of research, Credit Default Swaps (CDS). In short, a proxy for credit or insolvency risk. At the end, the literature review focuses on previous research connecting both themes, the use of internet search data and Credit Default Swaps (CDS), to lay the foundation for examining the research question of this thesis with empirical studies.

2.1. Nowcasting

Nowcasting is defined as the real-time estimation of an economic variable, for example quarterly GDP, meaning that the latest or current changes of this variable can be measured (Buono et al., 2017). Further, nowcasting is often based on incomplete data sets and uses specific statistical methods different from the ones used for the regular estimates. Babii et al. (2022) describe nowcasting as a mixed-frequency data problem, where the regular estimates of a certain variable are low-frequency data series (for example, quarterly GDP), and the real-time information is available on a daily, weekly, or monthly basis (high-frequency data series) to update the current level of the estimate. Or nowcasting can be explained as the exploitation of early published high-frequency information to obtain an early estimate of the target variable of interest, which becomes available at a later stage (Banbura et al., 2013).

In recent years, nowcasting has become a relevant tool in economics for policymakers and financial investors to assess the present state of the economy with reliable real-time information (Consoli et al., 2021). Especially during uncertain times and fast-changing economic circumstances, the accessibility of real-time data is crucial for policymakers, who aim to evaluate forecasts and detect turning points in an economic cycle to make meaningful decisions (Castle et al., 2009). Moreover, leading macroeconomic indicators are published with a significant delay and are revised over time (Burri and Kaufmann, 2020). For example, in Switzerland, the most important measure of economic activity, GDP, is published with a lag of nine weeks (Burri and Kaufmann, 2020).

The interest in economic nowcasting among both academics and professionals has been growing over the past years. A prominent example is the quarterly estimate of GDP. Giannone et al. (2008) developed a nowcast model to measure the quarter growth rate of GDP, with higher-frequency macroeconomic data that becomes available during the quarter in a more timely manner. The authors showed that exploiting rich macroeconomic data sets within the quarter increases the precision of the nowcast. Further, their framework makes it possible to evaluate the effect each new data release has on the quarter's GDP growth rate. A similar empirical study confirmed these findings and revealed that the GDP nowcast emerges more precise as more macroeconomic data become available during the quarter (Banbura et al., 2013). Further, they found that daily financial data is not useful to improve the precision of GDP nowcasting. Both aforementioned studies analysed the US GDP. Kholodilin and Siliverstovs (2010) were the first to attempt to nowcast Swiss GDP growth rate using monthly standard macroeconomic indicators and suggested that their nowcast traced the actual GDP growth rate fairly well and was in particular able to predict negative growth rates during the Global Financial Crisis 2008. The recent example of the outbreak of the COVID-19 pandemic emphasised the demand for reliable high-frequency information. To monitor the health of the Swiss economy during the coronavirus pandemic, Burri and Kaufmann (2020) developed a daily indicator of Swiss economic activity using publicly available financial market and news data. Their indicator accurately tracks the Swiss economic activity (GDP growth) during normal times and provides warning signals if the health of the economy worsens, such as during the Global Financial Crisis, the euro area debt crisis, or the recent COVID-19 crisis.

Several central banks developed their own nowcasting models to track the economy more accurately and strengthen their decision-making. For example, Bank of England released an article that describes three approaches the bank uses to nowcast quarterly GDP growth (Anesti et al., 2017). Another example is the nowcasting report of the Federal Reserve Bank of New York. The report publishes nowcasts of GDP growth by incorporating a broad range of macroeconomic data as it becomes available (*FEDERAL RESERVE BANK of NEW YORK*, n.d.). The Federal Reserve Bank of Atlanta also introduced a nowcasting model called *GDPNow,* estimating real GDP growth by using available economic data for the current measured quarter (*Federal Reserve Bank of Atlanta*, n.d.).

Until some years ago, economic nowcasting was usually done using standard official macroeconomic data releases, such as labour market data, construction spending, production data, retail trade, price indices, opinion surveys, or high-frequency financial data (Consoli et al., 2021; Babii et al., 2022). Especially business surveys have been popular due to their timeliness and reliability as indicators of economic activity (Ashwin et al., 2021; Giannone et al., 2009). Nowadays, economic nowcasting increasingly relies on non-standard high-frequency data, or so-called alternative datasets taken from various sources of information (Consoli et al., 2021). For instance, macroeconomists make use of textual analysis, payment system information, or GPS tracking data (Babii et al., 2022).

This paragraph outlines some examples of researchers who empirically examined alternative datasets. Askitas and Zimmermann (2013) demonstrated that they can nowcast the survey-based German Production Index by using German toll data, which is a proxy for the transportation activity of heavy vehicles. Another study showed that retail payment transaction data improves accurately nowcasting Italian GDP growth and household consumption (Aprigliano et al., 2019). More recently, Ashwin et al. (2021) suggested that textual data from newspaper articles contain useful information to nowcast quarterly GDP growth in Europe, especially in times of crisis.

As presented above, macroeconomic nowcasting employing alternative data can involve various types of data. However, a vast and growing number of researchers address the use of internet search data to nowcast the economy's current state, which is covered in the next section.

2.2. Nowcasting with Online Search Data

As of 2021, 96% of the Swiss population aged between 16 and 74 use the internet at least once a week (*Statista*, 2022a). Further, almost 30% of the web traffic worldwide comes from online search activities (*Statista*, 2022b). From this extensive use of the internet has emerged a useful data source, which can be used as an indicator of current economic activity (McLaren and Shanbhogue, 2011). Valuable information on internet search behaviour and individuals' intentions are revealed when consumers and business decision-makers search online for specific search terms (Wu and Brynjolfsson, 2015). For instance, searches for specific products made by internet users could indicate future economic transactions and therefore help to analyse demand and supply.

Online search data have several benefits as economic indicators. They are timely available, reach an enormous number of respondents, and are collected as a side product of normal activity. Consequently, information is continually captured on a broad range of topics, and the interest of the society is observed in real time, which can help to recognise unexpectedly arising issues (McLaren and Shanbhogue, 2011). Moreover, online search data can be accessed quickly and at a high frequency and filtered by geographic origin (Combes and Bortoli, 2016). In addition, the data is never revised compared to conventional economic data and is not likely to be redefined over time, such as components of macroeconomic indices (Chen et al., 2015).

Internet search data have been widely used in empirical studies on a large variety of applications. In economic literature, the use of internet search queries started with the paper of Ettredge et al. (2005). The authors used a keyword report from the website WordTracker and illustrated that web search terms are positively associated with the official unemployment data in the United States.

Given that Google is the most widely used search engine in Switzerland, the subsequent part of this work is about Google search data only. In Switzerland, Google has a market share of 91.66% as of 2021 (*Statista*, 2022b) and, therefore, represents the online search behaviour for the majority of internet users in Switzerland. On a global level, Google has a market share of 88% as of 2021 (*Statista*, 2022b).

2.3. Nowcasting with Google Trends

Google Trends is an online application launched by Google. The tool provides real-time and free-of-charge information on how often a particular search term is entered on the Google search engine (*Google Trends*, 2022).

Google search data have been used in a wide range of academic research in economics, finance, or the health sector. The first study in scientific research using Google Trends data was published by Ginsberg et al. (2009), who were able to track influenza illnesses in the US population one to two weeks ahead of the traditional surveillance report.

In economic research, nowcasting with Google Trends was commenced by Choi and Varian in 2009, who aimed to familiarise readers with Google Trends data (Choi and Varian, 2009a). The paper is the baseline for the use of Google search volumes, describes the data and statistical background, and walks through examples. They illustrate that prediction models for retail, automotive, home sales, and travel activity, including Google Trends variables, outperform the models without these variables. In a later work from 2009, the authors demonstrated that Google Trends could help predict initial claims for unemployment benefits in the US (Choi and Varian, 2009b). In 2012, the two published an updated and streamlined version of the papers released in 2009. In the updated version, they added an example of how to use Google Trends to nowcast the Consumer Confidence Index in Australia (Choi and Varian, 2012).

A number of researchers are considering Google Trends to examine unemployment rates. D'Amuri and Marcucci (2010) tested the predictive power of Google job-search-related queries for the US unemployment rate and showed that the models, including Google search data had the best performances in most periods. A few years later, the same authors published an updated version of their paper, being able to use a larger data set, and came to a similar conclusion (D'Amuri and Marcucci, 2017). Another paper demonstrated a strong correlation between German unemployment rates and Google keyword searches, even under complex and fast-changing economic conditions (Askitas and Zimmermann, 2009). Niesert et al. (2020) found out that Google Trends improved unemployment nowcasts for the US, UK, Canada, and Japan (but not for Germany). On the other hand, they discovered that Google search data were unreliable in predicting consumer price index and consumer confidence. This led them to the conclude that Google search data is most helpful when the variable under investigation is connected to a person's individual circumstances.

Google Trends data have also been applied to nowcast GDP. Empirical studies showed that Google search data improves nowcasts of GDP growth, particularly before macroeconomic information is released. This was presented by Kohns and Bhattacharjee (2022) for the US and by Ferrara and Simoni (2021) for the euro area, US, and Germany for different economic periods. As an example, OECD is publishing the *Weekly Tracker* *of Economic Activity*. The indicator provides estimates of weekly GDP growth for 46 countries using machine learning and Google Trends data related to consumption, labour markets, housing, trade, industrial activity, and economic uncertainty (*OECD*, n.d.).

Other papers analysed whether Google Trends data could be used to nowcast private consumption. The work of Kholodilin et al. (2010) investigated the possibility of using Google searches to predict monthly private consumption in the US. The authors found evidence that models, including Google search data, improve the nowcast accuracy compared to the benchmark model. A similar study was conducted using Google Trends data to estimate household consumption of goods and the manufacturing production index for France. The authors found no significant improvement in the accuracy of these indicators when Google search data was incorporated (Combes and Bortoli, 2016). The effectiveness of Google search data in observing the consumer attitude towards a product was assessed by Jun et al. (2014). The study revealed that Google search traffic can be used to analyse past and present consumer attitudes towards a product and helps forecast consumer preferences.

2.4. Nowcasting Financial Markets with Google Trends

Several empirical studies have been conducted with the purpose of testing the predictive capability of Google Trends data towards financial markets or, in other words, if Google Trends data contains information regarding investors' sentiment. Joseph et al. (2011) showed, based on all stocks in the S&P 500, that an increase in online ticker searches is an indication of abnormal stock returns and excessive trading volume in the following week. They conclude that the intensity of online searches for ticker symbols is a good proxy for investor sentiments. This findings were confirmed for German stocks in the short run (Bank et al., 2011). The paper demonstrated that the intensity of a company's name queries on Google is significantly related to trading activity and future stock returns in the short run. They further concluded that Google search volumes measure the attention of uninformed investors. This goes in line with the work published by Da et al. (2011), who empirically proved that Google search frequencies capture the attention of retail investors, and that stocks searched more frequently on Google suggest higher stock prices in the coming two weeks with a subsequent price reversal within the year. The paper covered the Russell 3'000 index, which contains the 3'000 largest US companies and represents more than 90% of US equity market capitalisation (Da et al., 2011). These findings are in contrast to the study of Bijl et al. (2016) using Google searches to predict returns for individual stocks. Bijl et al. (2016) found that high Google search volumes are followed by negative returns. The divergent result was explained by using a more recent dataset, and by this time, information inherent from Google Trends was incorporated faster into the market.

By investigating changes in Google query volumes for 98 search terms related to the stock markets, Preis et al. (2013) implemented a theoretical investment strategy. The performance of their Google Trends strategies was significantly higher than the performance of the random investment strategies over the same period (2004–2011). The Google Trends strategy took long positions when the intensity of the Google search volumes decreased and took short positions as soon as Google search volumes increased.

The relation between stock market volatility and Google Trends data was examined by several studies. Dimpfl and Jank (2016) found a strong correlation between the volatility of the Dow Jones index and the quantity of Google search queries of its name. Perlin et al. (2017) came to the same conclusion for Google search frequency related to the word *stock*. The paper covered the USA, UK, Australia, and Canada. The authors showed that an increase in Google search queries could predict an increase in volatility in the following week and a decrease in stock prices. Further, it was pointed out that the predictability of Google Trends for index returns was stronger during the financial crisis of 2009. Similar evidence was found in the Brazilian stock market (Ramos et al., 2017).

With regard to portfolio- and risk diversification, Kristoufek (2013) implemented a strategy based on the popularity of stocks measured by search queries made on Google. The implementation was based on the assumption that Google search queries of stocks are correlated with the riskiness of that stock. Therefore, the strategy underweighted the popular stocks and overweighted the ones that seemed to be less popular on Google to reduce the overall risk of the portfolio. The result showed that the implemented portfolio strategy outperformed both the benchmark and the uniformly weighted portfolio. More recently, the use of Google search volumes as an indicator of the risk of a stock was also shown by Maggi and Uberti (2021). They illustrated that the risk-adjusted performance of a portfolio improves when Google-based indicators are included.

On the level of individual firms' financial performance, researchers demonstrated that high Google Trends search volumes of companies' corporate names are negatively associated with firms' financial performance measured by return on asset (ROA) and return on equity (ROE)(Liu et al., 2021). Conversely, they showed that high search volumes on a firm's major major product names are positively related to ROA and ROE. The analysis was conducted for the five most prominent US technology firms.

2.5. Credit Default Swaps

A Credit Default Swap (CDS) is a credit derivative that enables market participants to protect themselves against the default risk of a particular reference entity. The reference entity of a CDS contract is usually a company (corporate) or a sovereign entity (Hull et al., 2004). The buyer of a CDS contract periodically pays an amount to the seller and, in return, has the right to sell a bond issued by the reference company for its nominal value if a credit event occurs. A credit event includes bankruptcy of the reference company or the failure to pay coupons (Cuthbertson et al., 2019). The annualised rate of payment made by the buyer is called CDS spread (Hull et al., 2004). A CDS spread can be interpreted as the price of a CDS contract and reflects the default risk of the reference company during the duration of the CDS contract (Zhang, 2018). So a rise in CDS spreads indicates an increase in the credit risk of the reference company, while a reduction in CDS spreads signals a decrease in credit risk (Shahzad et al., 2017). Often, CDS spreads are used as a reliable early indicator of a company's increasing default risk (Hasan et al., 2016).

CDS were introduced by the investment bank JP Morgan in 1994 and experienced substantial growth since then (Fu et al., 2021). The historical high, with USD 50 trillion outstanding notional amount of CDS contracts worldwide, was reached before the financial crisis at the end of 2007 (Cuthbertson et al., 2019). CDS became one of the most controversial derivative instruments during the financial crisis 2007-2009, as they led to a domino effect that deepened the crisis (Shahzad et al., 2017). After the financial crisis, there was a need for a more transparent and standardised CDS market which has been implemented in many developed countries with centralised clearing process and collateral being posted (Cuthbertson et al., 2019). By the end of 2020, the notional amount outstanding in the credit default market reached USD 8.5 trillion globally (Bomfim, 2022).

As CDS are over-the-counter (OTC) instruments, they are only available for large institutional investors, and therefore, the market participants are recognised as more sophisticated and informed agents (Wang and Bhar, 2014). The most commonly traded CDS contracts have a five-year tenor, however, other maturities are also available (Cuthbertson et al., 2019). It can be distinguished between single-name CDSs and index CDSs. A single-name CDS refers to a bond of only one reference entity, whereas an index CDS is written on the debt of a basket of different reference entities (Shahzad et al., 2017).

Earlier research has extensively discussed the appropriate determinants of CDS prices as it is of high importance for policymakers and analysts to assess the financial stability of an economy or a company and for investors to make informed decisions about their investments. Annaert et al. (2013) explained CDS spread changes for Euro area banks by using variables suggested by structural credit risk models, indicators of liquidity in the CDS market, and variables related to general economic conditions. The study revealed that the determinants of banks' CDS spreads vary strongly over time. Further, they found that the risk-free rate, the leverage variable, CDS liquidity (proxied with bid-ask spreads of the CDS quotes), and market returns are able to explain CDS spread changes, whereas equity volatility is not. On the contrary, the results of Hasan et al. (2016), who examined a sample of global banks in 23 countries, showed that equity return volatility is a significant determinant of CDS spreads among other variables, such as market-value-based leverage measures, asset quality, and cost efficiency.

Another empirical study analysing CDS spread changes of US companies found that firm-specific variables explain CDS spreads to a large extent (Galil et al., 2014). Further, they proved that stock returns, stock return volatility, and changes in the median CDS spreads per rating class have the strongest explanatory power for changes in CDS spreads. With regard to credit ratings, they observed that the ability of credit ratings to predict CDS spreads was disrupted by the financial crisis and declined almost to zero.

Similarly, Kajurova (2015), analysing CDS spreads on debt of UK companies, considered the following theoretical company-level and market factors: leverage, liquidity, equity volatility, risk-free interest rate, slope of term structure, market return, and market volatility. The empirical study examined the defined determinants over three periods, before, during, and after the financial crisis. The result revealed that the chosen theoretical determinants significantly influence CDS spreads, but the individual variables' impact varies in the different periods. Limited explanatory power was noticed for the variables in calm times, thus before the financial crisis.

A more recent study that examines the determinants of CDS spreads of 86 international banks from 25 countries showed that the level of capitalisation and the size of a bank seem to be significant determinants of a bank's CDS spreads (Mazzuca et al., 2017). Further, they demonstrated that banks' ratings are also associated with CDS spreads when switching from investment to non-investment grade. The bank's CDS were also affected by the sovereign CDS spreads.

Two papers claim that CDS spreads have a nonlinear relationship with stock prices and other financial determinants (Shahzad et al., 2017; Guesmi et al., 2018). Both studies consider the CDS index spreads of US industries. They suggest that the sensitivities to positive and negative changes are dependent on the industry. Shahzad et al. (2017) further outline that the impacts of macro-finance variables on CDS spreads are as expected in the long run. For most industries, a significantly negative long-run effect of industry stock prices and the five-year treasury yield on CDS index spreads was found. The VIX revealed a significantly positive relation to the CDS spreads for a broad range of industries in the long run. On the other hand, the WTI crude oil prices did not show a significant impact on the CDS spreads of most industries.

The relationship between CDS spreads and credit ratings from rating agencies is also widely discussed in the literature, as both measures make a statement about credit risk. CDS spreads are market prices of the credit risk with respect to the reference entity, and credit ratings are independent assessments of the credit risk of a company. Kiesel and Spohnholtz (2017) concluded that both credit ratings agencies and CDS spreads reflect the creditworthiness of corporates. However, changes in the creditworthiness of corporates are adapted faster in the CDS spreads. The underlying data of the paper were 103 European firms and 207 firms from the USA. Another paper analysed the relationship between sovereign debt ratings and CDS spreads and showed that CDS spreads could explain average sovereign ratings. In contrast, rating changes have no predictive power on CDS spread changes (Rodríguez et al., 2019). Chava et al. (2019) pointed to the fact that a large number of companies do not have CDS trading on their debt. Further, they infer that CDS spread should be used in addition to credit ratings, as they provide a market-based view of default risk.

2.6. Nowcasting Credit Risk with Google Trends data

This subchapter of the literature review addresses the relationship between Google search data and Credit Default Swaps (CDS) or credit risk in general. However, there is a lack of literature investigating this connection. In academic literature, only a few papers were found that can be used as a reference for this part of the literature review.

The first paper analysing the association between Google Trends data and credit risk was by Dergiades et al. (2015). More precisely, the authors examined whether the information on social media (Twitter, Facebook, Google blogs) and Google Trends data contributed to movements on the sovereign spread between GIIPS and the German government bond yield during the Greek debt crisis. They found evidence that social media discussions and Google search queries have predictive power on Greek and Irish spreads and, to a much lesser extent, on the rest of the GIIPS states. In terms of social media, they further explained that this new data source is especially important in times of negative economic news when traditional models, which only use financial control variables, are possibly insufficient.

Smales (2016) analysed the relationship between the sentiment of newswire messages reported over Reuters and CDS spreads for a set of major international banks. The result showed that CDS spreads are significantly related to news sentiment.

More recently, two papers from the same authors were published discussing the ability of Google search queries to predict credit risk measures. The first paper constructed an investor sentiment index through Google search data, with keywords related to bank credit risk, to analyse bank credit risk in European countries (González-Fernández and González-Velasco, 2020a). European bank credit risk was measured with CDS data. The findings unveiled that Google search data is able to capture investor sentiment and that the sentiment index is highly correlated to bank CDS. Further, the Google-based sentiment index is helpful in predicting bank credit risk, especially in times of economic turmoil and in the presence of bad news.

The second work studied the association between a constructed sovereign-risk sentiment index based on Google search queries and European sovereign CDSs (González-Fernández and González-Velasco, 2020b). The study demonstrated that Google search data is useful to proxy investor sentiment regarding sovereign risk. Moreover, they found that the Google-based index positively correlates with CDSs and is a better proxy for investor sentiment regarding sovereign risk in times of financial distress in sovereign debt markets in peripheral countries.

Anastasiou and Drakos (2021) created two Google search-based crisis sentiment indicators by employing search volume data on crisis-related queries. The indicators measured the depositors' fear and were found to have statistically significant negative impact on the banks' deposit flows across EU countries. This result indicated that high search intensity of crisis-related keywords is associated with higher bank deposit outflows.

So far, no studies have been found analysing the relationship between Google search data and the credit risk of Swiss companies. This thesis attempts to fill this gap and examines the predictive power of Google Trends data on the CDSs of Swiss companies.

3. Data

This paper investigates the potential explanatory power of Google Trends data on companies' credit risk. Therefore, two sets of time-series are utilised to conduct the quantitative analysis. First, economic sentiment indices based on Google search trends in Switzerland provided by the website *trendEcon* (https://www.trendecon.org/) as the independent variables. And second, Credit Default Swap (CDS) spreads of Swiss companies as the dependent variable. In this section, the characteristics and sources of the two data sets are described. This section also covers the descriptive statistics of the data. The analyzes covers a period from August 2, 2017, to August 29, 2022. Detailed information regarding the Python coding involved in the data retrieval and data processing can be found in the Jupyter Notebook file in Appendix III.

3.1. trendEcon

The website *trendEcon* (https://www.trendecon.org/) provides the data for the study's independent variables. The website was initiated in late March 2020 by a group of collaborating economists working for data consulting company cynkra, KOF Swiss Economic Institute, the economic forecast division of the State Secretariat for Economic Affairs (SECO), the Swiss Federation of Trade Unions (SGB), and the University of St. Gallen. The initial goal of the project was to provide timely information about the Swiss economy to estimate the impact of the Covid-19 pandemic, as traditional indicators became available with a delay of several months (*TrendEcon*, n.d.).

The website *trendEcon* provides a set of indicators based on Google Trends data for Switzerland. They provide Google-based indicators in various fields of the Swiss economy. Their main indicator captures the *Perceived Economic Situation* in Switzerland. Additionally, they provide indicators modelling private consumption, such as *Watches and Jewellery, Clothing and Shoes,* or *Food Delivery*. They also provide indicators for *Gardening and Home Improvement*, *Cultural Events,* and indices of *Travel Abroad* and *Mobility*. The Google-based indicators are updated daily, are public and freely available, and can be downloaded directly from the website as a CSV (comma-separated values) file. Further, the website provides the open-source R-package *trendecon* with their novel sampling technique to compile stable daily Google Trends results (*TrendEcon*, n.d.). The provided daily economic sentiment indices by *trendEcon* are significantly correlated with traditional leading economic indicators (Eichenauer et al., 2020, 2022).

The indicators provided on the website *trendEcon* have already been processed with a novel technique that constructs consistent and harmonised daily, weekly, and monthly series of Google search volumes over a long period. The economists have also adapted the indicators to the small sampling issue in smaller economies, such as Switzerland. Further, the *trendEcon* time series has already been seasonally adjusted and normalised (Eichenauer et al., 2020, 2022). Each economic indicator indicates the relative change in Google search volume over time. For example, an index value of two implies that the Google search volume is two standard deviations above its long-term average (Eichenauer et al., 2020, 2022).

3.2. Economic Sentiment Indicators by trendEcon

For the quantitative analysis, three economic sentiment indicators provided by the website *trendEcon* are used as independent variables. The three selected *trendEcon* indicators are *Perceived Economic Situation, Mobility,* and *Clothing and Shoes*. The *trendEcon* indicators were chosen based on their assumed relevance to the research question of this study. The three daily indicators were downloaded from the website as CSV files via the Python tool Jupyter Notebook. The data on non-business days (in Switzerland) was removed to match the series of the control variables and the dependent variables. The final sample of the three *trendEcon* indicators consists of 3’825 observations (1’275 observations each) and covers a period from August 2, 2017, to August 29, 2022.

In the subsequent paragraphs, the three economic sentiment indicators from *trendEcon* are explained in detail. Figure 1 to 3 present the evolution of the *trendEcon* indicators over the defined period. An overview of the considered keywords for each indicator is shown in Table 1. The descriptive statistics of the three *trendEcon* variables during the period from August 2017 to August 2022 are depicted in Table 2.

Table 1: *Daily Economic Sentiment Indicators from trendEcon*

***trendEcon* Indicator**	**Google Keywords (in German)**	
Perceived Economic Situation (PES)	Wirtschaftskrise	arbeitslos
	Kurzarbeit	Insolvenz
Mobility (Mob)	Fahrplan	Sixt
	Taxi	Google Maps
Clothing & Shoes (CS)	Mango	blue tomato
	Zara	Dosenbach
	H&M	Schuhe kaufen
	PKZ	Ochsner Schuhe

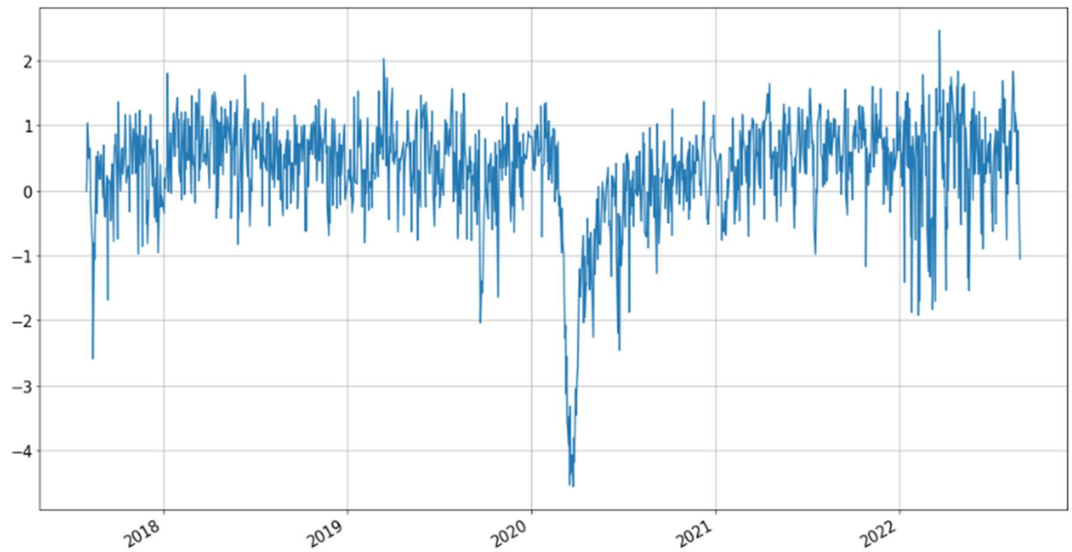
Note: Own representation. Data Source: (*TrendEcon*, n.d.). The abbreviations in parentheses were used for coding in Jupyter Notebook.

Perceived Economic Situation (PES)

The daily sentiment index of *Perceived Economic Situation* is the main indicator provided by *trendEcon* and mirrors people's concerns about the state of the economy. The more frequently the terms 'economic crisis', 'short-time work', 'unemployed', and 'insolvency' are searched for (in German), the worse the sentiment of the Swiss economic development (*TrendEcon*, n.d.). Figure 1 plots the indicator from August 2017 to the end of August 2022. In this period, the indicator of *Perceived Economic* Situation ranged between –4.56 and 2.47 and has a mean of 0.32, as reported in Table 2. The daily economic sentiment index responded strongly to the Covid-19 crisis, as shown in Figure 1. It remained fairly stable between values of -1 and 2.00 until 2020. The indicator started to fall in February 2022, when the special situation in Switzerland was declared due to the Covid-19 crisis. The indicator further declined to its lowest point at –4.56 in March 2020 when the extraordinary situation, according to Swiss pandemic law, was announced, and stores, restaurants, bars, and schools needed to close ("lockdown"). The index remained volatile in April and May 2020 due to the nationwide shutdown.

The extraordinary situation in Switzerland was lifted by the end of May 2020. Since July 2020, the indicator has gradually recovered to its usual fluctuations. In January 2022, the volatility increased again due to the Russia-Ukraine War, price increases, and the tense energy situation. The expected higher inflation and rising interest rates are expected to result in a cooling of the Swiss economic outlook. These times of economic uncertainties in the course of the current year are evident in Figure 1, with increased volatility of Google search volumes related to people's economic concerns.

Figure 1: *Perceived Economic Situation Indicator over time*



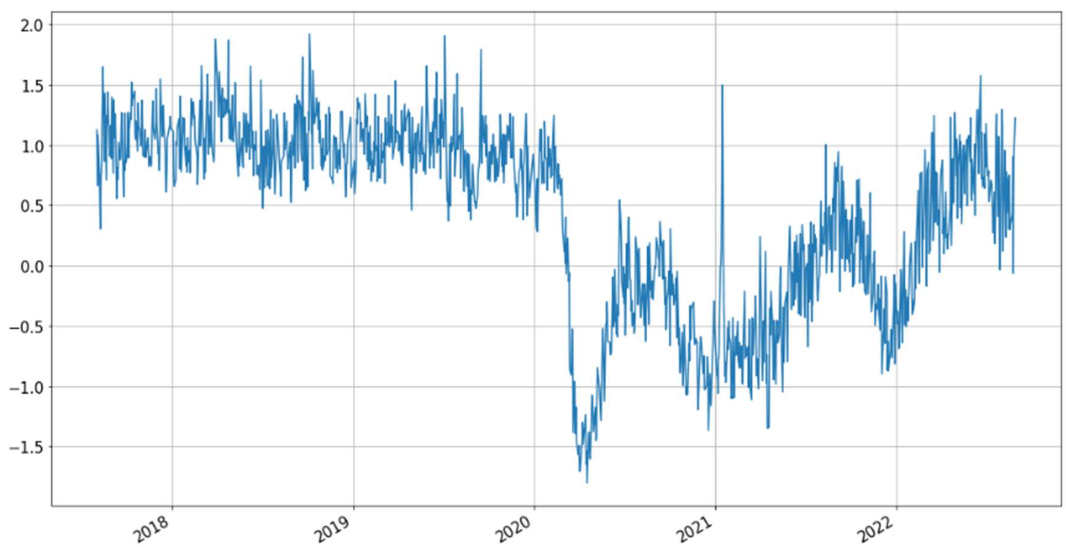
Note: Own representation. Data Source: (*TrendEcon*, n.d.). Time-series plot from 02 August 2017 to 29 August 2022.

<u>Mobility (Mob)</u>

The *Mobility* indicator is related to the demand for ground transportation, such as using the railway or calling a taxi service (*TrendEcon*, n.d.). Figure 2 displays the *Mobility* indicator from August 2017 to the end of August 2022. During this period, the indicator ranged between –1.80 and 1.92 and had a mean of 0.43, as stated in Table 2. The outbreak of the Covid-19 crisis is clearly noticeable in Figure 2. With the declaration of the special situation and the extraordinary situation in March 2020, the *Mobility* index plummeted to its lowest point at –1.80. Private and public events were prohibited, and companies introduced home offices, which reduced the need for public transport distinctly. From the beginning of April 2020 onwards, physical mobility started to recover when the first stage of easing of restrictions was introduced. The *Mobility* index declined again towards the end of 2020 due to further containment measures and probably also the avoidance of public transport due to people's health concerns. It remained low until May

2021 due to closed facilities and mandatory working from home. In the summer of 2021, physical mobility increased as a consequence of easing measures. The declaration of compulsory Covid-19 certificates resulted in another downward trend by the end of 2022. The decreasing demand for ground transportation may also be attributed to poorer weather in the winter months. The *Mobility* indicator normalised during 2022 but could not reach a stable pre-pandemic level. This might be the result of Swiss companies retaining the possibility of working from home.

Figure 2: *Mobility Indicator over time*

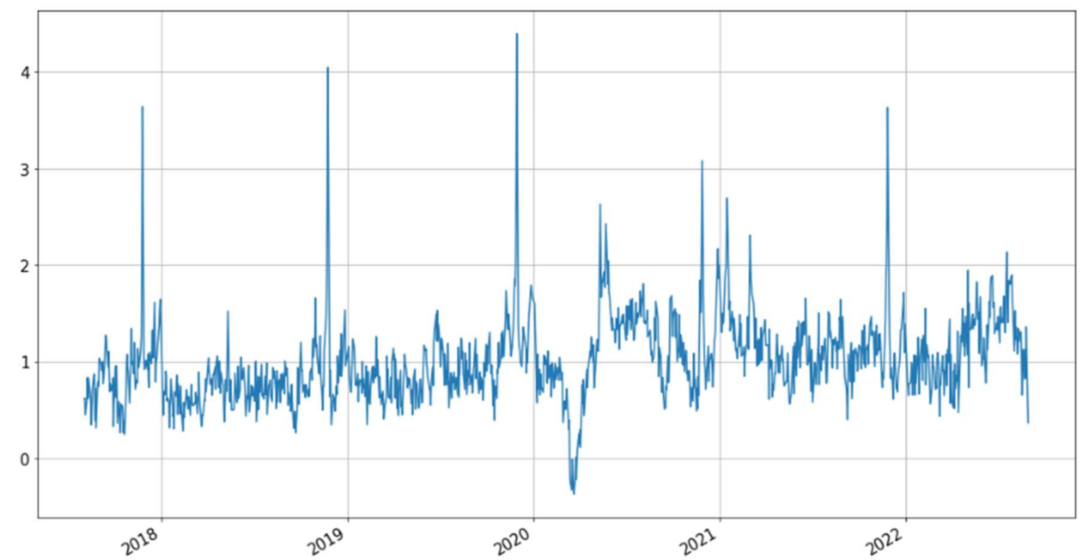


Note: Own representation. Data Source: (*TrendEcon*, n.d.). Time-series plot from 02 August 2017 to 29 August 2022.

Clothing and Shoes (CS)

The *Clothing and Shoes* indicator depicts the demand to buy shoes and clothing and also includes the direct search for brands (*TrendEcon*, n.d.). Its mean was at 1.00 and the values ranged from lowest –0.37 to a maximum of 4.39, as reported in Table 2. Figure 3 shows how the *Clothing and Shoes* indicator evolved over the past five years, from August 2, 2017 to August 29, 2022. The *Clothing and Shoes* index represents the spending activity of Swiss people for fashion articles and is a cyclical index. Purchases of such products are sensitive to the economic situation. Spending on these articles is cut during downturns. This is visible in Figure 3 when the demand for clothing and shoes dropped quickly to its lowest level in March 2020 when the special and shortly after the extraordinary situation in Switzerland was declared due to the Covid-19 pandemic. Shortly after, Google search volumes for clothing and shoes surged again and returned to the pre-Covid level in April 2020 already. However, the index remained more volatile compared to the times before the pandemic. Although the consumption of clothes and shoes tends to be sensitive to the business cycle, the downward reaction was not as strong as for the other two *trendEcon* indicators, as visible in Figure 3. This circumstance could be reasoned by the fact that online shopping activity might have increased during the Covid-19 pandemic, as local stores were closed due to the lockdown.

Figure 3: *Clothing & Shoes Indicator over time*



Note: Own representation. Data Source: (*TrendEcon*, n.d.). Time-series plot from 02 August 2017 to 29 August 2022.

The annual peaks of the *Clothing and Shoes* indicator in November are due to Black Friday and Cyber Monday, which increase the online search activity of Swiss people for fashion articles drastically. Graphically, it appears that the demand to purchase clothes and shoes on these two discount days has declined after the Covid-19 crisis.

The three *trendEcon* indicators are normalised so that the long-term average is zero and the standard deviation is one (Eichenauer et al., 2020, 2022). Table 2 presents the descriptive statistics of the *trendEcon* variables from August 2017 to August 2022.

The mean value of 0.32 of the index *Perceived Economic Situation* implies that the search volume is 0.32 standard deviations above its long-run average. It can be interpreted that the search volumes on Google for the respective keywords of the index were, on average, higher during the period from August 2017 to August 2022 than during the whole period of the available data (*trendEcon* series can be retrieved since January 2007). This is the case for all three *trendEcon* variables used in the analysis.

The highest average amount of variability of the three *trendEcon* indicators exhibits the index of *Perceived Economic Situation* with a standard deviation of 0.84, closely followed by *Mobility* with 0.75. The index of *Perceived Economic Situation* has the highest range, with 7.03, followed by the indicator for *Clothing and Shoes,* with a range of 4.77. The range for the *Mobility* indicator is 3.72.

Table 2: *Descriptive Statistics for the trendEcon Variables*

	N	**mean**	**std**	**min**	**max**
PES	1’275	0.319657	0.840408	-4.563329	2.468673
Mob	1’275	0.431636	0.756922	-1.804200	1.922752
CS	1’275	1.002220	0.427818	-0.371860	4.396477

Note: Own representation. PES = Perceived Economic Situation; Mob = Mobility; CS = Clothing and Shoes; N = number of observations; std = standard deviation; min = minimum value; max = maximum value; the sample period runs from 02 August 2017 to 29 August 2022; non-trading days in Switzerland are omitted.

3.3. Control Variables

In addition to the *trendEcon* indicators, the independent variables were extended by three control variables as the baseline for the regression models. The same time period and frequency are considered as for the *trendecon* variables, namely from August 2, 2017 to August, 29 2022. The following three determinants of CDS spreads, widely used and discussed in previous empirical analysis, were chosen as explanatory control variables. First, the returns of a market-wide stock index (Annaert et al., 2013). As this thesis analyses indicators based on Google searches made in Switzerland, the Swiss Market Index (SMI) is considered. Second, a risk-free interest rate (Mazzuca et al., 2017) that is proxied in this study with the two-year Swiss Government Bond Yield (CH2YT). And third, a market-wide volatility index (Annaert et al., 2013). In this study the Euro Stoxx 50 Volatility Index, often referred to as VSTOXX (V2TX), is utilised.

All control variables were recalled directly from Refinitiv Eikon API to Jupyter Notebook. Refinitiv is one of the largest financial market data and infrastructure providers worldwide and offers solutions for asset and wealth management, investment banking, trading, risk, and compliance (*Refinitiv*, 2022). API stands for Application Programming Interface and allows two or more different software programs to communicate with each other. It is generally used to exchange all kinds of data online.

3.4. Credit Default Swap Spreads

As the dependent variable of the regression analysis, differences in daily Credit Default Swap (CDS) spreads of Swiss companies are used. Following the literature, CDS spreads are an appropriate indicator of credit risk. The source of the CDS data is Refinitiv. The data was directly obtained from Refinitiv Eikon API to Jupyter Notebook.

The study utilises daily time series of CDS spreads with five-year maturities since five-year CDS are the most commonly traded contracts on the market (Avino and Cotter, 2014). The downloaded time-series consists of CDS spreads closing prices in basis points. This work focuses on single-name CDSs where the CDS contracts refer to senior unsecured reference obligations. The Swiss companies in the sample were selected based on the availability of CDS contracts written on their debt. CDS contacts are usually available on the debt of large companies only. Available CDS contracts of Swiss companies were screened over the Refinitiv Advance CDS Search function (Refinitiv Code: CDSSRCH). Further, a congruent list of available CDS contracts of Swiss firms was provided by IHS markit via email. The sample of Swiss companies with corresponding CDS prices was reduced to companies with complete or nearly complete CDS pricing data. The few still missing data points were interpolated using data from the preceding and succeeding days. The regression analysis focuses on changes in CDS spreads instead of the CDS spread levels to make sure that the CDS data is stationary.

For each company in the sample, the log-differences of the CDS spreads were calculated as follows:

$$\log(CDS\ spread_{i,t}) - \log(CDS\ spread_{i,t-1}) = \Delta\ CDS\ spread_{i,t}$$

where $CDS\ spread_{i,t}$ is the CDS spread of company *i* at time *t*.

The final sample consists of CDS contracts written on the debt of 15 individual Swiss companies, as represented in Table 3. The pricing data of their corresponding CDSs covers the period from August 2, 2017 to August 29, 2022.

Table 3: *Swiss Companies' single-name CDSs*

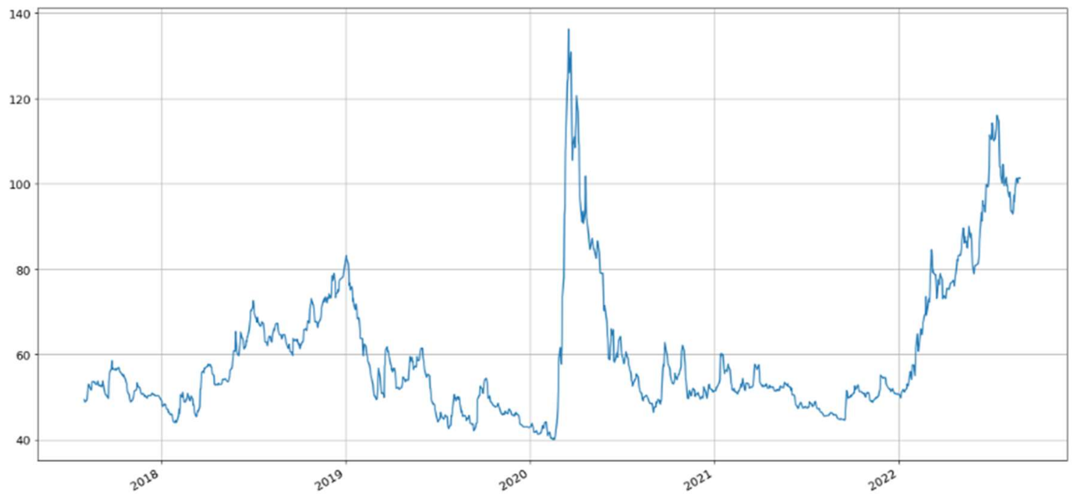
Company	**Industry**	**Refinitiv CDS Ticker**
BASF Schweiz AG	Chemicals	BASP5YUSAM=R
Clariant AG	Chemicals	CLN5YEUAM=R
Glencore Intl AG	Materials	GLEB5YEUAM=R
UBS Group AG	Banking	UBSN5YEUAM=R
Credit Suisse AG	Banking	CSGN5YEUAM=R
Swisscom AG	Telecommunication	SCMN5YEUAM=R
Roche Holding Ltd	Pharmaceuticals	ROG5YEUAM=R
TE Connectivity	Technology	TELY5YUSAX=FN
Nestlé SA	Food & Beverage	NESN5YEUAM=R
Swiss Reins Co Ltd	Reinsurance	RUKN5YEUAM=R
Novartis AG	Pharmaceuticals	NOVB5YEUAM=R
Zurich Ins Co Ltd	Insurance	ZURB5YEUAM=R
Syngenta AG	Chemicals	SYNN5YEUAM=R
Adecco Group AG	Human Resources Services	ADEC5YEUAM=MG
Holcim AG	Construction	HOLN5YEUAM=R

Note: Own representation. Data Source: (Refinitiv, 2022). Single-name CDS, denoted in EUR, five-year tenor; senior unsecured debt; BASP5YUSAM=R, TELY5YUSAX=FN and ACE5YUSAX=R are CDS contracts denoted in USD; exchange rate challenges were disregarded as daily log-differences in CDS spreads are analysed.

The companies in the sample are operating worldwide and in different industries, as listed in Table 3 (except for Swisscom which only operates nationally). The sample consists of companies like Clariant AG, employing about 13’000 employees, and goes up to over 270’000 employees working for Nestlé AG.

Figure 4 depicts the development of the average CDS spreads over the entire sample period from the beginning of August 2017 until the end of August 2022. Table 4 outlines the descriptive statistics of CDS spreads per industry during the sample period. The number in parentheses shows the number of companies per industry. It is worth noting that the sample size per industry is small to obtain representative results on the industry level. Considering the whole sample, the average CDS spread is 59.493 basis points, with a standard deviation of 16.043 basis points. The average CDS spreads range from the lowest at 39.990 basis points up to the highest at 136.278 basis points. This range is noticeable in Figure 4. The average CDS spreads increased sharply in March 2020 up to 136.278 basis points due to the extraordinary circumstances caused by the Covid-19 pandemic. Before that, the average CDS spreads moved in a range between 40 and 80 basis points. As default risk depends on the economic circumstances and on market wide sentiments, the uncertainty due to the Covid-19 pandemic let the CDS spreads rise dramatically. Although, the average CDS spread level recovered fast and stabilised around the pre-Covid-19 level. The recent increase in average CDS spreads in 2022 is the result of the Russia-Ukraine War, which intensified the pressure on the energy market. Higher energy prices increase the business risks for companies with energy intensive productions. Also the tightening economic situation and the uncertainty around the future inflation path increased the average CDS spreads as investors demand higher risk premiums to hold debt. The time series plots of the CDS spreads of the individual companies in the sample can be found in the Appendix II.

Figure 4: *Development of Average Credit Default Swap Spreads*



Note: Own representation. Data Source: (*Refinitiv*, 2022). Evolution of the time series of average CDS spreads (in basis points). Time-series plot from 02 August 2017 to 29 August 2022.

Table 4 shows that the chemicals and materials industry registers the highest average CDS spreads with 102.947 basis points and a standard deviation of 27.964 basis points. The lowest average CDS spread exhibits the pharmaceutical industry with 19.888 basis points and a standard deviation of 3.621 basis points. The highest range in CDS spreads during the sample period experiences the industry chemicals and materials with a range of 191.93 basis points. The lowest range of 19.77 basis points is experienced by the pharmaceutical industry. This observation is in line with the credit rating classes included in the different industries. Low credit risk, and therefore a good credit rating, goes along with low CDS spreads and vice versa. The companies in the pharmaceutical industry are rated by Moody's in the high-quality section of investment grade with Aa2 (Roche) and A1 (Novartis). At the same time, the chemicals and materials industry contains Moody's credit ratings, which are in the lower-quality section of the investment grade and even contain a non-investment grade rating (Syngenta).

Table 4: *Descriptive Statistics CDS spreads per Industry*

	Chemicals & Materials (4)	**Financials** (4)	**Pharma** (2)	**Technology** (2)	**Food & Beverage** (1)	**Services** (1)	**Construction** (1)	**Full Sample** (15)
mean	102.937	46.541	19.888	50.066	20.518	47.272	86.785	59.493
max	262.720	124.655	32.960	84.965	50.050	126.492	233.860	136.278
min	70.785	26.045	13.190	35.590	11.560	28.417	52.450	39.990
std	27.964	17.871	3.621	7.421	6.823	18.666	30.071	16.043
N	1275	1275	1275	1275	1275	1275	1275	1275

Note: Own representation. in basis points; max = maximum value; min = minimum value; std = standard deviation; N = number of observations; number of companies per industry are given in parentheses; the sample period runs from 02 August 2017 to 29 August 2022; non-trading days in Switzerland are omitted.

The CDS spreads summary statistics and the credit rating of each individual company in the sample can be found in Appendix I. Eight companies are rated in the credit rating class A (following the methodology of Moody's), and six companies in the sample have a credit rating in class B. The highest average CDS spread in the sample registered by the materials company Glencore with an average of 159.622 basis points, followed by the chemical company Syngenta with an average CDS spread of 143.653 basis points during the sample period. This observation is consistent with the higher probabilities of default among companies in the lower end of the rating classes, thus rating class B. However, there are also companies in the sample with the same credit rating (Baa1), but lower average CDS spreads. The pharmaceutical company Novartis shows the lowest average CDS spreads with 16.580 basis points. The highest standard deviation with 57.579 basis points is also reported by Glencore, followed by Syngenta, with a standard deviation of 45.591 basis points. The lowest amount of variation is exhibited by the chemical company BASF with a standard deviation of 2.872 basis points, followed by Novartis, with a standard deviation of 3.213 basis points. It is interesting to observe that the CDS spreads and the credit rating from Moody's are not always aligned despite the fact that both figures aim to capture credit risks. This observation confirms the findings of Kiesel and Spohnholtz (2017), who demonstrated that CDS spreads and agency ratings are indeed positively correlated. However, CDS spreads cannot be assigned to an agency rating unambiguously. The authors found that, for example, CDS spreads of 100 basis points were present in seven different rating grades.

4. Methodology

This study conducts several multiple regression analyses to discover whether Google search volumes, represented by three *trendEcon* indicators, exhibit explanatory power for CDS spreads of Swiss firms. The use of multiple regression models allows the determination of the impacts of various independent variables on a dependent variable. This section defines the methodology utilised for this study. The multiple regression models illustrated in the following sections are estimated using the ordinary least squares (OLS) technique. The ordinary least squares procedure is a statistical method used to compute the estimated coefficients of a linear regression equation, which minimises the sum of squared errors/residuals. The ordinary least squares regression technique is widely implemented in statistical software packages (Newbold et al., 2019). The analysis of this thesis is conducted with the programming language Python, using the Jupyter Notebook environment. Jupyter Notebook is an open-source and web-based tool that enables users to perform scientific data analysis and calculations in various programming languages.

First, the estimations are done by regressing daily changes in CDS spreads on the control variables and the *trendEcon* indicators on the overall sample. This is done by a pooled OLS regression. A pooled OLS regression is a linear regression model using the OLS procedure but on a panel data set. Second, an OLS regression is performed on time-series data for each company in the sample. To ensure that the variables under the analysis are stationary, the non-stationary variables in the raw data set are transformed into daily log-differences. The following two sections define the multiple regression models analysed in this study. Initially, the five regression models run on the panel data set are described, followed by the specifications of two time-series regression models.

4.1. Panel Data Regression Models

To answer the research question of this thesis, pooled OLS regression models are run on a panel data set. Previously, the collected data, as described in section three, was transformed into a balanced panel data set. A balanced panel data set implies that the repeated observations of variables are done over the same time intervals. A stepwise analysis is conducted. Initially, only the control variables are used and the *trendEcon* variables are added successively. Finally, a regression model is run using the control and all *trendEcon* variables.

The baseline panel data Regression Model 1 (Equation 1) consists of three control variables and is specified as follows:

$$\varDelta CDS\ spread_{i,t} = a + \beta_1\ \Delta SMI_t + \beta_2 2year_t + \beta_3 \Delta VXX_t + \varepsilon_{i,t} \tag{1}$$

where $\varDelta CDS\ spread_{i,t}$ represents the CDS spread log changes of company *i* at time *t* (in basis points). ΔSMI_t are the log returns of the SMI. $2year_t$ stands for the two-year Swiss government bond yield at time *t*. ΔVXX_t represents the log changes in market volatility based on the Euro Stoxx 50 at time *t*. The term $\varepsilon_{i,t}$ is the error term, assumed to be well behaved.

In Regression Model 2, the *trendEcon* variable of *Perceived Economic Situation* is added to the baseline model. Denoting the variable by PES_t, the model specification (Equation 2) is as follows:

$$\varDelta CDS\ spread_{i,t} = a + \beta_1 PES_t + \beta_2 \Delta SMI_t + \beta_3 2year_t + \beta_4 \Delta VXX_t + e_{i,t} \tag{2}$$

In Model 3, the *trendEcon Mobility* indicator is added to the baseline model. Denoting this variable by Mob_t, the following model is defined.

$$\varDelta CDS\ spread_{i,t} = a + \beta_1 Mob_t + \beta_2 \Delta SMI_t + \beta_3 2year_t + \beta_4 \Delta VXX_t + e_{i,t} \tag{3}$$

In Model 4, the *Clothing and Shoes* indicator is included in the model and is labelled as CS_t.

$$\varDelta CDS\ spread_{i,t} = a + \beta_1 CS_t + \beta_2 \Delta SMI_t + \beta_3 2year_t + \beta_4 \Delta VXX_t + e_{i,t} \tag{4}$$

Lastly, Regression Model 5 regresses the CDS spread changes against all three *trendEcon* indicators and the control variables. The specification of the model is provided in Equation 5.

$$\begin{aligned}\varDelta CDS\ spread_{i,t} \\ &= a + \beta_1 PES_t + \beta_2 Mob_t + \beta_3 CS_t + \beta_4 \Delta SMI_t \\ &+ \beta_5 2year_t + \beta_6 \Delta VXX_t + e_{i,t}\end{aligned} \tag{5}$$

The coefficients of interest are β, the effects of *trendEcon* variables on CDS spread changes. The regression coefficients β measure the relationship between the independent and dependent variable, the changes in CDS spreads. The sign of the coefficient indicates the direction of the relation. Further, the result presented in section five discusses the coefficient of determination (hereinafter referred to as R^2). The R^2 measures the proportion of total variability, which is explained by the regression model (Newbold et al., 2019). This means that the R^2 values provide information about how well the regression model fits the collected data, thus measuring the quality of the regression model. The R^2 values range between zero and one. The higher the R^2 value, the more explanatory power the model has on the dependent variables. The estimated intercepts (a) are not evaluated and commented on in the result section, as they have no meaningful interpretation for the models of this study. However, they will be presented in the result tables for the sake of completeness.

4.2. Single Company (Time-Series) Regression Models

To uncover the relationship between Google search queries represented by *trendEcon* indicators and the CDS spreads of individual companies, two multiple regression models are run on the time series of each company in the sample. First, the analysis regresses the baseline OLS regression model containing the control variables only (Equation 6), and in the second step running an OLS regression also considering the three *trendEcon* variables (Equation 7).

The baseline regression model (Equation 6) for the OLS regression on the individual company CDS spread changes composed of three control variables is as follows:

$$\Delta CDS\ spread_t = a + \beta_1 \Delta SMI_t + \beta_2 2year_t + \beta_3 \Delta VXX_t + \varepsilon_t \tag{6}$$

Daily observations are indexed by *t*. $\Delta CDS\ spread_t$ represents the CDS spread log changes at time *t* (in basis points). ΔSMI_t represents the log returns of the SMI. $2year_t$ stands for the two-year Swiss government bond yield at time *t,* and ΔVXX_t represents the log changes in market volatility based on the Euro Stoxx 50 at time *t*. The variable ε_t is the error term assumed to be well behaved.

Next, the regression model consisting of all three *trendEcon* variables (Equation 7) is specified as follows:

$$\begin{aligned} \Delta CDS\ spread_t &= a + \beta_1 PES_t + \beta_2 Mob_t + \beta_3 CS_t + \beta_4 \Delta SMI_t \\ &+ \beta_5 2year_t + \beta_6 \Delta VXX_t + e_t \end{aligned} \tag{7}$$

where PES_t represents the *trendEcon* variable of *Perceived Economic Situation*, the *Mobility* indicator is denoted by Mob_t, and CS_t stands for the *Clothing and Shoes* index.

5. Result

This section presents the main results from the regression analyses. It begins by discussing the results of the panel data regression. After that, the regression results based on single companies are presented. The individual outputs of the regression models will be exemplified. The obtained regression results have been computed with the Python codes in Appendix IV and V. The result analysis focuses on the estimated coefficient parameters describing the size and direction of the relationship between the independent and dependent variables. The significance levels of the estimated coefficients are commented on as well.

5.1. Panel Regression

To discover whether Google search volumes proxied by *trendEcon* indicators exhibit explanatory power for CDS spreads, five pooled OLS regressions were run on the overall sample as described in the previous section. The results of the panel regression models are presented in Table 5. Model 1 is the baseline regression model estimating the control variables only. In the subsequent Models 2 to 4, the *trendEcon* variables are added individually. In Model, 5 all *trendEcon* variables are included next to the control variables.

In Model 1, the log returns of the Swiss Market Index (SMIlog), the two-year Swiss Government Bond Yields (CH2YT), and the log returns of the Euro Stoxx 50 Volatility Index (V2TXlog) explain the CDS spread changes. All variables enter the regression with statistically significant coefficients. The estimated coefficient value of minus 0.6753 for the SMI return shows the extent to which a 1% increase in SMI returns has an impact on the CDS spread changes. All else equal, a 1% increase in SMI returns implies a decrease of CDS spreads changes on average by 0.6753%. The SMI return coefficient is significant at the 1% level. This theoretically expected relation is reasonable considering that positive equity returns (here SMI returns) increase a firm's value and therefore lower the expected probability of default and, thus, CDS spreads. This coefficient is assumed to be negative for the other regression models as well. The two-year Swiss Government bond yields record a moderate positive relation (0.0018) to CDS spread changes at the 5% significance level. The government bond yields can be interpreted as a macro-economic factor. This would mean that interest rates are positively associated with the general conditions of an economy. Higher interest rates imply higher economic growth and therefore lower the default risk, and decreasing CDS spreads are observed. Although, this interpretation is not supported by the positive coefficient in Model 1. The volatility index VSTOXX (V2TXlog) exhibits an expected positive relationship to CDS spread changes and is significant at the 1% level. All else equal, a 1% increase in equity volatility, here VSTOXX, suggests a rise in CDS spreads by 0.0830%. This relation is in line with the assumption that positive return volatility leads to higher CDS spreads due to the increased risk of default during volatile times. This coefficient is also expected to stay positive in the other regression models. Model 1 exhibits an R^2 of 15.56%, meaning that 15.56% of the observed variation in CDS spread changes can be explained by Model 1.

In Model 2, the *trendEcon* variable *Perceived Economic Situation (PES)* is added. All Model 2 parameter coefficients are found to be significant at less than the 5% level. In Model 2, the control variables SMI returns, two-year Swiss Government bond yields, and volatility index VSTOXX exhibit the same negative, respectively, positive signs as in Model 1. The result parameter indicates a moderate negative relationship between the Google-based economic sentiment indicator and CDS spread changes. This means a 1% increase in the *Perceived Economic Situation* indicator (meaning that people are less concerned about the economy) implies an average reduction in CDS spread changes by 0.0007%. This association is sensible, considering that companies' default risk is lower during normal economic times and higher during times of financial distress. The overall model fit slightly increases to 15.60% compared to the baseline model when the *trendEcon* variable *Perceived Economic Situation (PES)* is added.

Table 5: *Pooled OLS Regression Coefficients*

Dependent variable: CDS spreads (log returns)					
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Constant	0.0018	0.0021	0.0015	0.0059	0.0055
	(0.0020)	(0.0003)	(0.0123)	(0.0000)	(0.0000)
SMIlog	-0.6753	-0.6730	-0.6733	-0.6659	-0.6628
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CH2YT	0.0018	0.0019	0.0018	0.0029	0.0029
	(0.0210)	(0.0130)	(0.0212)	(0.0002)	(0.0002)
V2TXlog	0.0830	0.0833	0.0830	0.0839	0.0841
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PES		-0.0007			-0.0007
		(0.0029)			(0.0044)
Mob			0.0007		0.0006
			(0.0094)		(0.0393)
CS				-0.0033	-0.0029
				(0.0000)	(0.0000)
R^2	0.1556	0.1560	0.1559	0.1576	0.1580
N	19'110	19'110	19'110	19'110	19'110

Note: Own representation. Table depicts the coefficients of the pooled OLS regressions of Equations 1 to 5. P-values are given in parentheses. All coefficients are significant at the 5% level. SMIlog = SMI log-returns; CH2YT = two-year Swiss Government Bond Yield; V2Txlog = volatility index VSTOXX; PES = Perceived Economic Situation; Mob = Mobility; CS = Clothing and Shoes.

In Model 3, the *trendEcon* variable *Mobility (Mob)* is attached to the control variables. The Mobility coefficient value is 0.0007 and is statistically significant at the 1% level. This suggests a moderate positive relationship between the change in demand for group transportation and CDS spread changes. This positive relationship was theoretically not expected. It can be assumed that increased demand for transportation goes along with a flourishing economy and therefore implies a reduction in the probability of default, which leads to lower CDS spreads. Although, this assumption could potentially be disrupted by Covid-19 when more people opted to work from home, and many of them still do on a regular basis.

Model 4 includes the *trendEcon* variable for *Clothing and Shoes*. The coefficient shows a negative effect of changes in the demand for clothes and shoes on CDS spreads at a significance level of 1%. The average effect of a 1% increase in the demand for clothing and shoes on CDS spread changes is minus 0.0033%. This observed negative relationship is reasonable. Higher spending activity in an economy implies an overall positive consumer sentiment, which in turn has a positive impact on the economy. This leads to decreased probabilities of default and should be reflected in lower CDS spreads. Model 4 exhibits a higher R^2 of 15.76% compared to a value of 15.56% for the baseline model without any *trendEcon* variables. This is the highest R^2 value when the models with only one *trendEcon* variable are compared.

In Model 5, all *trendEcon* and control variables are included. All coefficients are statistically significant on the 1% level, except for the Mobility coefficient, which is significant on the 5% level. All *trendEcon* variables seem to have explanatory power for CDS spread changes, however, the impact is small. As illustrated in Table 5, Model 5 exhibits the highest explained variation, with an R^2 of 15.80% compared to the other models.

All models expressed in Table 5 show similar results. The same independent variables have the same negative respectively positive sign and are all significant at less than the 5% level. The estimated coefficients and the R^2 values are similar across all models. The R^2 values slightly improve with the inclusion of *trendEcon* variables and are the highest when all *trendEcon* variables are used, as in Model 5. However, the difference is minimal. Model 5, which includes all *trendEcon* variables, shows an R^2 of 15.80%, whereas the R^2 of the baseline model is at 15.56%.

Taken together, the panel regression results shed light on the applicability of *trendEcon* indicators to explain CDS spread changes. Across all models, the SMI returns are statistically significant, and the coefficient sign is negative, as theory would predict. Although the Swiss Government bond yield was statistically significant in all models, the estimates did not meet the expectations about the negative relation on changes in CDS spreads. Across all models, the volatility index VSTOXX remains a positive and significant determinant of CDS spread changes. The results of the panel regressions indicate that the explanatory power of Google search volumes on CDS spread changes appears to exist but has little impact. In Models 2 and 5, where the *trendEcon* variable *Perceived Economic Situation (PES)* is included, the coefficients show significant predictable power for CDS spreads and are in line with the expected negative relationship. The *Mobility* indicator is statistically significant in both models it is included in, but the nature of the relationship is not in accordance with theoretical assumptions. On the other hand, the *trendEcon* variable for *Clothing and Shoes* exhibits a theoretically expected negative and highly significant impact on CDS spread changes in both models in which the variable is examined.

5.2. Single Company Baseline Regression

To develop how effectively Google search data is explaining the behaviour of CDS spreads of specific companies, two OLS regression models are estimated on time-series data of each company in the sample. Table 6 sets out the OLS estimation results of the baseline regression model (Equation 6), which explains CDS spreads only by the control variables. After that, the results of the regression models using all *trendEcon* variables (Equation 7) are reported in Table 7.

Observing the results in Table 6, not all regression models explain the CDS spread changes well. The results show poor R^2 values for certain companies. At first sight, it seems to be related to the industry the company is operating in. It appears that the CDS spread changes of the two pharmaceutical companies, Roche and Novartis, are not explained well by the baseline model. Looking at R^2, the regression equation explains only 2.60%, respectively 4.60%. The chemical company BASF and Swisscom operating in the telecommunications industry show similar poor R^2 values of 0.40%, respectively 3.00%. Further, most of the estimated coefficients in the model of these companies are highly insignificant. This part of the work will not further comment on the regression result of BASF as the whole model is insignificant, inspecting the probability of the F-statistic of 0.1930 (not reported in the result table). The F-statistics indicate whether any of the independent variables in the model is significantly related to the dependent variable.

Instead, the regression results of both banks in the sample present very reasonable R^2 values, 33% for the model of Credit Suisse and 25% for UBS Group. High explanatory power is also witnessed in the model regressing on CDS spread changes of TE Connectivity, a technology company, with an R^2 of 27%.

Table 6: *Single Company OLS Regression Coefficients (Equation 6)*

Dependent variable: CDS spreads (log returns)								
Variables	**BASF**	**Clariant**	**Glencore**	**UBS Group**	**Credit Suisse**	**Swisscom**	**Roche**	**TE Connect.**
	Chemicals	Chemicals	Materials	Banking	Banking	Telecom.	Pharmaceutical	Technology
Constant	0.0000	0.0008	0.0004	0.0030	0.0050	0.0006	0.0028	-0.0009
	(0.9500)	(0.6640)	(0.8670)	(0.1720)	(0.0100)	(0.7790)	(0.0940)	(0.6090)
SMIlog	0.0049	-0.9255	-0.7198	-0.9477	-1.0297	-0.0804	-0.2209	-1.0210
	(0.8790)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4320)	(0.0080)	(0.0000)
CH2YT	-0.0003	0.0002	-0.0001	0.0031	0.0057	0.0008	0.0034	-0.0020
	(0.7550)	(0.9490)	(0.9680)	(0.3040)	(0.0270)	(0.7820)	(0.1250)	(0.3920)
V2TXlog	0.0065	0.0731	0.1211	0.1080	0.1079	0.0559	0.0173	0.0536
	(0.0980)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0900)	(0.0000)
R^2	0.0040	0.2370	0.2210	0.2540	0.3340	0.0360	0.0260	0.2730
N	1'274	1'274	1'274	1'274	1'274	1'274	1'274	1'274

Before further elaborating on the overall model results and the possible connection to the company's industry, the estimated coefficient parameters are examined. As expected, the result presented in Table 6 indicates a negative influence of the SMI returns (SMIlog) on each company's CDS spread changes in the sample (except BASF, which is not further assessed). That means deteriorating SMI returns on a trading day results in higher CDS spreads. This is consistent with the theory that higher equity returns increase the value of the company and, therefore, should result in lower CDS spreads. The same observation was made for the panel data regression. However, in most cases, the impact of the SMI returns is much stronger on the estimated single-company regression models. All estimated SMI return coefficients are statistically significant at the 1% level, except the model explaining CDS spread changes of Novartis, which is only significant on the

10% level, and for Swisscom with a p-value of 0.4230, indicating that the coefficient is statistically insignificant. Therefore, the effect of the SMI returns on the CDS spreads of Swisscom is not significantly different from zero.

Table 6: *(continued)*

Variables	**Nestlé**	**Swiss Reins**	**Novartis**	**Zurich Ins**	**Syngenta**	**Adecco**	**Holcim**
	Food/Beverage	Reinsurance	Pharmaceutical	Insurance	Chemicals	HR Services	Construction
Constant	0.0018	0.0036	-0.0008	0.0051	0.0011	0.0021	0.0021
	(0.4560)	(0.1830)	(0.7500)	(0.0700)	(0.6590)	(0.3500)	(0.3370)
SMIlog	-0.9205	-0.5032	-0.2174	-0.7048	-0.9305	-0.8053	-1.1081
	(0.0000)	(0.0000)	(0.0970)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CH2YT	0.0022	0.0043	-0.0013	0.0064	0.0005	0.0021	0.0019
	(0.5040)	(0.2430)	(0.7110)	(0.0930)	(0.8680)	(0.5050)	(0.5090)
V2TXlog	0.0896	0.1889	0.0713	0.1877	0.0537	0.0383	0.0725
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0070)	(0.0000)
R^2	0.1870	0.2290	0.0460	0.2460	0.1430	0.1110	0.2380
N	1'274	1'274	1'274	1'274	1'274	1'274	1'274

Note: Own representation. Table depicts the coefficients of the single company OLS regressions (Equation 6). P-values are given in parentheses. SMIlog = SMI log-returns; CH2YT = two-year Swiss Government Bond Yield; V2Txlog = volatility index VSTOXX.

In contrast to the panel data regression results the estimated coefficients of the Swiss Government Bond Yields (CH2YT) are not statistically significant in the single-company regression models for almost all companies (except for Credit Suisse, where the coefficient has a positive sign and is significant on the 5% level). This implies that the effect of the two-year Swiss Government Bond Yields is not significantly different from zero. Further, the result shows that Swiss Government Bond Yields exhibit mixed relationships to CDS spread changes. It can be concluded that on a single company level, the relationship between the two-year Swiss Government Bond Yields and the CDS spread changes of these companies remains inconclusive.

As presented in Table 6, the signs of the coefficients of the stock market volatility index VSTOXX (V2TXlog) are all positive and highly significant. The positive relationship was expected. The assumption is that higher stock market volatility implies higher uncertainty about the economic prospects, thus, investors are willing to pay more for their protection, and therefore CDS spreads increase. The statistical significance is given at the 1% level for all companies except for Roche, which is only significant at the 10% level. The positive impact of the VSTOXX coefficient is particularly high for companies in the finance industry, thus banking, insurance, and reinsurance. In the case of Swiss Re, a 1% increase in volatility implies an average raise of Swiss Re's CDS spreads by 0.1889%.

Overall, the result of the single company baseline model shows that the SMI returns, as well as the volatility index VSTOXX, explain the variation in CDS spreads well. This is not true for the two-year Swiss Government Bond Yields, which have no significant impact on firm-specific CDS spread changes. These findings can be observed in all industries. On the level of the whole models, 11 out of the total 15 models show reasonable R^2 values ranging from 11.10% (Adecco) to 33.40% (Credit Suisse).

5.3. Single Company Regression with *trendEcon* Variables

In the next phase, the analysis is extended by studying the explanatory power of the three *trendEcon* variables on CDS spread changes of each company in the sample. For this purpose, the three *trendEcon* variables are included in the regression model (Equation 7). The results of these regression models are presented in Table 7. Examining the single company regression results, it can be observed that the overall explanatory power of the regression models increases when the three *trendEcon* variables are included. The R^2 values are slightly higher in all regression models with the Google-based *trendEcon* variables. Using the example of Credit Suisse, the R^2 value increases from 33.40% (Equation 6) to 34% when the three *trendEcon* variables are included in the model. This implies that 34% of the variation in the CDS spreads of Credit Suisse can be explained by the independent variables. The R^2 values for the models of Swisscom, Roche, and Novartis remain very low even if the *trendEcon* variables are included.

Consistent with the previous regression results, the SMI returns (SMIlog) have a negative impact on the CDS spread of the individual companies in the sample. The SMI returns are statistically significant at the 1% level, except the coefficient for Novartis, which is insignificant with a p-value of 0.1050. Further, the SMI return estimates in the model of Swisscom are not nearly significant, with a p-value of 0.4870. The observed inverse relationship between SMI returns and CDS spread changes is in accordance with the argument that higher equity returns reflect higher earnings of a company today and in the future, implying better financial health and, consequently, lower CDS spreads.

Table 7: *Single Company OLS Regression Coefficients including trendEcon Variables (Equation 7)*

Dependent variable: CDS spreads (log returns)								
Variables	**BASF**	**Clariant**	**Glencore**	**UBS Group**	**Credit Suisse**	**Swisscom**	**Roche**	**TE Connect.**
	Chemicals	Chemicals	Materials	Banking	Banking	Telecom.	Pharmaceutical	Technology
Constant	-0.0003	0.0033	0.0067	0.0097	0.0104	0.0026	0.0043	0.0027
	(0.7620)	(0.2700)	(0.0520)	(0.0040)	(0.0000)	(0.4000)	(0.0870)	(0.3050)
PES	-0.0003	-0.0005	-0.0025	-0.0010	-0.0017	-0.0016	-0.0002	-0.0010
	(0.3720)	(0.5330)	(0.0160)	(0.2970)	(0.0440)	(0.0840)	(0.7450)	(0.1930)
Mob	0.0000	0.0005	0.0018	-0.0002	0.0004	0.0003	0.0007	0.0006
	(0.9140)	(0.6250)	(0.1240)	(0.8530)	(0.6470)	(0.7660)	(0.4300)	(0.4970)
CS	0.0003	-0.0019	-0.0048	-0.0049	-0.0039	-0.0012	-0.0014	-0.0027
	(0.5360)	(0.2650)	(0.0170)	(0.0130)	(0.0230)	(0.5150)	(0.3450)	(0.0750)
SMIlog	0.0048	-0.9168	-0.6932	-0.9309	-1.0117	-0.0711	-0.2143	-1.0083
	(0.8810)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4870)	(0.0100)	(0.0000)
CH2YT	-0.0003	0.0009	0.0020	0.0049	0.0074	0.0015	0.0039	-0.0009
	(0.7010)	(0.7310)	(0.5280)	(0.1070)	(0.0050)	(0.6040)	(0.0860)	(0.7120)
V2TXlog	0.0066	0.0738	0.1234	0.1097	0.1097	0.0568	0.0178	0.0547
	(0.098)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0820)	(0.0000)
R^2	0.0050	0.2390	0.2310	0.2590	0.3400	0.0390	0.0280	0.2770
N	1'274	1'274	1'274	1'274	1'274	1'274	1'274	1'274

Table 7: *(continued)*

Variables	**Nestlé**	**Swiss Reins**	**Novartis**	**Zurich Ins**	**Syngenta**	**Adecco**	**Holcim**
	Food/Beverage	Reinsurance	Pharmaceutical	Insurance	Chemicals	HR Services	Construction
Constant	0.0032	0.0107	0.0020	0.0095	0.0071	0.0052	0.0053
	(0.3850)	(0.0090)	(0.6140)	(0.0270)	(0.0500)	(0.1400)	(0.1100)
PES	0.0003	-0.0019	0.0017	-0.0006	-0.0010	0.0000	-0.0008
	(0.7740)	(0.1230)	(0.1460)	(0.6500)	(0.3590)	(0.9740)	(0.4050)
Mob	0.0014	0.0002	0.0004	0.0006	0.0004	0.0002	0.0019
	(0.2720)	(0.891)	(0.7490)	(0.6780)	(0.7720)	(0.8770)	(0.0940)
CS	-0.0017	-0.0051	-0.0031	-0.0035	-0.0047	-0.0025	-0.0029
	(0.4250)	(0.0340)	(0.1860)	(0.1580)	(0.0280)	(0.2190)	(0.1290)
SMIlog	-0.9127	-0.4819	-0.2128	-0.6912	-0.9129	-0.7977	-1.0918
	(0.0000)	(0.0000)	(0.1050)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CH2YT	0.0027	0.0064	-0.0006	0.0077	0.0023	0.0029	0.0031
	(0.420)	(0.0890)	(0.8680)	(0.0480)	(0.4850)	(0.3600)	(0.3050)
V2TXlog	0.0900	0.1911	0.0713	0.1888	0.0553	0.0389	0.0737
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0070)	(0.0000)
R^2	0.1890	0.2340	0.0500	0.2480	0.1480	0.1120	0.2420
N	1'274	1'274	1'274	1'274	1'274	1'274	1'274

Note: Own representation. Table depicts the coefficients of the OLS regressions, including all *trendEcon* variables (Equation 7). P-values are given in parentheses. PES = Perceived Economic Situation; Mob = Mobility; CS = Clothing and Shoes; SMIlog = SMI log-returns; CH2YT = two-year Swiss Government Bond Yield; V2Txlog = volatility index VSTOXX.

In 13 out of the total 15 models, the estimated coefficients for the Swiss Government Bond Yields (CH2YT) are not statistically significant. Only the model of Credit Suisse and Zurich Insurance is significant at the 5% level. Mostly insignificant coefficients for the Swiss Government Bond Yields were also observed in the single-company baseline model (Equation 6). Most estimated coefficients exhibit a moderate positive relationship to CDS spread changes. However, in theory, the government bond yields are expected to be negatively related to CDS spreads because an increase in risk-free rates implies higher economic growth, which should result in lower insolvency risk and, thus, lower CDS spreads.

The overall positive coefficients of the market volatility index VSTOXX (V2TXlog) reported in Table 7 indicate that VSTOXX is positively associated with the individual CDS spread changes. The VSTOXX coefficients are significant on the 1% level, apart from the estimate of Roche with a significance level of 10%. This positive observed relationship is consistent with the previous regression results of this study and is in line with the theory. An increase in volatility implies higher economic uncertainty and raises the likelihood of a company defaulting; therefore, higher CDS spreads follow as investors seek protection and are willing to pay more for this protection.

Having identified the relationships between the control variables and CDS spread changes in the previous sections, the subsequent paragraphs examine the explanatory power of the *trendEcon* variables on the CDS spread changes. The coefficient of *Perceived Economic Situation (PES)* measures the sensitivity of the Google-based sentiment indicator to contemporaneous CDS spread changes. The regression results outlined in Table 7 show that only two out of 15 estimated coefficients of Perceived Economic Situation are statistically significant at the 5% level. The coefficients show moderate negative signs across most models. The negative direction of the relation was expected. As the overall economic condition improves (people are less concerned about the economy, and the index of *Perceived Economic Situation* moves upward), CDS spreads decrease because a lower probability of default is expected.

In all single-company models, the *Mobility* index does not enter the regressions with statistically significant coefficients. The estimated coefficients show highly insignificant results and do not seem to be related to the CDS spread changes at the single-company level. The signs of the estimated *Mobility* coefficients are slightly positive in almost all cases.

The *trendEcon* indicator of *Clothing and Shoes (CS)* seems to have the ability to predict the CDS spread changes of the Swiss companies in the sample. In five out of the total 15 models, the estimated coefficients are statistically significant at the 5% level. The estimated Clothing and Shoes coefficient in the model of TE Connectivity shows a p-value of 0.0750, which would be significant at the 10% level. In all single-company models, the Clothing and Shoes coefficients retain their expected negative signs. According to the estimates, an increase in Google search activity related to the demand for clothes and shoes translates into a contemporaneous decrease in CDS spread changes. This direction is expected in theory. Higher demand for goods is a sign of economic growth and makes it easier for companies to pay back their debt. This results in higher creditworthiness and, consequently, lower CDS spreads.

To summarise, there is evidence that Google-based variables from *trendEcon* have predictive power on the CDS spreads of individual Swiss companies. Particularly, the indicator *Perceived Economic Situation (PES)* and *Clothing and Shoes (CS)* show robust and constant results. However, the ability of the Mobility indicator to explain CDS spread changes vanishes in the single-company regression models.

5.4. Discussion of the Result

The results of the panel regression show that the Google-based indicators from *trendEcon* have the capability to explain CDS spread changes. All *trendEcon* variables exhibit statistically significant coefficients. Looking at the R^2 values, the regression models gain strength, even if rather minor, when the *trendEcon* variables are included. The estimated negative signs of the coefficients of *Perceived Economic Situation* and *Clothing and Shoes* on CDS spread changes can be supported in theory, as already explained in the result section. The positive coefficient of the *Mobility* indicator fails to deliver the expected relation to CDS spreads in theory. There is no available empirical research that could comment on this result. However, it is possible that the *Mobility* indicator might have gone through structural changes over the last two years since many companies have moved permanently to flexible workplace models.

The panel regression results further unveil that the variables SMI returns and stock market volatility are the strongest two explanatory variables of changes in CDS spreads in the panel regression Models 1 to 5, and their coefficients are highly significant. The significant impact of equity returns and stock market volatility in explaining CDS spread changes is in line with the evidence reported by, among others, Galil et al. (2014), Hasan et al. (2016), and Shahzad et al. (2017).

The positive sign of the two-year Swiss Government Bond Yield coefficients is not consistent with the theoretically expected relation. From a theoretical perspective, an inverse association between the Swiss Government bond yields was expected. High interest rates are often observed during periods of economic upswing or boom where the credit or default risk tends to be lower. On the other hand, the positive relation illustrated in the regression results could be explained by the higher interest costs for heavily indebted companies, which could deteriorate a company's financial situation and consequently increase CDS spreads.

The regression results on the panel data set revealed that Google-based indicators are applicable to explain CDS spread changes. However, the findings of the single-company regressions are not as constant and robust as in the panel regression. To begin with, the overall model fit (R^2) in the single company regression models could be improved when the three *trendEcon* variables are included. However, the enhancement is minor. Regardless of the *trendEcon* variables, some regression models exhibit poor R^2 values, implying that the model specifications in this study are not appropriate for certain companies. Observing that for both pharmaceutical companies in the sample, the R^2 values are extremely low. In contrast, the companies in the financial industry show reasonable R^2 values, one might imply that the regression results and overall model fit depend on the industry the company is operating in.

Also, in the single-company models, the estimated coefficients for SMI returns and stock market volatility show the expected signs and exhibit statistical significance in almost all cases regardless of whether the *trendEcon* variables are included or not. The SMI returns are negatively associated with CDS spreads, whereas the stock market volatility exhibits a positive impact on the CDS spreads of the individual companies. The same observation has already been empirically proven by previous studies.

The coefficients of the two-year Swiss Government Bond Yields are insignificant in the single-company regression models in almost all cases. The results state a positive relation to CDS spreads, which was not expected. However, the impact of the bond yields could be explained in two ways. On the one hand, high interest rates indicate a strong economy which decreases the likelihood of a default and consequently is followed by lower CDS spreads (negative relationship). On the other hand, high interest rates could also imply an increase in the cost of debt for heavily leveraged companies. They are more negatively exposed to interest rate fluctuations, which results in higher CDS spreads. The ambiguous relationship has also been discussed in empirical literature, among others, by Annaert et al. (2013), Shahzad et al. (2017), and Zhu (2013).

Moving on to the *trendEcon* variables in the single-company regression models. In contrast to the panel regression results, the results in the single-company regressions are not significant in all models. The indicator of *Perceived Economic Situation* only enters the regression with two out of 15 statistically significant coefficients. The *Clothing and Shoes* index presents five out of 15 statistically significant coefficients. None of the estimated coefficients of the *Mobility* indicator exhibit significance. Although not all coefficients are significant, the indicators of *Perceived Economic Situation* and *Clothing and Shoes* show the expected negative association to CDS spreads of individual companies.

6. Conclusion

This section completes the thesis by concluding the results, elaborating on the limitations of the study, discussing the implication of the findings, and providing an outlook for further research.

6.1. Conclusion of Findings

In the last decade, the interest in alternative, non-traditional data, whose source differs from those of conventional and well-examined data, has been growing extensively due to the potential to enhance economic and statistical analyses. Especially data originating from the internet and social media have become popular among economists and researchers to assess macroeconomic conditions and financial markets. This development was accelerated by the outbreak of the Covid-19 pandemic, when the need for timely available data to capture the current state of the economy was even higher. This thesis focuses on Google search volume data.

Previous empirical literature has shown that Google search volumes are helpful in predicting various macroeconomic indicators. Further, researchers empirically proved that Google search volumes also have predictive capabilities towards financial markets. Relatively little empirical research was found addressing the link between Google search volumes and credit risk measured by CDS spreads. The aim of this thesis is to examine the interconnection between Google search volumes and CDS spreads.

To shed light on the research question, the empirical analysis examines whether Google search data from Switzerland is associated with the CDS spread changes of large Swiss companies. In order to answer the research question, several multivariate regressions were conducted. Three Google-based indicators from *trendEcon* are utilised as independent variables of the regression models. Google search volumes pose significant challenges when collecting and analysing the raw data. *TrendEcon* introduced a technique that overcomes the issues when applying and analysing Google search volumes. They provide a set of pre-processed economic indicators for Switzerland based on Google search trends. In addition to the *trendEcon* variables, three control variables, the SMI returns, the two-year government bond yields, and the European stock market volatility index VSTOXX, were defined. The natural logarithm of CDS spreads changes serves as the dependent variable of the regression analysis. The sample period spans from August 2017 to August 2022.

The first part of the empirical results is delivered by the pooled OLS regression on a panel data set covering the whole sample. The results provide evidence that the Google-based indicators from *trendEcon* exhibit explanatory power for CDS spread changes of Swiss companies. The Google-based indicators have the capability to increase the overall model fit when explaining CDS spread changes. Especially the index of *Perceived Economic Situation* and the *Clothing and Shoes* indicator seem to work well and show the expected relations towards CDS spreads. The Google-based indicator for *Mobility* shows significant results indeed, however, the effect on CDS spreads should be treated with caution as the direction of the relation is not comprehensible.

The second part of the results is provided by several OLS regressions run on the time-series data of each company in the sample. The results suggest that the Google-based indicator for Clothing and Shoes performs well in explaining CDS spreads, however, only for the CDS spread changes of certain companies. The index of *Perceived Economic Situation* shows a reasonable direction for relation to CDS spreads. However, only in two models, the indicator is convincible with significant coefficients. The results of the single-company regression models provide no evidence that the Google-based indicator of Mobility can explain CDS spreads.

Overall, the findings confirm that variables based on Google search volumes have explanatory power on CDS spreads and, therefore, can help to identify indications of declining creditworthiness. This ability to explain CDS spreads is particularly apparent when regressing on the overall sample with a panel regression. Nevertheless, the relationship between the *trendEcon* variables and CDS spread changes is much weaker on the single company level and varies strongly depending on the industry the company is operating in.

6.2. Limitations

The analysis is limited to the region of Switzerland. First, it must be said that this regional distinction is reasonable because the level of usage of the Google search engine is different in each country. However, as Switzerland is a small country, only a few companies are available with CDS contracts written on their debt. Therefore, the sample size of the empirical analysis was limited.

Further, it needs to be questioned if Google search volumes and CDSs can be linked. CDS contracts are traded by large institutional and sophisticated investors. These qualified investors monitor the economy all the time and are probably not using Google to obtain information about the economy, as they have professional information systems at their disposal. On the other hand, Google search data tends to represent retail investors who are rather uninformed (Da et al., 2011; Dimpfl and Jank, 2016).

6.3. Implications and Recommendations

It is beyond question that understanding the determinants of CDS spreads is crucial for all market participants, policymakers, and economists. It allows the identification of possible deterioration in the CDS market and enables rapid action to be taken if needed. Combining the analysis of the determining factors of CDSs with new alternative datasets, such as internet search data, holds great potential. The present thesis contributes to the literature by connecting CDS spreads with Google-based sentiment indicators. The empirical results offer valuable first insights into using Google-based indicators from *trendEcon* and where the indicators are most effective when analysing CDS spreads. It must be mentioned that internet search data should be used as complementing determinants of CDS spreads rather than as substitutes.

Despite numerous appealing benefits of this effortlessly traced data, there are also some drawbacks associated with using internet search data. Data availability could become an issue, as the continuity of the data provision is not guaranteed. Google could potentially terminate the provision of the data, or internet users could prohibit tracking their internet activities by using specific software (Buono et al., 2018). Further, the popularity of Google could change in the future, or the general online search behaviour could change over time. This means that it will be necessary to observe the relationship between internet searches and real economic activity over the course of time. Consequently, researchers and practitioners need to be aware of these downsides and find ways to overcome these difficulties.

6.4. Future Outlook

The use of alternative data like Google search volumes is clearly an important topic, and economists, policymakers, financial analysts, and other market participants have realised the potential new technologies have brought. This thesis leaves room for further research. The empirical analysis has been limited to explaining CDS spreads. However, the methodology could be applied to other credit risk measures like bond spreads as well. On a methodological level, the study could be enhanced by creating new long daily series from Google Trends using other and maybe more adequate search words related to credit risk and CDS spreads. *TrendEcon* provides an R package on their website so that everyone can construct new daily indicators based on the novel sampling technique.

Further, it would be helpful to extend this study by analysing different time periods. This would make it possible to investigate if there are differences in the predictive power of the Google-based indicators on CDS spread changes specific to a time period of crisis or booming economy. This would be particularly interesting because, in other contexts, researchers have found that internet search data has shown better predictive performance during time of financial crisis (Perlin et al., 2017; González-Fernández and González-Velasco, 2020a, 2020b).

Above all, the course of time will allow further studies to work with larger sample sizes of internet search data. Today, a sizeable portion of the population still has no or only limited access to the internet (Buono et al., 2018). This representativeness issue by missing out on search activities of older people or people residing in poorer regions will hopefully improve in the future.

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Appendix I: Descriptive Statistics CDS Spreads per Company

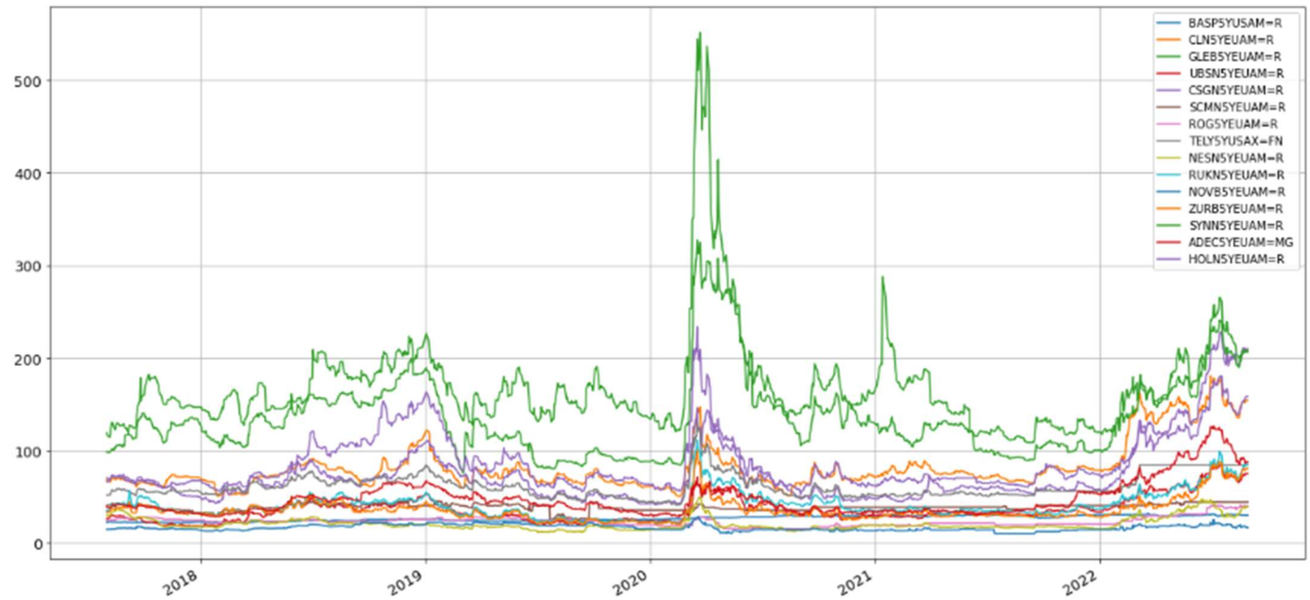
	BASF Chemicals	**Clariant** Chemicals	**Glencore** Materials	**UBS Group** Banking	**Credit Suisse** Banking	**Swisscom** Telecom.	**Roche** Pharmaceutical	**TE Connect.** Technology
Rating	A3	BBB-*	Baa1	A-*	Baa2	A2	Aa2	n/a
mean	26.697	81.776	159.622	35.908	73.673	38.908	23.195	61.223
max	31.980	180.720	551.640	84.630	228.170	45.750	40.970	131.500
min	21.880	50.340	103.000	17.430	41.250	25.180	15.370	41.000
std	2.872	25.737	57.579	13.484	34.778	3.658	4.856	12.649
N	1275	1275	1275	1275	1275	1275	1275	1275

(continued)

	Nestle Food/Beverage	**Swiss Reins** Reinsurance	**Novartis** Pharmaceutical	**Zurich Ins** Insurance	**Syngenta** Chemicals	**Adecco** HR Services	**Holcim** Construction
Rating	Aa3	Aa3	A1	A1	Ba1	Baa1	Baa1
mean	20.518	41.087	16.580	35.496	143.653	47.272	86.785
max	50.050	111.130	28.470	99.980	327.520	126.492	233.860
min	11.560	20.490	10.340	19.670	75.920	28.417	52.450
std	6.823	14.088	3.213	11.957	45.591	18.666	30.071
N	1275	1275	1275	1275	1275	1275	1275

Note: Own representation. in basis points; Rating = Moody's Long-term Issuer Rating; * Rating from Standard & Poor's; max = maximum value; min = minimum value; std = standard deviation; N = number of observations; the sample period runs from 02 August 2017 to 29 August 2022; non-trading days in Switzerland are omitted.

Appendix II: Development of Individual CDS Spreads



Note: Own representation. Data Source: (Refinitiv, 2022). Evolution of the time series of individual Company’s CDS spreads (in basis points). Time-series plot from 02 August 2017 to 29 August 2022.

Appendix III: Python Coding Data Retrieval and Processing

```
import math
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import scipy
import seaborn as sns
import xlsxwriter
import math
from math import exp, sqrt, log
import statsmodels.api as sm
from statsmodels.regression.linear_model import OLS
from statsmodels.tsa.stattools import adfuller
from statsmodels.stats.stattools import jarque_bera
from statsmodels.stats.stattools import durbin_watson

import statsmodels.formula.api as smf
import statsmodels.stats.api as sms

import pylab
import statistics

%matplotlib inline

from scipy import stats
```

Data Retrieval from trendEcon

Three Economic sentiment indicators from website trendEcon (https://www.trendecon.org/) as independent variable of the regression analysis

- Perceived Economic Situation (x_PES)
- Mobility (x_Mob)
- Clothing & Shoes (x_CS)

```
# download data (CSV File) from website into DataFrame
# Perceived EconomicS ituation
x_PES = pd.read_csv("https://raw.githubusercontent.com/trendecon/data/master/
data/ch/trendecon_sa.csv")
x_PES.rename(columns={'value':'x_PES'}, inplace=True)
x_PES

            time     x_PES
0     2006-01-01 -0.677525
1     2006-01-02 -0.034448
2     2006-01-03  0.000332
3     2006-01-04 -0.055055
4     2006-01-05 -0.558833
...          ...       ...
6080  2022-08-25  0.926409
6081  2022-08-26 -0.029170
6082  2022-08-27 -0.345352
6083  2022-08-28  0.024123
6084  2022-08-29 -1.051782

[6085 rows x 2 columns]
```

```
# Mobility
x_Mob = pd.read_csv("https://raw.githubusercontent.com/trendecon/data/master/
data/ch/mobility_sa.csv")
x_Mob.rename(columns={'value':'x_Mob'}, inplace=True)
x_Mob
```

```
            time     x_Mob
0     2006-01-01 -3.038472
1     2006-01-02 -2.709065
2     2006-01-03 -2.917017
3     2006-01-04 -2.539158
4     2006-01-05 -3.090765
...          ...       ...
6080  2022-08-25 -0.064953
6081  2022-08-26  0.882928
6082  2022-08-27  1.110606
6083  2022-08-28  1.078163
6084  2022-08-29  1.225804

[6085 rows x 2 columns]
```

```
# Clothing & Shoes
x_CS = pd.read_csv("https://raw.githubusercontent.com/trendecon/data/master/d
ata/ch/clothing_sa.csv")
x_CS.rename(columns={'value':'x_CS'}, inplace=True)
x_CS
```

```
            time      x_CS
0     2006-01-01 -2.052012
1     2006-01-02 -1.637669
2     2006-01-03 -1.648742
3     2006-01-04 -2.306419
4     2006-01-05 -1.118668
...          ...       ...
6080  2022-08-25  1.359417
6081  2022-08-26  1.093192
6082  2022-08-27  1.169805
6083  2022-08-28  0.641161
6084  2022-08-29  0.366676

[6085 rows x 2 columns]
```

```
# consolidate all trendEcon variables into one DataFrame
# dates (time) are matching, DataFrames can be merged
x_trendecon = pd.concat([x_PES, x_Mob, x_CS], axis=1)
x_trendecon.head()
```

```
            time     x_PES        time     x_Mob        time      x_CS
0     2006-01-01 -0.677525  2006-01-01 -3.038472  2006-01-01 -2.052012
1     2006-01-02 -0.034448  2006-01-02 -2.709065  2006-01-02 -1.637669
2     2006-01-03  0.000332  2006-01-03 -2.917017  2006-01-03 -1.648742
3     2006-01-04 -0.055055  2006-01-04 -2.539158  2006-01-04 -2.306419
4     2006-01-05 -0.558833  2006-01-05 -3.090765  2006-01-05 -1.118668
```

```
# remove column 'time' except from first one
x_Mob = x_Mob.drop(columns = ['time'], axis =1)
x_CS = x_CS.drop(columns = ['time'], axis =1)

x_trendecon = pd.concat([x_PES, x_Mob, x_CS], axis=1)
x_trendecon.head()
```

```
           time     x_PES     x_Mob      x_CS
0    2006-01-01 -0.677525 -3.038472 -2.052012
1    2006-01-02 -0.034448 -2.709065 -1.637669
2    2006-01-03  0.000332 -2.917017 -1.648742
3    2006-01-04 -0.055055 -2.539158 -2.306419
4    2006-01-05 -0.558833 -3.090765 -1.118668
```

```
# no missing values in trendEcon data
x_trendecon.isnull().sum()
```

```
time     0
x_PES    0
x_Mob    0
x_CS     0
dtype: int64
```

```
# remove rows to match time series of CDS spreads (dependent variable)
# time period 2017-08-02 to 2022-08-29
x_trendecon1 = x_trendecon.drop(x_trendecon.index[0:4231], axis = 0)
x_trendecon1
```

```
           time     x_PES     x_Mob      x_CS
4231 2017-08-02 -0.012651  1.126671  0.615251
4232 2017-08-03  0.157887  0.662762  0.621989
4233 2017-08-04  1.042680  1.086091  0.449422
4234 2017-08-05  0.749563  1.054133  0.614471
4235 2017-08-06  0.461566  0.986842  0.369376
...         ...       ...       ...       ...
6080 2022-08-25  0.926409 -0.064953  1.359417
6081 2022-08-26 -0.029170  0.882928  1.093192
6082 2022-08-27 -0.345352  1.110606  1.169805
6083 2022-08-28  0.024123  1.078163  0.641161
6084 2022-08-29 -1.051782  1.225804  0.366676

[1854 rows x 4 columns]
```

```
# x_trendcon1 data set has more rows than the other data sets due to the week
ends
# classify column 'time' as datetime to be able to sort for weekdays
x_trendecon1['time']= pd.to_datetime(x_trendecon1['time'], format="%Y-%m-%d")

# create new column with weekdays to be able to drop Saturday and Sunday
x_trendecon1['weekday'] = x_trendecon1['time'].dt.day_name()
x_trendecon1
```

```
           time     x_PES     x_Mob      x_CS    weekday
4231 2017-08-02 -0.012651  1.126671  0.615251  Wednesday
4232 2017-08-03  0.157887  0.662762  0.621989   Thursday
4233 2017-08-04  1.042680  1.086091  0.449422     Friday
4234 2017-08-05  0.749563  1.054133  0.614471   Saturday
4235 2017-08-06  0.461566  0.986842  0.369376     Sunday
...         ...       ...       ...       ...        ...
6080 2022-08-25  0.926409 -0.064953  1.359417   Thursday
6081 2022-08-26 -0.029170  0.882928  1.093192     Friday
6082 2022-08-27 -0.345352  1.110606  1.169805   Saturday
6083 2022-08-28  0.024123  1.078163  0.641161     Sunday
6084 2022-08-29 -1.051782  1.225804  0.366676     Monday

[1854 rows x 5 columns]
```

```python
# remove rows with weekday = Saturday or Sunday
x_trendecon2 = x_trendecon1[~x_trendecon1['weekday'].str.contains('Saturday|S
unday')]
x_trendecon2.head()
```

```
           time     x_PES     x_Mob      x_CS    weekday
4231 2017-08-02 -0.012651  1.126671  0.615251  Wednesday
4232 2017-08-03  0.157887  0.662762  0.621989   Thursday
4233 2017-08-04  1.042680  1.086091  0.449422     Friday
4236 2017-08-07  0.496160  0.802876  0.602640     Monday
4237 2017-08-08  0.584780  0.540721  0.834845    Tuesday
```

```python
# create DatetimeIndex for x_trendecon to merge with x_controlv (below)
x_trendecon3= x_trendecon2.set_index(pd.DatetimeIndex(x_trendecon2['time']))
x_trendecon3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1324 entries, 2017-08-02 to 2022-08-29
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   time     1324 non-null   datetime64[ns]
 1   x_PES    1324 non-null   float64
 2   x_Mob    1324 non-null   float64
 3   x_CS     1324 non-null   float64
 4   weekday  1324 non-null   object
dtypes: datetime64[ns](1), float64(3), object(1)
memory usage: 62.1+ KB
```

```python
x_trendecon3.head()
```

```
                 time     x_PES     x_Mob      x_CS    weekday
time
2017-08-02 2017-08-02 -0.012651  1.126671  0.615251  Wednesday
2017-08-03 2017-08-03  0.157887  0.662762  0.621989   Thursday
2017-08-04 2017-08-04  1.042680  1.086091  0.449422     Friday
2017-08-07 2017-08-07  0.496160  0.802876  0.602640     Monday
2017-08-08 2017-08-08  0.584780  0.540721  0.834845    Tuesday
```

```python
# remove column 'time' as DatetimeIndex is set (and also weekday as this colu
mn is not used anymore)
x_trendecon4 = x_trendecon3.drop(columns = ['time', 'weekday'], axis = 1)
x_trendecon4.head()
```

```
               x_PES     x_Mob      x_CS
time
2017-08-02 -0.012651  1.126671  0.615251
2017-08-03  0.157887  0.662762  0.621989
2017-08-04  1.042680  1.086091  0.449422
2017-08-07  0.496160  0.802876  0.602640
2017-08-08  0.584780  0.540721  0.834845
```

```python
# trendEcon data (x_trendecon4) has still more rows because the non business
days are still included
# x_trendecon4 will be merged with the control variables further below
```

Data Retrieval from Refinitiv

control variables (independent variables)

- SMI / Swiss Market Index

- 2 year Swiss Government Bond Yield
- 10 year Swiss Government Bond Yield
- Euro Stoxx 50 Volatility (VSTOXX)

```
# get key to import data from eikon, https://developers.refinitiv.com/en/api-
catalog/eikon/eikon-data-api/quick-start
import eikon as ek
ek.set_app_key('7ae0b0ff4d4d48d1bd5365f7375e81221b5fa8b3')

# .SSMI       = SMI
# CH2YT=RR    = 2 year Swiss Government Bond Yield
# CH10YT=RR   = 10 year Swiss Government Bond Yield
# .V2TX       = Euro Stoxx 50 Volatility (VSTOXX)
Control_Ticker = [".SSMI", "CH2YT=RR", "CH10YT=RR", ".V2TX"]

x_controlv = pd.DataFrame()
for ric in Control_Ticker:
    x_controlv[ric] = ek.get_timeseries(ric,
                     fields='CLOSE',
                     start_date='2017-08-02',
                     end_date='2022-08-29',
                     interval='daily')['CLOSE']
x_controlv.head()

                .SSMI  CH2YT=RR  CH10YT=RR    .V2TX
Date
2017-08-02   9122.68    -0.778     -0.012  13.7531
2017-08-03   9136.61    -0.784     -0.049  13.7302
2017-08-04   9176.99    -0.774     -0.064  13.0654
2017-08-07   9155.13    -0.795     -0.069  13.1992
2017-08-08   9162.33     -0.78     -0.074  12.7883

# check for missing values in x_controlv data
x_controlv.isnull().sum()

.SSMI        0
CH2YT=RR     0
CH10YT=RR    1
.V2TX        1
dtype: int64

# locate missing values in x_benchmark data
x_controlv[x_controlv.isna().any(axis=1)]

              .SSMI  CH2YT=RR  CH10YT=RR    .V2TX
Date
2019-10-03  9760.44    -0.898      -0.77     <NA>
2020-03-16  8227.08     -0.73       <NA>  85.6206

# fill in missing values by interpolation
x_controlv1 = x_controlv.interpolate(method='ffill', axis=1, limit_direction=
'forward')
x_controlv1.head()

                .SSMI  CH2YT=RR  CH10YT=RR    .V2TX
Date
2017-08-02   9122.68    -0.778     -0.012  13.7531
2017-08-03   9136.61    -0.784     -0.049  13.7302
2017-08-04   9176.99    -0.774     -0.064  13.0654
2017-08-07   9155.13    -0.795     -0.069  13.1992
2017-08-08   9162.33     -0.78     -0.074  12.7883
```

```
# no missing values in x_controlv1 anymore
x_controlv1.isnull().sum()
```

```
.SSMI        0
CH2YT=RR     0
CH10YT=RR    0
.V2TX        0
dtype: int64
```

```
# merge all independent variables (x) into one dataFrame (x_trendecon4 and x_
controlv1)
# x_trendecon4 has more rows because non business days are included
# only row with same index date will be merged
x_data = pd.merge(x_trendecon4, x_controlv1, how='inner', left_index=True, ri
ght_index=True)
x_data.head()
```

```
x_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1276 entries, 2017-08-02 to 2022-08-29
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   x_PES      1276 non-null   float64
 1   x_Mob      1276 non-null   float64
 2   x_CS       1276 non-null   float64
 3   .SSMI      1276 non-null   Float64
 4   CH2YT=RR   1276 non-null   Float64
 5   CH10YT=RR  1276 non-null   Float64
 6   .V2TX      1276 non-null   Float64
dtypes: Float64(4), float64(3)
memory usage: 84.7 KB
```

Credit Default Swaps (CDS) Spreads

Dependent variable

```
# available CDS Ticker of Swiss firms according to Refinitiv CDS Advance Sear
ch function (CDSSRCH) and
# list of available Swiss CDS Single Names contracts provided by IHS markit
# ACE5YUSAX=R (Chubb Ltd) and ABBN5YEUAM=R (ABB Ltd) removed from the sample
list due to too many missing values
CDS_Ticker = ["BASP5YUSAM=R", "CLN5YEUAM=R", "GLEB5YEUAM=R", "UBSN5YEUAM=R",
"CSGN5YEUAM=R", "SCMN5YEUAM=R", "ROG5YEUAM=R", "TELY5YUSAX=FN", "NESN5YEUAM=R
", "RUKN5YEUAM=R", "NOVB5YEUAM=R", "ZURB5YEUAM=R", "SYNN5YEUAM=R", "ADEC5YEUA
M=MG", "HOLN5YEUAM=R"]
```

```
# get time series of CDS Ticker
y_CDS = pd.DataFrame()
for ric in CDS_Ticker:
    y_CDS[ric] = ek.get_timeseries(ric,
                    fields='CLOSE',
                    start_date='2017-08-01',
                    end_date='2022-08-29',
                    interval='daily')['CLOSE']
y_CDS.head()
```

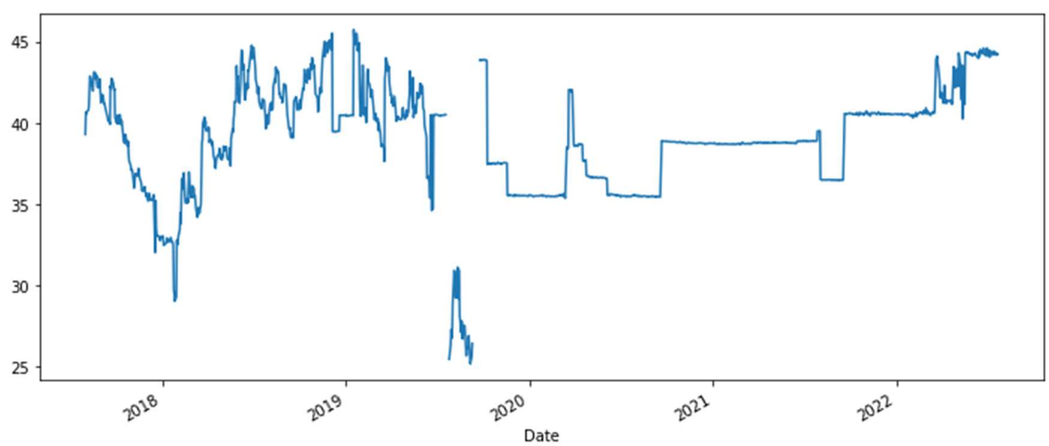
```
# check for missing values in y_CDS
y_CDS.isnull().sum()
```

```
BASP5YUSAM=R       0
CLN5YEUAM=R        1
GLEB5YEUAM=R       2
UBSN5YEUAM=R       2
CSGN5YEUAM=R       1
SCMN5YEUAM=R      40
ROG5YEUAM=R       12
TELY5YUSAX=FN     38
NESN5YEUAM=R       1
RUKN5YEUAM=R       4
NOVB5YEUAM=R      18
ZURB5YEUAM=R       2
SYNN5YEUAM=R       5
ADEC5YEUAM=MG     50
HOLN5YEUAM=R      28
dtype: int64
```

```
# see rows to find missing values in SCMN5YEUAM=R (Swisscom AG)
y_CDS[y_CDS['SCMN5YEUAM=R'].isna()].head()
```

```
# plot time series to be able to see missing data points SCMN5YEUAM=R (Swissc
om AG)
# total 40 missing values -> missing values will be interpolated
plt.figure(figsize=(12,5))
y_CDS['SCMN5YEUAM=R'].plot()
```

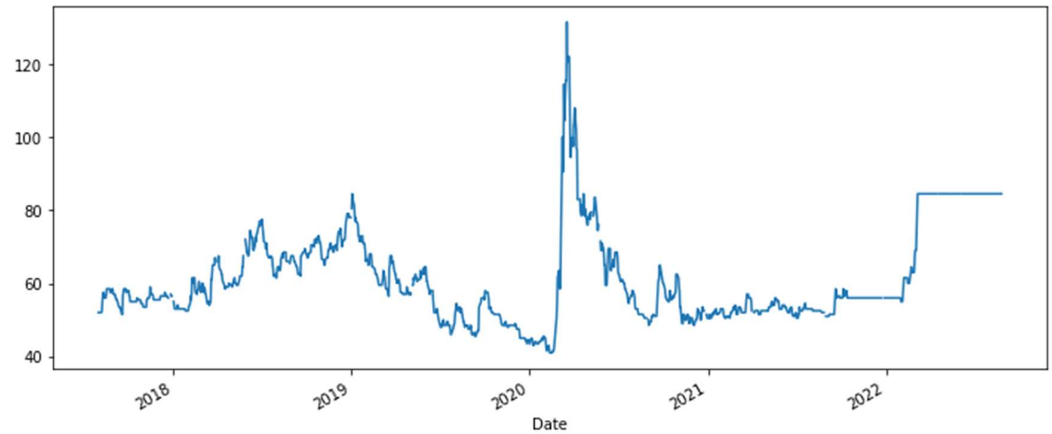
```
<AxesSubplot:xlabel='Date'>
```




```
# see rows to find missing values in TELY5YUSAX=FN (TE Connectivity)
y_CDS[y_CDS['TELY5YUSAX=FN'].isna()].head()
```

```
# plot time series to be able to see missing data points ROG5YEUAM=R (Roche H
olding Ltd)
# total 38 missing values -> missing values will be interpolated
plt.figure(figsize=(12,5))
y_CDS['TELY5YUSAX=FN'].plot()
```

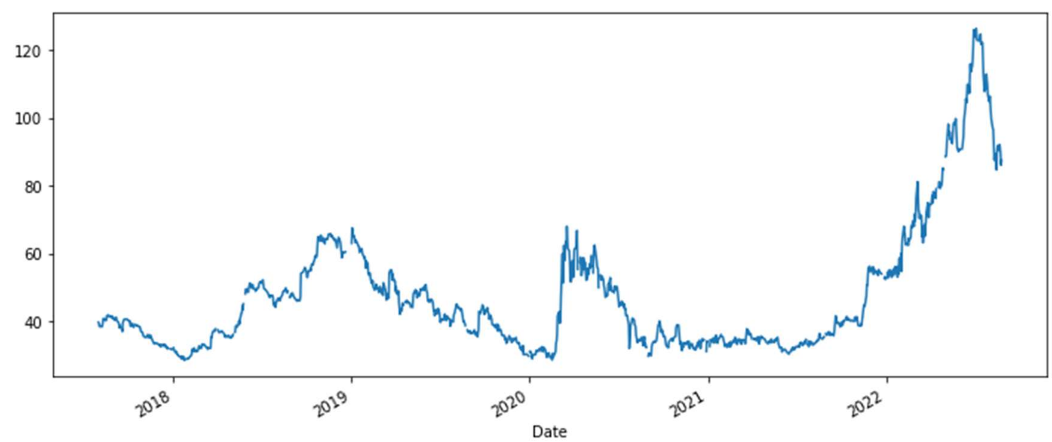
```
<AxesSubplot:xlabel='Date'>
```




```python
# see rows to find missing values in ADEC5YEUAM=MG (Adecco Group AG)
y_CDS[y_CDS['ADEC5YEUAM=MG'].isna()].head()
```

```python
# plot time series to be able to see missing data points ADEC5YEUAM=MG (Adecc
o Group AG)
# total 50 missing values -> missing values will be interpolated
plt.figure(figsize=(12,5))
y_CDS['ADEC5YEUAM=MG'].plot()
```

```
<AxesSubplot:xlabel='Date'>
```




```python
# fill in missing values by interpolation
y_CDS1 = y_CDS.interpolate(method='ffill', axis=1, limit_direction='forward')
```

```python
# only one missing value in y_CDS1
y_CDS1.isnull().sum()
```

```
BASP5YUSAM=R      0
CLN5YEUAM=R       0
GLEB5YEUAM=R      0
UBSN5YEUAM=R      0
CSGN5YEUAM=R      0
SCMN5YEUAM=R      0
ROG5YEUAM=R       1
TELY5YUSAX=FN     0
NESN5YEUAM=R      0
RUKN5YEUAM=R      0
NOVB5YEUAM=R      0
ZURB5YEUAM=R      0
```

```
SYNN5YEUAM=R     0
ADEC5YEUAM=MG    0
HOLN5YEUAM=R     0
dtype: int64
```

```
# first value of ROG5YEUAM=R missing
# first row 2018-08-01 is dropped anyway as there are missing values on that
day due to Swiss Holiday
y_CDS1 = y_CDS1.drop(y_CDS1.index[0:1], axis = 0)
y_CDS1.head()
```

```
# no missing values for y_CDS1 dependent data set (2017-08-02 to 2022-08-29)
y_CDS1.isnull().sum()
```

```
BASP5YUSAM=R     0
CLN5YEUAM=R      0
GLEB5YEUAM=R     0
UBSN5YEUAM=R     0
CSGN5YEUAM=R     0
SCMN5YEUAM=R     0
ROG5YEUAM=R      0
TELY5YUSAX=FN    0
NESN5YEUAM=R     0
RUKN5YEUAM=R     0
NOVB5YEUAM=R     0
ZURB5YEUAM=R     0
SYNN5YEUAM=R     0
ADEC5YEUAM=MG    0
HOLN5YEUAM=R     0
dtype: int64
```

```
# data y_CDS1 has 1322 rows (including Swiss non business days)
# x_data has 1276 rows (Swiss non business days NOT included)
# adapt y_CDS1 to match x_data by merging both into one dataFrame
all_data = pd.merge(y_CDS1, x_data, how='inner', left_index=True, right_index
=True)
all_data.head()
```

```
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1274 entries, 2017-08-03 to 2022-08-29
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   BASP5YUSAM=R   1274 non-null   Float64
 1   CLN5YEUAM=R    1274 non-null   Float64
 2   GLEB5YEUAM=R   1274 non-null   Float64
 3   UBSN5YEUAM=R   1274 non-null   Float64
 4   CSGN5YEUAM=R   1274 non-null   Float64
 5   SCMN5YEUAM=R   1274 non-null   Float64
 6   ROG5YEUAM=R    1274 non-null   Float64
 7   TELY5YUSAX=FN  1274 non-null   Float64
 8   NESN5YEUAM=R   1274 non-null   Float64
 9   RUKN5YEUAM=R   1274 non-null   Float64
 10  NOVB5YEUAM=R   1274 non-null   Float64
 11  ZURB5YEUAM=R   1274 non-null   Float64
 12  SYNN5YEUAM=R   1274 non-null   Float64
 13  ADEC5YEUAM=MG  1274 non-null   Float64
 14  HOLN5YEUAM=R   1274 non-null   Float64
 15  x_PES          1274 non-null   float64
```

```
 16   x_Mob           1274 non-null   float64
 17   x_CS            1274 non-null   float64
 18   .SSMI           1274 non-null   Float64
 19   CH2YT=RR        1274 non-null   Float64
 20   CH10YT=RR       1274 non-null   Float64
 21   .V2TX           1274 non-null   Float64
dtypes: Float64(19), float64(3)
memory usage: 252.6 KB

# save dataFrame 'all_data' to excel for further use
all_data.to_excel("all_data.xlsx")

# separate dataFrame again into x-variables and y-variables
# and save dataFrames to excel for further use
y_data_final = all_data.iloc[:,:-7]
y_data_final.head()

y_data_final.to_excel("y_data_final.xlsx")

x_data_final = all_data.iloc[:,15:]
x_data_final.head()

x_data_final.to_excel("x_data_final.xlsx")

# data cleaned and saved, no missing values
# Regression analysis is conducted in a separate Jupyter Notebook file
```

Appendix IV: Python Coding Panel Regression

```
import math
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import scipy
import seaborn as sns
import xlsxwriter
import math
from math import exp, sqrt, log
import statsmodels.api as sm
from statsmodels.regression.linear_model import OLS
from statsmodels.tsa.stattools import adfuller
from statsmodels.stats.stattools import jarque_bera
from statsmodels.stats.stattools import durbin_watson

import statsmodels.formula.api as smf
import statsmodels.stats.api as sms

import pylab
import statistics

%matplotlib inline

from scipy import stats

all_data = pd.read_excel('all_data.xlsx')
all_data
```

Create Panel Data Set

Transform variables into log differences if data is not stationary

```
# transform data in log-differences to ensure variables are stationary
# independent variables from trendEcon x_PES, x_Mob and x_CS are already rela
tive changes over time
# (according to https://www.trendecon.org/#fa)
# CH2YT=RR and CH10YT=RR no transformation needed
all_data['BASP5YUSAM=Rlog']=np.log(all_data['BASP5YUSAM=R'])-np.log(all_data[
'BASP5YUSAM=R'].shift(periods=1))
all_data['CLN5YEUAM=Rlog']=np.log(all_data['CLN5YEUAM=R'])-np.log(all_data['C
LN5YEUAM=R'].shift(periods=1))
all_data['GLEB5YEUAM=Rlog']=np.log(all_data['GLEB5YEUAM=R'])-np.log(all_data[
'GLEB5YEUAM=R'].shift(periods=1))
all_data['UBSN5YEUAM=Rlog']=np.log(all_data['UBSN5YEUAM=R'])-np.log(all_data[
'UBSN5YEUAM=R'].shift(periods=1))
all_data['CSGN5YEUAM=Rlog']=np.log(all_data['CSGN5YEUAM=R'])-np.log(all_data[
'CSGN5YEUAM=R'].shift(periods=1))
all_data['SCMN5YEUAM=Rlog']=np.log(all_data['SCMN5YEUAM=R'])-np.log(all_data[
'SCMN5YEUAM=R'].shift(periods=1))
all_data['ROG5YEUAM=Rlog']=np.log(all_data['ROG5YEUAM=R'])-np.log(all_data['R
OG5YEUAM=R'].shift(periods=1))
all_data['TELY5YUSAX=FNlog']=np.log(all_data['TELY5YUSAX=FN'])-np.log(all_dat
a['TELY5YUSAX=FN'].shift(periods=1))
all_data['NESN5YEUAM=Rlog']=np.log(all_data['NESN5YEUAM=R'])-np.log(all_data[
'NESN5YEUAM=R'].shift(periods=1))
all_data['RUKN5YEUAM=Rlog']=np.log(all_data['RUKN5YEUAM=R'])-np.log(all_data[
```

```
'RUKN5YEUAM=R'].shift(periods=1))
all_data['NOVB5YEUAM=Rlog']=np.log(all_data['NOVB5YEUAM=R'])-np.log(all_data[
'NOVB5YEUAM=R'].shift(periods=1))
all_data['ZURB5YEUAM=Rlog']=np.log(all_data['ZURB5YEUAM=R'])-np.log(all_data[
'ZURB5YEUAM=R'].shift(periods=1))
all_data['SYNN5YEUAM=Rlog']=np.log(all_data['SYNN5YEUAM=R'])-np.log(all_data[
'SYNN5YEUAM=R'].shift(periods=1))
all_data['ADEC5YEUAM=MGlog']=np.log(all_data['ADEC5YEUAM=MG'])-np.log(all_dat
a['ADEC5YEUAM=MG'].shift(periods=1))
all_data['HOLN5YEUAM=Rlog']=np.log(all_data['HOLN5YEUAM=R'])-np.log(all_data[
'HOLN5YEUAM=R'].shift(periods=1))
all_data['.SSMIlog']=np.log(all_data['.SSMI'])-np.log(all_data['.SSMI'].shift
(periods=1))
all_data['.V2TXlog']=np.log(all_data['.V2TX'])-np.log(all_data['.V2TX'].shift
(periods=1))
all_data

# Create new table with log-changes
all_data_log = all_data[['Date','BASP5YUSAM=Rlog', 'CLN5YEUAM=Rlog', 'GLEB5YE
UAM=Rlog',
       'UBSN5YEUAM=Rlog', 'CSGN5YEUAM=Rlog', 'SCMN5YEUAM=Rlog',
       'ROG5YEUAM=Rlog', 'TELY5YUSAX=FNlog', 'NESN5YEUAM=Rlog',
       'RUKN5YEUAM=Rlog', 'NOVB5YEUAM=Rlog', 'ZURB5YEUAM=Rlog',
       'SYNN5YEUAM=Rlog', 'ADEC5YEUAM=MGlog', 'HOLN5YEUAM=Rlog', 'x_PES',
        'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', 'CH10YT=RR', '.V2TXlog']].co
py()
all_data_log.head()

# Drop first row with NaN values
all_data_log = all_data_log.drop(all_data_log.index[0:1],axis=0)
all_data_log.head()

# create new column with the differences of the ten- and the two-year Swiss G
overnment bond yields
# (CH10YT=RR minus CH2YT=RR = Diff_CH10-2YT )
# not clear yet if this control variable (Diff_CH10-2YT) will be used in the
analysis
all_data_log['Diff_CH10-2YT'] = all_data_log['CH10YT=RR']-all_data_log['CH2YT
=RR']

all_data_log.columns

Index(['Date', 'BASP5YUSAM=Rlog', 'CLN5YEUAM=Rlog', 'GLEB5YEUAM=Rlog',
       'UBSN5YEUAM=Rlog', 'CSGN5YEUAM=Rlog', 'SCMN5YEUAM=Rlog',
       'ROG5YEUAM=Rlog', 'TELY5YUSAX=FNlog', 'NESN5YEUAM=Rlog',
       'RUKN5YEUAM=Rlog', 'NOVB5YEUAM=Rlog', 'ZURB5YEUAM=Rlog',
       'SYNN5YEUAM=Rlog', 'ADEC5YEUAM=MGlog', 'HOLN5YEUAM=Rlog', 'x_PES',
       'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', 'CH10YT=RR', '.V2TXlog',
       'Diff_CH10-2YT'],
      dtype='object')

# create panel data set
panel_data = pd.melt(all_data_log, id_vars= ['Date'], value_vars= ['BASP5YUSA
M=Rlog', 'CLN5YEUAM=Rlog', 'GLEB5YEUAM=Rlog',
       'UBSN5YEUAM=Rlog', 'CSGN5YEUAM=Rlog', 'SCMN5YEUAM=Rlog', 'ROG5YEUAM=Rl
og', 'TELY5YUSAX=FNlog', 'NESN5YEUAM=Rlog',
       'RUKN5YEUAM=Rlog', 'NOVB5YEUAM=Rlog', 'ZURB5YEUAM=Rlog', 'SYNN5YEUAM=R
log', 'ADEC5YEUAM=MGlog', 'HOLN5YEUAM=Rlog'],
 var_name='Company', value_name='CDS', col_level=None)
panel_data
```

```
             Date          Company       CDS
0     2017-08-07  BASP5YUSAM=Rlog  0.022037
1     2017-08-08  BASP5YUSAM=Rlog -0.002619
2     2017-08-09  BASP5YUSAM=Rlog -0.010987
3     2017-08-10  BASP5YUSAM=Rlog -0.000884
4     2017-08-11  BASP5YUSAM=Rlog -0.003101
...          ...              ...       ...
19075 2022-08-23  HOLN5YEUAM=Rlog -0.007229
19076 2022-08-24  HOLN5YEUAM=Rlog  0.006385
19077 2022-08-25  HOLN5YEUAM=Rlog  0.015914
19078 2022-08-26  HOLN5YEUAM=Rlog  0.010681
19079 2022-08-29  HOLN5YEUAM=Rlog -0.000253

[19080 rows x 3 columns]
```

```
# prepare independent variables to add to the panel data
x_log = all_data_log[['x_PES', 'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', 'CH10
YT=RR', 'Diff_CH10-2YT', '.V2TXlog']].copy()
x_log.head()

x_log_repeated = pd.concat([x_log]*15, axis=0, ignore_index=True)
x_log_repeated

# merge both dataFrames into one panel data set
panel_data1 = pd.concat([panel_data, x_log_repeated], axis= 1)
panel_data1

# check if values of independent variables are repeated for every company
panel_data1[2545:2560]

# set MultiIndex on panel data set
panel_data1 = panel_data1.set_index(['Company', 'Date'])
panel_data1

# check panel data set again after setting multiindex
panel_data1[5090:5100]
```

Panel Data Regression

Pooled OLS Regression

```
import statsmodels.api as sm
from linearmodels.panel import PooledOLS

# Pooled OLS Regression
# dependent = endogenous variables / explanatory = exogenous variables
# Baseline Regression Model with control variables (Equation 1)
exog_vars = ['.SSMIlog', 'CH2YT=RR', '.V2TXlog']
exog = sm.add_constant(panel_data1[exog_vars])
mod = PooledOLS(panel_data1.CDS, exog)
pooled_result_1 = mod.fit()
print(pooled_result_1)
```

```
                          PooledOLS Estimation Summary
================================================================================
Dep. Variable:                    CDS   R-squared:                        0.1557
Estimator:                  PooledOLS   R-squared (Between):            2.22e-16
No. Observations:               19080   R-squared (Within):               0.1557
Date:                Thu, Nov 17 2022   R-squared (Overall):              0.1557
Time:                        08:49:38   Log-likelihood                 4.074e+04
Cov. Estimator:            Unadjusted
                                        F-statistic:                      1172.6
```

```
Entities:                          15   P-value                           0.0000
Avg Obs:                       1272.0   Distribution:                  F(3,19076)
Min Obs:                       1272.0
Max Obs:                       1272.0   F-statistic (robust):             1172.6
                                        P-value                           0.0000
Time periods:                    1272   Distribution:                  F(3,19076)
Avg Obs:                       15.000
Min Obs:                       15.000
Max Obs:                       15.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          0.0018     0.0006     3.0890     0.0020      0.0007      0.0029
.SSMIlog      -0.6752     0.0290    -23.306     0.0000     -0.7319     -0.6184
CH2YT=RR       0.0018     0.0008     2.3041     0.0212      0.0003      0.0033
.V2TXlog       0.0831     0.0036     23.167     0.0000      0.0761      0.0901
==============================================================================
```

```
# Regression Model 2 (Equation 2)
# trendEcon variable of Perceived Economic Situation (x_PES) is added
exog_vars = ['x_PES', '.SSMIlog', 'CH2YT=RR', '.V2TXlog']
exog = sm.add_constant(panel_data1[exog_vars])
mod = PooledOLS(panel_data1.CDS, exog)
pooled_result_2 = mod.fit()
print(pooled_result_2)
```

```
                          PooledOLS Estimation Summary
================================================================================
Dep. Variable:                    CDS   R-squared:                        0.1561
Estimator:                  PooledOLS   R-squared (Between):            2.22e-16
No. Observations:               19080   R-squared (Within):               0.1561
Date:                Thu, Nov 17 2022   R-squared (Overall):              0.1561
Time:                        08:49:51   Log-likelihood                 4.075e+04
Cov. Estimator:            Unadjusted
                                        F-statistic:                      882.07
Entities:                          15   P-value                           0.0000
Avg Obs:                       1272.0   Distribution:                  F(4,19075)
Min Obs:                       1272.0
Max Obs:                       1272.0   F-statistic (robust):             882.07
                                        P-value                           0.0000
Time periods:                    1272   Distribution:                  F(4,19075)
Avg Obs:                       15.000
Min Obs:                       15.000
Max Obs:                       15.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          0.0021     0.0006     3.6058     0.0003      0.0010      0.0033
x_PES         -0.0007     0.0002    -3.0137     0.0026     -0.0012     -0.0003
.SSMIlog      -0.6728     0.0290    -23.221     0.0000     -0.7296     -0.6160
CH2YT=RR       0.0019     0.0008     2.4835     0.0130      0.0004      0.0035
.V2TXlog       0.0834     0.0036     23.252     0.0000      0.0764      0.0904
==============================================================================
```

```
# Regression Model 3 (Equation 3)
# trendEcon variable Mobility (x_Mob) is added
exog_vars = ['x_Mob', '.SSMIlog', 'CH2YT=RR', '.V2TXlog']
exog = sm.add_constant(panel_data1[exog_vars])
mod = PooledOLS(panel_data1.CDS, exog)
pooled_result_3 = mod.fit()
print(pooled_result_3)
```

```
                        PooledOLS Estimation Summary
================================================================================
Dep. Variable:                    CDS   R-squared:                        0.1560
Estimator:                  PooledOLS   R-squared (Between):              0.0000
No. Observations:               19080   R-squared (Within):               0.1560
Date:                Thu, Nov 17 2022   R-squared (Overall):              0.1560
Time:                        08:49:56   Log-likelihood                 4.075e+04
Cov. Estimator:            Unadjusted
                                        F-statistic:                      881.35
Entities:                          15   P-value                           0.0000
Avg Obs:                       1272.0   Distribution:                 F(4,19075)
Min Obs:                       1272.0
Max Obs:                       1272.0   F-statistic (robust):             881.35
                                        P-value                           0.0000
Time periods:                    1272   Distribution:                 F(4,19075)
Avg Obs:                       15.000
Min Obs:                       15.000
Max Obs:                       15.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          0.0015     0.0006     2.5051     0.0123      0.0003      0.0026
x_Mob          0.0007     0.0003     2.5782     0.0099      0.0002      0.0012
.SSMIlog      -0.6732     0.0290    -23.232     0.0000     -0.7300     -0.6164
CH2YT=RR       0.0018     0.0008     2.3002     0.0214      0.0003      0.0033
.V2TXlog       0.0831     0.0036     23.173     0.0000      0.0761      0.0901
==============================================================================
```

```
# Regression Model 4 (Equation 4)
# trendEcon variable Clothing & Shoes is added
exog_vars = ['x_CS', '.SSMIlog', 'CH2YT=RR', '.V2TXlog']
exog = sm.add_constant(panel_data1[exog_vars])
mod = PooledOLS(panel_data1.CDS, exog)
pooled_result_4 = mod.fit()
print(pooled_result_4)
```

```
                        PooledOLS Estimation Summary
================================================================================
Dep. Variable:                    CDS   R-squared:                        0.1577
Estimator:                  PooledOLS   R-squared (Between):            2.22e-16
No. Observations:               19080   R-squared (Within):               0.1577
Date:                Thu, Nov 17 2022   R-squared (Overall):              0.1577
Time:                        08:50:00   Log-likelihood                 4.076e+04
Cov. Estimator:            Unadjusted
                                        F-statistic:                      892.56
Entities:                          15   P-value                           0.0000
Avg Obs:                       1272.0   Distribution:                 F(4,19075)
Min Obs:                       1272.0
Max Obs:                       1272.0   F-statistic (robust):             892.56
                                        P-value                           0.0000
Time periods:                    1272   Distribution:                 F(4,19075)
Avg Obs:                       15.000
Min Obs:                       15.000
Max Obs:                       15.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          0.0059     0.0008     6.9791     0.0000      0.0042      0.0075
x_CS          -0.0033     0.0005    -6.6718     0.0000     -0.0043     -0.0023
.SSMIlog      -0.6657     0.0290    -22.977     0.0000     -0.7225     -0.6089
CH2YT=RR       0.0029     0.0008     3.6578     0.0003      0.0013      0.0045
```

```
.V2TXlog       0.0839     0.0036     23.411     0.0000     0.0769     0.0909
==============================================================================

# Regression Model 5 (Equation 5)
# all trendEcon variables included in the model
exog_vars = ['x_PES', 'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', '.V2TXlog']
exog = sm.add_constant(panel_data1[exog_vars])
mod = PooledOLS(panel_data1.CDS, exog)
pooled_result_5 = mod.fit()
print(pooled_result_5)

                          PooledOLS Estimation Summary
================================================================================
Dep. Variable:                    CDS   R-squared:                        0.1581
Estimator:                  PooledOLS   R-squared (Between):              0.0000
No. Observations:               19080   R-squared (Within):               0.1581
Date:                Thu, Nov 17 2022   R-squared (Overall):              0.1581
Time:                        08:50:08   Log-likelihood                 4.077e+04
Cov. Estimator:            Unadjusted
                                        F-statistic:                      596.93
Entities:                          15   P-value                           0.0000
Avg Obs:                       1272.0   Distribution:                F(6,19073)
Min Obs:                       1272.0
Max Obs:                       1272.0   F-statistic (robust):             596.93
                                        P-value                           0.0000
Time periods:                    1272   Distribution:                F(6,19073)
Avg Obs:                       15.000
Min Obs:                       15.000
Max Obs:                       15.000

                             Parameter Estimates
==============================================================================
            Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
------------------------------------------------------------------------------
const          0.0055     0.0009     6.2617     0.0000      0.0038      0.0072
x_PES         -0.0007     0.0003    -2.8755     0.0040     -0.0013     -0.0002
x_Mob          0.0006     0.0003     2.0575     0.0396   2.849e-05      0.0012
x_CS          -0.0029     0.0005    -5.7316     0.0000     -0.0039     -0.0019
.SSMIlog      -0.6626     0.0290    -22.864     0.0000     -0.7195     -0.6058
CH2YT=RR       0.0029     0.0008     3.6740     0.0002      0.0014      0.0045
.V2TXlog       0.0842     0.0036     23.476     0.0000      0.0771      0.0912
==============================================================================
```

Appendix V: Python Coding Single Company Regression

```
import math
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

import scipy
import seaborn as sns
import xlsxwriter
import math
from math import exp, sqrt, log
import statsmodels.api as sm
from statsmodels.regression.linear_model import OLS
from statsmodels.tsa.stattools import adfuller
from statsmodels.stats.stattools import jarque_bera
from statsmodels.stats.stattools import durbin_watson

import statsmodels.formula.api as smf
import statsmodels.stats.api as sms

import pylab
import statistics

%matplotlib inline

from scipy import stats

# import data
y_data = pd.read_excel('y_data_final.xlsx', index_col = [0])
y_data.head()

x_data = pd.read_excel('x_data_final.xlsx', index_col = [0])
x_data

# transform y_data in log-differences to ensure dependent variables are stati
onary
y_data['BASP5YUSAM=Rlog']=np.log(y_data['BASP5YUSAM=R'])-np.log(y_data['BASP5
YUSAM=R'].shift(periods=1))
y_data['CLN5YEUAM=Rlog']=np.log(y_data['CLN5YEUAM=R'])-np.log(y_data['CLN5YEU
AM=R'].shift(periods=1))
y_data['GLEB5YEUAM=Rlog']=np.log(y_data['GLEB5YEUAM=R'])-np.log(y_data['GLEB5
YEUAM=R'].shift(periods=1))
y_data['UBSN5YEUAM=Rlog']=np.log(y_data['UBSN5YEUAM=R'])-np.log(y_data['UBSN5
YEUAM=R'].shift(periods=1))
y_data['CSGN5YEUAM=Rlog']=np.log(y_data['CSGN5YEUAM=R'])-np.log(y_data['CSGN5
YEUAM=R'].shift(periods=1))
y_data['SCMN5YEUAM=Rlog']=np.log(y_data['SCMN5YEUAM=R'])-np.log(y_data['SCMN5
YEUAM=R'].shift(periods=1))
y_data['ROG5YEUAM=Rlog']=np.log(y_data['ROG5YEUAM=R'])-np.log(y_data['ROG5YEU
AM=R'].shift(periods=1))
y_data['TELY5YUSAX=FNlog']=np.log(y_data['TELY5YUSAX=FN'])-np.log(y_data['TEL
Y5YUSAX=FN'].shift(periods=1))
y_data['NESN5YEUAM=Rlog']=np.log(y_data['NESN5YEUAM=R'])-np.log(y_data['NESN5
YEUAM=R'].shift(periods=1))
y_data['RUKN5YEUAM=Rlog']=np.log(y_data['RUKN5YEUAM=R'])-np.log(y_data['RUKN5
YEUAM=R'].shift(periods=1))
y_data['NOVB5YEUAM=Rlog']=np.log(y_data['NOVB5YEUAM=R'])-np.log(y_data['NOVB5
YEUAM=R'].shift(periods=1))
```

```
y_data['ZURB5YEUAM=Rlog']=np.log(y_data['ZURB5YEUAM=R'])-np.log(y_data['ZURB5
YEUAM=R'].shift(periods=1))
y_data['SYNN5YEUAM=Rlog']=np.log(y_data['SYNN5YEUAM=R'])-np.log(y_data['SYNN5
YEUAM=R'].shift(periods=1))
y_data['ADEC5YEUAM=MGlog']=np.log(y_data['ADEC5YEUAM=MG'])-np.log(y_data['ADE
C5YEUAM=MG'].shift(periods=1))
y_data['HOLN5YEUAM=Rlog']=np.log(y_data['HOLN5YEUAM=R'])-np.log(y_data['HOLN5
YEUAM=R'].shift(periods=1))
y_data.head()

# transform x_data in log-differences to ensure independent variables are sta
tionary
# independent variables from trendEcon x_PES, x_Mob and x_CS are already rela
tive changes over time
# (according to https://www.trendecon.org/#fa)
# CH2YT=RR and CH10YT=RR no transformation needed
x_data['.SSMIlog']=np.log(x_data['.SSMI'])-np.log(x_data['.SSMI'].shift(perio
ds=1))
x_data['.V2TXlog']=np.log(x_data['.V2TX'])-np.log(x_data['.V2TX'].shift(perio
ds=1))
x_data

# Create new tables
y_data_log = y_data[['BASP5YUSAM=Rlog', 'CLN5YEUAM=Rlog', 'GLEB5YEUAM=Rlog',
       'UBSN5YEUAM=Rlog', 'CSGN5YEUAM=Rlog', 'SCMN5YEUAM=Rlog',
       'ROG5YEUAM=Rlog', 'TELY5YUSAX=FNlog', 'NESN5YEUAM=Rlog',
       'RUKN5YEUAM=Rlog', 'NOVB5YEUAM=Rlog', 'ZURB5YEUAM=Rlog',
       'SYNN5YEUAM=Rlog', 'ADEC5YEUAM=MGlog', 'HOLN5YEUAM=Rlog']].copy()
y_data_log

x_data_log = x_data[['x_PES', 'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', 'CH10Y
T=RR', '.V2TXlog']].copy()
x_data_log

# Drop first row with NaN values
y_data_log = y_data_log.drop(y_data_log.index[0:1],axis=0)
y_data_log.head()

x_data_log = x_data_log.drop(x_data_log.index[0:1],axis=0)
x_data_log.head()

# create new column with the differences of the ten- and the two-year Swiss G
overnment bond yields
# (CH10YT=RR minus CH2YT=RR = Diff_CH10-2YT )
# not clear yet if this control variable (Diff_CH10-2YT) will be used in the
regression analysis
x_data_log['Diff_CH10-2YT'] = x_data_log['CH10YT=RR']-x_data_log['CH2YT=RR']
x_data_log.head()

# both dataframes y_data_log and x_data_log have same amount of rows
# no missing values

y_data_log.isnull().sum()

BASP5YUSAM=Rlog     0
CLN5YEUAM=Rlog      0
GLEB5YEUAM=Rlog     0
UBSN5YEUAM=Rlog     0
CSGN5YEUAM=Rlog     0
SCMN5YEUAM=Rlog     0
ROG5YEUAM=Rlog      0
```

```
TELY5YUSAX=FNlog    0
NESN5YEUAM=Rlog     0
RUKN5YEUAM=Rlog     0
NOVB5YEUAM=Rlog     0
ZURB5YEUAM=Rlog     0
SYNN5YEUAM=Rlog     0
ADEC5YEUAM=MGlog    0
HOLN5YEUAM=Rlog     0
dtype: int64
```

```
x_data_log.isnull().sum()
```

```
x_PES            0
x_Mob            0
x_CS             0
.SSMIlog         0
CH2YT=RR         0
CH10YT=RR        0
.V2TXlog         0
Diff_CH10-2YT    0
dtype: int64
```

Time Series Regression

OLS Regression

```
# Regression loop on the baseline OLS regression model (Equation 6)
fit_base = {}
for i in y_data_log:
        y = y_data_log[i]
        x = x_data_log[['.SSMIlog', 'CH2YT=RR', '.V2TXlog']]
        x = sm.add_constant(x)

        fit_base = sm.OLS(y,x).fit()
        print(fit_base.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        BASP5YUSAM=Rlog   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.576
Date:                Thu, 17 Nov 2022   Prob (F-statistic):              0.193
Time:                        09:05:21   Log-Likelihood:                 4322.1
No. Observations:                1273   AIC:                            -8636.
Df Residuals:                    1269   BIC:                            -8616.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        3.91e-05      0.001      0.062      0.951      -0.001       0.001
.SSMIlog       0.0048      0.032      0.151      0.880      -0.058       0.067
CH2YT=RR      -0.0003      0.001     -0.309      0.758      -0.002       0.001
.V2TXlog       0.0065      0.004      1.654      0.098      -0.001       0.014
==============================================================================
Omnibus:                      259.673   Durbin-Watson:                   2.470
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5924.803
Skew:                          -0.303   Prob(JB):                         0.00
Kurtosis:                      13.551   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:         CLN5YEUAM=Rlog   R-squared:                       0.237
```

```
Model:                            OLS   Adj. R-squared:                  0.236
Method:                 Least Squares   F-statistic:                     131.6
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           3.07e-74
Time:                        09:05:21   Log-Likelihood:                 2896.8
No. Observations:                1273   AIC:                            -5786.
Df Residuals:                    1269   BIC:                            -5765.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0008      0.002      0.436      0.663      -0.003       0.005
.SSMIlog      -0.9251      0.098     -9.473      0.000      -1.117      -0.734
CH2YT=RR       0.0001      0.003      0.056      0.955      -0.005       0.005
.V2TXlog       0.0731      0.012      6.047      0.000       0.049       0.097
==============================================================================
Omnibus:                      447.881   Durbin-Watson:                   1.815
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8843.534
Skew:                           1.126   Prob(JB):                         0.00
Kurtosis:                      15.715   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        GLEB5YEUAM=Rlog   R-squared:                       0.221
Model:                            OLS   Adj. R-squared:                  0.220
Method:                 Least Squares   F-statistic:                     120.3
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           1.37e-68
Time:                        09:05:21   Log-Likelihood:                 2698.4
No. Observations:                1273   AIC:                            -5389.
Df Residuals:                    1269   BIC:                            -5368.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0004      0.002      0.168      0.867      -0.004       0.005
.SSMIlog      -0.7196      0.114     -6.305      0.000      -0.943      -0.496
CH2YT=RR      -0.0001      0.003     -0.045      0.964      -0.006       0.006
.V2TXlog       0.1211      0.014      8.572      0.000       0.093       0.149
==============================================================================
Omnibus:                      669.553   Durbin-Watson:                   1.754
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            19135.740
Skew:                           1.863   Prob(JB):                         0.00
Kurtosis:                      21.625   Cond. No.                         172.
==============================================================================


                            OLS Regression Results
==============================================================================
Dep. Variable:        UBSN5YEUAM=Rlog   R-squared:                       0.254
Model:                            OLS   Adj. R-squared:                  0.252
Method:                 Least Squares   F-statistic:                     144.1
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           2.33e-80
Time:                        09:05:21   Log-Likelihood:                 2724.5
No. Observations:                1273   AIC:                            -5441.
Df Residuals:                    1269   BIC:                            -5420.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0030      0.002      1.365      0.172      -0.001       0.007
.SSMIlog      -0.9477      0.112     -8.476      0.000      -1.167      -0.728
CH2YT=RR       0.0031      0.003      1.028      0.304      -0.003       0.009
.V2TXlog       0.1080      0.014      7.801      0.000       0.081       0.135
==============================================================================
```

```
Omnibus:                      292.242   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2167.557
Skew:                           0.856   Prob(JB):                         0.00
Kurtosis:                       9.159   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        CSGN5YEUAM=Rlog   R-squared:                       0.334
Model:                            OLS   Adj. R-squared:                  0.332
Method:                 Least Squares   F-statistic:                     211.8
Date:                Thu, 17 Nov 2022   Prob (F-statistic):          2.19e-111
Time:                        09:05:21   Log-Likelihood:                 2909.2
No. Observations:                1273   AIC:                            -5810.
Df Residuals:                    1269   BIC:                            -5790.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0050      0.002      2.579      0.010       0.001       0.009
.SSMIlog      -1.0296      0.097    -10.645      0.000      -1.219      -0.840
CH2YT=RR       0.0057      0.003      2.213      0.027       0.001       0.011
.V2TXlog       0.1079      0.012      9.014      0.000       0.084       0.131
==============================================================================
Omnibus:                      381.628   Durbin-Watson:                   1.634
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3173.775
Skew:                           1.147   Prob(JB):                         0.00
Kurtosis:                      10.387   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        SCMN5YEUAM=Rlog   R-squared:                       0.036
Model:                            OLS   Adj. R-squared:                  0.034
Method:                 Least Squares   F-statistic:                     15.98
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           3.36e-10
Time:                        09:05:21   Log-Likelihood:                 2839.1
No. Observations:                1273   AIC:                            -5670.
Df Residuals:                    1269   BIC:                            -5650.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0006      0.002      0.280      0.779      -0.003       0.005
.SSMIlog      -0.0803      0.102     -0.786      0.432      -0.281       0.120
CH2YT=RR       0.0008      0.003      0.276      0.783      -0.005       0.006
.V2TXlog       0.0559      0.013      4.415      0.000       0.031       0.081
==============================================================================
Omnibus:                      846.322   Durbin-Watson:                   2.077
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1874261.794
Skew:                           1.449   Prob(JB):                         0.00
Kurtosis:                     190.955   Cond. No.                         172.
==============================================================================


                            OLS Regression Results
==============================================================================
Dep. Variable:         ROG5YEUAM=Rlog   R-squared:                       0.026
Model:                            OLS   Adj. R-squared:                  0.024
Method:                 Least Squares   F-statistic:                     11.33
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           2.47e-07
Time:                        09:05:21   Log-Likelihood:                 3109.6
No. Observations:                1273   AIC:                            -6211.
Df Residuals:                    1269   BIC:                            -6191.
Df Model:                           3
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0028      0.002      1.674      0.094      -0.000       0.006
.SSMIlog      -0.2209      0.083     -2.674      0.008      -0.383      -0.059
CH2YT=RR       0.0034      0.002      1.532      0.126      -0.001       0.008
.V2TXlog       0.0173      0.010      1.696      0.090      -0.003       0.037
==============================================================================
Omnibus:                      890.265   Durbin-Watson:                   1.954
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            65700.582
Skew:                           2.512   Prob(JB):                         0.00
Kurtosis:                      37.834   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       TELY5YUSAX=FNlog   R-squared:                       0.273
Model:                            OLS   Adj. R-squared:                  0.271
Method:                 Least Squares   F-statistic:                     159.0
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           1.79e-87
Time:                        09:05:21   Log-Likelihood:                 3057.0
No. Observations:                1273   AIC:                            -6106.
Df Residuals:                    1269   BIC:                            -6085.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0009      0.002     -0.512      0.609      -0.004       0.002
.SSMIlog      -1.0210      0.086    -11.857      0.000      -1.190      -0.852
CH2YT=RR      -0.0020      0.002     -0.856      0.392      -0.007       0.003
.V2TXlog       0.0536      0.011      5.027      0.000       0.033       0.074
==============================================================================
Omnibus:                      743.670   Durbin-Watson:                   1.972
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            25585.090
Skew:                           2.112   Prob(JB):                         0.00
Kurtosis:                      24.553   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:      NESN5YEUAM=Rlog   R-squared:                       0.187
Model:                            OLS   Adj. R-squared:                  0.185
Method:                 Least Squares   F-statistic:                     97.39
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           9.82e-57
Time:                        09:05:21   Log-Likelihood:                 2603.3
No. Observations:                1273   AIC:                            -5199.
Df Residuals:                    1269   BIC:                            -5178.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0018      0.002      0.745      0.456      -0.003       0.007
.SSMIlog      -0.9206      0.123     -7.485      0.000      -1.162      -0.679
CH2YT=RR       0.0022      0.003      0.668      0.504      -0.004       0.009
.V2TXlog       0.0896      0.015      5.888      0.000       0.060       0.120
==============================================================================
Omnibus:                      180.633   Durbin-Watson:                   1.975
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2263.438
Skew:                           0.087   Prob(JB):                         0.00
Kurtosis:                       9.530   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:        RUKN5YEUAM=Rlog   R-squared:                       0.229
Model:                            OLS   Adj. R-squared:                  0.227
Method:                 Least Squares   F-statistic:                     125.5
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           3.52e-71
Time:                        09:05:21   Log-Likelihood:                 2469.2
No. Observations:                1273   AIC:                            -4930.
Df Residuals:                    1269   BIC:                            -4910.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0036      0.003      1.332      0.183      -0.002       0.009
.SSMIlog      -0.5028      0.137     -3.680      0.000      -0.771      -0.235
CH2YT=RR       0.0043      0.004      1.161      0.246      -0.003       0.011
.V2TXlog       0.1890      0.017     11.170      0.000       0.156       0.222
==============================================================================
Omnibus:                      415.801   Durbin-Watson:                   1.993
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9115.788
Skew:                           0.976   Prob(JB):                         0.00
Kurtosis:                      15.963   Cond. No.                         172.
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        NOVB5YEUAM=Rlog   R-squared:                       0.046
Model:                            OLS   Adj. R-squared:                  0.044
Method:                 Least Squares   F-statistic:                     20.59
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           4.98e-13
Time:                        09:05:21   Log-Likelihood:                 2522.6
No. Observations:                1273   AIC:                            -5037.
Df Residuals:                    1269   BIC:                            -5017.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0008      0.003     -0.318      0.751      -0.006       0.004
.SSMIlog      -0.2170      0.131     -1.656      0.098      -0.474       0.040
CH2YT=RR      -0.0013      0.004     -0.378      0.706      -0.008       0.006
.V2TXlog       0.0713      0.016      4.394      0.000       0.039       0.103
==============================================================================
Omnibus:                      332.568   Durbin-Watson:                   2.246
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            17944.034
Skew:                          -0.286   Prob(JB):                         0.00
Kurtosis:                      21.384   Cond. No.                         172.
==============================================================================
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        ZURB5YEUAM=Rlog   R-squared:                       0.247
Model:                            OLS   Adj. R-squared:                  0.245
Method:                 Least Squares   F-statistic:                     138.4
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           1.43e-77
Time:                        09:05:21   Log-Likelihood:                 2427.6
No. Observations:                1273   AIC:                            -4847.
Df Residuals:                    1269   BIC:                            -4827.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0051      0.003      1.814      0.070      -0.000       0.011
.SSMIlog      -0.7045      0.141     -4.990      0.000      -0.981      -0.427
CH2YT=RR       0.0063      0.004      1.676      0.094      -0.001       0.014
.V2TXlog       0.1877      0.017     10.740      0.000       0.153       0.222
==============================================================================
```

```
Omnibus:                      266.665   Durbin-Watson:                   2.047
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3748.130
Skew:                           0.549   Prob(JB):                         0.00
Kurtosis:                      11.334   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       SYNN5YEUAM=Rlog   R-squared:                       0.143
Model:                           OLS   Adj. R-squared:                  0.141
Method:                Least Squares   F-statistic:                     70.85
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           2.29e-42
Time:                       09:05:21   Log-Likelihood:                 2626.7
No. Observations:               1273   AIC:                            -5245.
Df Residuals:                   1269   BIC:                            -5225.
Df Model:                          3
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0011      0.002      0.441      0.659      -0.004       0.006
.SSMIlog      -0.9305      0.121     -7.707      0.000      -1.167      -0.694
CH2YT=RR       0.0005      0.003      0.166      0.868      -0.006       0.007
.V2TXlog       0.0537      0.015      3.591      0.000       0.024       0.083
==============================================================================
Omnibus:                      831.315   Durbin-Watson:                   1.789
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            57280.565
Skew:                           2.268   Prob(JB):                         0.00
Kurtosis:                      35.547   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:      ADEC5YEUAM=MGlog   R-squared:                       0.111
Model:                           OLS   Adj. R-squared:                  0.109
Method:                Least Squares   F-statistic:                     52.63
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           4.64e-32
Time:                       09:05:21   Log-Likelihood:                 2684.8
No. Observations:               1273   AIC:                            -5362.
Df Residuals:                   1269   BIC:                            -5341.
Df Model:                          3
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0021      0.002      0.937      0.349      -0.002       0.007
.SSMIlog      -0.8049      0.115     -6.977      0.000      -1.031      -0.579
CH2YT=RR       0.0020      0.003      0.659      0.510      -0.004       0.008
.V2TXlog       0.0383      0.014      2.682      0.007       0.010       0.066
==============================================================================
Omnibus:                      266.535   Durbin-Watson:                   2.429
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4614.551
Skew:                           0.468   Prob(JB):                         0.00
Kurtosis:                      12.280   Cond. No.                         172.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       HOLN5YEUAM=Rlog   R-squared:                       0.238
Model:                           OLS   Adj. R-squared:                  0.236
Method:                Least Squares   F-statistic:                     132.0
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           2.10e-74
Time:                       09:05:21   Log-Likelihood:                 2749.9
No. Observations:               1273   AIC:                            -5492.
Df Residuals:                   1269   BIC:                            -5471.
Df Model:                          3
Covariance Type:           nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0021      0.002      0.960      0.337      -0.002       0.006
.SSMIlog      -1.1081      0.110    -10.110      0.000      -1.323      -0.893
CH2YT=RR       0.0019      0.003      0.661      0.509      -0.004       0.008
.V2TXlog       0.0725      0.014      5.347      0.000       0.046       0.099
==============================================================================
Omnibus:                      415.352   Durbin-Watson:                   1.865
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7433.136
Skew:                           1.036   Prob(JB):                         0.00
Kurtosis:                      14.655   Cond. No.                         172.
==============================================================================
```

```python
# Regression loop on OLS regression model using all independent variables fro
m trendEcon (Equation 7)
fit_all = {}
for i in y_data_log:
        y = y_data_log[i]
        x = x_data_log[['x_PES', 'x_Mob', 'x_CS', '.SSMIlog', 'CH2YT=RR', '.V
2TXlog']]
        x = sm.add_constant(x)

        fit_all = sm.OLS(y,x).fit()
        print(fit_all.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        BASP5YUSAM=Rlog   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.9716
Date:                Thu, 17 Nov 2022   Prob (F-statistic):              0.443
Time:                        09:05:27   Log-Likelihood:                 4322.7
No. Observations:                1273   AIC:                            -8631.
Df Residuals:                    1266   BIC:                            -8595.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0003      0.001     -0.309      0.757      -0.002       0.002
x_PES         -0.0003      0.000     -0.891      0.373      -0.001       0.000
x_Mob       3.416e-05      0.000      0.106      0.916      -0.001       0.001
x_CS           0.0004      0.001      0.628      0.530      -0.001       0.001
.SSMIlog       0.0047      0.032      0.147      0.883      -0.058       0.067
CH2YT=RR      -0.0003      0.001     -0.382      0.702      -0.002       0.001
.V2TXlog       0.0065      0.004      1.656      0.098      -0.001       0.014
==============================================================================
Omnibus:                      258.202   Durbin-Watson:                   2.474
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5855.875
Skew:                          -0.298   Prob(JB):                         0.00
Kurtosis:                      13.490   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        CLN5YEUAM=Rlog   R-squared:                       0.239
Model:                            OLS   Adj. R-squared:                  0.235
Method:                 Least Squares   F-statistic:                     66.16
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           1.21e-71
Time:                        09:05:27   Log-Likelihood:                 2898.0
No. Observations:                1273   AIC:                            -5782.
Df Residuals:                    1266   BIC:                            -5746.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0033      0.003      1.118      0.264      -0.002       0.009
x_PES         -0.0005      0.001     -0.628      0.530      -0.002       0.001
x_Mob          0.0005      0.001      0.493      0.622      -0.001       0.002
x_CS          -0.0020      0.002     -1.134      0.257      -0.005       0.001
.SSMIlog      -0.9164      0.098     -9.364      0.000      -1.108      -0.724
CH2YT=RR       0.0009      0.003      0.340      0.734      -0.004       0.006
.V2TXlog       0.0738      0.012      6.101      0.000       0.050       0.098
==============================================================================
Omnibus:                      438.822   Durbin-Watson:                   1.819
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8857.880
Skew:                           1.086   Prob(JB):                         0.00
Kurtosis:                      15.739   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       GLEB5YEUAM=Rlog   R-squared:                       0.231
Model:                           OLS   Adj. R-squared:                  0.228
Method:                Least Squares   F-statistic:                     63.46
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           5.63e-69
Time:                       09:05:27   Log-Likelihood:                 2706.4
No. Observations:               1273   AIC:                            -5399.
Df Residuals:                   1266   BIC:                            -5363.
Df Model:                          6
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0067      0.003      1.953      0.051   -3.13e-05       0.013
x_PES         -0.0025      0.001     -2.410      0.016      -0.004      -0.000
x_Mob          0.0018      0.001      1.543      0.123      -0.000       0.004
x_CS          -0.0048      0.002     -2.413      0.016      -0.009      -0.001
.SSMIlog      -0.6928      0.114     -6.091      0.000      -0.916      -0.470
CH2YT=RR       0.0020      0.003      0.628      0.530      -0.004       0.008
.V2TXlog       0.1234      0.014      8.773      0.000       0.096       0.151
==============================================================================
Omnibus:                      620.670   Durbin-Watson:                   1.777
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            17124.918
Skew:                           1.678   Prob(JB):                         0.00
Kurtosis:                      20.652   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       UBSN5YEUAM=Rlog   R-squared:                       0.259
Model:                           OLS   Adj. R-squared:                  0.255
Method:                Least Squares   F-statistic:                     73.74
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           5.44e-79
Time:                       09:05:27   Log-Likelihood:                 2728.7
No. Observations:               1273   AIC:                            -5443.
Df Residuals:                   1266   BIC:                            -5407.
Df Model:                          6
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0097      0.003      2.860      0.004       0.003       0.016
x_PES         -0.0010      0.001     -1.042      0.297      -0.003       0.001
x_Mob         -0.0002      0.001     -0.185      0.853      -0.002       0.002
x_CS          -0.0049      0.002     -2.485      0.013      -0.009      -0.001
.SSMIlog      -0.9309      0.112     -8.328      0.000      -1.150      -0.712
CH2YT=RR       0.0049      0.003      1.612      0.107      -0.001       0.011
.V2TXlog       0.1097      0.014      7.933      0.000       0.083       0.137
==============================================================================
Omnibus:                      265.788   Durbin-Watson:                   2.003
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1942.690
Skew:                           0.763   Prob(JB):                         0.00
Kurtosis:                       8.856   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       CSGN5YEUAM=Rlog   R-squared:                       0.340
Model:                           OLS   Adj. R-squared:                  0.336
Method:                Least Squares   F-statistic:                     108.5
Date:               Thu, 17 Nov 2022   Prob (F-statistic):          2.11e-110
Time:                       09:05:27   Log-Likelihood:                 2914.8
No. Observations:               1273   AIC:                            -5816.
Df Residuals:                   1266   BIC:                            -5780.
Df Model:                          6
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0104      0.003      3.557      0.000       0.005       0.016
x_PES         -0.0017      0.001     -2.020      0.044      -0.003   -5.05e-05
x_Mob          0.0004      0.001      0.459      0.646      -0.001       0.002
x_CS          -0.0039      0.002     -2.288      0.022      -0.007      -0.001
.SSMIlog      -1.0115      0.097    -10.474      0.000      -1.201      -0.822
CH2YT=RR       0.0074      0.003      2.790      0.005       0.002       0.013
.V2TXlog       0.1097      0.012      9.182      0.000       0.086       0.133
==============================================================================
Omnibus:                      349.827   Durbin-Watson:                   1.654
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2880.513
Skew:                           1.034   Prob(JB):                         0.00
Kurtosis:                      10.073   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       SCMN5YEUAM=Rlog   R-squared:                       0.039
Model:                           OLS   Adj. R-squared:                  0.035
Method:                Least Squares   F-statistic:                     8.642
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           3.10e-09
Time:                       09:05:27   Log-Likelihood:                 2841.1
No. Observations:               1273   AIC:                            -5668.
Df Residuals:                   1266   BIC:                            -5632.
Df Model:                          6
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0026      0.003      0.844      0.399      -0.003       0.009
x_PES         -0.0016      0.001     -1.730      0.084      -0.003       0.000
x_Mob          0.0003      0.001      0.298      0.766      -0.002       0.002
x_CS          -0.0012      0.002     -0.653      0.514      -0.005       0.002
.SSMIlog      -0.0710      0.102     -0.694      0.488      -0.272       0.130
CH2YT=RR       0.0015      0.003      0.518      0.604      -0.004       0.007
.V2TXlog       0.0568      0.013      4.491      0.000       0.032       0.082
==============================================================================
Omnibus:                      822.619   Durbin-Watson:                   2.084
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1834861.118
Skew:                           1.352   Prob(JB):                         0.00
Kurtosis:                     188.972   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        ROG5YEUAM=Rlog   R-squared:                       0.028
Model:                           OLS   Adj. R-squared:                  0.023
Method:                Least Squares   F-statistic:                     5.997
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           3.39e-06
```

```
Time:                        09:05:27   Log-Likelihood:                 3110.7
No. Observations:                1273   AIC:                            -6207.
Df Residuals:                    1266   BIC:                            -6171.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0043      0.003      1.711      0.087      -0.001       0.009
x_PES         -0.0002      0.001     -0.326      0.745      -0.002       0.001
x_Mob          0.0007      0.001      0.789      0.430      -0.001       0.002
x_CS          -0.0014      0.001     -0.945      0.345      -0.004       0.001
.SSMIlog      -0.2143      0.083     -2.588      0.010      -0.377      -0.052
CH2YT=RR       0.0039      0.002      1.720      0.086      -0.001       0.008
.V2TXlog       0.0178      0.010      1.739      0.082      -0.002       0.038
==============================================================================
Omnibus:                      886.370   Durbin-Watson:                   1.957
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            64895.750
Skew:                           2.497   Prob(JB):                         0.00
Kurtosis:                      37.620   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:       TELY5YUSAX=FNlog   R-squared:                       0.277
Model:                            OLS   Adj. R-squared:                  0.273
Method:                 Least Squares   F-statistic:                     80.75
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           1.29e-85
Time:                        09:05:27   Log-Likelihood:                 3060.2
No. Observations:                1273   AIC:                            -6106.
Df Residuals:                    1266   BIC:                            -6070.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0027      0.003      1.027      0.305      -0.002       0.008
x_PES         -0.0010      0.001     -1.303      0.193      -0.003       0.001
x_Mob          0.0006      0.001      0.680      0.497      -0.001       0.002
x_CS          -0.0027      0.002     -1.782      0.075      -0.006       0.000
.SSMIlog      -1.0083      0.086    -11.704      0.000      -1.177      -0.839
CH2YT=RR      -0.0009      0.002     -0.369      0.712      -0.006       0.004
.V2TXlog       0.0547      0.011      5.135      0.000       0.034       0.076
==============================================================================
Omnibus:                      711.027   Durbin-Watson:                   1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            24598.719
Skew:                           1.973   Prob(JB):                         0.00
Kurtosis:                      24.171   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        NESN5YEUAM=Rlog   R-squared:                       0.189
Model:                            OLS   Adj. R-squared:                  0.185
Method:                 Least Squares   F-statistic:                     49.13
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           2.06e-54
Time:                        09:05:27   Log-Likelihood:                 2604.7
No. Observations:                1273   AIC:                            -5195.
Df Residuals:                    1266   BIC:                            -5159.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0032      0.004      0.869      0.385      -0.004       0.011
x_PES          0.0003      0.001      0.287      0.775      -0.002       0.002
x_Mob          0.0014      0.001      1.098      0.273      -0.001       0.004
```

```
x_CS          -0.0017      0.002     -0.798      0.425      -0.006       0.003
.SSMIlog      -0.9127      0.123     -7.407      0.000      -1.154      -0.671
CH2YT=RR       0.0027      0.003      0.806      0.420      -0.004       0.009
.V2TXlog       0.0900      0.015      5.903      0.000       0.060       0.120
==============================================================================
Omnibus:                      180.260   Durbin-Watson:                   1.977
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2191.470
Skew:                           0.124   Prob(JB):                         0.00
Kurtosis:                       9.423   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        RUKN5YEUAM=Rlog   R-squared:                       0.234
Model:                            OLS   Adj. R-squared:                  0.230
Method:                 Least Squares   F-statistic:                     64.38
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           6.85e-70
Time:                        09:05:27   Log-Likelihood:                 2473.3
No. Observations:                1273   AIC:                            -4933.
Df Residuals:                    1266   BIC:                            -4897.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0108      0.004      2.610      0.009       0.003       0.019
x_PES         -0.0019      0.001     -1.546      0.122      -0.004       0.001
x_Mob          0.0002      0.001      0.140      0.889      -0.003       0.003
x_CS          -0.0052      0.002     -2.140      0.033      -0.010      -0.000
.SSMIlog      -0.4814      0.137     -3.524      0.000      -0.749      -0.213
CH2YT=RR       0.0064      0.004      1.697      0.090      -0.001       0.014
.V2TXlog       0.1911      0.017     11.309      0.000       0.158       0.224
==============================================================================
Omnibus:                      363.981   Durbin-Watson:                   2.006
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7890.561
Skew:                           0.786   Prob(JB):                         0.00
Kurtosis:                      15.095   Cond. No.                         241.
==============================================================================

                            OLS Regression Results
==============================================================================
Dep. Variable:        NOVB5YEUAM=Rlog   R-squared:                       0.050
Model:                            OLS   Adj. R-squared:                  0.045
Method:                 Least Squares   F-statistic:                     11.05
Date:                Thu, 17 Nov 2022   Prob (F-statistic):           4.96e-12
Time:                        09:05:27   Log-Likelihood:                 2524.8
No. Observations:                1273   AIC:                            -5036.
Df Residuals:                    1266   BIC:                            -5000.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0020      0.004      0.516      0.606      -0.006       0.010
x_PES          0.0017      0.001      1.452      0.147      -0.001       0.004
x_Mob          0.0004      0.001      0.324      0.746      -0.002       0.003
x_CS          -0.0031      0.002     -1.338      0.181      -0.008       0.001
.SSMIlog      -0.2123      0.131     -1.618      0.106      -0.470       0.045
CH2YT=RR      -0.0006      0.004     -0.169      0.866      -0.008       0.006
.V2TXlog       0.0713      0.016      4.396      0.000       0.040       0.103
==============================================================================
Omnibus:                      320.036   Durbin-Watson:                   2.249
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            17642.274
Skew:                          -0.161   Prob(JB):                         0.00
Kurtosis:                      21.235   Cond. No.                         241.
==============================================================================
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:       ZURB5YEUAM=Rlog   R-squared:                       0.248
Model:                           OLS   Adj. R-squared:                  0.245
Method:                Least Squares   F-statistic:                     69.67
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           4.55e-75
Time:                       09:05:27   Log-Likelihood:                 2429.1
No. Observations:               1273   AIC:                            -4844.
Df Residuals:                   1266   BIC:                            -4808.
Df Model:                          6                                         
Covariance Type:           nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0095      0.004      2.224      0.026       0.001       0.018
x_PES         -0.0006      0.001     -0.456      0.648      -0.003       0.002
x_Mob          0.0006      0.001      0.418      0.676      -0.002       0.003
x_CS          -0.0036      0.002     -1.427      0.154      -0.008       0.001
.SSMIlog      -0.6907      0.141     -4.883      0.000      -0.968      -0.413
CH2YT=RR       0.0076      0.004      1.974      0.049     4.8e-05       0.015
.V2TXlog       0.1889      0.017     10.796      0.000       0.155       0.223
==============================================================================
Omnibus:                     250.563   Durbin-Watson:                   2.052
Prob(Omnibus):                 0.000   Jarque-Bera (JB):             3608.167
Skew:                          0.470   Prob(JB):                         0.00
Kurtosis:                     11.194   Cond. No.                         241.
==============================================================================
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:       SYNN5YEUAM=Rlog   R-squared:                       0.148
Model:                           OLS   Adj. R-squared:                  0.144
Method:                Least Squares   F-statistic:                     36.66
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           4.11e-41
Time:                       09:05:27   Log-Likelihood:                 2630.1
No. Observations:               1273   AIC:                            -5246.
Df Residuals:                   1266   BIC:                            -5210.
Df Model:                          6                                         
Covariance Type:           nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0072      0.004      1.961      0.050   -4.32e-06       0.014
x_PES         -0.0010      0.001     -0.918      0.359      -0.003       0.001
x_Mob          0.0004      0.001      0.290      0.772      -0.002       0.003
x_CS          -0.0047      0.002     -2.200      0.028      -0.009      -0.001
.SSMIlog      -0.9129      0.121     -7.558      0.000      -1.150      -0.676
CH2YT=RR       0.0023      0.003      0.697      0.486      -0.004       0.009
.V2TXlog       0.0553      0.015      3.703      0.000       0.026       0.085
==============================================================================
Omnibus:                     840.835   Durbin-Watson:                   1.800
Prob(Omnibus):                 0.000   Jarque-Bera (JB):            60307.812
Skew:                          2.298   Prob(JB):                         0.00
Kurtosis:                     36.405   Cond. No.                         241.
==============================================================================
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:      ADEC5YEUAM=MGlog   R-squared:                       0.112
Model:                           OLS   Adj. R-squared:                  0.108
Method:                Least Squares   F-statistic:                     26.59
Date:               Thu, 17 Nov 2022   Prob (F-statistic):           6.16e-30
Time:                       09:05:27   Log-Likelihood:                 2685.7
No. Observations:               1273   AIC:                            -5357.
Df Residuals:                   1266   BIC:                            -5321.
Df Model:                          6                                         
Covariance Type:           nonrobust                                         
```

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0052	0.003	1.491	0.136	-0.002	0.012
x_PES	3.056e-05	0.001	0.030	0.976	-0.002	0.002
x_Mob	0.0002	0.001	0.159	0.874	-0.002	0.002
x_CS	-0.0026	0.002	-1.249	0.212	-0.007	0.001
.SSMIlog	-0.7971	0.116	-6.894	0.000	-1.024	-0.570
CH2YT=RR	0.0029	0.003	0.913	0.362	-0.003	0.009
.V2TXlog	0.0389	0.014	2.723	0.007	0.011	0.067

Omnibus:	267.110	Durbin-Watson:	2.434
Prob(Omnibus):	0.000	Jarque-Bera (JB):	4595.320
Skew:	0.474	Prob(JB):	0.00
Kurtosis:	12.260	Cond. No.	241.

OLS Regression Results

Dep. Variable:	HOLN5YEUAM=Rlog	R-squared:	0.242
Model:	OLS	Adj. R-squared:	0.238
Method:	Least Squares	F-statistic:	67.36
Date:	Thu, 17 Nov 2022	Prob (F-statistic):	8.16e-73
Time:	09:05:27	Log-Likelihood:	2753.4
No. Observations:	1273	AIC:	-5493.
Df Residuals:	1266	BIC:	-5457.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0053	0.003	1.598	0.110	-0.001	0.012
x_PES	-0.0008	0.001	-0.833	0.405	-0.003	0.001
x_Mob	0.0019	0.001	1.677	0.094	-0.000	0.004
x_CS	-0.0029	0.002	-1.519	0.129	-0.007	0.001
.SSMIlog	-1.0918	0.110	-9.959	0.000	-1.307	-0.877
CH2YT=RR	0.0031	0.003	1.026	0.305	-0.003	0.009
.V2TXlog	0.0737	0.014	5.434	0.000	0.047	0.100

Omnibus:	401.387	Durbin-Watson:	1.874
Prob(Omnibus):	0.000	Jarque-Bera (JB):	7004.336
Skew:	0.993	Prob(JB):	0.00
Kurtosis:	14.319	Cond. No.	241.